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Polarized Technologies*

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Abstract

We link U.S. patent and inventor records to individual voter register files and map politically polarized policy issues to related 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 and related technologies. These gaps are not explained by differences in inventive ability or by sorting across organizations or teams. Party-technology alignment has strengthened over the past two decades, a period of rising political polarization in U.S. society. Technology diffusion is also politically polarized: Democrats are more likely than Republicans to cite aligned technologies and less likely to cite misaligned ones. Together, these findings are consistent with political polarization and societal views being important drivers of the direction and diffusion of technological change and operating, at least in part, through inventors' technology choices, with implications for innovation policy.

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1. Introduction

Over the past decades, American society has become increasingly polarized, especially along partisan lines (Gentzkow, 2016, Bertrand and Kamenica, 2023, Desmet, Ortuño-Ortín and Wacziarg, 2025). While a large literature studies how this divide affects political behavior, its implications for economic activity are less well understood. In this paper, we study how political polarization shapes technological change by focusing on the *direction* of innovation—namely, which problems technologies are designed to address and, in turn, how the gains from technological progress are distributed across groups (Acemoglu, 2023).

We build on a growing body of evidence showing that innovation is shaped not only by incentives and technical opportunities, but also by inventors' identities and demographics, leading inventors to disproportionately develop innovations that benefit their own demographic group (Koning, Samila and Ferguson, 2020, 2021, Dossi, 2024, Einiö, Feng and Jaravel, 2025*a*,*b*). Because technologies are often designed to address specific needs and users, we hypothesize that heterogeneity in beliefs or preferences about which problems are important or worth solving can translate into systematic differences in the direction of innovation. For example, given sharp partisan differences in views on climate change, we examine whether inventors' political affiliations can shape the development of climate-mitigation technologies.

Our core finding is that inventors are more likely to develop and cite technologies aligned with the views associated with their political party. The evidence suggests that this alignment reflects, at least in part, inventors' choices over which technological problems to pursue, so that political views are reflected in the content of technological change. This interpretation aligns with a broader historical literature arguing that belief systems shape technological trajectories.[1]

We assemble a novel dataset combining the universe of U.S. patent and inventor records from the United States Patent and Trademark Office between 2001 and 2023 with voter registration data from four large U.S. states. Voter files provide individual-level information on party affiliation and demographics, allowing us to link a large share of inventors to their political affiliation. We focus on Florida, New Jersey, New York, and Pennsylvania, which are among the most innovative states and operate closed primary systems, creating strong incentives to register with a political party. We study technologies related to three highly polarized policy issues with a clear mapping to patentable innovation: climate change mitigation, women's reproductive health, and weapon-related technologies.

To discipline interpretation and guide the analysis, we develop a simple conceptual frame-

[1] For example, Mokyr (2016) argues that the Enlightenment fostered a "culture of growth" that redirected innovative effort toward socially valued forms of useful knowledge.

work in which inventors derive non-monetary returns from working on technologies aligned with the views of their political party. The framework highlights how differences in the perceived value of a technology—whether driven by beliefs about future returns or by preferences—can generate systematic sorting of inventors across technologies, even in the absence of skill or organizational differences. Guided by this framework, we document new empirical patterns.

First, we find systematic alignment between inventors' party affiliation and the technologies they develop. Compared to Republican inventors, Democrats are 31% more likely to patent green technologies and 35% more likely to patent technologies related to women's health, while they are 39% less likely to patent weapon-related technologies. The magnitude of these differences closely mirrors partisan gaps in public opinion: a 10 percent divide in views on a given issue is associated with a similar 10 percent divide in inventors' propensity to patent technologies addressing that issue.

These results are robust across a wide range of specifications and are present at both the extensive margin–whether an inventor ever patents a given technology–and the intensive margin, measured by the number and share of patents. They also 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. To address concerns about reverse causality, we restrict attention to inventors whose party affiliation was registered at age twenty-one or younger and find similar results. We further show that the findings extend beyond the four-state sample using an alternative measure of political affiliation based on campaign contributions.

Second, we examine the mechanisms underlying party-technology alignment by assessing whether it reflects differences in inventive skills, organizational environments, or inventors' own choices over which technological problems to pursue. Alignment is equally present among inventors with comparable citation intensity, which proxies for their inventive skills. It also persists when restricting comparisons to narrowly defined technological classes and when contrasting polarized technologies with closely related "placebo" technologies that draw on similar specific knowledge and skills. This points to inventors' own technological choice rather than the underlying capabilities required to produce it as the main driver of the alignment. Finally, alignment is equally strong among highly cited patents, suggesting that it reflects not only reallocation within existing technological trajectories but also the direction of the technological frontier.

We then study the role of organizations. Party-technology alignment is present in both small and large organizations, in politically homogeneous and heterogeneous workplaces, and remains economically meaningful when conditioning on organization fixed effects. Alignment also persists in settings where inventors plausibly enjoy greater autonomy over research direction, including among academic researchers and for solo-authored patents. Taken together, these findings suggest that alignment is primarily driven by inventors' own technology choices rather than by differences in skills, hiring, or project assignment.

Third, we show that party-technology alignment has strengthened over time. By 2015, a Democratic inventor who has not previously patented in these domains is 47% more likely than a Republican to patent green technologies, 63% more likely to patent female-health technologies, and 121% less likely to patent weapon-related technologies. Similar patterns hold when we restrict the analysis to older cohorts that were already active at the start of the sample. In this subsample, the widening gaps are driven primarily by within-career reallocation toward or away from polarized technologies, rather than by differential sorting into these domains based on fixed characteristics—such as parental background—that may independently shape both party affiliation and technology choice. These dynamics persist across a wide range of specifications comparing inventors within narrowly defined geographic and technological environments, suggesting that differential labor- or product-market demand faced by Democratic and Republican inventors is unlikely to explain the results. Instead, the widening gaps point to party-specific differences in perceived returns or other non-monetary payoffs playing an important role. Consistent with this interpretation, the strengthening of alignment coincides with a period of rising partisan polarization in U.S. public opinion, both overall and on these three policy issues.

Fourth, we examine how polarization shapes the diffusion of new technologies. Inventors disproportionately build on technologies aligned with their views and avoid unaligned ones, indicating that polarization affects not only what gets invented but also how knowledge spreads. Relative to Republicans, Democrats are 13% more likely to cite green technologies, 19% more likely to cite women's health technologies, and 27% less likely to cite weapon-related technologies. These gaps persist when excluding citations originating from patents within the same technology, ruling out the possibility that the results are mechanically driven by within-technology citation. Party-based homophily in knowledge networks explains part of these differences, while technological content itself also plays an independent role.

Finally, we return to the conceptual framework to discuss implications for innovation policy. Within the framework, technological alignment enters inventors' utility as a non-monetary return, creating a wedge relative to a benchmark in which only monetary incentives matter. If the distribution of alignment types across inventors varies across technologies, the effective supply of inventor labor will differ across technologies even when wages are the same. As polarization increases, this wedge grows: inventive effort shifts toward aligned domains even when pecuniary incentives are held fixed, and subsidies or other price-based instruments may need to compensate not only for technological or financial constraints but also for non-monetary misalignment. As a result, polarization can reshape the allocation of inventive effort across domains and, in turn, the direction of technological change, and may raise the fiscal cost of policies that seek to steer innovation toward or away from politically polarized technologies.

While existing work has emphasized how technological change influences societal polarization (e.g., Rodrik, 2017, Acemoglu and Restrepo, 2020), our findings suggest that *polarization itself* can shape technological change by influencing inventors' research choices. In polarized environments, policies that rely primarily on price incentives or demand-side subsidies may have limited ability to redirect inventive effort if research choices are constrained by political or ideological misalignment. More generally, these results suggest that societal shifts in views may affect technological change not only through product demand (Besley and Persson, 2023), but also through the *supply* of new technologies, by shaping inventors' willingness to work on particular domains. Because technological change is cumulative and path-dependent, these forces can have lasting consequences for innovation trajectories and for the distribution of gains from technological progress.

Related Literature. This paper relates to three strands of literature. First, we contribute to work on the economic implications of partisanship and political polarization. Prior research shows that political affiliation shapes a wide range of household decisions, including consumption (Gerber and Huber, 2009, Conway and Boxell, 2024), financial and real estate investment (Kaustia and Torstila, 2011, Meeuwis, Parker, Schoar and Simester, 2021, McCartney, Orellana and Zhang, 2021), health behaviors and outcomes (Allcott, Boxell, Conway, Gentzkow, Thaler and Yang, 2020, Wallace, Goldsmith-Pinkham and Schwartz, 2023, Bursztyn, Kolstad, Rao, Tebaldi and Yuchtman, 2025, Kim, 2025), and fertility (Dahl, Lu and Mullins, 2022). Political polarization has also been shown to affect labor market outcomes, including productivity (Teso, Spenkuch and Xu, 2023, Engelberg, Lu, Mullins and Townsend, 2025), hiring practices (Gift and Gift, 2014, Colonnelli, Pinho Neto and Teso, 2025, Colonnelli, McQuade, Ramos, Rauter and Xiong, 2025), occupational choice (McConnell, Margalit, Malhotra and Levendusky, 2018, Engelberg, Guzman, Lu and Mullins, 2022, Colonnelli, McQuade, Ramos, Rauter and Xiong, 2023, Adrjan, Gudell, Nix, Shrivastava, Sockin and Starr, 2024), and on-the-job decisions (e.g., Cohen and Yang, 2019, Boxell and Conway, 2022, Jelveh, Kogut and Naidu, 2024, Louis-Sidois, 2025). Recent work further documents extensive political sorting across colleges, occupations, industries, and employers, leading to substantial partisan segregation in the workplace (Chinoy and Koenen, 2024). Our paper is also related to contemporaneous work studying how political sentiment affects the *volume* of innovation

(Engelberg, Lu, Mullins and Townsend, 2025).[2] To the best of our knowledge, we are the first to link partisan differences to the *content* of innovative activity–specifically, to the direction of innovation.

Second, we contribute to the literature on the determinants of the direction of technical change. Recent theoretical work emphasizes that innovation may be distorted away from socially desirable outcomes by market incentives, externalities, and policy environments (e.g., Bryan and Lemus, 2017, Hopenhayn and Squintani, 2021, Acemoglu, 2023). Complementing this work, a growing empirical literature shows that the content of innovation reflects inventors' backgrounds, identities, and experiences. Exposure to specific technologies in childhood increases the likelihood of innovating in those domains later in life (Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018). Female scientists disproportionately develop innovations related to women's health (Koning, Samila and Ferguson, 2020, 2021), and inventors exhibit systematic homophily between their demographic characteristics and the consumers of their products (Einiö, Feng and Jaravel, 2025*b*). Related research highlights the role of institutional and social environments: exposure to gender diversity in universities increases gender-related research output (Truffa and Wong, 2025), scientists' race is linked to the content of their research (Dossi, 2024), and inventors disproportionately patent technologies addressing pathogens prevalent in their country of residence (Moscona and Sastry, 2025). We extend this literature by documenting a systematic link between inventors' political party affiliation and the direction of innovation, and by showing that political polarization and societal views can shape both which technologies are developed and how innovative effort is allocated across domains.

Third, we contribute to the literature on the diffusion of innovation and the role of social networks. Social interactions play a central role in knowledge exchange and spillovers (e.g., Jaffe, Trajtenberg and Henderson, 1993, Jaffe, Trajtenberg and Fogarty, 2000, Singh, 2005, Atkin, Chen and Popov, 2022). Recent evidence shows that homophily in network formation affects citation patterns and citation counts, particularly for female researchers and inventors (Subramani and Saksena, 2025). To the best of our knowledge, we are the first to show that inventors' political party shapes the diffusion of innovation.

The rest of the paper is organized as follows. Section 2 describes the data construction and validation. Section 3 outlines the conceptual framework. Section 4 presents the main results and robustness checks. Section 5 discusses the mechanisms. Section 6 describes the evolution of party-technology alignment over the period of analysis. Section 7 presents the result on diffusion, and Section 8 discusses the implications. Section 9 discusses our findings

[2] Engelberg, Lu, Mullins and Townsend (2025) document that overall patenting by U.S. inventors increases when a president of their own party is in power.

and concludes.

2. Data

This paper combines administrative patent records from the United States Patent and Trademark Office (USPTO) with voter registration files that provide information on individuals' party affiliation and demographics. The resulting voter-inventor dataset covers four U.S. states and includes approximately 100,000 inventors. Section 2.1 describes the construction and validation of the dataset. Section 2.2 defines polarized technologies, and Section 2.3 discusses why party affiliation provides a suitable proxy for inventors' views on polarized policy issues.

2.1. The Matched Inventor-Political Affiliation Dataset

We begin with data from PatentsView, a database maintained by the USPTO that provides information on inventors' names and cities of residence, as well as patent grant dates, assignees, titles, abstracts, technology classifications, and forward citations.[3] We restrict the sample to utility patents–the most common type issued by the USPTO and encompassing virtually all types of inventions–granted between 2001 and 2023.

We merge the patent data with voter registration files, which provide information on the party affiliation of registered voters and other demographic characteristics. Voter registration is required to participate in state and federal elections, and voter files therefore cover a large share of the eligible population: as of November 2020, 73% of adults eligible to vote were registered.[4] Non-registration is concentrated among younger, lower-income, and less-educated individuals and among racial and ethnic minorities (Table A.18). By contrast, inventors are disproportionately white (Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018, Akcigit and Goldschlag, 2025), highly educated (Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018), approximately 45 years old at the time of application (Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018, Kaltenberg, Jaffe and Lachman, 2023), and have relatively high incomes. As a result, voter registration among inventors is likely substantially higher than the national average, and the voter files should capture a large share of inventors eligible to vote.

We use voter registration data from four states: Florida (FL), New Jersey (NJ), New York (NY), and Pennsylvania (PA). These states are among the most innovative in the

[3] Patents are classified using the Cooperative Patent Classification (CPC) system, which is organized hierarchically into sections, classes, subclasses, groups, and subgroups.

[4] `https://www.census.gov/data/tables/time-series/demo/voting-and-registration/p20-585.html`. Table A.17 reports the distribution of registered voters in our voter register data.

United States during the period of analysis (Figure A.8) and operate closed primary systems, under which voters must register with a political party to participate in primary elections. Closed primaries substantially increase the observability of party affiliation: data from the Cooperative Congressional Election Study (CCES) show that registered voters in closed-primary states are more than twice as likely to be listed as Democrats or Republicans than those in open-primary states, even though overall registration rates are similar.[5]

Voter files contain information on each registrant's name, gender, date of birth, registration date, address, zip code, and party affiliation at the time of registration. Our analysis draws on voter-file snapshots from 2017, 2020, and 2022: we use 2020 records for New York and Pennsylvania, 2017 and 2022 records for Florida, and 2022 records for New Jersey (Sood, 2017, 2020*a*,*b*). Consistent with the timing of these snapshots, matched patents are concentrated in more recent years (Figure A.1).

Following standard practice in the literature, we treat party affiliation as time-invariant (Cohen and Yang, 2019, Teso, Spenkuch and Xu, 2023).[6] We link inventors to voters using exact names and city of residence, matching 304,229 unique patents out of 573,324, a match rate of 53%. Appendix Section D describes the matching procedure in detail.

Match validation. We validate the matching in three ways. First, we conduct two qualitative benchmarking exercises, comparing the observable characteristics of matched inventors to those reported in the prior literature and, separately, to the universe of registered voters. In both cases, differences are consistent with existing evidence and go in the expected direction (Appendix Section D.3.3). Second, we use campaign contribution data (Bonica, 2019) as an alternative way to define political affiliation. This approach allows us to span all U.S. states, though contributions are less common than voter registration, yielding a lower match rate of 24% of patents. Third, we assess potential selection into the matched sample using equivalence tests (Table 1).[7] We test the null that matched and unmatched inventors differ by more than 10% of a standard deviation across 20 characteristics related to demographics, location, and patenting activity. We reject this null for all but one characteristic. Matched and unmatched inventors have similar name length and consonant counts–proxies for socioeconomic background–as well as comparable gender, income, and city population. They also patent in similar technological sections and produce patents of comparable impact,

[5]From the CCES data, we compute that 76% of registered voters in closed-primary states are listed as Democrats or Republicans, compared with 30% in other states. These differences are similar among college-educated, high-income individuals–the demographic profile of inventors.

[6]Teso, Spenkuch and Xu (2023) report that only 2.6% of U.S. bureaucrats switch party affiliation between Democrat and Republican between 2014 and 2020.

[7]Following the literature, we use equivalence tests. Compared to difference tests, these are more appropriate in large samples and avoid over-rejecting the null of no meaningful difference (e.g., Teso, Spenkuch and Xu, 2023).

measured by forward citations.[8] Matched inventors receive patents slightly later on average (2014 versus 2013), consistent with the timing of the voter-file snapshots.[9]

Table 1: 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)
Female	0.134	0.341	0.151	0.358	-0.047	0.000
N. Consonants First Name	3.682	1.141	3.609	1.254	0.060	0.000
N. Consonants Middle Name	0.826	1.284	0.726	1.282	0.078	0.000
N. 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 Income (Log)	12.680	1.397	12.580	1.364	0.073	0.000
City-level Population (Log)	11.030	1.819	10.990	1.711	0.023	0.000
A Section	0.285	0.435	0.291	0.443	-0.012	0.000
B Section	0.197	0.368	0.172	0.358	0.068	0.000
C Section	0.162	0.349	0.192	0.383	-0.083	0.000
D Section	0.010	0.087	0.010	0.091	-0.001	0.000
E Section	0.043	0.191	0.034	0.174	0.047	0.000
F Section	0.100	0.281	0.081	0.260	0.072	0.000
G Section	0.366	0.452	0.358	0.459	0.018	0.000
H Section	0.235	0.395	0.260	0.420	-0.061	0.000
Y Section	0.151	0.316	0.151	0.329	0.001	0.000
Grant Year	2014	6.358	2013	6.822	0.149	1.000
N. 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-test 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. Referenced on page: 7.

Descriptive statistics. The final sample includes 95,600 unique inventors, of whom 90.6% are linked to more than one patent. Inventors are uniquely identified using first, middle, and last name and city of residence. The shares of registered Democrats and Republicans are similar (36% and 35%), while 26% are unaffiliated and 3% are affiliated with minor parties. Table 2 reports summary statistics by party. Compared to Republican inventors, Democrat inventors are twice as likely to be female (18% versus 9%), are on average three years younger,

[8]Because patents may span multiple CPC sections, we compute inventor-level shares across sections.

[9]Figure A.1 reports the distribution of, respectively, patent grant year and inventor age within our sample.

Table 2: Descriptive Statistics

	Democrat		Republican		Democrat-Republican	
	Mean (1)	Standard Deviation (2)	Mean (3)	Standard Deviation (4)	Standardized Difference (5)	P-value Difference Test (6)
Female	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 ($K)	120.0	50.8	110.0	40.1	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). Referenced on page: 8.

and reside in slightly wealthier zip codes ($120k versus $110k).[10] Party affiliation is also associated with differences in broad technological focus: for example, 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 (Table A.1).

