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Political ideology and innovation

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Abstract
We study the role of political ideology for a critical group of economic agents: inventors. We document that, in "politically polarizing" fields, inventors patent innovations aligned with their political beliefs. We construct a novel dataset matching data from the US Patent Office (USPTO) with individual Voter Register data for two large US states, and with the universe of US campaign contributions data. We proxy political ideology with individual party affiliation and focus on fields where the ideological distance between Republicans and Democrats is especially large in the general population. We find that, compared to Republicans, Democrats are: i) more likely to file green patents; ii) more likely to file female-health patents, and this persists in the sub-set of male inventors; and iii) less likely to file weapon-related patents. The magnitudes are large and range from one-fourth to one-third of total patent production in these technologies. This pattern is explained by inventors sorting into firms, rather than by within-firm dynamics. Socio-economic status, geography, or differential reactions to monetary incentives cannot explain our findings. Importantly, ideological sorting persists in research organizations, suggesting that inventors may derive intrinsic utility from producing innovation aligned with their beliefs. We rationalize our findings using a stylized model of the labor market where inventors derive amenity value from producing innovation close to their political ideology.

Keywords: political ideology, innovation, inventors

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1. Introduction

The ideological gap between Democrats and Republicans in the United States is widening and spans a variety of topics, including climate change and gender equality (Bertrand and Kamenica, 2023). While most of the academic research has been focused on investigating the root causes of these trends (see Guriev and Papaioannou (2022) for a review), less attention has been devoted to understanding the potential implications, especially in *apolitical* settings (McConnell, Margalit, Malhotra and Levendusky, 2018). In this paper, we investigate the role of political ideology for a critical group of economic agents: inventors. Understanding how political ideology shapes the production of new technologies is important not only because innovation is the main driver of long-run economic growth in advanced economies (Bloom, Van Reenen and Williams, 2019), but also because inventors are intrinsically motivated agents (Stern, 2004) whose background plays a crucial role in shaping the direction of innovation (Einio, Feng and Jaravel, 2022, Koning, Samila and Ferguson, 2020).

In this paper we study how the political ideology of inventors relates to the content of their innovation. We assemble a novel dataset which combines individual-level voter registration data for the states of Florida and New York with patent and inventor data from the United States Patent and Trademark Office (USPTO).[1] The matched sample comprises more than 65,000 inventors and 228,000 patents from 1976 to 2022. Voter registration data report information on the political affiliation of registered voters. In Florida and New York State, affiliation to a given party is required in order to participate in its primary elections.[2] While these data do not allow us to precisely measure the political ideology and beliefs of inventors, but provide a robust proxy that has been utilized in prior studies (e.g., Teso, Spenkuch and Xu (2023)). From these data, we construct a set of binary variables indicating whether inventors are registered Republicans, registered Democrats, or other registered voters.[3] To test whether inventors patent in areas close to their ideology, we construct various indicators for whether a patent falls within a certain criterion or not. We select three broad categories of patents: environmental, women's health, and weapon-related.[4] These three topics mimic those that appear to be especially polarized from the analysis of general population surveys (Figure 1). We jointly refer to these technologies as "polarized".

We show that inventors innovate in fields that align with their political beliefs. First,

[1] Throughout the paper we refer to patents as "filed" or "granted" interchangeably.

[2] We describe these data more in detail in Section 2.

[3] "Other" includes individuals registered to vote without a party affiliation, as well as those registered with small parties.

[4] In the analysis, we split the environmental category into "green", "adaptation to climate change", and "dirty".

Democrat inventors are up to 29% more likely to file green patents and 35% less likely to file polluting patents, compared to Republican inventors. Second, Democrat inventors are 29% more inclined to file patents directed to women's health, even when it comes to male inventors, compared to Republican inventors.[5] However, Democrat inventors are no more likely to file male health patents when compared to Republican inventors working in similar technologies. This implies that results on women's health cannot be solely explained by Democrat inventors being more represented in the health sector. Third, Democrat inventors are 34% less likely to file a patent falling into the weapon category. To test whether our results extend beyond Florida and New York state, we replicate the main specification in a different dataset constructed by linking political campaign donors with inventors and spanning the entire US. The main findings are remarkably consistent between the two samples.

Our results have sensible economic implications. We find that polarized patents have 7 to 8% higher impact and market value and 38% higher probability of being in the top decile of the novelty distribution compared to non-polarized patents. Their stock market value over the full period amounts to more than 57 million USD.[6]

To understand *why* inventors patent in fields close to their political ideology, we test several potential mechanisms. First, we rule out the hypothesis that the political affiliation of inventors could act as a proxy for their socio-economic background by controlling for median family income. To do so, we link the matched voter-inventor dataset to the median family income of voters' zipcodes of residence. Second, we find that Democrats and Republicans are not patenting in areas with differential monetary returns. This means that the selection of inventors into patent categories cannot be explained by differential reactions to monetary incentives. This empirical exercise is in line with the idea that financial incentives may not be the sole driver of the decisions of intrinsically motivated agents (Besley and Ghatak, 2005, Bénabou and Tirole, 2003). Finally, we document that similar results hold for a subset of inventors with more discretion on the patented topics, i.e., inventors working for research-oriented organizations. This finding supports the idea that results cannot be solely due to demand-side factors.

To rationalize our findings, we build a stylized model of the labor market where workers' ideologies lead to assortative matching between workers and technologies. The model shows that it is theoretically possible to think about this assortative matching as coming from workers sorting into firms, rather than from employers discriminating along ideological lines (Colonnelli, Pinho Neto and Teso, 2022). The "ideological sorting" that emerges from this

[5]Male Democrat inventors are 32% more likely to patent female-health technologies, compared to male Republican inventors.

[6]These figures refer only to patents by inventors residing in Florida and New York.

model has clear policy implications: when it is present, it might be more complex, as well as more costly, to design market subsidies for a given technology.

This paper speaks to three streams of literature. First, our results are closely related to the emerging literature on the economic consequences of political ideology. For instance, political beliefs have been related to consumption (Gerber and Huber, 2009, Ray and Kamdar, 2023, Mian, Sufi and Khoshkhou, 2023), labor market (Colonnelli, Pinho Neto and Teso, 2022, McConnell, Margalit, Malhotra and Levendusky, 2018, Gift and Gift, 2014), entrepreneurship (Engelberg, Guzman, Lu and Mullins, 2021), donations (Pizziol, Demaj, Paolo and Capraro, 2023), judges' sentencing decisions (Cohen and Yang, 2019), bureaucrats productivity (Teso, Spenkuch and Xu, 2023), acceptance of humanitarian aid (Bursztyn, Callen, Ferman, Gulzar, Hasanain and Yuchtman, 2020), firms' stock market returns (Fos, Kempf and Tsoutsoura, 2022), capital allocation (Kempf, Luo, Schäfer and Tsoutsoura, 2021), credit ratings (Kempf and Tsoutsoura, 2021), health insurance take-up (Bursztyn, Kolstad, Rao, Tebaldi and Yuchtman, 2022), vaccines take-up (Wallace, Goldsmith-Pinkham and Schwartz, 2022), the content of school library programs (Mumma, 2022), portfolio decisions (Bonaparte, Kumar and Page, 2012, Meeuwis, Parker, Schoar and Simester, 2021), residential choice (McCartney, Orellana and Zhang, 2021), and securities prices (Dagostino, Gao and Ma, 2020). To the best of our knowledge, this is the first study to link political ideology and innovation. Second, this paper contributes to the literature on intrinsic motivation (Bénabou and Tirole, 2003, Besley and Ghatak, 2005, Teso, Spenkuch and Xu, 2023). It is plausible that inventors, like scientists, are influenced by factors beyond financial rewards. In the context of scientists, Stern (2004) documents an inverse association between wages and the propensity to conduct scientific research. Similarly, Myers (2020) shows that inducing scientists to alter the direction of their research requires substantial funding. While traditionally papers, like Einio, Feng and Jaravel (2022), link inventors' intrinsic motivation to socio-demographic characteristics, this paper stresses the importance of political ideology in motivating the choices of innovators. Third, we offer evidence on what may drive the direction of innovation. Peer exposure, gender, parental background, and race (Koning, Samila and Ferguson, 2020, Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018, Einio, Feng and Jaravel, 2022, Dossi, 2023), have been found to be important factors in shaping innovation, while, to the best of our knowledge, beliefs and political ideology have not been investigated in the literature.

The remainder of this paper is organized as follows. In Section 2, we describe the data sources, the matching procedure, the construction of the main outcome variables, and the use of partisanship as a proxy for political ideology. In Section 3, we explain the empirical strategy adopted. Section 4 presents our main results, while Section 5 discusses mechanisms.