2.2. Mapping Views to the Content of Innovation

To link views to the content of innovation, we focus on three policy issues at the center of contemporary political debate: climate change, women's reproductive rights, and gun control. Using data from the Cooperative Congressional Election Study (CCES), Figure 1 shows that party affiliation is systematically associated with views on each of these issues in the general population as well as among high-income, college-educated respondents–demographic groups

[10]We use gender as reported in the voter records when available and rely on the imputed measure from USPTO data when missing.

that closely resemble the inventor population.[11]

For each domain, we construct an index by harmonizing survey responses to a common scale, where higher values correspond to more liberal positions (e.g., greater support for climate action). To account for demographic and geographic differences, we residualize these indices on individual demographic characteristics and then compute mean adjusted views by party of registration. Relative to Republicans, Democrats are 30% more likely to support urgent action on climate change, 37% more likely to support abortion rights, and 37% more likely to favor restrictions on gun sales and use. Individuals registered as unaffiliated or with third parties hold views that are, on average, approximately halfway between those of Democrats and Republicans.

We focus on these three issues as they exhibit substantial partisan polarization and have a clear mapping to patentable technologies: among all policy domains covered by the CCES–which also includes questions on support for public health care, immigration, trade, taxation, and affirmative action–these are the ones that can be directly linked to clearly defined technological domains.[12]

The association between these issues and party identity has emerged relatively recently: abortion, gun regulation, and environmental protection did not constitute consistent partisan cleavages for much of the twentieth century and were not tightly aligned with party identity through the 1970s and 1980s. Over subsequent decades, partisan sorting and coalition changes gradually made them central components of party identity (e.g., Desmet, Ortuño-Ortín and Wacziarg, 2025, Longuet-Marx, 2025).[13] Because the alignment between parties and these issues developed over time, the relationship between party affiliation and related technologies is unlikely to reflect fixed, long-standing differences across political groups, but rather increased party-based polarization.

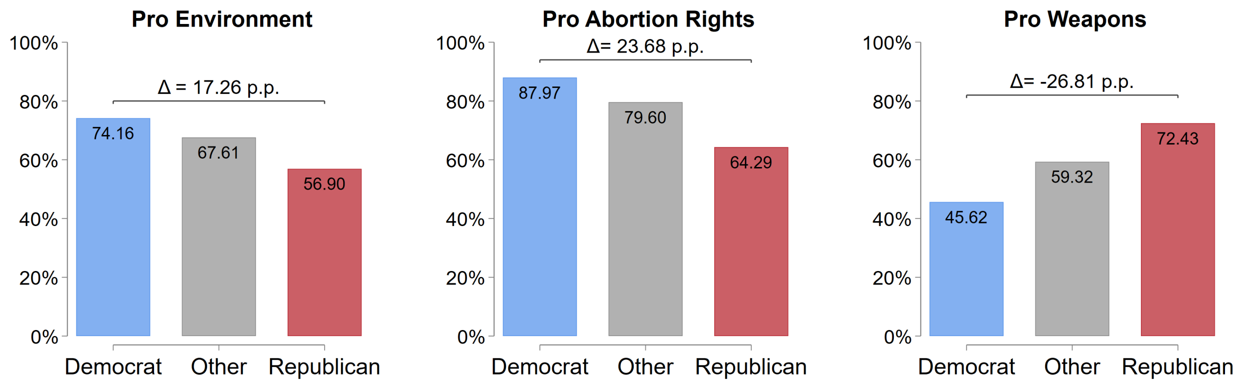
[11] Similar results hold—in the general population and in the subsample with the characteristics of inventors—using data from the General Social Survey (GSS) (Figure A.7). Here, we can define the sample similar to inventors based on detailed occupation (not reported in the CCES) and education codes. The CCES is our preferred evidence as it reports information on party registration (rather than leaning), and detailed geography (rather than macro-area).

[12] Appendix Section B provides additional evidence on partisan gaps across the full set of CCES topics.

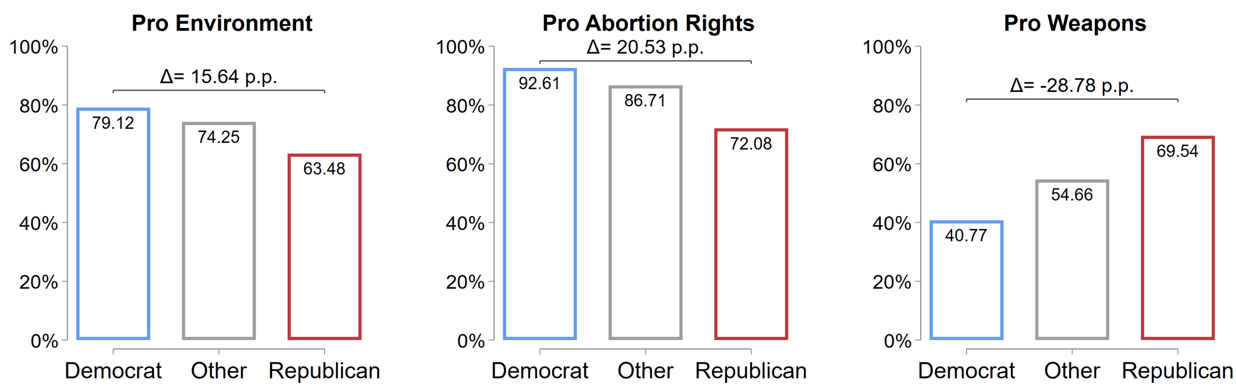
[13] Abortion was not a stable partisan cleavage for much of the twentieth century. Survey evidence from the 1970s indicates that abortion attitudes were more strongly associated with religiosity than with party affiliation, and both major parties contained substantial pro- and anti-abortion constituencies (e.g., Adams, 1997). Environmental protection enjoyed broad bipartisan support through the 1970s, but climate change became increasingly polarized in subsequent decades, with large and widening partisan gaps emerging since the 1990s (e.g., McCright and Dunlap, 2011). While gun policy has long been politically contested, attitudes toward gun control were historically structured more by regional and rural–urban cleavages. Only in recent decades did gun policy become sharply polarized along partisan lines (e.g., Layman, 2002).

Figure 1: Support by Issue and Party Affiliation, CCES

Panel A: Full Sample



Panel B: Sample With the Characteristics of Inventors



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. Panel A restricts the sample to US citizens, excluding individuals with no record or unknown party registration. This sample includes 111,208 respondents. Panel B further restricts the sample to respondents aged 25-55, employed full-time, college-educated, and with high-income to approximate inventors' demographics. This sample includes 4,331 respondents. The y-axis reports the percentage of respondents supporting a given issue, residualized by age of respondents and fixed effects for county, year, employment status, female, race, education, and family income. Each variable is constructed by harmonizing related CCES questions into three discrete values (0, 0.5, 1) and rescaling them to be in the range [0, 100]. On the x-axis, "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. Δ indicates the percentage point difference in support for each issue between registered Democrats and Republicans. Referenced on pages: 9, 13, A.29.

Technology classification. We map views on climate change to green technologies, views on women's reproductive rights to female-health technologies, and views on gun control to weapon-related technologies.[14] Our preferred measure identifies patents that explicitly signal an intent to address a given policy issue. We classify a patent as green if its abstract includes climate-related terms such as "global warming" or "reduction of carbon dioxide;" as related to female health if it mentions organs or diseases that disproportionately affect women due to biological sex differences, such as "endometriosis" or "abortion;" as weapon-related if it includes terms referring to weapons or their components, such as "handgun" or "ammunition." To limit false positives, we further restrict the sample using Cooperative Patent Classification (CPC) codes. Green technologies are required to fall within CPC class Y02 ("Technologies or Applications for Mitigation or Adaptation Against Climate Change"), while weapon-related technologies must belong to classes F41 ("Weapons") or F42 ("Ammunition; Blasting"). Because no single CPC class captures female-health innovations, we identify these patents using a combination of health- and women-related CPC classes. Appendix Section D.5 provides full details.[15]

In addition to the dictionary approach, we implement two complementary classification strategies. First, we construct a measure based on a large language model (LLM) that prompts identification of the main policy-related intent of each patent based on its abstract (Appendix Section A.2.2). Second, we build outcome variables based exclusively on CPC codes, abstracting from textual content (Appendix Section A.2.3). Both approaches yield qualitatively similar results. We adopt the dictionary-based measure as our preferred specification for four reasons. First, it captures explicit references to policy-related terms in the patent text. The LLM measure instead infers the primary policy-related intent of each patent, which is conceptually distinct and useful when policy orientation is central to the invention. However, patents frequently reference multiple issue domains or mention policy concerns that are not the dominant focus of the abstract. Restricting classification to a single inferred intent may therefore omit substantively relevant content. Second, the dictionary applies fixed, pre-specified keyword rules symmetrically across patents. By contrast, LLM classifications rely on contextual semantic inference. If partisan groups systematically differ in how they describe similar technologies, interpretation-based classification may introduce differential measurement error correlated with party affiliation. Substantively comparable patents could thus receive different labels simply because they employ language more com-

[14] We interpret views on abortion rights as capturing broader differences in views regarding women's reproductive autonomy and investment in female-specific medical care, which plausibly shape innovation in women's health more broadly. Consistent with this interpretation, data from the General Social Survey (GSS) and the Pew Research Center document large partisan divides in support for women's rights and gender equality.

[15] Specifically, for female-health patents we restrict attention to CPC classes: A41, A61, C07, C12, G01, and G06. In manual audits of 100 randomly selected patents per category, 91% of green, 80% of female-health, and 95% of weapon-related classifications were confirmed as true positives.

mon in Democratic versus Republican discourse. Third, the dictionary measure provides a more targeted mapping than CPC-based classifications. CPC codes are relatively coarse and are assigned by patent examiners rather than inventors and, as such, they reflect technological function or legal scope rather than the policy-relevant motivation behind the invention. For example, CPC group Y02A50/30 ("Against vector-borne diseases") includes technologies addressing mosquito- or waterborne diseases that are not necessarily related to climate change mitigation. Examiner-assigned classes may therefore fail to capture policy intent from the inventor's perspective. Fourth, because inventors searching for prior art typically rely on keyword searches of abstracts, the dictionary measure also proxies how patents are framed, perceived, and discovered by other innovators.

These three polarized domains account for a small share of overall patented invention: under our preferred (intentionally conservative) classification, they represent about 1.5% of USPTO utility patents granted over 2001–2023. We nonetheless focus on these technologies because they are tightly connected to policy-relevant issues with large social externalities and distributional consequences—climate-change mitigation, women's reproductive health, and weapons—so even modest shifts in innovative effort can have meaningful downstream effects.[16] Moreover, the 1.5% figure should be interpreted as a lower bound on the extent of politically polarized innovation: political content is likely present in a broader set of technologies, but it is harder to measure when issue linkages are diffuse or when patent text does not explicitly signal policy intent. Our approach therefore trades off breadth for measurement precision by focusing on domains where the mapping from views to technologies is transparent.

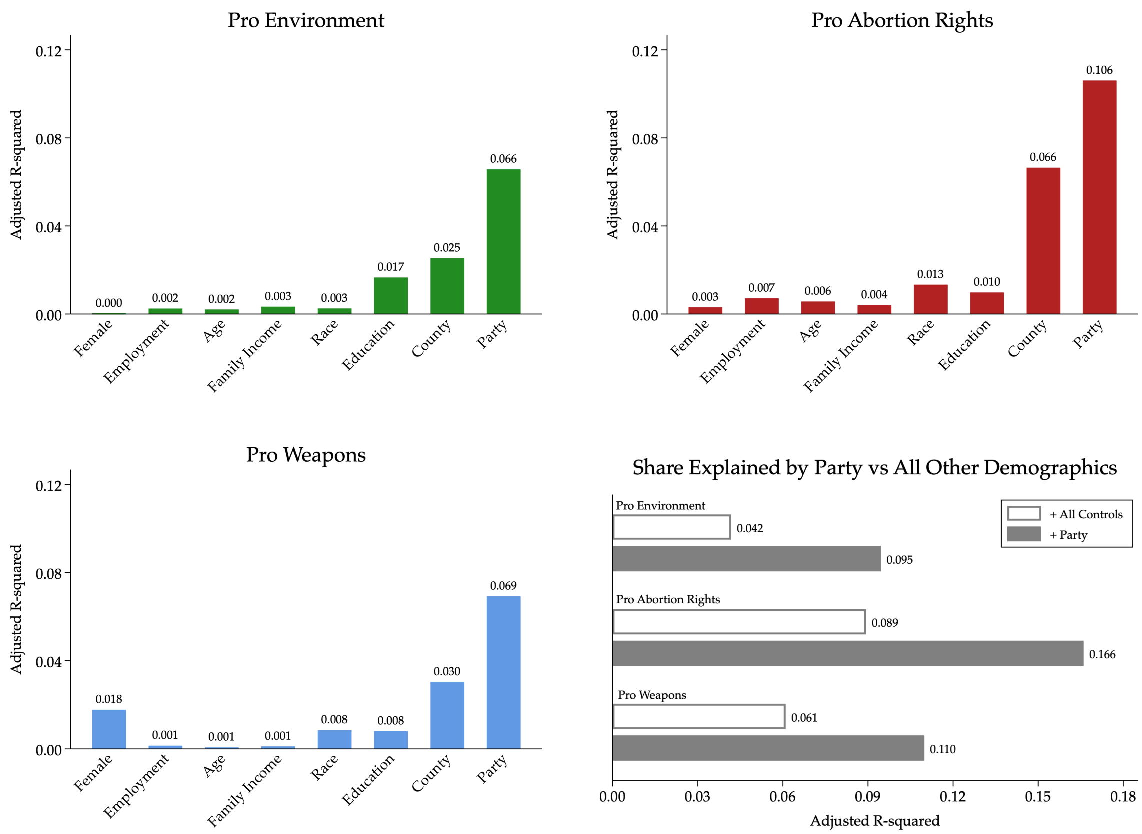
2.3. Why Focus on Party Affiliation?

Our analysis studies the role of individuals' views in driving innovation, asking whether inventors' perceptions of which problems are socially important influence the technologies to which they direct their inventive effort. We use party affiliation as a proxy for views for two reasons. First, it explains a substantially larger share of variation in views in U.S. society than other observable demographic characteristics. Figure 2 illustrates this point: across the three policy issues, party affiliation has the highest explanatory power among demographic

[16] In the climate domain, a large literature documents that emissions-reducing technologies can generate substantial positive externalities through improved air quality, including on health outcomes (e.g., Deryugina, Heutel, Miller, Molitor and Reif, 2019, Baran, Currie, Dursun and Tekin, 2025). In the reproductive-health domain, innovations and access conditions can have first-order consequences for women's life-cycle outcomes and inequality (Goldin and Katz, 2002, Bailey, 2006). In the defense domain, innovation can generate economically meaningful spillovers beyond the military application through dual-use technologies and knowledge diffusion (Moretti, Steinwender and Van Reenen, 2025).

variables, often exceeding that of other characteristics by an order of magnitude. Even when conditioning on a full set of demographic controls, party affiliation alone explains as much as—and in some cases up to twice as much as—the combined contribution of all other observable characteristics.[17]

Figure 2: Share Explained by Demographics and Party Affiliation



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. The sample includes US citizens who are registered as either Democrats or Republicans (variable `vv_party_gen`). This sample includes 111,208 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," "Pro Abortion Rights," and "Pro Weapons" like in Figure 1. "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. Referenced on pages: 13, 20.

Second, party affiliation does not merely reflect pre-existing views but also actively shapes

[17]For example, women are 4% more likely than men to support abortion rights, whereas Democrats are 35% more likely to do so than Republicans, with similarly large partisan gaps within gender (own calculations from CCES data). A comparable but smaller pattern emerges for support of women's rights: women are 2% more likely than men to express supportive views, while party affiliation explains a substantially larger share of the variation (12%) (own calculations from the General Social Survey (GSS) over the same period).

them. A growing body of evidence shows that parties and broader processes of political polarization influence individuals' beliefs and attitudes over time, reinforcing alignment along partisan lines rather than simply aggregating fixed preferences (e.g., Gennaioli and Tabellini, 2025). As a result, party affiliation captures both individuals' underlying views and the social and informational environments that shape how those views evolve.

3. Conceptual Framework

This section develops a parsimonious framework to formalize how inventors' party affiliation can shape the direction of innovation, with the purpose of deriving testable implications that discipline the empirical analysis. We first describe the economic environment (Section 3.1). We then specify inventors' preferences and technology choice (Section 3.2) and derive implications that guide the empirical analysis in the remainder of the paper (Section 3.3).

3.1. Environment

We consider a static environment populated by a unit mass of inventors indexed by $i \in [0, 1]$. Inventors operate within a given technological field (e.g., a CPC class) and choose among technology domains $j \in \mathcal{J}$ within that field. Some domains are politically polarized (e.g., solar panels), while others are politically neutral (e.g., semiconductors). Each inventor is affiliated with a political group $g \in \{D, R, O\}$, which proxies for a broader ideological identity bundling views over salient policy and social issues. Let θ_g denote the population share of inventors affiliated with group g, with $\theta_D + \theta_R + \theta_O = 1$. We treat these shares as exogenous. Let a_{gj} denote the alignment between political group g and technology j. Higher values indicate stronger alignment, while negative values capture misalignment. For politically neutral technologies, $a_{gj} = 0$ for all g.[18]

3.2. Utility and Technology Choice

Inventors derive utility from wages and from alignment between their political views and the technology they work on. Utility from working on technology j is:

$$U_{ij} = w_j + \rho \cdot a_{g(i)j} + \varepsilon_{ij} \tag{1}$$

[18] The term a_{gj} can be interpreted as a continuous index of ideological alignment between political group g and the policy issue underlying technology j. Empirically, this alignment can be proxied using party-specific support for the corresponding issue in survey data such as the CCES.

where w_j denotes the market return in technology j, ε_{ij} is an idiosyncratic shock, and $\rho \geq 0$ governs the salience of political alignment in decision-making. Inventors choose the technology that maximizes utility:

$$j^*(i) = \arg\max_{j \in \mathcal{J}} U_{ij} \tag{2}$$

Under standard random-utility assumptions, the share of inventors from group g working on technology j corresponds to:

$$\Pr(j^*(i) = j \mid g(i) = g) \tag{3}$$

which is increasing in a_{gj} and in ρ.

Interpretation of subjective alignment returns. The term $\rho \cdot a_{g(i)j}$ is a reduced-form representation of the perceived value of a technology to an inventor, capturing two potential channels. First, inventors affiliated with different political groups may hold systematically different beliefs about the future financial returns to working on a given technology. For example, if Democrat inventors expect carbon emissions to become heavily taxed, they may anticipate higher future earnings from working on green technologies. This mechanism is consistent with evidence of partisan polarization in beliefs about economic and policy-relevant facts (e.g., Alesina, Miano and Stantcheva, 2020). Differences in expectations about regulation, public investment, or market growth can therefore translate into different subjective expected returns across political groups.

Second, inventors may derive direct non-monetary utility or disutility from working on specific technologies, independently of financial returns. This channel is consistent with evidence that non-pecuniary job characteristics are important determinants of occupational choice (e.g., Stern, 2004, Cassar and Meier, 2018, Burbano, Padilla and Meier, 2024). Utility may derive from producing innovation aligned with one's own views, or from a desire to align with the views of one's political party due to social image concerns (e.g., Bénabou and Tirole, 2006).[19] In reduced form, both channels operate as subjective returns that shift the relative attractiveness of technologies, generating sorting even if current wages are identical.

3.3. Predictions for Technology Choice

Throughout, we assume that wages and skill requirements are comparable across technologies within a given field and that there are no informational or access barriers.[20] Under these

[19]Comparable identity-based labor supply gaps arise in other high-skill labor markets. For example, physicians decline to provide abortion or reproductive services on grounds of conscience or religious belief, even when financially compensated (e.g., Curlin, Lawrence, Chin and Lantos, 2007, Chavkin, Leitman, Polin and for Choice, 2013).

[20]We abstract from party-based discrimination in hiring or project assignment (e.g., Colonnelli, Pinho Neto and Teso, 2025) to restrict attention to supply-side mechanisms.

assumptions, sorting reflects supply-side alignment rather than skills or wages. We derive two predictions to guide the empirical analysis.

Prediction 1. If technology j is more strongly aligned with Democrats than with Republicans, so that $a_{Dj} > a_{Rj}$, then:

$$\Pr(j^*(i) = j \mid g(i) = D) > \Pr(j^*(i) = j \mid g(i) = R) \tag{4}$$

The magnitude of this difference increases with the alignment gap $(a_{Dj} - a_{Rj})$ and with the salience parameter ρ.

Prediction 2. Suppose that political polarization evolves over time, either through widening issue-specific alignment gaps $(a_{Djt} - a_{Rjt})$ or through an increase in the salience parameter ρ_t. Then cross-group differences in technology choice widen over time:

$$\frac{\partial}{\partial t}\Big[\Pr(j^*(i) = j \mid g(i) = D) - \Pr(j^*(i) = j \mid g(i) = R)\Big] > 0 \tag{5}$$

In particular, among inventors not previously active in technology j, increases in alignment a or salience ρ induce differential entry into aligned domains, generating widening gaps along the extensive margin even when wages and skills remain comparable.[21]

4. Empirical Results

This section provides empirical evidence on the alignment between inventors' party affiliation and the technologies they patent. Section 4.1 outlines the empirical specification. Section 4.2 presents the main findings and Section 4.3 discusses the robustness of the results.

4.1. 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 to a green, female health, or weapon-related technology, and zero otherwise:

$$y_i = \beta_1 \text{Democrat}_i + \beta_2 \text{Other}_i + \beta_3 \text{Female}_i + \gamma_{t(i)} + \delta_{c(i)} + \zeta_{s(i)} + \mu_{a(i)} + \epsilon_i \tag{6}$$

where i denotes an inventor, $t(i)$ the year a patent has been granted to inventor i, $c(i)$ the county of residence of inventor i, $s(i)$ the technology-section of the patents granted to inventor i, and $a(i)$ the birth year of inventor i. "Democrat" is an indicator equal to one if

[21] Appendix C presents a stylized two-technology case illustrating these comparative statics.

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," which is an indicator equal to one if an inventor is a registered Republican, and equal to zero otherwise.

Year dummies $\gamma_{t(i)}$, which equal one if inventor i is active (i.e., is granted a patent) in year t, absorb common time shocks to the propensity to patent in technology j (e.g., national policy, funding, or technology-wide booms) as well as changes in the composition of active inventors over time. County fixed effects $\delta_{c(i)}$ absorb persistent local factors—industry mix, local innovation ecosystems, and local political context that may jointly correlate with party affiliation and technology choice. Technology-section fixed effects $\zeta_{s(i)}$ control for sorting of inventors into broad technological fields and related education and skills. We also include birth-year fixed effects $\mu_{a(i)}$ and a female indicator, since both covary with party affiliation and may also be correlated with the propensity to patent in 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 in propensity between a female and a male inventor. Standard errors are clustered at the county level to account for within-county correlation in unobserved shocks.

4.2. Party-Technology Alignment

We begin by testing Prediction 1 of Section 3, namely that inventors are more likely to patent technologies that are more closely aligned with their party's views. In Table 3, we report estimates of Equation (6) for the sample of inventors matched to voter registration data. Each column reports a "scaled difference," defined as $\hat{\beta}_1$ divided by the mean of the dependent variable among Republican inventors. Thus, in each panel we present the difference in the average propensity of Democratic and Republican inventors to patent in technology j, scaled by the Republican mean, so the coefficients can be interpreted as percentage differences.

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 22% more likely to patent green technologies than Republican inventors. The gap increases to 32% after adding technology-section fixed effects (column 2). In our preferred specification in column 3, which includes birth cohort fixed effects and a female dummy, the coefficient of "Democrat" remains positive and significant, and the scaled difference is essentially unchanged. The increase in magnitude after conditioning on technology-section fixed effects indicates that partisan differences in green patenting operate primarily through within-field technology choice, rather than through broad sorting across technological areas.

Columns 4 to 6 report the results of estimating Equation (6) 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 68% more likely to patent these technologies compared to Republican ones (column 5). Adding technology-section fixed effects reduces the magnitude to 42%, and adding inventor-level controls further reduces it to 35%. The attenuation of the estimates after adding technology-section and inventor-level controls suggests that part of the baseline gap reflects broader field sorting–in fact, Democrat inventors are more likely to specialize in health-related technologies–though a meaningful within-field difference remains.

Columns 7 to 9 report the results of estimating Equation (6) on a dummy variable taking value one if the inventor has ever patented a weapon-related technology, and equal to zero otherwise. Across all technology sections (column 7), Democrat inventors are 58% less likely to ever patent weapon-related technologies compared to Republican ones. After conditioning on technology-section in column 8, the scaled difference remains negative and statistically significant and becomes equal to 39%. This remains virtually unchanged after adding inventor-level controls in column 9. The stability of the estimates across specifications suggests that partisan differences in weapon-related patenting arise largely within technological fields, rather than from differences in field-level specialization.

Taken together, these results are consistent with Prediction 1 of the conceptual framework: inventors are more likely to work on technologies that are more closely aligned with their views. Mapping these results back to differences in views by party affiliation from the CCES, a 10% larger divide in views on a given issue in the public opinion is associated with a 10% higher divide in the propensity of inventors to patent the associated technologies.[22]

Unaffiliated inventors. For each specification, we also report the coefficient on the indicator "Other." This category includes inventors registered with minor parties as well as unaffiliated inventors, who constitute the majority of the group. For green technologies, inventors in this category are less likely than Democrats but more likely than Republicans to ever patent in the field (column 3). A similar pattern holds for female-health technologies, although these differences are not statistically significant (column 6). For weapon-related technologies, inventors in the "Other" category are more likely than Democrats but less likely than Republicans to ever patent (column 9).

[22] A 30% divide in public opinion between Democrats and Republicans on action against climate change corresponds to a 31% difference in the likelihood of Democrat versus Republican inventors to patent green technologies. Similarly, a 37% divide in views on abortion rights corresponds to a 35% higher likelihood of Democrat inventors to focus on female reproductive health technologies. Finally, a 37% divide in views on gun control maps to a 39% difference in the propensity to patent weapon-related technologies.

Table 3: 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 $\hat{\beta}_3$			0.0013			0.0068***			-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]	[0.0881]	[0.0170]	[0.1394]	[0.5072]	[0.0000]	[0.0007]	[0.0006]
N. of Inventors	95,595	95,595	95,315	95,595	95,595	95,315	95,595	95,595	95,315
% of Dem.	35.78	35.78	35.79	35.78	35.78	35.79	35.78	35.78	35.79
$\mathbb{E}(LHS)$ 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	30.95	68.12	41.63	34.70	-57.74	-39.05	-39.43
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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on pages: 18, 20, 21, A.12.

Across technology domains, estimates for unaffiliated inventors lie between those for Democrats and Republicans, consistent with survey evidence that unaffiliated individuals hold, on average, intermediate views between the two groups. The coefficient on "Other" therefore provides a natural benchmark for interpreting the partisan gap. That this group's propensity to patent polarized technologies is roughly midway between that of Democrats and Republicans suggests the gap reflects both greater engagement with party-aligned technologies and lower engagement with unaligned ones.

Female inventors. Table 3 also reports the coefficients on a "Female" dummy, confirming that female inventors are more likely to patent technologies addressing typically female diseases (Koning, Samila and Ferguson, 2020, 2021). In addition to gender differences, we uncover pronounced heterogeneity in the propensity to patent female-health technologies by party affiliation. Among male inventors, Democrats are 32% more likely than Republicans to patent female-health technologies; a similarly sized Democrat-Republican gap (36%) emerges among female inventors (Table A.2). These patterns mirror partisan differences in views on abortion and women's rights documented in survey data (Figure 2) and suggest that sorting into female-health technologies reflects not only gender-based homophily, but also *view*-based alignment.

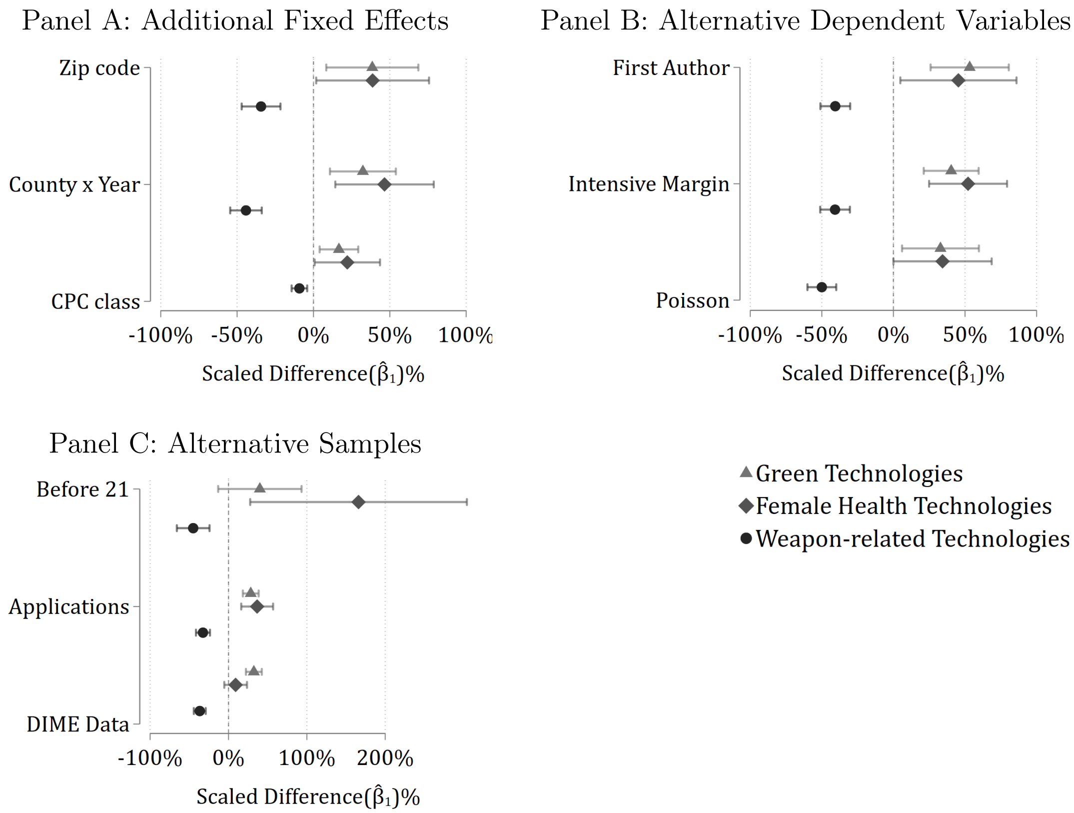
4.3. Robustness Checks

We conduct a comprehensive set of robustness checks, summarized in Figure 3. As in the main analysis, all panels report differences in the average propensity of Democrat and Republican inventors to patent in technology j, divided by the mean propensity among Republican inventors.

Additional fixed effects. Panel A examines robustness to progressively more demanding fixed effects. In the top rows, we add zip-code fixed effects, which absorb hyper-local differences in innovation ecosystems (e.g., proximity to research labs, large employers, or inventor networks) that may correlate with both party affiliation and technology choice. The estimates are unchanged, indicating that our results are not driven by differences across local innovation clusters. (Ganguli, Lin and Reynolds, 2020, Engelberg, Lu, Mullins and Townsend, 2025). In the middle rows, we include county-by-grant-year fixed effects to absorb spatially correlated, time-varying county-specific factors–such as local demand or policy shocks–that could differentially affect patenting across technologies. The estimates remain stable. In the bottom rows, we further tighten the comparison by restricting attention to closely related technologies within a given CPC class (e.g., Y02, "Technologies or Applications for Mitigation or Adaptation Against Climate Change"). This comparison conditions on inventors working within the same climate-related technology field and thus rules out sorting across broad technology categories. Even within this narrow technology space, alignment between inventors and polarized technologies persists.

Alternative outcome variables. Panel B assesses robustness to alternative outcome variables. In the top rows, the dependent variable equals one if inventor i ever patented technology j as the first-listed inventor, and equal to zero otherwise. 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 list 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

Figure 3: Party Affiliation and Polarized Technologies: Robustness Checks



Notes. All panels report scaled differences for the coefficient of "Democrat" ($\hat{\beta}_1$), estimated with Equation (6), 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 (6): 1. zip code (top rows, N=94,819); 2. county×year (middle rows, N=66,722); 3. CPC class (bottom rows, N=95,315). In Panel B, y is: 1. probability of ever patenting j as first inventor (top rows, N=95,308); 2. number of patents in j over total number of patents granted to the inventor over the period (middle rows, N=95,315); 3. total number of patents in j granted to the inventor over the period, estimated through a Poisson model (bottom rows, N=12,478). Panel C shows estimates from Equation (6) 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=110,055); 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 in Section 4.3. 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 Table A.8. Referenced on page: 21.

are similar to those shown in Table 3, 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 6 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 addition, we replicate the analysis using alternative technology definitions that do not rely on the dictionary-based classification. We construct these alternative dependent variables as described in Section 2.2. Table A.5 reports results using an LLM-based classification based on the semantic content of abstracts. Although some magnitudes are attenuated–consistent with greater measurement error relative to the intent-based dictionary–the signs and qualitative patterns closely match the baseline results. Table A.6 uses CPC codes to map patents into broader technological classes linked to each policy issue. Because CPC categories reflect technological fields rather than stated intent, they provide a coarser proxy for policy-relevant content. The qualitative patterns are unchanged: Democrats are more likely to patent in green and female-health technologies and less likely to patent in weapon-related technologies, though scaled differences are generally smaller, consistent with attenuation from measurement error.

Alternative samples. Panel C examines alternative samples designed to address concerns related to political sorting over the life cycle, patent grant outcomes, and the measurement of party affiliation. In the top rows, we restrict the sample to inventors who registered with their current party at age twenty-one or earlier, mitigating concerns that political affiliation reflects post-entry sorting or changes in views after entering the labor market.[23] In the middle rows, we use patent applications rather than granted patents, showing that party-technology alignment is already present at a stage closer to idea generation and is unlikely to be driven by differential grant outcomes or examiner discretion. In the bottom rows, we construct an alternative measure of party affiliation using campaign-contribution records from Stanford's Database on Ideology, Money in Politics, and Elections (DIME) (Bonica, 2019). Following Fos, Kempf and Tsoutsoura (2022), we infer affiliation from cumulative giving: an individual is classified as a Democrat (Republican) if total donations to Democratic (Republican) committees exceed those to the opposing party over their donation history. Individuals donating to both parties are excluded, and remaining contributors are coded as "Other." The matching procedure mirrors that used for voter data and is described in Appendix D.4. Because political giving is relatively rare, fewer inventors can be matched under this measure.[24] Campaign contributions are also a noisier proxy for political affiliation, as they may reflect influence-seeking behavior or be directed toward committees without a clear partisan orientation (Fos, Kempf and Tsoutsoura, 2022). Nevertheless, the results remain qualitatively similar, albeit smaller in magnitude.

[23] We also verify that the findings hold in the subsample of inventors born after 1980, whom we observe from age 21 onward, alleviating concerns that the results are driven by inventors first observed later in their careers (Figure A.3).

[24] In 2016, 12% of Americans donated to an individual running for office (see `https://www.pewresearch.org/short-reads/2017/05/17/5-facts-about-u-s-political-donations/`).

Alternative specifications. We re-estimate Equation (6) using an inventor-year panel and obtain quantitatively similar results (Table A.4). Relative to the inventor-level cross-section, where each inventor receives equal weight, the inventor-year specification places greater weight on inventors observed in more years. In the data, 68% of inventors are granted at least one patent in more than two distinct years, so this specification gives more influence to more persistently active inventors. The results are robust to this alternative weighting. Party-technology alignment also emerges with similar magnitudes in the patent-level sample (Table A.7). For solo-authored patents, we assign party affiliation based on the inventor's registration. For team-authored patents, we assign party affiliation using the share of inventors registered with each party. While our preferred specification is at the inventor level—reflecting our focus on individual sorting decisions—these results show that alignment remains economically meaningful when looking at patent production, a more direct metric of innovation output.

5. Mechanisms

This section examines the mechanisms underlying the alignment between inventors' political affiliation and polarized technologies. We first assess whether the results reflect differences in the skills required to work on these technologies, rather than differences in technology content (Section 5.1). We then study whether organizational sorting or project assignment can account for the observed patterns (Section 5.2).

Our conceptual framework focuses on a simple idea: inventors may choose technologies partly because of how well those technologies fit their (or their group's) views, not because they have different skills or different access to firms. The empirical patterns documented above show a clear link between party affiliation and the technologies inventors work on. This section asks whether that pattern remains when we restrict attention to settings where skill differences and organizational environments are held fixed as much as possible–comparing inventors within narrow technology fields, among inventors with similar observable ability, and within the same organizations, including firms that differ in size, political composition, and the degree of inventor discretion.

5.1. The Role of Technology-Specific Skills

This section evaluates whether party-technology alignment can be explained by differences in the skills required to work on polarized technologies. First, we test whether alignment varies with inventive ability, proxied by the technological value of inventors' patents. Second, we compare inventors operating within narrowly defined technological classes that plausibly require similar skills, and we compare polarized technologies with closely related placebo technologies that draw on comparable knowledge and human capital. Finally, we examine whether alignment mostly reflects inventors reallocating effort among existing technologies, or whether it is also present in the introduction of new technologies within the same technological field.

Selection on inventive ability. We begin by examining whether party-technology alignment reflects differences in inventive ability. We proxy inventive ability with the average number of forward citations received by an inventor's patents, a standard proxy of inventions' technological value.[25] Panel A of Figure 4 reports estimates of Equation (6) separately for below- and above-median inventors. We find similar party-technology alignment in both groups, suggesting this is not primarily due to Democrats and Republicans differing in inventive ability, but instead reflects differences in the technologies they work on. In robustness checks, we implement analogous splits using two alternative measures commonly used in the literature that do not rely on citations, patent market value (Kogan, Papanikolaou, Seru and Stoffman, 2017) and a text-based measure of patent importance (Kelly, Papanikolaou, Seru and Taddy, 2021) (Figures A.2 and A.3), and document similar patterns.