Section 6 rationalizes our findings and draws policy implications using a stylized model of the labor market. Section 7 discusses other potential alternative explanations and describes ongoing research. Lastly, we conclude in Section 8.

2. Data

This paper utilizes two main datasets. The first one includes inventor-patent-classes data from USPTO. By leveraging detailed inventor characteristics, we can combine this with a second dataset - voter registration data. The resulting sample consists of the merged voter-inventor-patent dataset for Florida and New York state and accounts for over 65,000 inventors and 228,000 patents. Lastly, we merge this dataset with the median family income by zipcode of residence taken from the Missouri Census Data Center (Missouri Census Data Center, 2023) for additional specifications in Appendix A.6.

2.1. Patent data

We collect patent data from PatentsView, a joint team project with the United States Patent and Trademark Office (USPTO). PatentsView data contain detailed information on inventors, patents, and assignees, from 1976 up to 2022.[7] We focus on the universe of granted patents, instead of patent applications for twofold reasons. First, patent application data are not available before 2001 and this would sensibly reduce the size of our final sample. Second, 73% of the applications become granted patents within 3 years.[8] We restrict the sample to utility patents, which is standard in the literature. Inventor-patent data include a variety of variables: inventors' names, city and location of residence, attributed gender, patents' titles, abstracts, and date of when the patent is granted. We combine these data with Cooperative Patent Classification (CPC) and International Patent Classification (IPC) data, also available on PatensView. The CPC system is an extension of the IPC and is jointly managed by the European and the US patent offices. The CPC system categorizes patents into nine broad sections, which in turn are split into more fine-grained categories. The classification data are necessary to define some of the outcome variables. Additionally, using the USPTO patent identifier, we merge the patent dataset with the one on breakthrough innovations developed by Kelly, Papanikolaou, Seru and Taddy (2021) and the one on the economic importance of patents assembled by Kogan, Papanikolaou, Seru and Stoffman (2017).

[7] We downloaded the data on November 10, 2022, from https://patentsview.org/download/data-download-tables

[8] https://www.patentbots.com/stats/uspto-grant-rates

2.2. Voter register data

In the US voter registration is required for state and federal elections. This means that registered voters are a large fraction of the total US population. In November 2020, 72.7% of the voting-eligible population in the United States was registered to vote.[9] According to Census data, unregistered US citizens typically belong to ethnic minorities, have lower levels of education, are younger, and have lower incomes. Considering that inventors are typically white (Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018, Akcigit and Goldschlag, 2023, Dossi, 2023), highly educated (Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018), with an average age of 44-45 at the time of application (Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018, Kaltenberg, Jaffe and Lachman, 2023), and tend to have a relatively high income, it is reasonable to assume that the registration rate for US citizens who share these characteristics is higher than the national average (for more details, see Table A.2 in Appendix). Thus, voter registration data should –in principle– capture a substantial share of all US inventors who are eligible to vote.[10]

This paper employs voter registration data from two US states with distinct political leanings: New York (Sood, 2020), which tends to support the Democratic party, and Florida (Sood, 2017), which has a stronger inclination towards the Republican party.[11] These states are also among the most relevant in terms of total innovation in the US.[12] The NY dataset is a snapshot taken in 2020, while the FL dataset is a combination of two snapshots from 2017 and 2022. Both include active, inactive, and purged voters, meaning that individuals who registered in prior years but did not renew their registration may also be included.[13]

While 2020 NY statewide data include more than 19 million records, a figure close to the total NY population, FL statewide data for both waves combined report roughly 16 million observations – quite below the total FL population. This can be attributed to the fact that voters registered in FL can request a public record exemption, which would exclude them from the dataset. This could potentially bias the results in Section 4 in the case that inventors with different political preferences have a different probability of asking for an exemption and this is correlated with the type of innovation they patent. To alleviate this concern, in the Appendix, we perform the same regression using the NY subsample

[9] https://www.census.gov/data/tables/time-series/demo/voting-and-registration/p20-585.html

[10] US citizenship is required for voter registration.

[11] Registered Republicans exceeded registered Democrats in 2022 in FL, but not in 2017. However, since the 1950s, FL has predominantly voted for Republican candidates in presidential elections.

[12] They are among the top 10 US states for total innovation in the most recent years, and top 11 in the overall sample period. The evolution of the yearly share of patents for FL and NY is shown in Figure A.1.

[13] The status of inactive or purged can derive from various reasons, like court cases, death, or change of residence.

(Table A.7 in Appendix A.6), where voters do not have the option to request a public record exemption. Similarly, Table A.10 shows the results from the main econometric specification using the matched inventor-campaign contributors dataset, which is not affected by this issue as political campaign donors cannot ask to be removed from the FEC data.

We selected these two states not only because of their different political stances and their relevance for innovation, but also because they both operate in a closed primary system. To be able to participate in a given party's primaries, voters need to be registered under that party. This incentivizes voters with a mild political preference for a given party to label themselves under that party, instead of being unaffiliated.[14] Indeed, the share of unaffiliated voters is quite balanced across the datasets (Table A.1).

The FL and NY voter registration data contain very detailed information on voters. In particular, voters' names, gender, date of birth, address, zipcode, and political affiliation at the registration date. We proxy political ideology with the declared party at the moment of registration. As both datasets do not provide the full voter history, this measure of political ideology is time-invariant at the individual level, which is standard in the literature (e.g., Cohen and Yang (2019), Teso, Spenkuch and Xu (2023)) especially in the US context where citizens do not switch political preferences easily.[15]

2.3. Merge

In order to capture the political ideology of inventors, we link individual inventors in the USPTO data with the individual voters from the NY and FL statewide voter registration data. Before matching the two datasets, we clean and standardize string variables accordingly. The matching procedure adopted is quite conservative and aims at reducing the number of false positives. We develop an algorithm that uses a combination of names and cities of residence. We provide a detailed description in Appendix A.3. Overall, we are able to match 228,832 of 457,646 unique patents in both NY and FL, which corresponds to a match rate of 50%.[16] Some inventors remain unmatched and this could be due to various reasons. Firstly, as mentioned above, the matching procedure prioritizes minimizing the number of false positives, which may introduce biases into the estimate, over maximizing

[14] Additionally, by going through the NY voter registration application, we noticed that the portal is structured in a manner that nudges voters to declare a political preference, as leaving the preference blank is not readily apparent in the top-down menu of parties.

[15] Teso, Spenkuch and Xu (2023) mention that in the matched bureaucrat-voter sample only 6% change party affiliation. This figure is probably substantially lower for those who switch from Democrats to Republicans and vice-versa, due to strong animosity between members of these parties (Iyengar, Lelkes, Levendusky, Malhotra and Westwood, 2019).

[16] This is in line with the literature. For instance, Teso, Spenkuch and Xu (2023) match 67.5% of bureaucrats with commercial voter data. We adopt a much more conservative procedure.

the number of matches. Additionally, not all inventors are registered voters, as we discussed above.[17] Another reason why we fail to match inventors is that voter data are recent snapshots, meaning that older inventors may no longer be alive[18]. The NY Board of Elections receives monthly reports of deaths and immediately cancels the related registration data, while in FL the name is removed within seven days from the notification.[19] In line with the idea that many of the unmatched inventors are no longer present in the voter data, Figure A.2 shows the distribution of the number of inventors by the issue year and year of birth. Clearly, the masses of these distributions are concentrated in more recent years. Lastly, inventors who migrate to other US states and change their residential addresses could be excluded from our sample.[20] However, voters who fail to update their status are kept in the record for four years in NY and up to eight years in FL. Overall, we do not expect the sample to be representative of all FL and NY inventors, but rather of inventors who are registered voters in the snapshot years. Similarly, in the robustness exercise with campaign contribution data, the matched sample is representative of all inventors who are political campaign donors (Appendix A.7).

2.4. Validation

We validate the matching procedure in three main ways. First, in Appendix A.5, we qualitatively compare the characteristics of our final sample with other data. In particular, we show that the inventors' characteristics of the final sample are in line with those found in the literature. We also check that the differences in observable characteristics between the matched inventors and the full sample of voters are reasonable. Second, in Appendix A.5, we conduct equivalence tests and we do not find any economically large difference between matched and unmatched inventors for most of the observable characteristics. Third, we utilize a completely different dataset to infer political ideology and still most of the results remain unchanged. Specifically, we merge the inventor data to the Campaign Contribution Data (DIME) provided by Bonica (2019).[21] Details regarding the DIME data and the results obtained are presented in Appendix A.7.