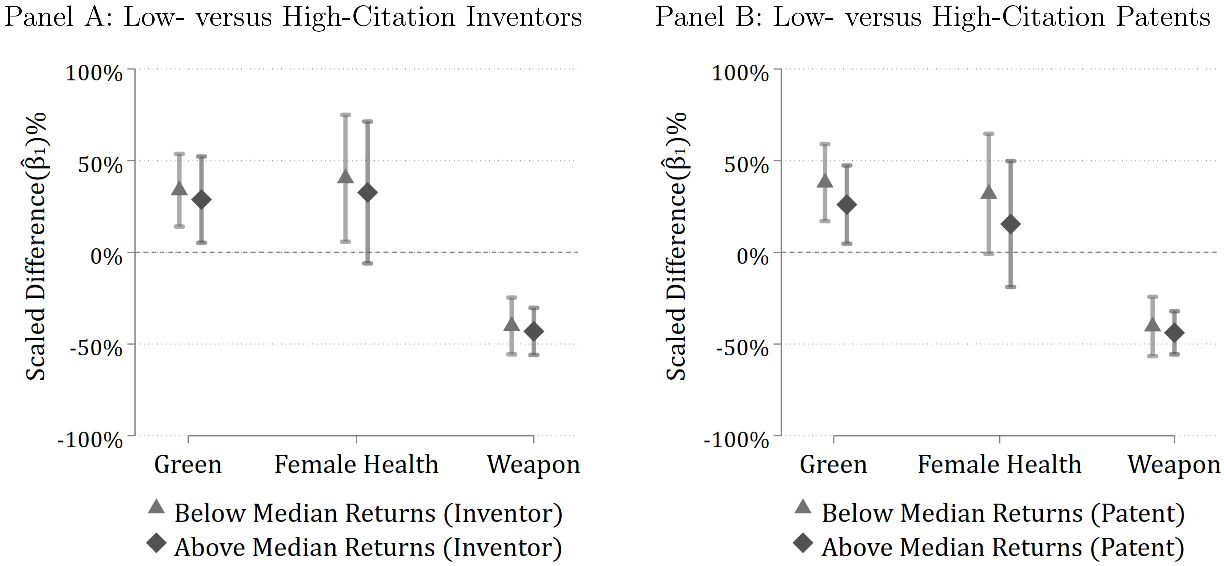
Selection on technology-specific skills. We next examine whether party-technology alignment simply reflects inventors sorting into broad technology areas that require different skills, potentially because Democrats and Republicans made different educational or training choices earlier in life.[26] As described in Section 4.3, we re-estimate Equation (6) including CPC class fixed effects, so the comparison is made only among inventors working within the same CPC technology class. Alignment remains present even under this within-class comparison, suggesting it is not driven by differences in skills or training across broad technological fields.

We then assess whether the results reflect differences in skills rather than technology content by comparing polarized technologies to closely related placebo technologies following Bell, Chetty, Jaravel, Petkova and Van Reenen (2018). For each polarized technology, we identify other technologies patented by the same inventors, rank them by the degree of inventor overlap, and group them into deciles, with lower deciles corresponding to technologies most closely related to the polarized one. Because these placebo technologies are patented

[25] Citation counts are adjusted for truncation following Hall, Jaffe and Trajtenberg (2001). The sample is restricted to patents issued through 2021. Citation counts are weighted by the number of inventors, with similar results obtained without weighting.

[26] Consistent with this possibility, recent work documents substantial partisan sorting in college choice and enrollment, implying that political affiliation may correlate with educational pathways and human-capital accumulation well before labor-market entry (Acton, Cook and Ugalde A., 2025).

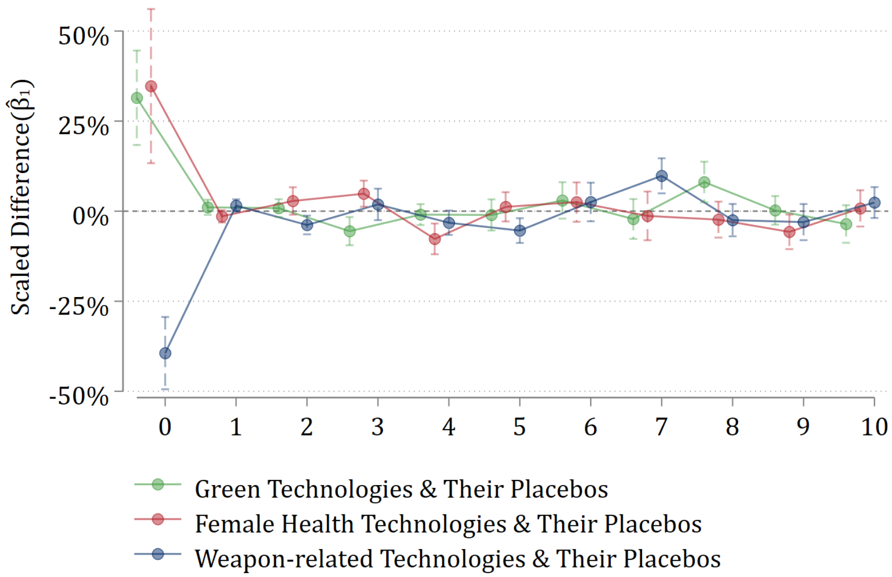
Figure 4: The Role of Technology-Specific Skills



Notes. Each plot reports scaled differences for the coefficient of "Democrat" ($\hat{\beta}_1$), estimated using Equation (6). We adjust forward citation counts for truncation, following Hall, Jaffe and Trajtenberg (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, Baslandze and Stantcheva (2016). We split observations based on the median value of the inventor-level average adjusted citation count and estimate Equation (6) on each inventor-level subsample ($N_{below} = 44,335, N_{above} = 27,784$). 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 (6) on each inventor-level subsample ($N_{below} = 49,049, N_{above} = 44,064$). 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 Table A.9. Referenced on pages: 25, 26.

by the same inventors and are therefore likely to rely on similar training and human capital, they provide a demanding benchmark for skill-based explanations, including those rooted in earlier educational choices. We estimate Equation (6) using an indicator equal to one if an inventor has ever patented in a given polarized or placebo technology. Figure 5 shows that, across green, female-health, and weapon-related technologies, alignment with party affiliation is substantially larger for polarized technologies than for any placebo counterpart and is always statistically significant. This contrast indicates that the results are tied to the political salience and content of technologies, rather than to differences in inventive ability or skills.

Figure 5: Comparison of Polarized Technologies 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 (6) 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, Chetty, Jaravel, Petkova and Van Reenen (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. Referenced on page: 25.

Selection across inventions. While the previous analyses focus on selection across inventors, Panel B of Figure 4 examines selection across *inventions*. We split patents at the median of the citation distribution and re-estimate Equation (6) separately for lower- and higher-cited patents. Party-technology alignment is similar across the two subsamples, indicating that it is not driven by sorting into lower-value technologies. Because highly cited patents are more likely to reflect novel or frontier ideas rather than incremental improvements, the persistence of alignment in the upper tail suggests that views shape not only who works within polarized domains, but also the creation of new ideas and technological trajectories within them. Figures A.2 and A.3 report similar results when using patent market value and the text-based measure of patent importance.

5.2. The Role of Organizations

We next examine whether party-technology alignment can be explained by organizational sorting rather than by inventors' own choices over which technological problems to pursue. A natural alternative explanation is that inventors sort into organizations specializing in technologies aligned with their views, or that organizations allocate inventors to projects in politically polarized ways.[27] In line with this hypothesis, recent evidence documents substantial political sorting across firms and shows that workers are willing to trade off wages for ideologically congruent workplaces, suggesting that organizational selection can generate meaningful political segregation in the labor market (Chinoy and Koenen, 2024). We assess the importance of this channel using four complementary tests: heterogeneity by organizational size, differences by workplace political composition, specifications conditioning on organization fixed effects, and settings in which inventors plausibly enjoy greater autonomy over research direction.

Hiring practices. Panel A of Figure 6 examines heterogeneity by organization size, measured as the total number of inventors granted a patent by the USPTO with a given organization over the sample period. This test is motivated by evidence that smaller firms rely more heavily on informal or network-based hiring (Colonnelli, Pinho Neto and Teso, 2025). We classify organizations with three or fewer inventors per year as small, and the remainder as large. Party-technology alignment is similar across small and large organizations, suggesting that differences in hiring practices or politically segmented hiring networks are unlikely to be the primary drivers of the observed alignment.

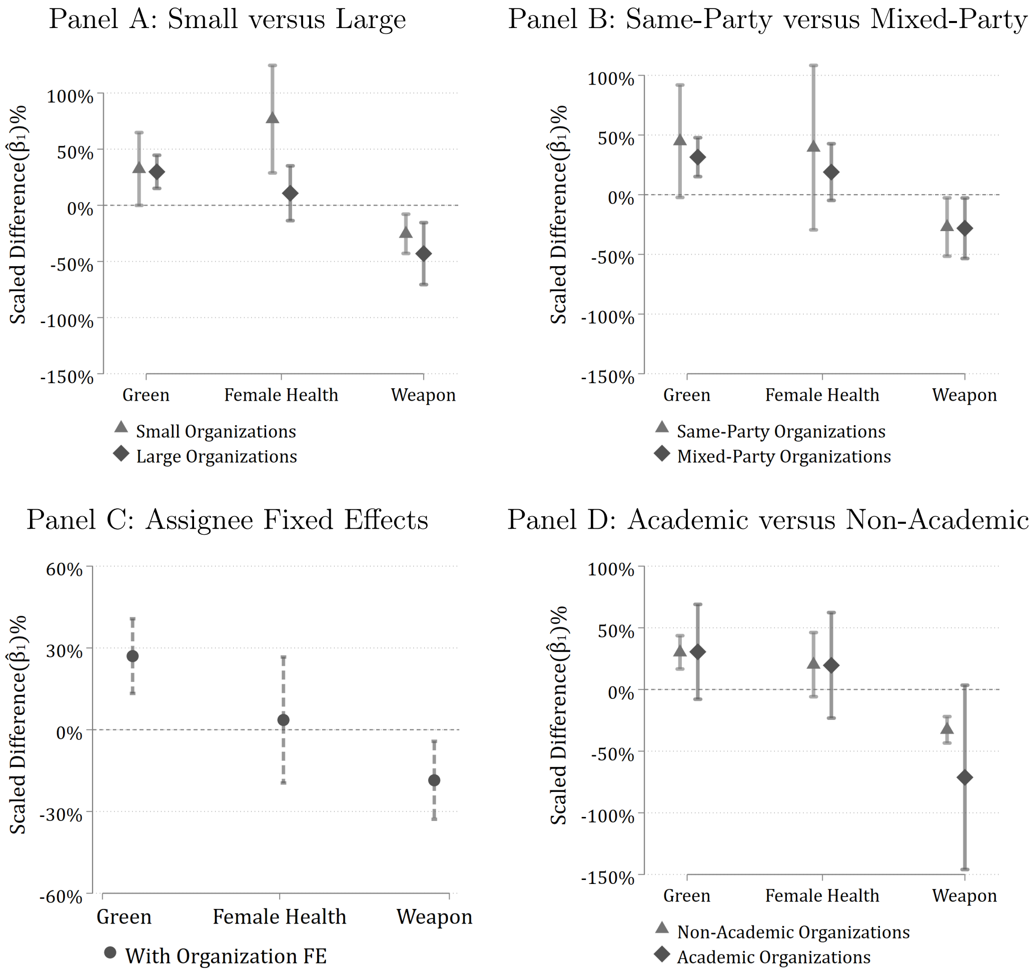
Workplace composition. Panel B examines whether alignment varies with the political composition of the workplace. We classify an organization-year as "same-party" if all inventors granted a patent are affiliated with the same political party, and as "mixed-party" if at least one Democrat and one Republican are present.[28] The estimated alignment is similar in politically homogeneous and politically mixed organizations, indicating that preferences for politically homogeneous workplaces alone are unlikely to account for the observed patterns.

Technologies versus organizations. Panel C assesses whether party-technology alignment persists within organizations. We re-estimate Equation (6) including organization fixed effects, which absorb all time-invariant differences across organizations, including technology

[27] Organizations (assignees) are the owners of the intellectual property associated with patents and typically correspond to the firms, universities, or other entities employing or collaborating with the listed inventors.

[28] This variable is defined at the organization-year level and restricts the sample to organization-years with at least two inventors. Results are similar using alternative thresholds or defining the measure at the organization-city-year level.

Figure 6: The Role of Organizations



Notes. Panels A, B, and D report scaled differences for the coefficient of "Democrat" ($\hat{\beta}_1$) estimated with Equation (6) 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," N = 32,569), and those with 4 or more inventors ("Large," N = 52,967). 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," N = 54,723) and those with only Democrat or only Republican inventors ("Same-Party," N = 21,363). We remove observations with fewer than two inventors per assignee-year. In Panel C, we add assignee fixed effects to Equation (6), 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 = 92,703, with 69,594 unique inventors). Standard errors are clustered at the county-assignee level. 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," N = 8,618) or not ("Non-Academic," N = 72,324). 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 Table A.10. Referenced on page: 28.

specialization and persistent hiring practices.[29]

Although over 60% of assignees are dropped in this specification, the estimated alignment remains statistically significant—though smaller—for green and weapon-related technologies, while it is not statistically distinguishable from zero for female-health technologies. The loss in precision for female-health technologies reflects their concentration among small assignees, which are disproportionately excluded when conditioning on organization fixed effects. Accounting for organization fixed effects reduces the estimated alignment by approximately 38–42% for green and weapon-related technologies (Table A.11). These results suggest that organizational sorting explains an important share of the baseline relationship, but does not fully account for the observed alignment, which continues to operate within organizations.[30]

Individuals versus teams. Finally, we assess whether alignment primarily reflects assignment to teams or projects within organizations, or instead differences in technology choice at the level of individual inventors. Panel D restricts the sample to inventors patenting with academic organizations, where researchers plausibly have greater discretion over research agendas than in corporate settings (e.g., Aghion, Dewatripont and Stein, 2008). Although the estimates are less precise due to a much smaller sample size, party-technology alignment persists in this subsample.

We further examine the role of team formation by changing the unit of analysis from inventors to patents (Appendix Section A.2.4). This allows us to test whether alignment is driven mainly by Democrats and Republicans working in different teams.[31] Alignment remains economically meaningful in both cases, suggesting that the observed patterns are unlikely to be driven solely by sorting of inventors into teams.

Taken together, these results indicate that a substantial share of the observed party-technology alignment appears to operate within organizations and at the level of individual inventors' technology choices, rather than being fully explained by organizational sorting alone.

[29] We collapse the data to the inventor–organization level, as some inventors are linked to multiple organizations. Standard errors are two-way clustered at the company and county levels.

[30] Organization fixed effects compare inventors within the same assignee, absorbing time-invariant differences across assignees. When assignees are technologically specialized, organization and technology effects are not separately identified, because technology varies little within an assignee. In that case, assignee fixed effects may absorb part of the technology-level variation. We therefore interpret this exercise as a demanding robustness check rather than a clean decomposition of organizational sorting versus technology choice.

[31] For solo-inventor patents, where there is no team to sort into, we assign party affiliation based on the inventor listed on the patent. For multi-inventor patents, we assign the team's political composition using the share of inventors affiliated with each party.

6. The Dynamics of Party-Technology Alignment

The cross-sectional analysis documents substantial differences in technology choice by party affiliation. We next examine how party-technology alignment evolves over time. Section 6.1 presents the dynamic empirical specification. Section 6.2 shows that alignment increases markedly through 2015 and remains elevated thereafter. Finally, Section 6.3 argues that these dynamics are consistent with supply-side alignment dynamics.

6.1. Empirical Specification

We estimate a variant of Equation (6) at the inventor-year level, interacting party indicators with time dummies:

$$\begin{aligned} y_{i,t} = &\sum_{p \neq p_0} \beta_{1,p} \left(\text{Democrat}_i \times \mathbb{1}[t \in p]\right) + \sum_{p \neq p_0} \beta_{2,p} \left(\text{Other}_i \times \mathbb{1}[t \in p]\right) \\ &+ \beta_3 \text{Female}_i + \gamma_t + \delta_{c(i)} + \zeta_{s(i)} + \mu_{a(i)} + \epsilon_{i,t} \end{aligned} \tag{7}$$

where i indexes inventors and t the patent grant year. We estimate Equation (7) separately for each technology $j \in \{$green, female-health, weapon$\}$, where $y_{i,t}^j$ equals one if inventor i is granted at least one patent in domain j in year t, and equal to zero otherwise. As in the baseline specification, we include fixed effects for county of residence, technology section, and birth cohort. This specification therefore compares inventors within the same technology section and geographic area, such as inventors working in chemistry or metallurgy (Section C) residing in Miami-Dade County.[32]

To improve precision, we group years into six multi-year periods with comparable numbers of inventor-year observations, using 2001-2005 as the baseline.[33] The coefficient $\hat{\beta}_{1,p}$ measures the difference in the propensity to enter technology j between Democrat and Republican inventors in period p, relative to 2001-2005. In the baseline, we further restrict attention to inventors who did *not* patent in a given technology during the baseline period in order to isolate changes in marginal technology choice rather than persistent specialization.

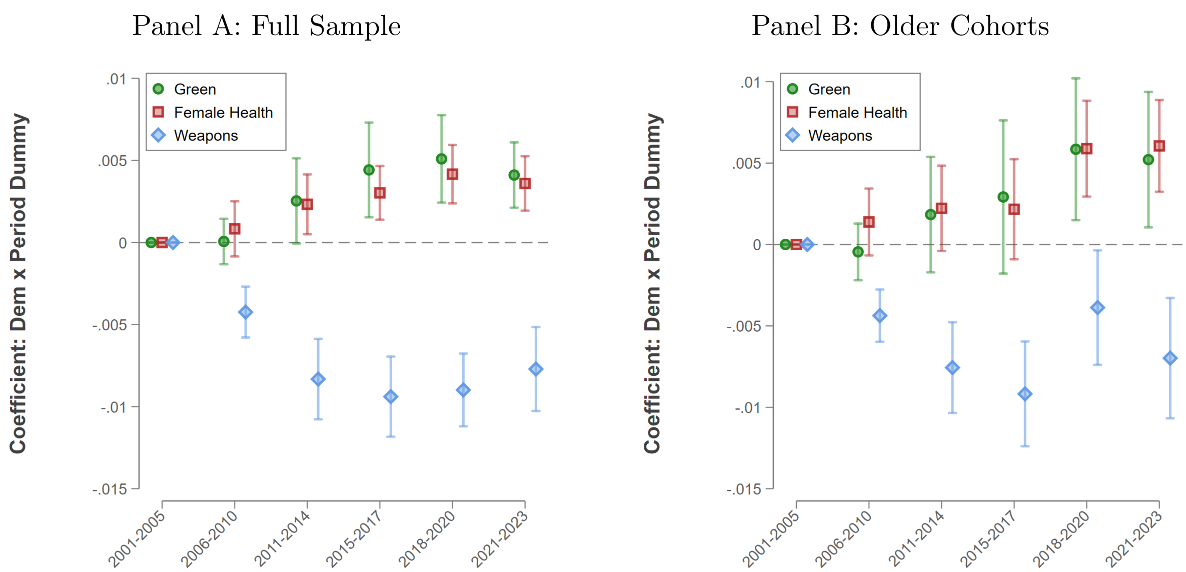
[32] For computational reasons, the fixed effects are not interacted with period dummies in the baseline specification. Results are similar when each set of fixed effects is interacted with period indicators one at a time.

[33] The periods are 2001-2005, 2006-2010, 2011-2014, 2015-2017, 2018-2020, and 2021-2023.

6.2. Party-Technology Alignment Strengthened Over Time

Panel A of Figure 7 shows that party-technology alignment strengthens over time across all three technologies. By 2015, a Democrat inventor not previously active in these domains is 47% more likely than a Republican to patent green technologies, 63% more likely to patent female-health technologies, and 121% less likely to patent weapon-related technologies.[34]

Figure 7: The Dynamics of Party-Technology Alignment



Notes. The unit of observation is an inventor-year. In Panel A, 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 (N=262,512). In Panel B, we restrict the sample to older inventor cohorts (N=138,825). We define "older cohorts" as inventors born before the sample median birth year (1962). For each technology $j \in$ green, female-health, weapon, we then remove those inventors who were patenting j in period p_0 (2001-2005). The figure reports the interaction coefficients $\hat{\beta}_{1,p}$ between the Democrat indicator and period p indicators from Equation (7), estimated separately by technology. For each technology $j \in$ green, female-health, weapon, the outcome is an indicator equal to one if inventor i was ever granted at least one patent in technology j in year t (and zero otherwise). Coefficients are shown over six periods; 2001-2005 is the omitted category. Periods are: 2001-2005, 2006-2010, 2011-2014, 2015-2017, 2018-2020, and 2021-2023. Green circles denote estimates for green technologies, red squares for female-health technologies, and blue diamonds for weapon-related technologies. Capped lines show 90% confidence intervals based on standard errors clustered at the county level. Referenced on pages: 31, 33.

Sorting or reallocation? The widening party gaps could reflect changes in who enters innovation over time (selection) or within-career reallocation by incumbents (switching).

[34]These scaled differences are computed by dividing the each period's $\hat{\beta}_{1,p}$ by the mean of the left-hand side for Republicans, and by the averaging the last four periods. Figure 7 reports $\hat{\beta}_{1,p}$ rather than scaled differences to isolate the change in estimated coefficients from the change in the mean of the dependent variable.

Distinguishing between these channels is important: while selection can be generated by fixed traits shaped by early-life environment and persistent specialization, switching points to time-varying alignment forces.[35] As a result, establishing whether the widening party gap is dynamic rather than static helps isolate it (i) from time-invariant demographics that may correlate with party affiliation and with labor market outcomes, and (ii) as a force shaping innovation that is not only individual-specific but also time-varying.

To address this point, Panel B of Figure 7 restricts attention to inventors born before the median birth year in our sample (1962), who were plausibly already active in the labor market at the start of the sample period. Results are similar to those in Panel A. For these older cohorts, party affiliation and initial career trajectories were largely determined prior to the period in which alignment begins to increase in our data. The observed divergence therefore plausibly reflects within-career reallocation toward—or away from—polarized technologies, rather than differences in early-life exposure or compositional changes at entry.[36] As comparable patterns are observed among younger cohorts (Figure A.5), both entry and a shift among incumbents appear to contribute to the overall increase in alignment.

6.3. Supply-Side Alignment versus Demand Shocks

The strengthening of party-technology alignment raises the question of whether these dynamics reflect shifts in product or labor *demand*, or instead changes in the *supply* of innovation.

We first show that the results are robust to absorbing a wide range of local and technology-wide shocks. Panels A and B of Figure A.4 add zip-code fixed effects and detailed CPC class fixed effects. The geographic fixed effects absorb time-invariant local conditions, such as regional labor demand, industry composition, and exposure to place-specific policy environments, so identification comes from inventors operating within the same local economic context. The detailed CPC class fixed effects compare inventors within narrowly defined technological areas, holding constant field-specific skills and specialization, thereby limiting scope for the results to reflect differences in comparative advantage or sorting across broad technology categories. Panels C and D further include county-by-year and section-by-year fixed effects, which absorb time-varying local conditions (e.g., labor demand, policy incentives, or investment flows) and technology-section-wide trends (e.g., changes in aggregate demand or

[35] One example is the childhood environment. This can have lasting effects on the direction of innovation (Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018), and, at the same time, on political affiliation (e.g., Brown, Cantoni, Chinoy, Koenen and Pons, 2023, Daniele, Galletta, Le Moglie and Masera, 2025). Cross-sectional correlations between party affiliation and technology choice may therefore reflect common early-life influences even in the absence of time-varying alignment effects.

[36] This time variation contrasts for example with the evidence on gender, where the direction of invention by inventor gender appears stable over decades (Koning, Samila and Ferguson, 2021) and gender-based innovator-consumer homophily shows little change over time (Einiö, Feng and Jaravel, 2025*b*).

funding within a section). The strengthening alignment is therefore identified from differential responses of Democrats and Republicans within the same location and narrowly defined technological field.

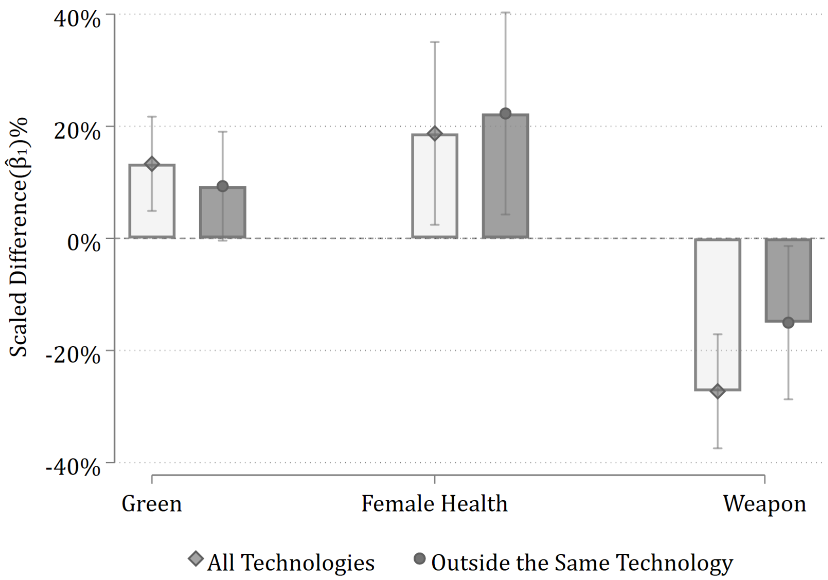
These patterns are difficult to reconcile with changes in objective local product demand or labor demand for particular skills: absent party-specific differences in perceived or non-pecuniary returns, shocks that raise the objective profitability of a technology, such as higher product demand, increased funding, or regulatory support, should increase innovative activity for both political groups facing the same opportunities, rather than systematically widening the gap between them. For demand to generate our findings, it would need to translate into differential effective returns by party within the same county and technology section—for example, because inventors sort into different employers or networks that respond differently to the same underlying shock. We view this as closer to a supply-side mechanism in our framework: it requires the perceived or non-pecuniary attractiveness of innovating in a domain to change differently across parties, even when objective local and field-level conditions are held fixed. This interpretation aligns with Prediction 2 of the conceptual framework. In the model, effective alignment is governed by $\rho_t(a_{Dj} - a_{Rj})$: increases in issue-specific alignment gaps or in the salience of alignment raise the marginal non-pecuniary return to working in aligned domains, inducing differential entry and within-career reallocation. Consistent with this mechanism, the timing of the increase in alignment coincides with documented increases in partisan polarization in U.S. public opinion—including rising polarization over climate change during the late 2000s and early 2010s (e.g., McCright and Dunlap, 2011) and broader partisan sorting of issue positions (e.g., Levendusky, 2009). While our design does not establish a causal link, the coincidence in timing is consistent with shifts in views and issue salience changing the relative attractiveness of innovating in these domains.

7. The Diffusion of Polarized Technologies

Next, we examine whether party-technology alignment extends from the *development* to the *diffusion* of new technologies. Following a standard approach in the literature, we measure diffusion using patent citations, which trace knowledge flows by linking patents to the prior technologies on which they build (Jaffe, Trajtenberg and Henderson, 1993, Jaffe, Trajtenberg and Fogarty, 2000). We adopt an empirical strategy symmetric to the one used earlier in the paper and estimate Equation (6) using a dependent variable equal to one if inventor i ever cited technology j, and zero otherwise. This specification captures the extensive margin of diffusion–whether knowledge from a given technology ever reaches an inventor–rather than citation intensity, which we examine in robustness analyses.

Figure 8 reports the results. Relative 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 weapon-related technologies. In each set of bars, the left one reports citations from all patents, while the right one excludes citations originating from patents within the same technology j. The stability of these estimates across these specifications helps rule out the possibility that the results are mechanically driven by within-technology citation. The findings are robust to alternative diffusion measures, including citation counts and citation shares (Tables A.12 and A.13).

Figure 8: The Diffusion of Polarized Technologies



Notes. Each plot reports scaled differences for the coefficient of "Democrat" ($\hat{\beta}_1$), estimated using Equation (6). 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 (6) 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 Table A.14. Referenced on pages: 34, 36.

What mechanisms account for the observed alignment in diffusion? One possibility is party-based homophily in knowledge networks. Consistent with this interpretation, we find that inventors are substantially more likely to cite others who share their party affiliation

(Table 4). Conditional on year and county fixed effects, Democrats are 21% more likely to cite other Democrats and 19% less likely to cite Republicans (columns 1 and 7), while showing no differential propensity to cite unaffiliated inventors (column 4). The estimates are essentially unchanged when conditioning on technology-section fixed effects and inventor demographics. These findings align with existing evidence that party affiliation shapes social interactions and information environments (e.g., Gentzkow and Shapiro, 2011), and that diffusion depends not only on geographic but also on *social* proximity (e.g., Jaffe, Trajtenberg and Henderson, 1993, Jaffe, Trajtenberg and Fogarty, 2000, Singh, 2005, Subramani and Saksena, 2025, Kalyani, Bloom, Carvalho, Hassan, Lerner and Tahoun, 2025).

Table 4: The Diffusion of 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, 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, 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, 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 35.

To assess whether the "citation divide" displayed in Figure 8 reflects network-based homophily alone or also differential engagement with polarized technologies themselves, we further split the results by the party affiliation of the cited inventor. We find that inventors are up to three times more likely to cite same-party inventors when the cited patent is a polarized technology aligned with their party's views (Table A.15). At the same time, they are not disproportionately less likely to cite these technologies when they are patented by the opposing party, even though, on average, Democrats are about 19% less likely to cite Republican inventors overall.[37] This indicates that technological content plays an independent role in shaping diffusion, over and above baseline party-based homophily.[38]

Taken together, these findings suggest that polarized *innovation* leads to polarized *diffusion* through two distinct margins. First, because polarized technologies are more likely to be patented by aligned inventors and diffusion is more likely within party lines, these technologies are disproportionately transmitted within same-party knowledge networks. Second, diffusion is shaped by technological content itself: inventors are more likely to cite aligned technologies even holding constant the party affiliation of the cited inventor.

8. Policy Implications

After documenting empirical patterns consistent with the conceptual framework outlined in Section 3, we return to it to discuss implications for technological change and for the design of innovation policy. The framework delivers two qualitative insights.

First, rising political polarization amplifies sorting across technologies. An increase in issue-specific alignment a_{gj} or in the salience parameter ρ widens differences in subjective returns across political groups. Holding the mapping between technologies and political identities fixed, stronger polarization induces greater reallocation of inventive effort toward aligned domains and away from misaligned ones. If political groups are similarly represented among inventors, increased polarization need not, by itself, shift the aggregate direction of innovation. However, if group sizes diverge over time, polarization can also change the overall direction of innovation.[39]

Even holding groups fixed, the framework implies an important policy asymmetry. In polarized environments, the responsiveness of inventive effort to financial incentives can vary systematically with political alignment: subsidies or R&D support disproportionately increase activity among already-aligned inventors, while generating limited entry from misaligned inventors because a larger non-pecuniary wedge lowers their effective net return.

This mechanism is consistent with evidence showing that climate policies increase clean innovation largely through expansion by incumbent clean inventors, with limited cross-

[37]Table A.15 distinguishes whether technology j was patented by a Democrat, a Republican, or an unaffiliated inventor. In columns 2, 5, and 8, we estimate Equation (6) using a dependent variable equal to one if inventor i ever cited technology j patented by a Democrat. Columns 3, 6, and 9 analogously focus on citations to Republican-patented technologies.

[38]The results for female-health technologies are qualitatively similar but more muted, reflecting the smaller sample size in this category.

[39]Another potential channel that could affect aggregate outcomes even with equally-sized groups is talent misallocation. In our empirical setting, we compare closely related technologies, suggesting that unless talents are narrowly technology-specific, the implied misallocation of ability is likely to be limited. If this mechanism were important, increased sorting could nonetheless generate some talent misallocation.

technology reallocation (Dugoua and Gerarden, 2025), and that worker transitions from carbon-intensive ("dirty") to green jobs remain rare despite growth in green employment opportunities, indicating substantial frictions in cross-sector reallocation (Curtis, O'Kane and Park, 2024). The framework thus highlights that alignment can act as a friction that price instruments may struggle to overcome efficiently. Conversely, when policy targets domains that are already positively aligned with a substantial share of inventors, implementation may be faster and less fiscally costly, as non-monetary incentives reinforce pecuniary ones.[40][41]

Similar forces may operate along the diffusion margin. A widening in a_{gj} increases inventors' relative propensity to build on aligned technologies, even holding constant the identity of the cited inventor. At the same time, a rise in ρ strengthens identity-based segmentation of knowledge networks, reducing cross-party interaction and thereby limiting knowledge flows. Polarization may not only redirect inventive effort, but also concentrate diffusion within politically aligned communities.

Second, even holding the degree of polarization fixed, changes in society-wide alignment a_{gj}—which we interpret as shifts in the distribution of views in society—can reallocate inventive effort across technologies to the extent that inventors' views co-move with (or are representative of) societal views. When societal views toward a policy issue move, inventors may face different non-monetary benefits and costs from engaging with it, even if pecuniary incentives are unchanged. This highlights that changes in the societal landscape may shape technological progress not only through demand-side forces—such as shifts in consumers' product demand, as shown by Besley and Persson (2023)—but also through changes in the supply of innovation, i.e., the new technologies that inventors bring to the market.[42]

9. Conclusion

This paper documents systematic alignment between inventors' political affiliation, the technologies they develop, and how those technologies diffuse. These patterns persist within narrowly defined technological fields and within organizations, and they strengthen over time. Together, the evidence suggests that inventor-level choices—beyond differences in

[40] Appendix C illustrates different policy scenarios in a tractable special case.

[41] One alternative interpretation is that alignment reflects party differences in beliefs about the returns to specific technologies, in which case information provision could attenuate this friction. However, in politicized settings, informational interventions often have muted and short-lived effects on downstream attitudes and behavior (Nyhan, 2020). Relatedly, partisan "mindsets" can lead individuals to interpret the same evidence through different frames, limiting how much information alone closes group differences (Stantcheva, 2025).

[42] Besley and Persson (2023) study a dynamic model in which the share of citizens holding environmental values evolves over time and interacts with firms' technology choices in equilibrium. Because values shape both market demand and voting behavior, electoral incentives and limited policy commitment can prevent or delay a socially desirable green transition.

skills, product-market demand, or firm-level assignment—are an important driver of the link between party affiliation and the direction of technological change.

What mechanisms underlie this sorting? Inventors affiliated with different political groups may hold systematically different beliefs about the future returns to particular technologies, reflecting expectations about regulation, public investment, or policy support. They may also derive non-monetary utility or disutility from working on specific technologies, consistent with intrinsic motivation or social-image concerns tied to political identity.

Our findings contribute to growing evidence that innovators' characteristics shape the content of technological progress. We show that views are one such characteristic. As a result, societal shifts in views or political leaning may influence innovation not only through changes in product demand, but also through the *supply* of new technologies, by affecting inventors' willingness to work in particular domains.

Because technological change is cumulative and path-dependent, such shifts can have persistent effects on innovation trajectories and on the distribution of its benefits. In this sense, our results echo the perspective that technological progress depends not only on material incentives, but also on the broader cultural and ideological environment that shapes which ideas are pursued and developed.

Finally, this paper highlights a new channel linking politics and innovation. While much of the existing literature emphasizes how technological change influences societal polarization, the evidence presented in this paper is consistent with the reverse direction: polarization can shape innovation by influencing inventors' research choices and the diffusion of new technologies. As a result, political polarization may not merely respond to technological change, but also determine the technological frontier and how innovation evolves over time.

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Polarized Technologies

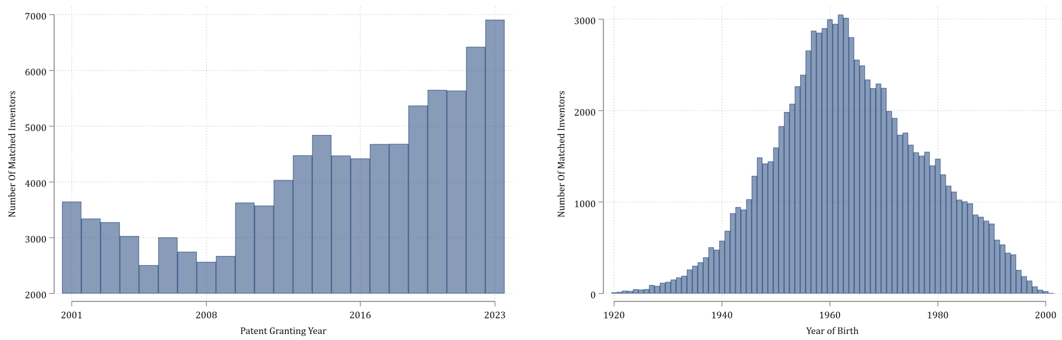
Online Appendix

Gaia Dossi **Marta Morando**

A. Supplementary Results

A.1. Additional Descriptive Evidence

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



Notes. This figure shows 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. Referenced on page: 7.

Table A.1: Differences in Means, Democrat versus Republican Inventors

	Democrat - Republican (Unconditional)			Democrat - Republican (Conditional)		
	Coefficient	Standard Error	P-value	Coefficient	Standard Error	P-value
	(1)	(2)	(3)	(4)	(5)	(6)
Female Dummy	0.095	0.003	0.000	0.081	0.003	0.000
Birth Year	2.978	0.106	0.000	1.400	0.172	0.000
Income	14591.510	350.618	0.000	-1803.527	1144.451	0.117
A Section	0.047	0.004	0.000	0.023	0.006	0.000
B Section	-0.077	0.003	0.000	-0.042	0.004	0.000
C Section	0.080	0.003	0.000	0.061	0.007	0.000
D Section	-0.001	0.001	0.317	-0.000	0.001	1.000
E Section	-0.038	0.002	0.000	-0.025	0.002	0.000
F Section	-0.068	0.003	0.000	-0.042	0.004	0.000
G Section	0.100	0.004	0.000	0.047	0.006	0.000
H Section	0.025	0.003	0.000	0.015	0.006	0.013
Y Section	-0.029	0.003	0.000	-0.013	0.004	0.001

Notes. This table reports differences in means (columns 1 and 4), standard error (columns 2 and 5), and p-value (columns 3 and 6) between Democrat and Republican inventors. Columns 1-3 report unconditional means; columns 4-6 condition on patent grant year dummies (equal to one for all years in which the inventor was granted a patent, to zero otherwise) and county fixed effects. 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. Referenced on page: 8.

A.2. Additional Robustness Checks

A.2.1. Alternative Samples

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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 20.