[17] Teso, Spenkuch and Xu (2023) claim that the share of registered voters among federal bureaucrats is –at most–86%. We expect a similar figure for inventors.

[18] This may be particularly true for inventors who were already old at the beginning of the patent period.

[19] `https://www.ncsl.org/elections-and-campaigns/voter-registration-list-maintenance`

[20] Voters moving outside the US are not removed from the voters' list and can maintain their last US address.

[21] The matching algorithm in this case is different as we can select matches based on the donors' occupation, thus removing all those not related to innovation (similar to Fos, Kempf and Tsoutsoura (2022)). However, DIME data do not contain information on the age of the donors.

2.5. Measuring the direction of innovation

We define a set of dummy variables over three different types of technologies: environment, women's health, and weapons. These technologies mirror those topics over which the attitudes and beliefs of Republicans and Democrats are most divided in the general population (see Figure 1).[22]

Environment-related technologies First, we construct a dummy denoting green technologies by searching words in the patents' abstract. We select words that clearly mention the motivation of the inventors to tackle climate change issues.[23] In Appendix A.4 there are some examples of the expression used to define this "green" dummy. Note that this variable does not include all the technologies that can indirectly contribute to environmental goals, but only those which show a clear intention of inventors to develop a technology that is helpful in tackling climate change. Also, we did not consider all those technologies whose main objective is ambiguous. For instance, technologies that improve energy efficiency. Of course, these patents help the environmental cause, but it is not clear whether the main objective pursued is the environmental one or the cost-efficiency one. To obtain a more objective measure of "green" patents, we employ the Y02A sub-classification of the CPC system. This includes "technologies for adaptation to climate change, i.e. technologies that allow adapting to the adverse effects of climate change in human, industrial (including agriculture and livestock) and economic activities".[24] Differently from environmental-friendly technologies, which are relatively easy to detect, it is challenging to classify a patent as "polluting". To overcome this issue, we use the classification adopted by Aghion, Dechezleprêtre, Hémous, Martin and Van Reenen (2016). They consider "dirty" innovations those patents in the automobile sector which are based on internal combustion engines.[25]

Gender-specific health technologies To examine whether inventors affiliated as either Democrats or Republicans show differential support for women's causes, we identify technologies related to women's health. We, thus, combine the approach used by Koning, Samila and Ferguson (2021), with our own classification of health technologies. Using a machine learning algorithm, Koning, Samila and Ferguson classify a patent as "Female" if it covers

[22] Among the polarizing topics, we restrict our attention to those that we can map to patenting technologies.

[23] We read most of the abstract for which the dummy detects a "green" technology to see that effectively we are not picking up something else and this does not seem to be the case.

[24] `https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y02A.html`

[25] To refine this variable, we excluded all ambiguous cases where a patent could be categorized as both "dirty" and "green" at the same time.

"female organs, diseases, physiologic processes, genetics, etc.". "Male" patents are defined in a similar way. They compile a list of the 100 words that are most over-represented among female patents compared to non-female patents, and similarly for male patents. We search the terms of these dictionaries in patents' abstracts. Patents that matched with a term in the female list were marked as female-related patents; analogously for male-related patents. As female-related patents may include words related to cosmetics, which may not capture the intrinsic motivation of one group to innovate in technologies related to women's health, we further restrict attention to a set of health subclasses.[26] Interestingly, these data allow us not only to define female-related health patents but also to construct a placebo for male-related health technologies in a similar manner. This is important because while female-related topics are subject to politically diverse views, male-related topics are not.

Weapon-related technologies Since weapon possession, as well as military interventions, are politically divisive topics in the US, we select technologies that are directly related to the development of weapon-related technologies. We consider weapon-related technologies that fall in the F41 and F42 categories of the CPC classification system. F42 covers ammunition and blasting, while F41 includes all sorts of weapons, e.g., guns, rifles, and missiles.

2.6. Measuring political ideology

In order to study the relationship between political ideology and inventor patenting activity we would ideally use survey data, which can capture beliefs more precisely. Unfortunately, these data are not systematically available for inventors. As an indirect way to measure ideology, we rely on partisanship from the voter registration data. Similarly to Teso, Spenkuch and Xu (2023), we interpret this measure as a proxy for all the unobservable beliefs and principles that inventors have over a variety of topics, i.e., their political ideology. Figure 1 shows that individuals' political identities are strongly associated with their beliefs about the environment, women's rights, and the role of the army.

3. Empirical strategy

In this section, we test the relationship between political ideology and the likelihood of filing a patent falling into a certain category, denoted by the binary variable $C_{i,p}$, at the inventor-patent level i, p. $C_{i,p}$ is one of the categories described in Section 2.5. We estimate the

[26] We consider as health-technologies the following CPC subclasses: A61B A61C A61D A61F A61G A61H A61J A61K A61L A61M A61N A61P A61Q C12M C12N C12P C12Q C12R C12Y.

following specification:

$$C_{ip} = \underbrace{\alpha_{c,t}}_{\text{County-by-Year FE}} + \underbrace{\alpha_s}_{\text{CPC Section FE}} + \beta \text{DEM}_i + \gamma \text{OTHER}_i + \delta X_i + \epsilon_{ip} \tag{1}$$

The econometric model adds county-by-issue year fixed effects to account for time-varying factors that influence the propensity to innovate in a certain field, time-invariant characteristics that are different between counties, and county-specific yearly effects.[27] We also control for inventor time-invariant characteristics X_i, specifically gender and age at the granting patent year. In the Florida subsample, results are invariant to including also race in the set of time-invariant individual controls. Our preferred specification includes CPC Section fixed effects, denoted by α_s. This allows us to compare inventors within the same set of skills and research interests. For instance, the CPC macro-section "F" gathers all the patents related to mechanical engineering. In this way, we are able to screen out the variation due to sorting into different areas of expertise and to focus on a more comparable control group. We categorize voters into three categories reflecting their party affiliation: Democrats, Republicans, and Others. The category "Other" mostly includes individuals who did not declare any party affiliation and those who registered with other parties (e.g., Independent, Green, Conservative, Libertarian, etc.). Equation 1 includes dummies for Democrats and Other, with Republicans as the omitted category. The coefficient of interest is β, which measures the difference in the likelihood of filing a patent in category $C_{i,p}$ between Democrats and Republicans. Similarly, γ captures the differential propensity between Other and Republicans to file a patent in the outcome category. Standard errors are clustered at the county level. Our preferred specification is the one of Equation 1. However, in Section 4, we present the results controlling for I. county-by-year FE; II. county-by-year and section FE; III. county-by-year, section FE, and demographics, i.e., age and gender. Note results are unchanged if instead of controlling for age, we add birth year FE. Appendix A.6 checks that the coefficients remain unchanged when adding city fixed effect or the income level of the area in which inventors reside.

4. Results

The results presented in Tables 1, 2 and 3 shed light on the relationship between political ideology and the content of innovation, revealing that inventors patent in areas that align with their political beliefs. Consistently with the attitudes shown in surveys (Figure 1),

[27] The issue year is the year in which the patent is granted.

being Democrat is associated with a higher probability of filing environmental-friendly and female-health related patents and a lower probability of filing an innovation falling in the weapon and polluting category, compared to Republicans. Table 1 indicates that Democrats are significantly more likely than Republicans to patent "green" technologies and innovations for climate change adaptation. The first specification (Columns (1) and (4)) includes only county-by-year fixed effects. The coefficient for Democrats is positive and significant. In Columns (2) and (5) we add CPC section fixed effects. Interestingly, the coefficient for Democrats remains positive and statistically significant, meaning that political ideology matters even when we compare inventors with similar backgrounds and working in similar areas of expertise. In Columns (3) and (6) we add age and gender as control variables, estimating the econometric model described in Equation 1. In this specification, Democrats exhibit a 29% and 22% higher likelihood –compared to Republicans– of filing patents classified as respectively "green" and promoting the adaptation to climate change. Instead, the coefficient for the unaffiliated and those registered with small parties, i.e., category Other, is not statistically significant at conventional levels in most specifications. Table 2 shows that both Democrats and non-affiliated individuals are less inclined than Republicans to patent weapon-related and polluting technologies. However, only the coefficient for Democrats is always statistically significant in all specifications. In our preferred specification, Democrats are 34% less likely than Republicans to file a weapon-related technology and 35% less likely to file a dirty patent, as classified by Aghion, Dechezleprêtre, Hémous, Martin and Van Reenen (2016) (Columns (3) and (6)). Including CPC section fixed effects does not affect the statistical significance or direction of the coefficient for the Democrat dummy. This implies that Democrats not only work in less polluting or weapon-related areas, but they also file fewer patents in these fields, compared to Republicans, even within the same patenting category. Additionally, Democrats are 29% more likely to patent technologies directed towards women's health, a result that holds true even when restricting the sample to male-only inventors. This indicates that male Democrats are more likely to file health technologies related to women compared to male Republicans (Table 3). For the subset of male inventors, the effect size is even larger, with male Democrats having a 32% higher probability of patenting women's health technologies, compared to male Republicans. In columns (4) to (6), we perform a "placebo" test on male-health technologies. Since male health is not a polarized topic in the political debate, we expect to find no correlation between ideology and the probability of patenting one of these technologies. Democrats are more likely to work in male-health areas than Republicans but the magnitudes are much smaller (one third to one fifth of the corresponding effect size for female health). In column (5) and (6), the coefficients are not statistically significant. In column (4), the coefficient is marginally significant, a pattern explained by the fact that Democrat inventors patent disproportionately more in the health sector, compared to Republican inventors, as shown by Table A.4 in Appendix A.5. Interestingly, partisan ideology is a more stable and significant predictor than gender, age, and zipcode income (see Appendix A.6) and it explains both between and within areas of expertise sorting into patents. This is a new insight for the discussion on the importance of inventor backgrounds in shaping the direction of innovation (Koning, Samila and Ferguson, 2020, Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018, Einio, Feng and Jaravel, 2022, Koning, Samila and Ferguson, 2021). To test whether our findings are valid beyond Florida and New York, in Appendix A.7 we show that ideological sorting persists using the campaign donor-inventor sample, which spans the entire US.

4.1. Economic importance

We also verify whether ideological sorting is solely related to marginal patents or whether it can carry strong economic implications for the patenting activity. We construct a dummy – called "polarized" patent – that is equal to one for all the categories where Democrats and Republicans have a different propensity to innovate. Thus, it includes all the patents that fall in the green, weapon, dirty, and women-health defined above. We merge our dataset with the one developed by Kogan, Papanikolaou, Seru and Stoffman (2017) on the number of citations and the stock market value of patents, as well as the one on the breakthrough measures developed by Kelly, Papanikolaou, Seru and Taddy (2021). Kelly, Papanikolaou, Seru and Taddy (2021) identify breakthrough innovations as those being more distant to previous work as well as more similar to future ones. We consider those in the top 5% and 10% of that distribution.[28] The results in Table 5 show that the probability of patenting polarized technologies is positively related to all patent "quality" measures. More specifically, they have 7% higher citations, 8% higher market value, 38% higher probability of being in the top decile of the novelty distribution, and 55% higher probability of being in the top 5% of the novelty distribution compared to non-polarized patents. Thus, "polarized" patents are not the marginal ones, but have meaningful monetary and creative value. A back-of-the-envelope calculation suggests that the stock market value of "polarized" patents over the full period amounts to more than 57 million USD (adjusted to 1982 CPI).

[28]For the sake of brevity, we refer to these outcomes as patent "quality".

5. Mechanisms

Why do inventors patent technologies aligned with their beliefs? In this section, we test several mechanisms. We begin by disentangling whether these findings are due to how workers choose firms or whether they are driven by within-firm dynamics. Our results support the first hypothesis, which is that inventors choose firms patenting technologies close to their ideology. Tables A.8 and A.9 in Appendix A.6 show exactly this. Table A.8 displays the relationship between the share of patents per category and the share of Democrats or Other inventors working in a given assignee-state-year. Results are consistent with the findings of the main analysis. This indicates that the ideological sorting is strongly explained by the allocation of inventors to technologies *across* organizations. Table A.9 adds assignee fixed effects to the specification in Equation 1. Within firms, political ideology does not correlate with the probability of filing a patent in the polarized categories. Thus, ideological sorting persists *across* firms and it is not explained by sorting *within* firms.

Second, we test whether our measure of political ideology is simply a proxy for the socio-economic status of inventors. To do so, we include a control for median income in the zipcode of residence of inventors in our main specifications (Appendix A.6). As zipcodes are very narrow geographic areas, their median income can be used as proxy for socio-economic status, which we use as a substitute for inventors' income. The coefficients and significance for the Democrat dummy are unchanged in all specifications and for all the outcome variables. These results suggest that political ideology matters in explaining the propensity to innovate in certain fields beyond individual socio-economic characteristics.

Third, we test whether inventors with different political ideologies respond differently to monetary incentives. Political affiliation may be associated with the degree to which inventors are willing to change the direction of their work in exchange for pecuniary rewards. This would imply that ideological sorting could be explained by inventors valuing returns differently based on their ideology. To check that this is not the case, we restrict the analysis to the sample of patents with an estimated market value. Table 4 displays the relationship between the economic importance of a patent and political ideology. The economic value of a patent is measured via the log of real and nominal stock market returns (Kogan, Papanikolaou, Seru and Stoffman, 2017).[29] In none of the specifications the coefficients for the Democrat and Other dummies are statistically significant, with effect sizes virtually equal to zero. The results are in line with the hypothesis that inventors are faced with the choice

[29] The number of observations, patents, and inventors is lower in Table 4 compared to the previous results, as Kogan, Papanikolaou, Seru and Stoffman (2017)'s dataset covers granted patents up to 2010, and only those for which a market value can be inferred from the data.

to pursue many different projects with similar expected pecuniary returns. Among these different opportunities, they select those closer to their ideology.

Last, to alleviate concerns related to demand-side factors, we show that similar patterns hold for a subset of inventors with discretionary power in deciding the type of patents to file, i.e., inventors working for research-oriented organizations.[30] In this setting we rely on the matched political campaign contributor-inventor dataset. These data have the benefit of spanning all US states, thus the overall sample size is much larger than the one of the matched voter-inventor data.[31] This gives us enough power to estimate the main regression specification restricting the attention to research inventors.[32] We describe these data in detail in Appendix A.7. Table A.11 exhibits remarkably similar patterns to the main findings. Since political ideology appears to be highly correlated with the choices of inventors who work in research organizations, it is unlikely that these findings are solely due to demand factors. If this were the case, then we should not observe any pattern for these inventors as their job is mostly free from any constraints imposed by their assignees. Concerns related to demand-side factors and geographical sorting are also alleviated by the battery of county-by-year fixed effects present in every baseline specification. In Appendix A.6 we test whether ideological sorting is explained by geographical sorting across cities by including city fixed effects. Also in this case results remain unchanged.

6. A stylized model of ideological sorting in the labor market

In this section, we develop a stylized model of the labor market where differences in workers' ideologies can result in assortative matching between workers and firms. The purpose of this exercise is to show that it is theoretically possible to think about this ideology-based assortative matching as coming from the supply side, rather than from employer discrimination as in Colonnelli, Pinho Neto and Teso (2022).[33] Importantly, the "ideological sorting" that emerges from this model has clear policy implications: when it is present, it might be more complex (and costly) to design market subsidies for a given technology.

[30] We classify inventors working in research by analyzing the assignee organizations' name.

[31] However, for each state we can match fewer inventors, since campaign donors are a much smaller fraction of the total US population, compared to registered voters.

[32] The only difference is that we do not control for age because this information is not present in the campaign contributors' data.

[33] Interestingly, a similar result has already been formalized in the context of race-based discrimination by Becker (1971).

6.1. Labor supply

We model the labor market as composed of a unit mass of individual workers (inventors), each denoted as i. Individual workers are employed by a set of firms, each denoted as j. The wage set by each firm is higher than the worker's reservation wage. The workers take the wage as fixed. For the sake of simplicity, we do not separate the sorting into firms from the one into the specific technology. Thus, every firm j specializes in just one specific type of technology. Inventors have utility function:

$$u_i = w_j + \rho_{i,j} + \epsilon_{i,j} \tag{2}$$

where w_j is the wage set by the firm, which is constant across workers. This implies that firms cannot pay their employees different wages based on the employee's ideology (i.e., we switch off the possibility of "political discrimination" as in Colonnelli, Pinho Neto and Teso (2022)). $\rho_{i,j}$ represents the "ideological match" and is proportional to the (inverse) ideological distance between the worker and the firm. The closer an individual's ideology to the firm's product, the more utility they get from the job. $\epsilon_{i,j}$ is the individual-specific utility from working in firm j.