Table A.3: Party Affiliation and Polarized Technologies, Inventors Born after 1979

	Green Technologies			Female-Health Technologies			Weapon-related Technologies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat $\hat{\beta}_1$	0.0060***	0.0056***	0.0054***	0.0044***	0.0043***	0.0038***	-0.0194***	-0.0143***	-0.0142***
	(0.0017)	(0.0016)	(0.0017)	(0.0014)	(0.0014)	(0.0014)	(0.0038)	(0.0030)	(0.0029)
N. of Inventors	14,042	14,042	14,027	14,042	14,042	14,027	14,042	14,042	14,027
% of Dem.	44.24	44.24	44.25	44.24	44.24	44.25	44.24	44.24	44.25
$\mathbb{E}(LHS)$ for Rep.	0.006	0.006	0.006	0.002	0.002	0.002	0.029	0.029	0.029
Scaled Difference (%)	94.53	88.10	85.29	207.44	201.83	179.45	-65.93	-48.73	-48.19
Patent Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Section FE	×	✓	✓	×	✓	✓	×	✓	✓
Individual Controls	×	×	✓	×	×	✓	×	×	✓

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. We restrict the sample to those inventors born after 1979, who were at least 21 years old in 2001 (i.e., at the beginning of our sample). 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" taking value 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 also control for 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 of "Democrat" divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 23.

Table A.4: Party Affiliation and Polarized Technologies, Inventor-Year Sample

	Green Technologies			Female-Health Technologies			Weapon-related Technologies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat $\hat{\beta}_1$	0.0020**	0.0027***	0.0027***	0.0022***	0.0015***	0.0012**	-0.0069***	-0.0044***	-0.0045***
	(0.0008)	(0.0008)	(0.0008)	(0.0006)	(0.0005)	(0.0005)	(0.0012)	(0.0009)	(0.0009)
Other $\hat{\beta}_2$	0.0010	0.0012*	0.0014**	0.0015**	0.0011*	0.0010**	-0.0038***	-0.0023**	-0.0023**
	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0010)	(0.0009)	(0.0009)
Female $\hat{\beta}_3$			0.0006			0.0052***			-0.0013***
			(0.0009)			(0.0010)			(0.0004)
$\hat{\beta}_2 - \hat{\beta}_1$	-0.0010	-0.0014	-0.0013	-0.0007	-0.0004	-0.0001	0.0031	0.0022	0.0022
P-value $\hat{\beta}_2 - \hat{\beta}_1$	[0.2192]	[0.0626]	[0.0971]	[0.2308]	[0.5196]	[0.7964]	[0.0001]	[0.0007]	[0.0006]
N. of Inventors	95,596	95,596	95,303	95,596	95,596	95,303	95,596	95,596	95,303
% of Dem.	36.47	36.47	36.49	36.47	36.47	36.49	36.47	36.47	36.49
$\mathbb{E}(LHS)$ for Rep.	0.007	0.007	0.007	0.004	0.004	0.004	0.011	0.011	0.011
Scaled Difference (%)	27.81	37.31	37.43	57.38	38.16	30.68	-61.03	-39.48	-39.94
Patent Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Section FE	×	✓	✓	×	✓	✓	×	✓	✓
Birth Year FE	×	×	✓	×	×	✓	×	×	✓

Notes. The unit of observation is an inventor-year. The sample includes USPTO inventors who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter register data. We estimate the following regression, at the inventor-year level, identical to Equation (6) $y_{i,t} = \beta_1 \text{Democrat}_i + \beta_2 \text{Other}_i + \beta_3 \text{Female}_i + \gamma_t + \delta_{c(i)} + \zeta_{s(i,t)} + \mu_{a(i)} + \epsilon_{i,t}$ where i denotes an inventor, t the year a patent has been granted to inventor i, $c(i)$ the county of residence of the inventor i, $s(i,t)$ the technology-section of the patents granted to the inventor i in year t, and $a(i)$ the birth year of inventor i. 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 23.

A.2.2. Alternative Outcome Variables: LLM Classification

We classify patents into green, female-health, and weapon-related technologies using a large language model (LLM) applied to patent abstracts. We adopt the Google generative model Gemini 2.5 (flesh), limiting our input to the following prompt:

```
You are an expert patent analyst. Your role is to read and classify US patent abstracts for academic economic research.

### MAIN RATIONALE:

1. Classify patents into green, female, and weapon categories to reflect invention’s intended PURPOSE from the abstract as a whole.
2. You are allowed to classify patents as NOT belonging to any of the three categories.
3. If more than one category seems plausible, choose the single BEST category and set the other two to 0.
4. If you are not sure, classify as 0.
5. Do not assign 1 based on a single keyword; require that the abstract states or strongly implies the invention’s purpose in that domain.

### CLASSIFICATION IDEA: We want to identify patents where the CORE PURPOSE aligns with one of the following domains:

1. GREEN (dummy variable: green_ai)
The technology’s main goal is addressing climate change mitigation or adaptation.

ASK YOURSELF:
- Is this technology designed to reduce carbon emissions or other greenhouse gases?
- Is it meant to replace fossil fuels or make energy cleaner?
- Is it specifically addressing climate change, global warming, or their effects?
- Would someone concerned about climate change see this as part of the solution?

Examples to INCLUDE (green_ai=1): Carbon capture, renewable energy (solar/wind/hydro), GHG capture or reduction, clean energy storage
Examples to EXCLUDE (green_ai=0): General efficiency, non-GHG ’’emissions’’ (radio/light/electron), tech that incidentally uses solar power

Key test: Is the primary purpose addressing climate change?

2. FEMALE HEALTH (dummy variable: female_ai)
The technology specifically addresses medical conditions, organs, procedures, or healthcare needs unique to women’s biology.

ASK YOURSELF:
- Does this target organs/conditions that only people with female reproductive
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anatomy have (e.g., uterus/endometrium/cervix/ovary/vagina/placenta, etc.)?
- Is this about pregnancy, childbirth, postpartum, menstruation, menopause, or female fertility/contraception?
- Is this breast health technology explicitly tied to women's health or female physiology (not just a generic cancer list)?
- Would this technology primarily benefit women due to biological sex differences?

EXAMPLES TO INCLUDE (female_ai=1): Contraception, pregnancy/partum/postpartum, childbirth, gynecological devices, mammography, (pre)menstrual cycle and conditions, IVF/female infertility, ovarian/endometrial conditions, preeclampsia, PMS/PMDD, cervical/uterine treatments
EXAMPLES TO EXCLUDE (female_ai=0): General health/medical technology, male-specific (prostate/erectile), (post)partum procedures only benefitting newborns but not mothers, veterinary/animal reproduction, female terms used only as an example or in a list, conditions affecting both sexes equally or not clearly affecting women more than men

Key test: Is the primary purpose benefitting women because of their biology?

3. WEAPON (dummy variable: weapon_ai)
Technology for weapons, ammunition, or military combat.

ASK YOURSELF:
- Is this designed to be a weapon or part of a weapon system?
- Is this ammunition or explosives for combat?
- Is this military hardware designed to harm adversaries?
- Would this be regulated as a firearm or weapon?

EXAMPLES TO INCLUDE (weapon_ai=1): Firearms, ammunition, missiles, bombs, grenades, weapon sights/suppressors, military combat systems, body armor
EXAMPLES TO EXCLUDE (weapon_ai=0): Industrial ''guns'' (spray gun, nail gun, electron gun, glue gun), fireworks, mining explosives, hunting accessories or civilian sports

Key test: Is this designed to be a weapon or ammunition, or part of a weapon system ?

SPECIFIC RULES

1. **Intent matters**: what is this technology FOR? A solar panel on a weapon

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   system isn't ''green tech.''
2. **Primary purpose**: many technologies have multiple applications. Classify
   based on what the patent emphasizes as the main purpose.
3. **Be conservative**: if you're unsure, classify as 0. False positives are worse
   than false negatives.
4. **Ignore incidental mentions**: a medical device patent mentioning it could work
    for ''female or male patients'' or if it lists both ovarian and prostate
   cancer isn't female-health tech.
5. **Novel terminology is fine**: the patent might use technical jargon you haven't
    seen. Reason about what it DOES, not whether it matches expected keywords.
6. **Zeros are good**: you are allowed to classify patents as NOT belonging to any
   of the three categories.
7. **Mutual exclusivity**: if more than one category is plausible, choose the
   single best match for the core purpose and set the other two to 0.
8. **No single-word triggers**: do not assign 1 based on one keyword; require
   purpose-level evidence from the entire abstract.
9. **No skipping**: you need to read and classify ALL the patents in the file
   provided, do not skip any of them.

## OUTPUT FORMAT

You must respond with ONLY a CSV table. No other text.

1. Use semicolon (;) as delimiter -- no spaces around semicolons
2. First row must be exactly: `patid;green_ai;female_ai;weapon_ai`
3. One row per patent, in the exact order given
4. Values are 0 or 1 only (1 = classified as that category, 0 = not)
5. Each row has exactly 4 fields separated by 3 semicolons
6. No text, comments, or explanations before or after the CSV
7. No blank lines

## EXAMPLES

Patent ID: 4666
Abstract: Adsorption of carbon dioxide from gas streams at temperatures in the
   range of 300 to 500 degree C. is carried out with a solid adsorbent containing
   magnesium oxide, preferably promoted with an alkali metal carbonate or
   bicarbonate so that the atomic ratio of alkali metal to magnesium is in the
   range of 0.006 to 2.60. Preferred adsorbents are made from the precipitate
   formed on addition of alkali metal and carbonate ions to an aqueous solution of
```

a magnesium salt. The process is especially valuable in pressure swing adsorption operations.

Patent ID: 4843

Abstract: An anti-personnel projectile launched from a 12 gauge shotgun shell required at impact to have a low lethality consequence, in which the projectile is fitted in the shell in a shape characterized by a blunt end in the direction of flight and maintained in this shape by oppositely directed air resistance and propelling forces to obviate a change of shape during flight that might cause a serious injury.

Patent ID: 5002

Abstract: An apparatus for treatment of female stress urinary incontinence with urethral hypermobility with a support harness adapted to fit over the superior edge of the pubic bone of a patient, left or right of the pubis symphysis, a sling adapted to rest against the anterior vaginal wall or submucosally at the level just below the urethrovesical junction, and vaginal shaft connecting the sling to the support harness and adapted to position the sling causing stabilization and support of the urethrovesical junction.

Patent ID: 5265

Abstract: An electronic device has reduced radio frequency interference (RFI) emissions. The electronic device includes a signal generator that is coupled to a reference clock signal and a first digital circuit. The signal generator generates a random signal derived from the reference clock signal. The first digital circuit is coupled to the signal generator. The random signal governs pulse characteristics of the first digital circuit.

Patent ID: 5474

Abstract: An improved durable, low density, high build polyurethane coating is disclosed, as well as its method of manufacture. A slow reacting polyisocyanate is combined with a polyol so as to form a uniform mixture with an extremely long pot life. The low viscosity uniform mixture can then be sprayed onto a substrate using a conventional spray gun. A polyurethane catalyst is introduced after formation of the uniform mixture, preferably via a second spray nozzle so that catalyst is externally mixed into the polyisocyanate/polyol spray stream.

Correct output:

‘‘‘

```
patid;green_ai;female_ai;weapon_ai
4666;1;0;0
4843;0;0;1
5002;0;1;0
5265;0;0;0
5474;0;0;0
‘‘‘

### Reasoning (NOT included in output):
- 4666: GREEN=1 -- CO2 adsorption technology for capturing carbon dioxide from gas
   streams
- 4843: WEAPON=1 -- Anti-personnel projectile launched from shotgun shell
- 5002: FEMALE=1 -- Treatment for female urinary incontinence, involves vaginal
   wall
- 5265: All 0 -- ’’Emissions’’ here means radio frequency interference, NOT
   greenhouse gases
- 5474: All 0 -- ’’Spray gun’’ is industrial coating equipment, NOT a weapon

---

## PATENTS TO CLASSIFY

{patents_input}

Respond with CSV only.
```

Table A.5: Party Affiliation and Polarized Technologies, Categories Defined through LLM

	Green Technologies			Female-Health Technologies			Weapon-related Technologies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat $\hat{\beta}_1$	0.0035**	0.0065***	0.0062***	0.0030***	0.0017*	0.0010	-0.0132***	-0.0095***	-0.0094***
	(0.0016)	(0.0014)	(0.0015)	(0.0010)	(0.0010)	(0.0010)	(0.0016)	(0.0013)	(0.0013)
Other $\hat{\beta}_2$	0.0026*	0.0036**	0.0036**	0.0014	0.0009	0.0008	-0.0078***	-0.0057***	-0.0055***
	(0.0016)	(0.0015)	(0.0016)	(0.0010)	(0.0009)	(0.0009)	(0.0014)	(0.0013)	(0.0012)
Female $\hat{\beta}_3$			0.0010			0.0116***			-0.0041***
			(0.0016)			(0.0014)			(0.0011)
N. of Inventors	95,581	95,581	95,301	95,573	95,573	95,293	95,565	95,565	95,285
% of Dem.	35.78	35.78	35.78	35.78	35.78	35.79	35.78	35.78	35.79
$\mathbb{E}(LHS)$ for Rep.	0.033	0.033	0.033	0.008	0.008	0.008	0.030	0.030	0.030
Scaled Difference (%)	10.79	19.95	18.90	37.13	21.34	12.30	-44.64	-31.99	-31.66
Patent Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Section FE	×	✓	✓	×	✓	✓	×	✓	✓
Birth Year FE	×	×	✓	×	×	✓	×	×	✓

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 through an LLM algorithm, as described in section A.2.2. 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 21.

A.2.3. Alternative Outcome Variables: CPC Classification

Table A.6 replicates Table 3 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 retained 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.6: Party Affiliation and Polarized Technologies, Categories Defined Through CPC

	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.2.3. 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on pages: 21, A.12.

A.2.4. Patent-level Analysis

We estimate a specification at the patent level:

$$y_p = \beta_1 \, \text{Democrat}_p + \beta_2 \, \text{Other}_p + \beta_3 \, \text{Female}_p + \gamma_{t(p)} + \delta_{c(p)} + \zeta_{s(p)} + \mu_{a(p)} + \epsilon_p \tag{A.3}$$

where p denotes a patent, $c(p)$ the county of residence of the first-listed inventor in patent p, $t(p)$ the grant year of patent p, $s(p)$ the technology section of patent p, and a the average birth year across inventors listed on patent p, 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.7, we report the results of estimating Equation (7). In columns 1-3, we restrict the sample to single-inventor patents. In columns 4-9, we restrict the sample to patents granted to teams (i.e., ≥ 2 inventors). In columns 4-6, party affiliation is defined as the share of Democrats in the team. In columns 7-9, a team is defined as "Democrat" if all members are Democrats, and similarly for "Other" and "Republican," and we construct a dummy for mixed-affiliation teams.

Table A.7: 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 (7) 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. j are: green (columns 1, 4, 7), female health (columns 2, 5, 8), and weapon-related (columns 3, 6, 9). All specifications also include: i.) patent grant year dummies; ii.) county of first-listed inventor fixed effects; 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 "Republican" teams (columns 7-9). Standard errors clustered by county of first-listed inventor are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on pages: 23, A.15.

A.3. Main Robustness Checks

Table A.8: 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 (6) 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 (6) 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 (6) 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 (6) 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 21.

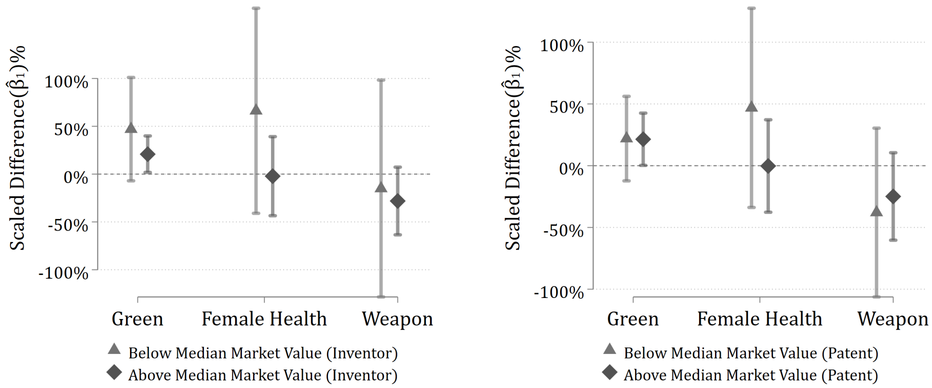
A.4. The Role of Technology-Specific Skills

Table A.9: 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

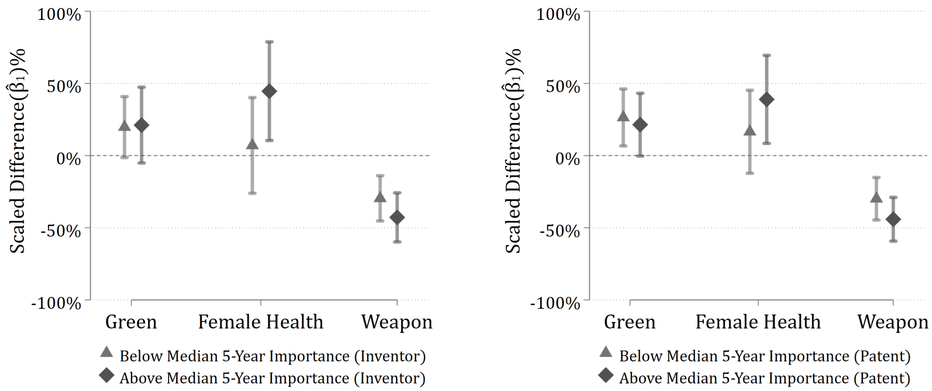
Notes. The unit of observation is an inventor. The sample includes all USPTO inventors who were granted a patent between 2001 and 2023 merged with NY, NJ, FL, and PA voter registration data. Panel A splits the sample by the median of the average citation count for inventors, while Panel B splits the 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, 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, Jaffe and Trajtenberg (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, Baslandze and Stantcheva (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 of patent-level average adjusted forward citations and estimate Equation (6) on each inventor-level subsample. "Scaled Difference" is the estimated coefficient divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 25.

Figure A.2: The Role of Technology-Specific Skills: Patent 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 (6) 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. Referenced on pages: 25, 26.

Figure A.3: The Role of Technology-Specific Skills: 5-Year Importance



Notes. Each plot reports scaled differences for the scaled coefficient of "Democrat" ($\hat{\beta}_1$). 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 and patent-level average of the 5-year patent importance, weighted by the number of inventors in each patent and residualized by year fixed effects. 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 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 (6) in each subsample. 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. Referenced on pages: 25, 26.

A.5. The Role of Organizations

Table A.10: 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
	Academic Organizations	Non-Academic Organizations	Academic Organizations	Non-Academic Organizations	Academic Organizations	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
	Small Organizations	Large Organizations	Small Organizations	Large Organizations	Small Organizations	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
	Without Organization FE	With Organization FE	Without Organization FE	With Organization FE	Without Organization FE	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–merged to their assignee–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 the estimated coefficient divided by the mean of the outcome variable for Republicans. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 28.