6.2. Labor demand

We assume that the labor market is composed of two firms $j = \{1, 2\}$, which hire workers in a perfectly competitive labor market. We further assume that the shares hired by each firm add up to 1. We impose these assumptions to focus on the labor supply side (following Folke and Rickne (2022)). Firms differ in the technologies they produce, and each specializes in one. Each firm (technology) has an associated "ideology", which we assume fixed. Firm 1 produces a *neutral* technology (e.g., semiconductors). Firm 2 produces a *polarized* technology (e.g., solar panels or another green technology).[34]

6.3. Equilibrium

In the baseline version of the model, we assume that $\epsilon_{i,j} = 0$, i.e., the is no individual idiosyncratic utility from working for firm j, except for the amenity coming from the ideological match $\rho_{i,j}$. We also normalize $\rho_{i,1} = 0$, i.e., there is no ideological match from working for

[34]With a slight abuse of language, for the purpose of the model we define technologies as "neutral" if they are not among the set of technologies where the ideological distance between Democrats and Republicans in the population is high. We define "polarized" those technologies over which the public opinion is especially divided.

a neutral firm. To simplify notation, we therefore refer to $\rho_{i,2}$ simply as ρ_i. The fraction of individuals that choose firm 2 is equal to $1 - F(w_1 - w_2)$. We define these individuals as "ideological" workers. Denoting $(w_1 - w_2) = \bar{\rho}$, this fraction is equal to $1 - F(\bar{\rho})$. If the pdf is continuous, the fraction of workers hired by firm 2 is equal to $L_2 = 1 - F(\bar{\rho})$ and the fraction of workers hired by firm 1 is equal to $L_1 = F(\bar{\rho})$. In Appendix A.8, we provide empirical evidence on the distribution of ρ for environment-related beliefs and a consistent theoretical example.

6.4. Policy implications

We can use this styled model to derive policy implications. In Appendix A.8, we show that using subsidies to finance a polarized innovation can be more costly when ideological workers who value the ideological match with that polarized technology are a minority. In this case, the government has to pay the amenity value to a larger share of neutral workers to induce them to innovate in the polarized field. We also argue that the degree of polarization matters for the design of subsidies. Intuitively, the higher the polarization, the higher the amenity value from the ideological match between ideological workers and the polarized technology. Thus, both the share of ideological workers and the degree of polarization may play a role in the effectiveness of subsidies directed to polarized technologies.

7. Future Work

The evidence shown in Section 5 is consistent with inventors deriving intrinsic utility from patenting technologies aligned with their political beliefs. However, our data do not allow us to rule out that labor demand factors generate the observed ideological sorting. First, our findings could be driven by local demand shocks: while we account for county-by-year fixed effects, our specifications would not be able to capture shocks that vary over time within counties. An example would be areas where more Democrat inventors are located experiencing increasing demand for inventors in green technologies. The growing availability of jobs in the green sector could induce Democrat inventors to self-select into these types of jobs. Second, ideological sorting could be generated by employer political discrimination, as shown by Colonnelli, Pinho Neto and Teso (2022) for Brazil. In ongoing research, we design an experiment to identify the role of the political ideology of inventors in determining ideological sorting in the labor market. Experimental variation is needed to disentangle supply- from demand-side factors and to identify the mechanisms leading to ideological sorting. More specifically, inventors may select into firms or technologies aligned with their ideology for *private* value or *social* value considerations. Private value considerations refer to inventors placing intrinsic value on the ideological match. Social value considerations refer to inventors deriving utility from aligning with the beliefs of their social group. We plan to administer this experiment to a sample of engineering students, a pool of job seekers with especially high probability of becoming inventors.

8. Conclusion

Political ideology plays a fundamental role in individual decisions such as consumption choices, vaccine take-up, and the selection of children's books. In this paper, we document a new margin along which ideology affects economic outcomes: by directing innovation efforts towards specific technologies. Our findings have potentially important implications for the production of innovation and for the direction of technological progress. We propose a theoretical framework to show that designing subsidies towards specific technologies will be more costly when a technology is "polarized", i.e. divisive in the political debate, compared to when it is "neutral". The model predicts that this cost will be higher, the higher the degree of political polarization in society: when the distance in beliefs between Democrats and Republicans increases, shifting innovation towards certain technologies will be especially costly. The time-varying component is a distinctive feature of political ideology compared to other demographic characteristics that have been shown to affect the direction of innovation, such as gender, race, and socio-economic status. This paper represents a first step towards understanding the relationship between political ideology and the direction of innovation. In ongoing work, we use experimental tools to disentangle the mechanism behind ideological sorting, as well as its costs.

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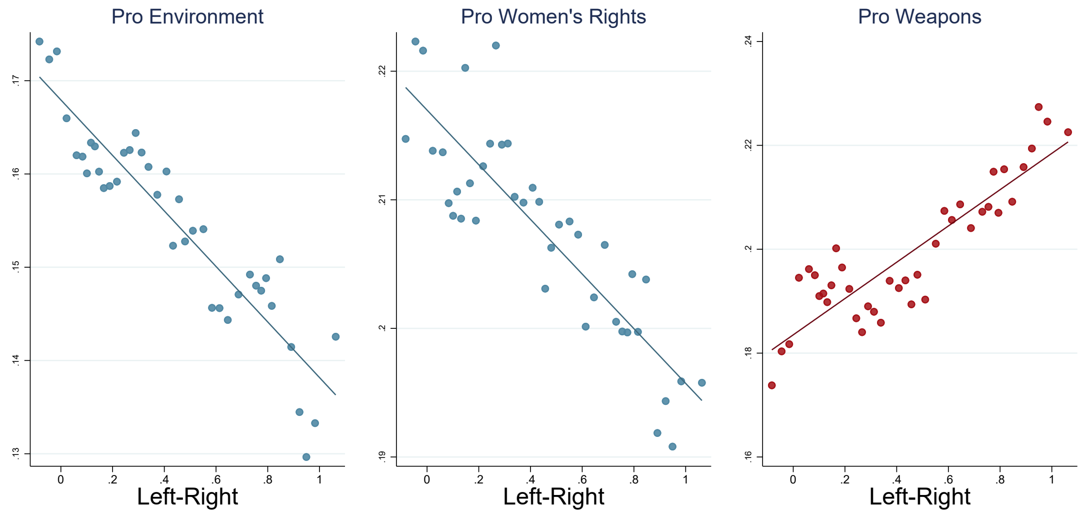
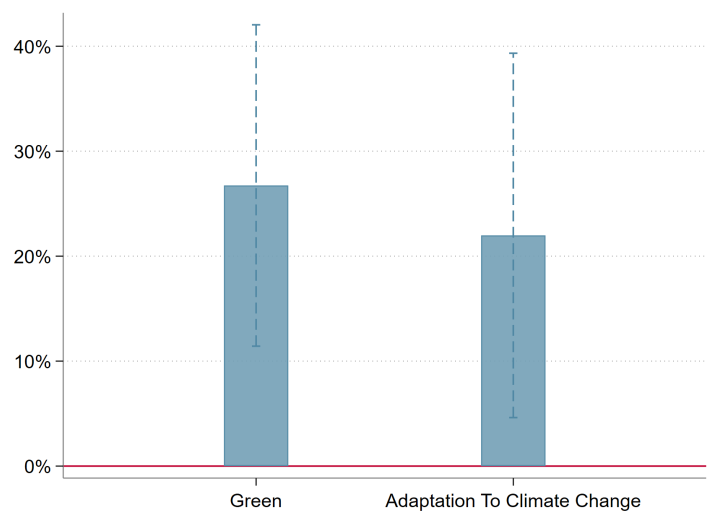
Figures

Figure 1: Individuals with different political views have different beliefs



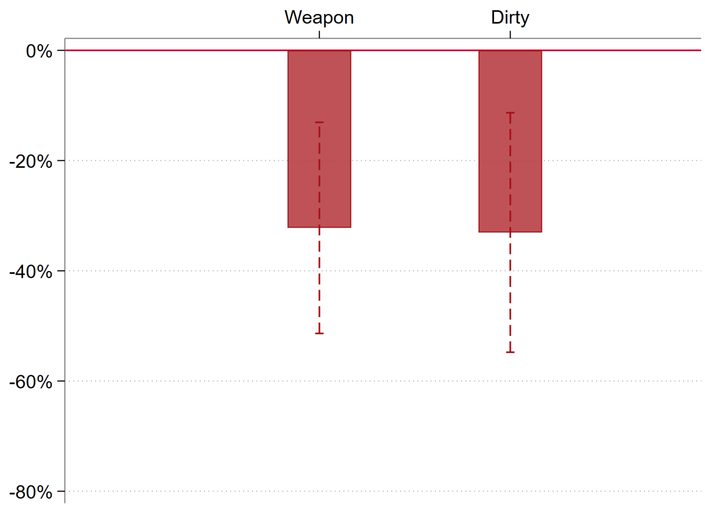
Notes. Sample of $\sim$ 40,000 US respondents from GSS (1974-2022); regression lines control for age, sex, race, income, education, occupational status FEs, year FEs, and region FEs.

Figure 2: Democrats are more likely to patent green technologies



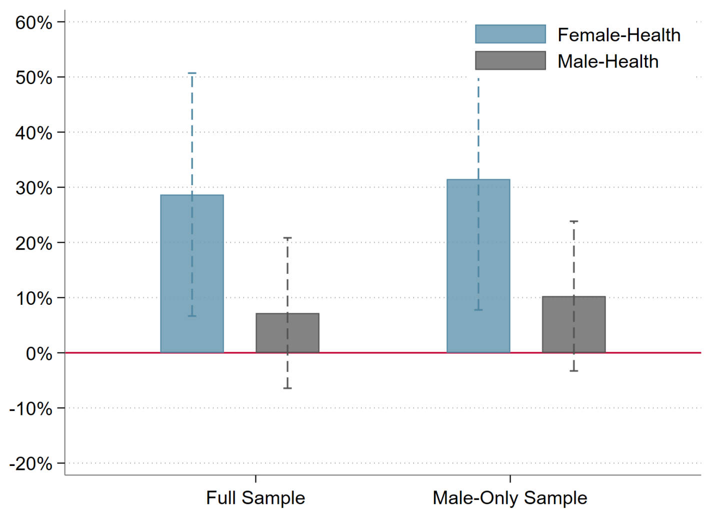
Notes. The unit of observation of an inventor-patent. The sample includes all the USPTO inventors merged with NY and FL voter data. The outcome variable = 1 if a patent falls within a "green" category, = 0 otherwise. Omitted party category: Republican. The corresponding regression results are shown in Table 1.

Figure 3: Democrats are less likely to patent weapons and dirty technologies



Notes. The unit of observation is an inventor-patent. The sample includes all USPTO inventors merged with NY and FL voter data. The outcome variable = 1 if the patent falls within a weapon or dirty category, = 0 otherwise. Omitted party category: Republican. The corresponding regression results are shown in Table 2.

Figure 4: Democrats are more likely to patent female-health technologies



Notes. The unit of observation of an inventor-patent. The sample includes all the USPTO inventors merged with NY and FL voter data. The outcome variables The outcome variable = 1 if the patent falls within a gender-related health category, = 0 otherwise. Omitted party category: Republican. The corresponding regression results are shown in Table 3.

Tables

Table 1: **Party Affiliation and Patenting in Green Technologies**

	Green Words			Adaptation to Climate Change		
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat	0.0010**	0.0014***	0.0015***	0.0017***	0.0012**	0.0013**
	[0.0004]	[0.0004]	[0.0004]	[0.0006]	[0.0005]	[0.0005]
Other	0.0010	0.0011*	0.0013**	0.0004	0.0001	0.0003
	[0.0006]	[0.0006]	[0.0006]	[0.0006]	[0.0006]	[0.0006]
Observations	334,535	334,535	334,535	334,535	334,535	334,535
Patents	228,361	228,361	228,361	228,361	228,361	228,361
Inventors	65,255	65,255	65,255	65,255	65,255	65,255
% of Dem.	0.350	0.350	0.350	0.350	0.350	0.350
$\mathbb{E}(LHS)$ for Rep.	0.005	0.005	0.005	0.006	0.006	0.006
Effect Size %	19.730	26.732	28.743	28.494	21.216	21.976
Patent Year FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Section FE	×	✓	✓	×	✓	✓
Demographics	×	×	✓	×	×	✓

Notes. The unit of observation of an inventor-patent. The sample includes all the USPTO inventors merged with NY and FL voters register microdata. The outcome variables represent whether or not the patent falls within a "green" category. Section FEs are 9 CPC section dummies. Demographics control for gender and age at the issue year. S.e. clustered at the county level. Omitted party category: Republican.

Table 2: **Party Affiliation and Patenting in Weapon or Dirty Technologies**

	Weapon			Dirty (Aghion et al.)		
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat	-0.0044***	-0.0028***	-0.0028***	-0.0020***	-0.0012***	-0.0012***
	[0.0010]	[0.0008]	[0.0008]	[0.0005]	[0.0004]	[0.0004]
Other	-0.0021**	-0.0015	-0.0015	-0.0010**	-0.0007*	-0.0008*
	[0.0010]	[0.0010]	[0.0010]	[0.0005]	[0.0004]	[0.0004]
Observations	334,535	334,535	334,535	334,535	334,535	334,535
Patents	228,361	228,361	228,361	228,361	228,361	228,361
Inventors	65,255	65,255	65,255	65,255	65,255	65,255
% of Dem.	0.350	0.350	0.350	0.350	0.350	0.350
$\mathbb{E}(LHS)$ for Rep.	0.009	0.009	0.009	0.004	0.004	0.004
Effect Size %	-50.164	-32.070	-32.211	-51.219	-30.511	-31.255
Patent Year FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Section FE	×	✓	✓	×	✓	✓
Demographics	×	×	✓	×	×	✓

Notes. The unit of observation of an inventor-patent. The sample includes all the USPTO inventors merged with NY and FL voters register microdata. The outcome variables represent whether or not the patent falls within a weapon or dirty category. Section FEs are 9 CPC section dummies. Demographics control for gender and age at the issue year. S.e. clustered at the county level. Omitted party category: Republican.

Table 3: **Party Affiliation and Patenting in Gender-related Health Technologies**

	Female-related Health			Male-related Health		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample						
Democrat	0.0058***	0.0036**	0.0037**	0.0022*	0.0008	0.0012
	[0.0020]	[0.0014]	[0.0014]	[0.0012]	[0.0012]	[0.0012]
Other	0.0030*	0.0019	0.0022*	0.0007	0.0001	0.0003
	[0.0017]	[0.0012]	[0.0013]	[0.0014]	[0.0012]	[0.0012]
Observations	334,535	334,535	334,535	334,535	334,535	334,535
Patents	228,361	228,361	228,361	228,361	228,361	228,361
Inventors	65,255	65,255	65,255	65,255	65,255	65,255
% of Dem.	0.350	0.350	0.350	0.350	0.350	0.350
$\mathbb{E}(LHS)$ for Rep.	0.013	0.013	0.013	0.017	0.017	0.017
Effect Size %	44.814	27.857	28.679	13.298	4.841	7.200
Patent Year FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Section FE	×	✓	✓	×	✓	✓
Demographics	×	×	✓	×	×	✓
Panel B: Male Sample						
Democrat	0.0055***	0.0036**	0.0038***	0.0028**	0.0016	0.0017
	[0.0018]	[0.0014]	[0.0015]	[0.0012]	[0.0011]	[0.0011]
Other	0.0031*	0.0020	0.0024*	0.0010	0.0003	0.0005
	[0.0017]	[0.0012]	[0.0013]	[0.0016]	[0.0013]	[0.0013]
Observations	305,016	305,016	305,016	305,016	305,016	305,016
Patents	215,379	215,379	215,379	215,379	215,379	215,379
Inventors	57,334	57,334	57,334	57,334	57,334	57,334
% of Dem.	0.336	0.336	0.336	0.336	0.336	0.336
$\mathbb{E}(LHS)$ for Rep.	0.012	0.012	0.012	0.016	0.016	0.016
Effect Size %	44.884	29.852	31.488	17.151	9.630	10.273
Patent Year FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Section FE	×	✓	✓	×	✓	✓
Age	×	×	✓	×	×	✓

Notes. The unit of observation of an inventor-patent. The sample includes all the USPTO inventors merged with NY and FL voters register microdata. The outcome variables represent whether or not the patent falls within a gender-related health category. Section FEs are 9 CPC section dummies. Demographics control for gender and age at the issue year. S.e. clustered at the county level. Omitted party category: Republican.

Table 4: **Party affiliation and Patents' Economic Importance**

	Real Stock Returns			Nominal Stock Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat	-0.0005	-0.0034	-0.0023	-0.0005	-0.0035	-0.0023
	[0.0119]	[0.0115]	[0.0120]	[0.0136]	[0.0130]	[0.0136]
Other	0.0028	-0.0016	0.0007	0.0019	-0.0029	-0.0005
	[0.0185]	[0.0161]	[0.0182]	[0.0213]	[0.0186]	[0.0209]
Observations	192,850	192,850	192,849	192,850	192,850	192,849
Patents	119,263	119,263	119,262	119,263	119,263	119,262
Inventors	26,022	26,022	26,021	26,022	26,022	26,021
% of Democrats	0.365	0.365	0.365	0.365	0.365	0.365
$\mathbb{E}(LHS)$	1.728	1.728	1.728	2.258	2.258	2.258
Effect Size %	-0.027	-0.194	-0.130	-0.021	-0.155	-0.103
Patent Year FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Section FE	×	✓	✓	×	✓	✓
Demographics	×	×	✓	×	×	✓

Notes. The unit of observation of an inventor-patent. The sample includes all the USPTO inventors merged with NY and FL voters register microdata and with data on the economic value of patents by Kogan, Papanikolaou, Seru and Stoffman (2017). The outcome variables are the log of the real and nominal stock market return. Section FEs are 9 CPC section dummies. Demographics control for gender and age at the issue year. S.e. clustered at the county level. Omitted party category: Republican.