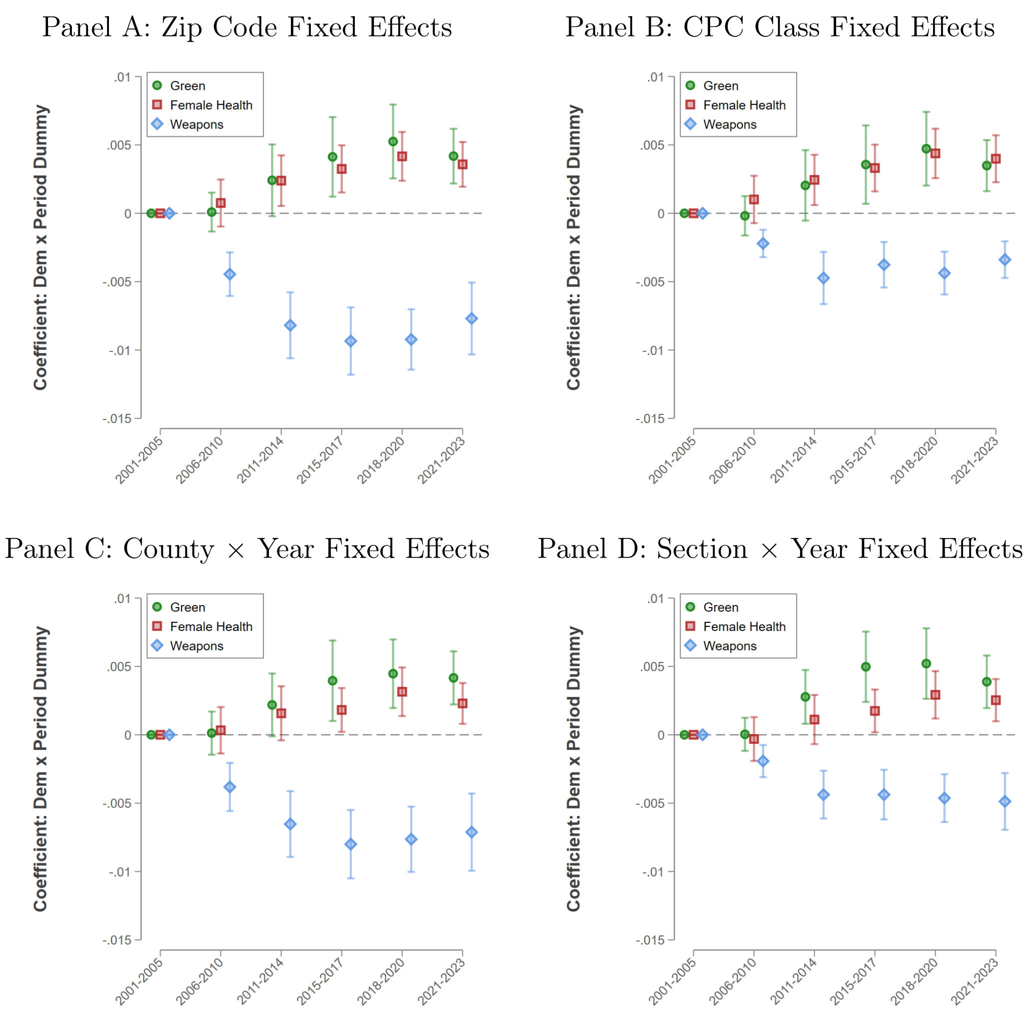
Table A.11: Party Affiliation and Polarized Technologies: Organization Fixed Effects

	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	+ Assignee FEs	Baseline	+ Assignee FEs	Baseline	+ Assignee FEs
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, merged to their assignee, who were granted a patent between 2001 and 2023, merged with NY, NJ, FL, and PA voter registration data. The unit of observation 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. Columns (2), (4), and (6) also control for company fixed effects. "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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 30.

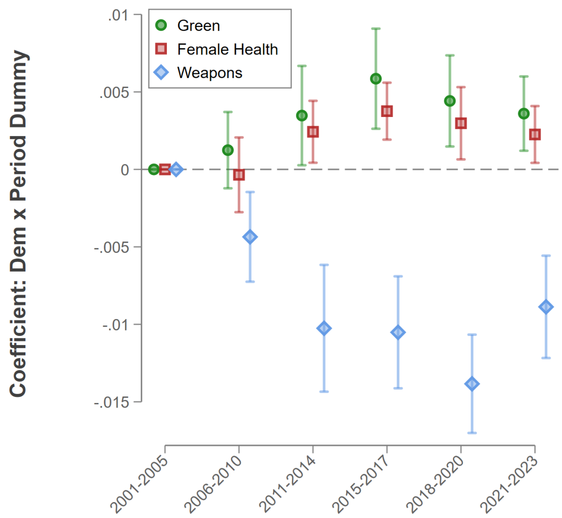
A.6. Dynamics of Party-Technology Alignment

Figure A.4: Party Affiliation and Polarized Technologies Over Time: Additional Fixed Effects



Notes. The unit of observation is an inventor-year. 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 (N=262,512). In Panel A, we add zip code fixed effects to Equation 7, while in Panel B, we add CPC class fixed effects. CPC class is defined as the modal class for an inventor in a given year. In Panel C, we add county×year fixed effects, while in Panel D we add CPC section × year fixed effects to Equation 7. For each technology $j \in$ green, female-health, weapon, we then remove those inventors who were patenting j in period p_0 (2001-2005). The figure reports the interaction coefficients $\hat{\beta}_{1,p}$ between the Democrat indicator and period p indicators from Equation (7), estimated separately by technology. For each technology $j \in$ green, female-health, weapon, the dependent variable is the proportion of patents in technology j relative to the total patents granted to inventor i in year t. Coefficients are shown over six periods; 2001-2005 is the omitted category. Periods are: 2001-2005, 2006-2010, 2011-2014, 2015-2017, 2018-2020, and 2021-2023. Green circles denote estimates for green technologies, red squares for female-health technologies, and blue diamonds for weapon-related technologies. Capped lines show 90% confidence intervals based on standard errors clustered at the county level. Referenced on page: 33.

Figure A.5: Party Affiliation and Polarized Technologies Over Time: Younger Cohorts



Notes. The unit of observation is an inventor-year. We restrict the sample to younger inventor cohorts (N=123,687). We define "younger cohorts" as inventors born after the sample median birth year (1962). For each technology $j \in$ green, female-health, weapon, we then remove those inventors who were patenting j in period p_0 (2001-2005). The figure reports the interaction coefficients $\hat{\beta}_{1,p}$ between the Democrat indicator and period p indicators from Equation (7), estimated separately by technology. For each technology $j \in$ green, female-health, weapon, the dependent variable is the proportion of patents in technology j relative to the total patents granted to inventor i in year t. Coefficients are shown over six periods; 2001-2005 is the omitted category. Periods are: 2001-2005, 2006-2010, 2011-2014, 2015-2017, 2018-2020, and 2021-2023. Green circles denote estimates for green technologies, red squares for female-health technologies, and blue diamonds for weapon-related technologies. Capped lines show 90% confidence intervals based on standard errors clustered at the county level. Referenced on page: 33.

A.7. The Diffusion of Polarized Technologies

Table A.12: Party Affiliation and the Diffusion of Innovation, Poisson Count Model

	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1) All Technologies	(2) Outside the Same Technology	(3) All Technologies	(4) Outside the Same Technology	(5) All Technologies	(6) 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 34.

Table A.13: Party Affiliation and the Diffusion of Polarized Technologies, Intensive Margin

	Green Technologies		Female-Health Technologies		Weapon-related Technologies	
	(1) All Technologies	(2) Outside the Same Technology	(3) All Technologies	(4) Outside the Same Technology	(5) All Technologies	(6) 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 34.

Table A.14: 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. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 35.

Table A.15: Party Affiliation and the Diffusion of Polarized Technologies, By Party of Cited Inventor

	Green Technologies			Female-Health Technologies			Weapon-related Technologies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Patented by Democrat	Patented by Republican	All	Patented by Democrat	Patented by Republican	All	Patented by Democrat	Patented by Republican
Democrat $\hat{\beta}_1$	0.0050***	0.0058***	0.0029*	0.0041*	0.0014	-0.0013	-0.0081***	-0.0002	-0.0041***
	(0.0019)	(0.0014)	(0.0015)	(0.0022)	(0.0012)	(0.0012)	(0.0018)	(0.0008)	(0.0014)
Other $\hat{\beta}_2$	0.0003	0.0028*	0.0007	0.0044**	-0.0008	-0.0002	-0.0070***	0.0002	-0.0043***
	(0.0025)	(0.0017)	(0.0016)	(0.0019)	(0.0013)	(0.0012)	(0.0021)	(0.0008)	(0.0013)
$\hat{\beta}_2 - \hat{\beta}_1$	-0.0048	-0.0029	-0.0022	0.0003	-0.0022	0.0011	0.0010	0.0004	-0.0002
P-value $\hat{\beta}_2 - \hat{\beta}_1$	[0.0492]	[0.0643]	[0.1467]	[0.8895]	[0.1357]	[0.3216]	[0.5047]	[0.5797]	[0.8380]
N. of Inventors	45,917	28,658	28,658	45,917	28,658	28,658	45,917	28,658	28,658
% of Dem.	36.51	37.01	37.01	36.51	37.01	37.01	36.51	37.01	37.01
$\mathbb{E}(LHS)$ for Rep.	0.038	0.010	0.010	0.022	0.007	0.007	0.030	0.003	0.010
Scaled Difference (%)	13.31	59.63	27.93	18.74	21.38	-19.14	-27.28	-5.19	-42.47

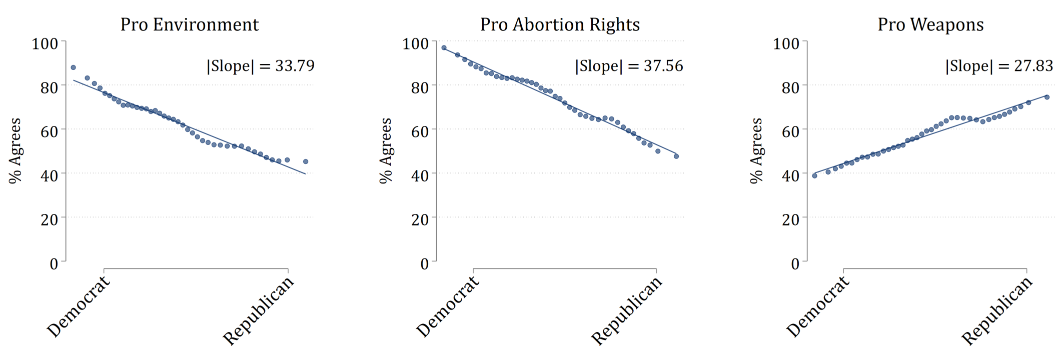
Notes. The unit of observation is an inventor. The sample includes USPTO inventors who were granted a patent between 2001 an 2023, merged with NY, NJ, FL, and PA voter registration data. This table shows citations patterns merging also the identity of the inventors of the cited patents. This explains why there are fewer observations in columns (2), (3), (5), (6), (8), and (9). In columns 1, 4, and 7, the outcome variable is a dummy equal to one if an inventor has ever cited a patent in technology j, and zero otherwise. In columns 2, 5, and 8, the outcome variable is a dummy equal to one if an inventor has ever cite a patent classified as technology j that was patented by a Democrat inventor, and zero otherwise. In columns 3, 6, and 9 the outcome variable is a dummy equal to one if an inventor has ever cited a patent classified as technology j that was patented by a Republican inventor, and zero otherwise. Technologies 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, inventor birth-year, technology-section fixed effects, and a female dummy. "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. "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 $\hat{\beta}_1$ divided by the mean of the dependent variable in the sample of Republican inventors. Standard errors clustered by county are reported in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Referenced on page: 36.

B. Survey Analysis

B.1. Comparison with Other Policy Issues

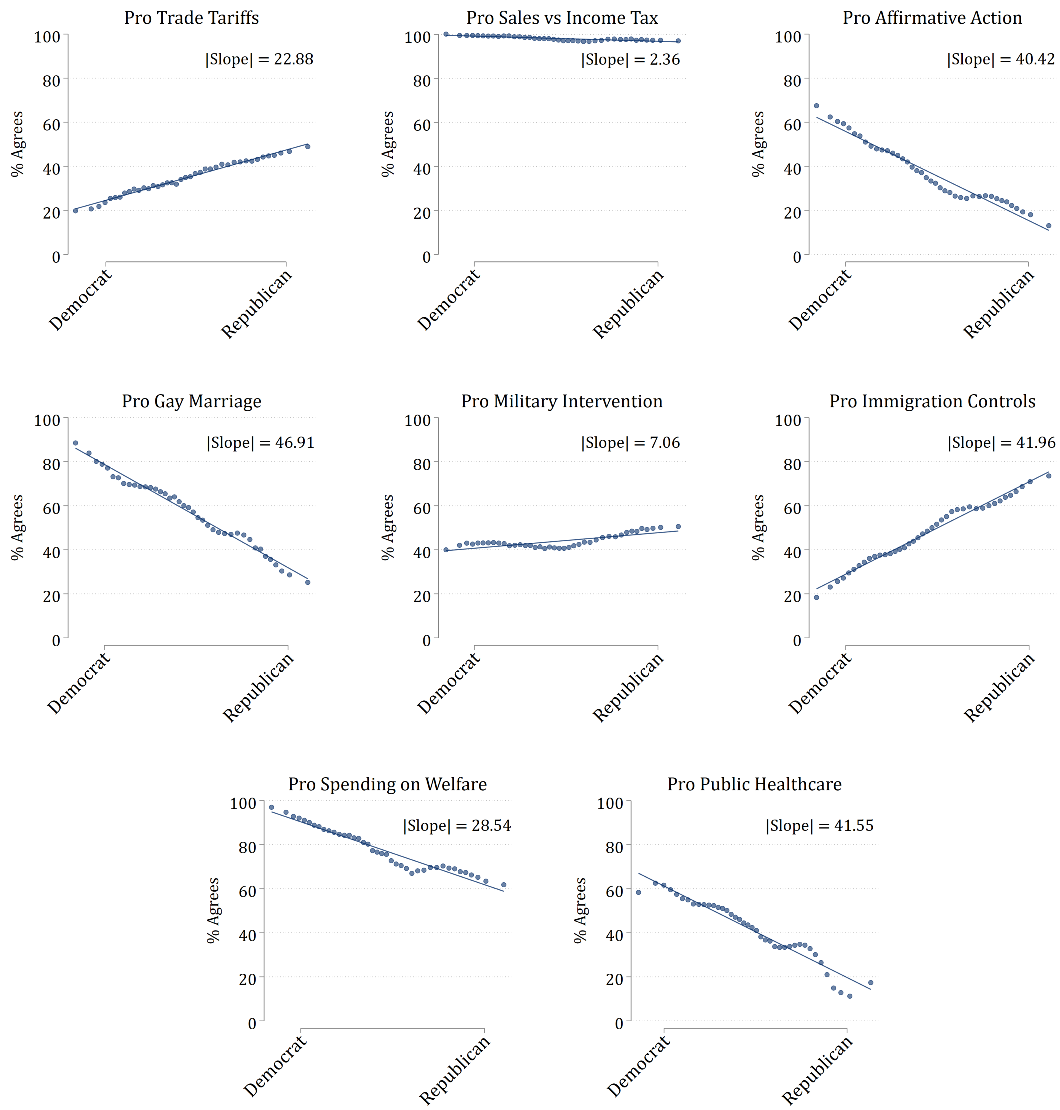
In this section, we analyze survey data from the Cumulative Cooperative Election Study (CCES) (Kuriwaki, 2024). The CCES aggregates and harmonizes all the yearly waves of the Cooperative Election Study (CES), a survey on a range of questions related to political behavior and preferences, from 2006 to 2021. Figure A.6 replicates Figure 1 using a 7-point scale of partisan identity (rather than party affiliation as reported in the main text). It shows the relationship between partisan identity and views on all CCES topics, including the environment, abortion rights, and gun control.[43] 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. 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.[44]

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



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

[44]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, based on occupational codes and education.

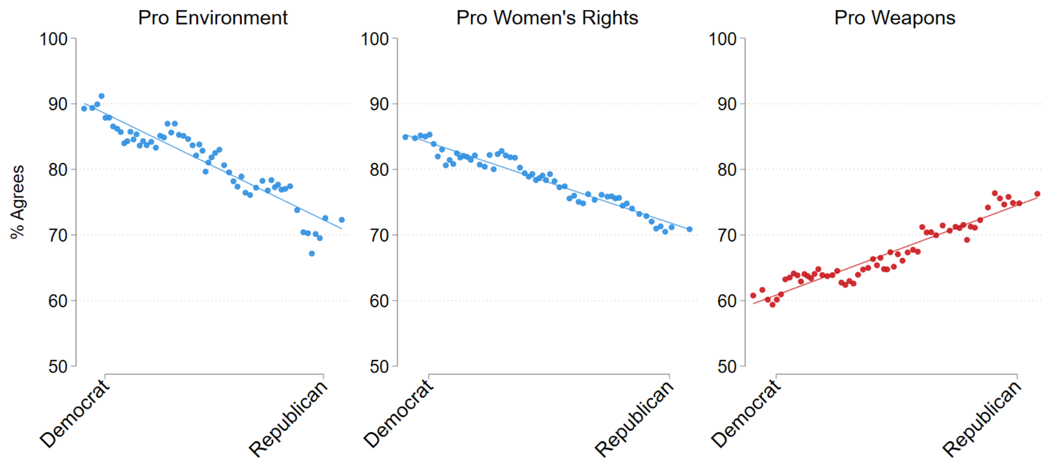


Notes. The figure reports binned scatter plots with 40 equally sized bins and the line of best fit showing the relationship between partisan identity and support for different issues from the Cooperative Congressional Election Study (CCES). We restrict the sample to US citizens and we drop individuals 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. Referenced on page: A.29.

Figure A.7: Comparing Partisan Gradients in Support for Fundamental Issues, GSS

Panel A: Full Sample



Panel B: Sample Similar to Inventors

Notes. The figure shows the proportion of General Social Survey (GSS) respondents who support the environment, women's rights, and the use of weapons. These indexes are constructed as averages of a set of GSS questions related to each topic after rescaling them to be in the range [0, 1]. Each GSS question is re-coded to ensure that higher values imply the respondent displays favorable values and/or attitudes towards the topic. Panel A includes the full sample of respondents from the United States for 2000 to 2022 (N=4,508). Panel B restricts the sample to occupations and education levels with the characteristics of inventors (N=1,457). We define these occupations as: engineers, designers, production and operation managers, scientists. We further restrict the sample in Panel B to respondents achieved education levels compatible with those of inventors with at least 12 years of schooling, corresponding to a high school degree. All correlations (both in Panel and in Panel B) control for age, sex, race, income, education, occupational status FEs, year FEs, and region FEs. Referenced on page: 9.

Index	GSS Variable	GSS Question
Pro Environment	`natenvir, natenviy, natenrgy`	We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount: Improving and protecting the environment / Developing alternative energy sources
Pro Environment	`spenviro`	Listed below are various areas of government spending. Please indicate whether you would like to see more or less government spending in each area. Remember that if you say "much more," it might require a tax increase to pay for it.: The Environment
Pro Environment	`intervir`	Are you very interested, moderately interested, or not at all interested in issues about environmental pollution?
Pro Environment	`grntaxes`	How willing would you be to pay much higher taxes in order to protect the environment?
Pro Environment	`grnprice`	How willing would you be to pay much higher prices in order to protect the environment?
Pro Environment	`grnecon`	How much do you agree or disagree with each of these statements? We worry too much about the future of the environment, and not enough about prices and jobs today.
Pro Environment	`grnsol`	How willing would you be to accept cuts in your standard of living in order to protect the environment?
Pro Environment	`grncon`	Generally speaking, how concerned are you about environmental issues? Please tell me what you think, where 1 means you are not at all concerned and 5 means you are very concerned.
Pro Environment	`grnsign`	In the last five years, have you signed a petition about an environmental issue?
Pro Environment	`grnmoney`	In the last five years, have you given money to an environmental group?
Pro Environment	`impgrn, grnexagg`	How much do you agree or disagree with each of these statements? There are more important things to do in life than protect the environment / Many of the claims about environmental threats are exaggerated
Pro Environment	`amprogrn, usdoenuf`	Some countries are doing more to protect the world environment than other countries are. In general do you think that America is doing?
Pro Environment	`redcehme, h2oless, nobuygrn, drivless`	How often do you reduce the energy or fuel you use at home/ save or re-use water/avoid buying certain products/cut back on driving a car for environmental reasons?
Pro Environment	`recycle`	How often do you make a special effort to sort glass or cans or plastic or papers and so on for recycling?
Pro Womens' Rights	`fepol, fepolv, fepolnv`	Tell me if you agree or disagree with this statement: Most men are better suited emotionally for politics than are most women.
Pro Womens' Rights	`fejobind`	Having a job is the best way for a woman to be an independent person.
Pro Womens' Rights	`fewkno`	Do you think that women should work outside the home full-time, part-time or not at all, when a couple has not yet had a child?
Pro Womens' Rights	`fehire, fechld, fechld2, fepresch, fepresch2, fefam`	Now I'm going to read several statements. As I read each one, please tell me whether you strongly agree, agree, neither agree nor disagree: Because of past discrimination, employers should make special efforts to hire and promote qualified women/A working mother can establish just as warm and secure a relationship with her children as a mother who does not work/A preschool child is likely to suffer if his or her mother works/It is much better for everyone involved if the man is the achiever outside the home and the woman takes care of the home and family
Pro Womens' Rights	`fepres`	If your party nominated a woman for President, would you vote for her if she were qualified for the job?
Pro Womens' Rights	`wrknokid, rwrknokd, wrkbaby, wkrsch`	Do you think that women should work outside the home full-time, part-time or not at all under these circumstances: After marrying and before there are children/When there is a child under school age/After the youngest child starts school.
Pro Womens' Rights	`abdefctw, abdefectw, abdefectg, abpoorw`	Do you personally think it is wrong or not wrong for a woman to have an abortion: A. If there is a strong chance of serious defect in the baby; B. If the family has a very low income and cannot afford any more children
Pro Womens' Rights	`hubbywrk, hubbywrk1`	A husband's job is to earn money; a wife's job is to look after the home and family.
Pro Womens' Rights	`mapaid, twoincs1`	Do you agree or disagree: Working women should receive paid maternity leave when they have a baby/ Both the husband and the wife should contribute to the household income
Pro Womens' Rights	`abfel, abmelgl`	Leaving aside what you think of abortion for yourself, do you think a woman should continue to be able to have an abortion legally or not, or would you say it depends?

Pro Womens' Rights	abmoral	Leaving aside whether or not you think abortion should be legal, are you morally opposed to abortion or not, or would you say it depends?
Pro Womens' Rights	abmedgov1, abmedgov2	Which of these statements comes closer to your view about what information a woman should have when she makes a decision about whether to have an abortion? 1. a woman and her medical professional should decide; 2. the government should decide
Pro Womens' Rights	abanyg,abdefect, abdefectg, abnomore, abnomoreg, abpoor, abpoorg	Please tell me whether or not you think it should be possible for a pregnant woman to obtain a legal abortion if: The woman wants it for any reason/If there is a strong chance of serious defect in the baby/If she is married and does not want any more children/If the family has a very low income and cannot afford any more children
Pro Womens' Rights	kidsuffr, famsuffr, homekid	Do you agree or disagree: A pre-school child is likely to suffer if his or her mother works / All in all, family life suffers when the woman has a full-time job / A job is alright, but what most women really want is a home and children
Pro Womens' Rights	gendereq	do you think it should or should not be the government's responsibility to: Promote equality between men and women?
Pro Weapons	gunsales	In most states a gun owner may legally sell his or her gun without proof that the buyer has passed a criminal history check. How strongly do you favor or oppose a law that required private gun sales to be subject to the same background check requirements as sales by licensed dealers?
Pro Weapons	guns911	As a result of the 9/11 terrorist attacks, do you think that gun control laws should be stricter, making it harder for people to purchase firearms or that gun control laws should be less strict, making it easier for people to purchase firearms?
Pro Weapons	gunsdrnk	In all states it is illegal to drive while under the influence of alcohol. Would you favor or oppose state laws making it illegal to carry a firearm while under the influence of alcohol?
Pro Weapons	gunlaw	Would you favor or oppose a law which would require a person to obtain a police permit before he or she could buy a gun?
Pro Weapons	rifles50	Currently under federal law, very high power, 50-caliber rifles that can penetrate armor from a mile away are available to people on the same basis as standard hunting rifles. Should such very high power rifles be 1) restricted only to the police and military, or 2) available to civilians like standard hunting rifles as they are at present?
Pro Weapons	hgunlaw	Please tell me whether you agree or disagree with the following statement: "There should be more legal restrictions on handguns in our society."
Pro Weapons	semiguns	Should semi-automatic, assault weapons or semi-automatic guns known as assault rifles be sold to the general public or should their sales be limited to the military and police?
Pro Weapons	natarms, natarmsy	Are we spending too much, too little, or about the right amount on the military, armaments and defense?
Pro Weapons	sparms	Please indicate whether you would like to see more or less government spending in each area. Remember that if you say "much more," it might require a tax increase to pay for it: The military and defense
Pro Weapons	conarmy	I am going to name some institutions in this country. As far as the people running these institutions are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them? The military
Pro Weapons	owngun, shotgun, pistol	Do you happen to have in your home (IF HOUSE: or garage) any guns or revolvers? Is it a pistol, shotgun, rifle, or what?
Pro Weapons	hguncrim	Some people argue that more restrictions on handguns would decrease violent crime by making it harder for criminals to get handguns. Other people argue that more restrictions on handguns would increase violent crime by making it harder for law-abiding citizens to defend themselves with handguns. Which of the following statements is closer to your own opinion?

B.2. Closed and Open Primary States

Open states are those with open primaries for presidential, congressional and state elections. Similarly for closed states. We assemble a classification from `https://openprimaries.org/rules-in-your-state/` and the National Conference of State Legislatures. The 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.

C. A Stylized Illustration of the Conceptual Framework

This appendix provides additional details for the stylized model underlying the conceptual framework in Section 3. The purpose of the model is to illustrate, in a tractable special case, how political alignment shapes inventors' technology choices and to clarify the comparative statics underlying the empirical and policy implications discussed in the main text. Throughout, we maintain the same utility structure as in the main text. The two-technology case is sufficient to illustrate sorting between aligned and neutral domains.

C.1. Economic Environment

The economy is populated by a unit mass of inventors indexed by $i \in [0, 1]$. Inventors supply one unit of labor inelastically and operate within a given technological field. Within that field, they choose among alternative technologies. For expositional clarity, we consider the case of two technologies, indexed by $j \in \{1, 2\}$. Technology 1 is politically neutral, while Technology 2 is politically polarized. This corresponds to a special case of the general framework in which $j \in \mathcal{J}$. We abstract from firm-side optimization and treat wages as exogenous, consistent with the assumptions in the main text. Let w_1 and w_2 denote the wages associated with Technologies 1 and 2.

C.2. Preferences and Alignment

Inventors derive utility from wages and from non-monetary alignment between their views and the technology they work on. Utility is additively separable and given by:

$$U_{ij} = w_j + \rho \cdot a_{g(i)j} + \varepsilon_{ij} \tag{A.4}$$

where $g(i) \in \{D, R, O\}$ denotes inventor i's political affiliation, $a_{g(i)j}$ measures the alignment between group $g(i)$ and technology j, $\rho \geq 0$ captures the weight placed on alignment, ε_{ij} is an idiosyncratic preference shock.

This is identical to the utility specification in Section 3. Under standard assumptions on the distribution of ε_{ij} (e.g., continuous with full support), the resulting sorting probabilities are increasing in alignment payoffs. For expositional clarity in the threshold derivations below, we temporarily set $\varepsilon_{ij} = 0$; this deterministic version yields identical qualitative sorting implications.

C.3. Alignment Structure

We normalize alignment with the neutral technology to zero for all groups:

$$a_{g1} = 0 \qquad \forall g \in \{D, R, O\}$$

Technology 2 is politically polarized. Alignment differs across political groups:

$$a_{D2} = \psi \qquad a_{R2} = -\pi \qquad a_{O2} = 0 \qquad \psi, \pi > 0$$

Thus the alignment gap emphasized in the main text is:

$$a_{D2} - a_{R2} = \psi + \pi$$

An increase in political polarization corresponds to an increase in this alignment gap, either through higher ψ, higher π, or a higher salience parameter ρ.

C.4. Technology Choice

Utility from each technology is:

$$U_{i1} = w_1, \tag{A.5}$$

$$U_{i2} = \begin{cases} w_2 + \rho\psi & \text{if } g(i) = D, \\ w_2 & \text{if } g(i) = O, \\ w_2 - \rho\pi & \text{if } g(i) = R. \end{cases} \tag{A.6}$$

Democrat inventors prefer the polarized technology whenever:

$$w_2 + \rho\psi \geq w_1,$$

while Republican inventors prefer the neutral technology whenever:

$$w_1 \geq w_2 - \rho\pi.$$

Even when wages and productivity are identical across technologies, inventors sort across domains based solely on alignment considerations. This illustrates Prediction 1 in the main text: if $a_{D2} > a_{R2}$, then Democrats are more likely to select the polarized technology than Republicans.

C.5. Labor Supply

Let θ_D, θ_R, and θ_O denote the population shares of Democrat, Republican, and unaffiliated inventors. In the deterministic version (setting $\varepsilon_{ij} = 0$ for expositional clarity), labor supply to the polarized technology is given by:

$$L_2(w_2) = \begin{cases} 0, & \text{if } w_2 < w_1 - \rho\psi, \\ \theta_D, & \text{if } w_1 - \rho\psi \leq w_2 < w_1, \\ \theta_D + \theta_O, & \text{if } w_1 \leq w_2 < w_1 + \rho\pi, \\ 1, & \text{if } w_2 \geq w_1 + \rho\pi. \end{cases}$$

This schedule illustrates how alignment shifts the wage thresholds at which inventors are willing to work on a given technology. In the probabilistic formulation of the main text (with ε_{ij} having continuous support), these thresholds translate into smooth differences in selection probabilities, but the qualitative comparative statics are identical.

C.6. Comparative Statics

We now vary individual primitives of the model while holding wages fixed. Each case corresponds to a distinct channel emphasized in the main text.

C.6.1. An Increase in Political Polarization

In the notation of the main text, political polarization corresponds to an increase in the alignment gap:

$$a_{D2} - a_{R2} = \psi + \pi.$$

This may occur through an increase in ψ (stronger positive alignment for Democrats), an increase in π (stronger negative alignment for Republicans), and/or an increase in the salience parameter ρ. As the alignment gap widens, Democrats become willing to work on the polarized technology at increasingly lower relative wages, while Republicans require increasingly large wage compensation to do so.

In the deterministic case, the interval of wage differences over which only aligned inventors supply labor expands. In the probabilistic formulation of the main text, this corresponds to an increase in:

$$\Pr(j^*(i) = 2 \mid g(i) = D) - \Pr(j^*(i) = 2 \mid g(i) = R).$$

Thus, an increase in polarization raises cross-group differences in innovation rates for the polarized technology, consistent with Prediction 2 in Section 3.3.

C.6.2. A Technology Becomes Politically Aligned

Suppose Technology 2 is initially neutral, so that:

$$a_{D2} = a_{R2} = 0.$$

In this case, technology choice depends only on wages, and there is no systematic sorting by political affiliation. Now suppose the technology becomes positively aligned with Democrats, so that:

$$a_{D2} = \psi > 0, \quad a_{R2} = 0.$$

This corresponds to a shift in the ideological content of the technology, holding population composition fixed. Democrat inventors now derive non-monetary utility from working on the technology, while Republicans do not. The result is one-sided sorting: Democrats become more likely to select the technology even absent wage changes, while Republicans' incentives remain unchanged. In the language of the main text, a change in a_{gj} reallocates inventive effort across domains through alignment payoffs, even without changes in wages, skills, or population composition.

C.6.3. Changes in Political Composition

Finally, consider a change in the political composition of the inventor population. Let θ_D increase, holding alignment parameters (ρ, ψ, π) fixed. This change does not alter individual-level incentives or wage thresholds. However, it increases the mass of inventors who derive positive alignment payoffs from the polarized technology. As a result, labor supply to the polarized technology increases over the range of wages for which aligned inventors are marginal. In the probabilistic formulation of the main text, this corresponds to an increase in the aggregate innovation rate in aligned technologies due purely to compositional change. Therefore, even absent rising polarization or changes in technology alignment, shifts in the political composition of inventors can reallocate innovative effort across domains.

C.7. Policy Implications

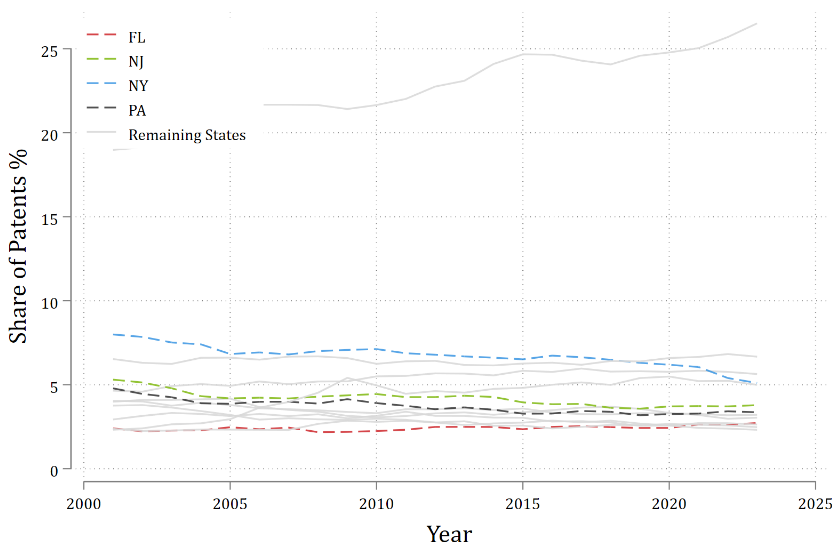
The model highlights a simple mechanism: alignment introduces a wedge between wages and the effective opportunity cost of labor. As the alignment gap widens, increasingly large wage differentials are required to induce inventors to work on misaligned technologies. Consequently, price-based innovation policies such as subsidies may have attenuated effects in highly polarized environments. Small subsidies primarily expand activity among inventors already aligned with the targeted technology, with limited reallocation from misaligned inventors. This mirrors the policy discussion in Section 8. The model is deliberately stylized and not intended to provide a structural welfare analysis. Its role is to clarify how non-monetary alignment, consistent with the utility structure in the main text, can generate systematic sorting across technologies and influence the direction of innovation.

D. Data Appendix

D.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.8.

Figure A.8: 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. Referenced on pages: 6, A.39.

D.2. Details on Voter Registration Data

Table A.17: Voter Distribution across Parties (All Registered Voters)

	Florida 2017		Florida 2022		New York 2020		New Jersey 2022		Pennsylvania 2020	
	Freq	Percent	Freq	Percent	Freq	Percent	Freq	Percent	Freq	Percent
BLK	2,781,664	23.56	3,285,809	25.96	3,747,053	20.16	2,367,110	36.49	981,003	11.48
DEM	4,537,250	38.43	4,328,284	34.19	9,471,160	50.96	2,518,980	38.83	4,067,944	47.60
REP	4,242,293	35.93	4,759,096	37.60	4,306,131	23.17	1,520,030	23.43	3,259,916	38.15
OTH	244,678	2.07	285,171	2.25	1,062,535	5.72	81,102	1.25	228,518	2.67

Notes. The table shows the distribution of registered voters across parties for the two snapshots of the Florida voter registration data (2017, 2022) the one for New York (2020), Pennsylvania (2020), and New Jersey (2022). These distributions are computed on cleaned voter registration data. “BLK” denotes unaffiliated voters, “DEM” those registered as Democrats, “REP” those registered as Republicans, and “OTH” includes voters registered as unaffiliated or under small parties. Referenced on page: 6.

Table A.18: Voter Distribution across Parties (All Registered Voters)

Source (1)	Voter characteristics (2)	Registration Rate (3)	Inventor characteristics (4)
Census2020	Some college degree	76%	86% attended college
Census2020	Bachelor’s degree	81.6%	86% attended college
Census2020	Advanced degree	85.2%	86% attended college
Census2012	HH Income $75,000-99,999	81.7%	(Individual) Income $100,000
Census2012	HH Income $100,000-149,999	84.9%	(Individual) Income $100,000

Notes. Column (3) reports voter registration rates among eligible U.S. citizens from the U.S. Census Bureau’s Voting and Registration Supplement to the Current Population Survey (November 2020 and November 2012). Column (2) lists the corresponding voter characteristics used to form the CPS cells; column (4) reports the analogous characteristics for inventors from Bell, Chetty, Jaravel, Petkova and Van Reenen (2018). Overall registration is 72.7% in 2020 and 72.4% in 2012. Income cells in the CPS are defined using household income brackets, while inventor income in column (4) refers to individual income. Registration rates cannot be computed for the joint distribution of these characteristics. Referenced on page: 6.

D.3. Details on Inventor-Voter Sample Construction

D.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, Chetty, Jaravel, Petkova and Van Reenen (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 (2009) finds 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, Jaffe and Lachman (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. 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).[45] We drop those voters that are registered as both Democrat and Republican (around 1% of the sample).

D.3.2. Matching Algorithm

We adopt a conservative matching algorithm that matches exact strings on first names, last names, and city of residence.[46] 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, Jaffe and Lachman (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.

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

[46]Following the procedures adopted by Bell, Chetty, Jaravel, Petkova and Van Reenen (2018), Teso, Spenkuch and Xu (2023) and Fos, Kempf and Tsoutsoura (2022).

D.3.3. Qualitative Match Validation

We also validate our matching procedure qualitatively. We compare the descriptive characteristics of our inventors to those documented in the literature, and we also show that the differences between matched inventors and the full sample of registered voters go in the expected direction.

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, 2025), 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 (2025), 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 (2025).

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)[47], they are prevalently white (79% compared to 60% in FL in 2017) or Asian (5% compared to 2% in FL in 2017)[48], they are mostly men (87% of inventors are men, while in the voter registration data gender is balanced).

D.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. 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,

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

[48] 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%.

Kempf and Tsoutsoura (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.

D.5. Outcome Variable Construction: Dictionary Approach

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

D.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."

D.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, Samila and Ferguson (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."

D.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."