Table 5: **Patents' Economic Importance and Probability of filing a Patent**

	Citations (1)	Real Stock Returns (2)	Nominal Stock Returns (3)	Breakthrough top5 (4)	Breakthrough top10 (5)
Polarized Patent	0.1009**	0.1331***	0.1496***	0.0336***	0.0402***
	[0.0389]	[0.0459]	[0.0510]	[0.0084]	[0.0088]
Observations	192,849	192,849	192,849	163,021	163,021
Patents	119,262	119,262	119,262	113,620	113,620
Inventors	26,021	26,021	26,021	38,176	38,176
% of Polarized Patents	1.500	1.500	1.500	2.980	2.980
$\mathbb{E}(LHS)$	1.596	1.659	2.215	0.064	0.113
Effect Size %	6.322	8.023	6.756	52.073	35.486
Patent Year FE	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓
Section FE	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓

Notes. The unit of observation of an inventor-patent. The sample includes all the USPTO inventors merged with NY and FL voters register microdata. The outcome variables in the first three columns are the log of the number of citations, the log of the real and nominal stock market return, obtained from Kogan, Papanikolaou, Seru and Stoffman (2017). In columns (4) and (5), the dependent variables are two measures of breakthrough innovation taken from Kelly, Papanikolaou, Seru and Taddy (2021). The main regressor "Polarized Patent" is a dummy for whether a patent falls into one of those categories where the propensity to innovate is different between Republican and Democrat inventors. Section FEs are 9 CPC section dummies. Demographics control for gender and age at the issue year. S.e. clustered at the county level.

Appendix

A.1. Contribution of FL & NY to total US innovation

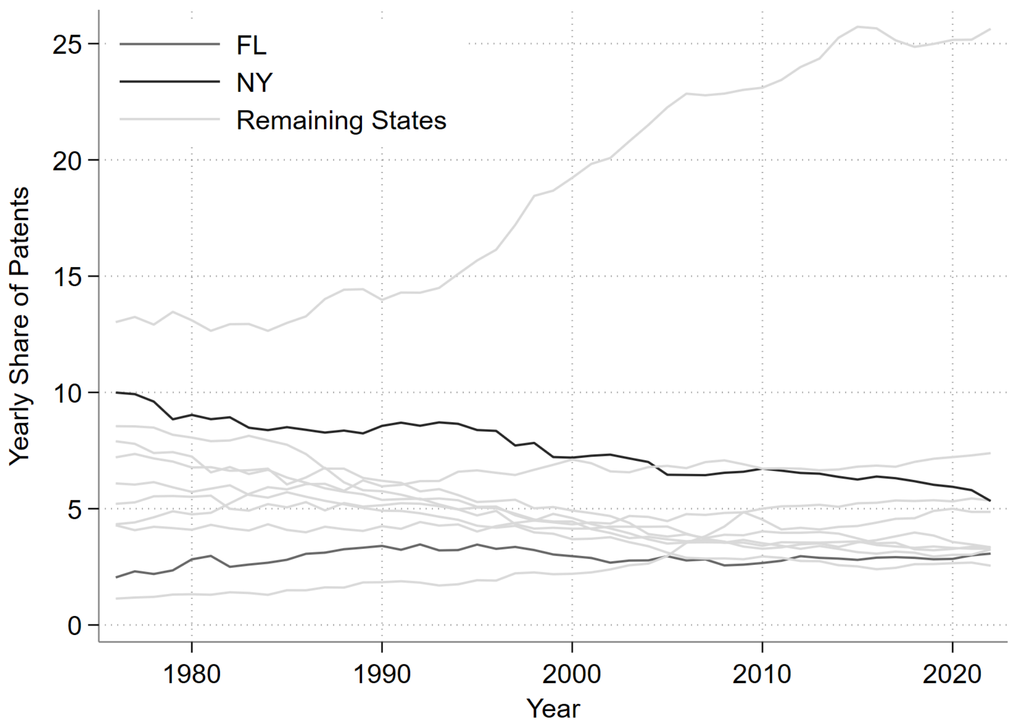


Figure A.1. The figure plots the evolution of the yearly share of patents (by residence of inventors) for the top 11 US states in terms of innovation.

A.2. Details on Voter Registration

Table A.1: **Voters Distribution across Parties (All Registered Voters)**

	Florida 2017		Florida 2022		New York 2020	
	Freq	Percent	Freq	Percent	Freq	Percent
BLK	3,022,354	25.17	3,582,111	27.61	3,776,192	19.91
DEM	4,539,637	37.81	4,333,270	33.40	9,643,606	50.84
REP	4,193,212	34.92	4,827,394	37.21	4,488,336	23.66
OTH	251,436	2.095	230,387	1.78	1,059,162	5.59

Notes. The table shows the distribution of registered voters across parties for the two snapshots of the Florida Voter Registration Data (2017, 2022) and the one for New York (2020). "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.

Table A.2: **Voter Registration Rate by Characteristics similar to Inventors**

Source (1)	Voter characteristics (2)	Registration Rate (3)	Inventor characteristics (4)	Reference (5)
Census2020	Age 45-64	77.3%	Mean age at application: 45.4[35]	Kaltenberg, Jaffe and Lachman (2023)
Census2020	Some college degree	76%	86% attended college	Bell, Chetty, Jaravel, Petkova and Van Reenen (2018)
Census2020	Bachelor's degree	81.6%	86% attended college	Bell, Chetty, Jaravel, Petkova and Van Reenen (2018)
Census2020	Advanced degree	85.2%	86% attended college	Bell, Chetty, Jaravel, Petkova and Van Reenen (2018)
Census2012	HH Income $75,000-99,999	81.7%	(Individual) Median Income $83,000	Bell, Chetty, Jaravel, Petkova and Van Reenen (2018)
Census2012	HH Income $100,000-149,999	84.9%	(Individual) Median Income $83,000	Bell, Chetty, Jaravel, Petkova and Van Reenen (2018)

Notes. This table displays the registration rates of eligible voters (Column 3) by observable characteristics (Column 2). These are obtained from the Voting and Registration in the Election of November 2020 and 2012 (US Census Bureau). The registration rate across *all* eligible US citizens is 72.7% in 2020 and 72.4% in 2012. We select socio-economic characteristics that share similarities with inventors. However, it is not possible to know neither the registration rates combining all these characteristics together, nor to screen on specific occupations. Column 5 presents the references for the inventors' characteristics mentioned in Column 4.

[35] I estimate an average age at the patent granting year of 48.7, in line with a 3 years lag between the application and the granting year.

A.3. Details on Data Cleaning and Merge

Pre-merge To merge the two datasets, it is necessary to clean and standardize 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 the nicknames –denoted by parenthesis or quotes– that appeared for some inventors in the USPO data. One major difference in how names are formatted between the two datasets is that the patent data present only the 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 the *imputed* first name, while the second string is the initial or the middle name. Some inventors' names are composed of more than 2 words. In those cases, we store these variables separately and we will consider only the first middle name for the merge. Lastly, after data cleaning, around 1,000 observations have been dropped because of empty first names.[36] The final patent dataset includes around 9 million inventor-patent pairs. In FL there are around 133,000 unique patents, while in NY 323,000 over the full period. To further reduce the possibility of false positives when merging the two datasets, we truncated voter data according to age.[37] Jones (2010) find that there are no great achievers before the age of 19 and that only 7% of the sample is 26 or fewer years old. Kaltenberg, 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 also drop those with the length of the last name or city of residence equal to one character or if the lengths of the first name and middle name are both equal to one character. We replace voters' gender with the most common value if it is missing. Whenever for one voter we have duplicate records with different parties, we follow a similar procedure to Teso, Spenkuch and Xu (2023). If one person 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).

Merge The merge algorithm matches strings exactly on first names, last names, and city of residence.[38] Either the initial letter of the middle name is the same or it should be missing in at least one of the two datasets. Whenever one inventor is matched to two voters, we keep the match if in the following cases: I. voters are registered as Democrats or Unaffiliated

[36]The first name variable is empty in these cases because it contained only words that have been stripped out like "deceased", "jr", "sr" or because it was equal to the last name.

[37]We drop those born after 1999.

[38]we followed the procedures adopted in Bell, Chetty, Jaravel, Petkova and Van Reenen (2018), Teso, Spenkuch and Xu (2023) and Fos, Kempf and Tsoutsoura (2022).

II. voters are registered as Republican or Unaffiliated III. voters are registered as Other or Unaffiliated. The registered party will be respectively I. Democrat II. Republican III. Other.[39] If after this step inventors are associated with more voters, we keep the records with non-missing middle names. After the merge, we keep all the inventors with ages –at the issue year– between 22 and 89 as in Kaltenberg, Jaffe and Lachman (2023). We plan to perform alternative merge procedures in the future, exploiting also age and patent year.

[39] Results are unchanged if instead, we drop these duplicate matches.

A.4. Green Words

Examples of adjacent words: greenhouse gas; global warming; carbon footprint; climate warming; climate change; adaptive capacity; alternative energ; solar panel; solar thermal; photovoltaic; wind power; wind energ; wind park; wind farm; wind plant; wind turbine; circular economy; hydrogen engine; green pellets; green energy; clean energy; emission control system; emission system; carbon dioxide removal; carbon dioxide control; reduction of co2; reducing co2; polluting emissions; non-fossil fuel
Example of non-adjacent words: c02 sorbent; c02 reduce, c02 remov; c02 recycl; c02 captur; renewable energy; renewable power; solar energy; solar power; geothermal energy; geothermal heat; sustainable energy; environment damaging; ozone layer; ozone shield; n2o sorbent; n2o reduction; n2o decrease; n2o sorbing; pollution traffic; pollution fuel; wind turbine energ; solar energ; renewable power; carbon dioxide power

A.5. Descriptives of the Matched Sample

We compare the descriptive statistics of the voter-inventor sample with those found in the literature. First, 12% of all inventors are women in the final sample, which is identical to 12% found in Einio, Feng and Jaravel (2022). Lastly, the average age at the issue year is 48.72. Considering that most patents are granted after 3 years since the first application, this figure is in line with the average age of 44-45 at the application year (Kaltenberg, Jaffe and Lachman, 2023, Bell, Chetty, Jaravel, Petkova and Van Reenen, 2018).

Also, relative to the full sample of voters in FL and NY, the matched sample of inventors displays reasonable characteristics. Inventors live in richer zipcode areas (median family income of 101,434 USD compared to 81,726 USD of FL and NY voters), they are prevalently white (80% compared to 60% in FL in 2017) or Asian (5% compared to 2% in FL in 2017)[40], they are mostly men (87.9% of inventors are men, while in the voter registration data gender is balanced and if anything there are more women).

To show more rigorously that our matched voter-inventor sample is not likely to be biased, we perform equivalence tests in Table A.3.[41] As Teso, Spenkuch and Xu (2023), we test the null hypothesis that the difference between matched and unmatched inventors is economically large and we consider "economically large" differences those that exceed 10% of a standard deviation. The p-values for equivalence tests are presented in the last column of Table A.3. For 17 out of 20 covariates, we do not find any economically large difference between the matched and unmatched. Importantly, unmatched and matched inventors have similar lengths and number of consonants in their names. This is reassuring as names strongly correlate with race and socio-economic status (Fryer and Levitt, 2004, Dossi, 2023). Matched and unmatched inventors are also similar in terms of gender, the income of the city of residence, the probability of being granted patents in most of the CPC sections, and the probability of patenting for at least one assignee classified as a research organization.

As discussed in the main text and shown in Figure A.2, the distribution of the matched inventors is concentrated towards the most recent years. This is due to the fact that the voter registration data are three snapshots dated 2017, 2020, and 2022. Coherently, we cannot reject the null of large differences for the patent issue year between matched and unmatched inventors. In particular, matched inventors are, on average, granted patents three years after the unmatched. We also reject the null of equivalence for the probability of being granted a patent in CPC section G. Also, matched inventors 4.8 p.p. more likely to

[40]Only 7% of inventors have Hispanic origins, while in 2017 they make up almost 16% of the total FL registered voters; also Black inventors are 4% of the matched sample, while in 2017 in FL they are almost 14%.

[41]When working with large samples it is more suitable to conduct equivalence tests rather than difference tests, as the latter may lead to overly rejecting the null of no difference.

have an assignee than unmatched inventors.

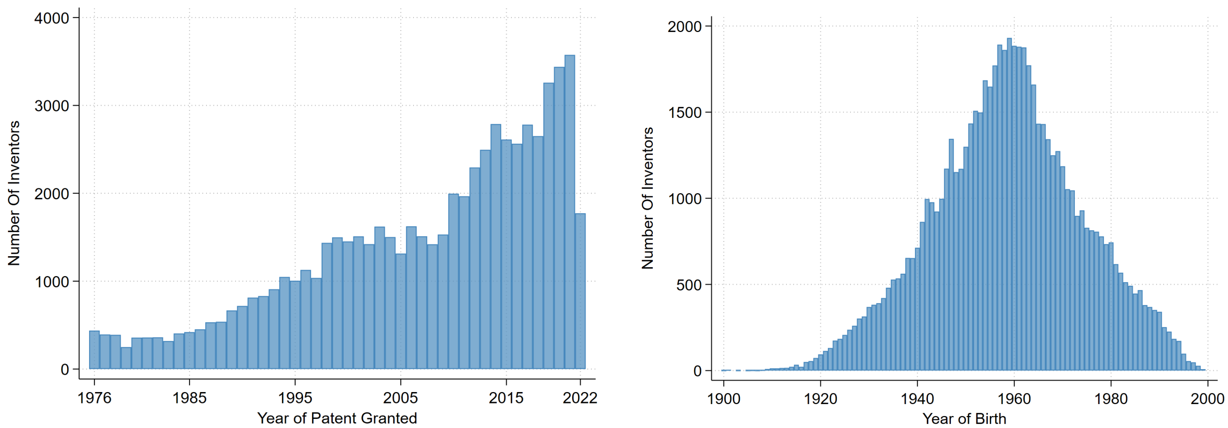


Figure A.2.. These figures show the distribution of the number of inventors in the matched sample by granting patent year (LHS) and by year of birth of inventors (RHS).

Table A.3: **Differences in observables between matched and unmatched inventors**

	Matched		Unmatched		Matched-Unmatched	
	Mean	Standard Deviation	Mean	Standard Deviation	Standardized Difference	P-value Equivalence Test
	(1)	(2)	(3)	(4)	(5)	(6)
Gender	.088	.283	.108	.31	-.067	0.000
Num Consonants First Name	3.702	1.129	3.644	1.217	.049	0.000
Num Consonants Middle Name	.842	1.153	.781	1.237	.051	0.000
Num Consonants Last Name	4.11	1.417	4.063	1.57	.031	0.000
Length First Name	5.863	1.537	5.842	1.728	.013	0.000
Length Middle Name	6.43	2.006	6.43	2.285	0	0.000
Length Last Name	1.181	1.754	1.124	1.905	.031	0.000
Log Income (City of Residence)	12.58	1.321	12.7	1.421	-.087	0.000
A Section	.174	.379	.201	.4	-.067	0.000
B Section	.178	.382	.168	.374	.024	0.000
C Section	.153	.36	.154	.361	-.002	0.000
D Section	.009	.094	.01	.101	-.015	0.000
E Section	.022	.148	.026	.16	-.025	0.000
F Section	.082	.274	.084	.277	-.007	0.000
G Section	.418	.493	.366	.482	.107	0.999
H Section	.33	.47	.33	.47	0	0.000
Y Section	.184	.388	.189	.392	-.012	0.000
Assignee Organization	.914	.281	.866	.341	.149	1.000
Research	.173	.379	.161	.367	.034	0.000
Issue Year	2008	10.5	2005	12.78	.249	1.000

Notes. 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 standardized difference between matched and unmatched in the full sample of FL and NY inventors. Column 6 reports the largest p-value for the equivalence test of means using a two one-sided t-tests approach. The null hypothesis is that the difference is larger than 10% of a standard deviation, or smaller than -10% of a standard deviation. The sample includes all inventors resident in FL and NY between 1976 to 2022.

Table A.4 presents descriptive statistics that shed light on the characteristics of Democrat and Republican inventors in the matched sample, controlling for the issue year and county fixed effects. We find that there are no significant differences in terms of income in the zipcodes where Democrats and Republicans reside and in the likelihood of working for a non-corporation assignee.[42] However, Democrats are more likely to be female, younger, and from non-white ethnic groups (based on the FL subsample). Moreover, they are more likely to work for research-oriented assignees, as inferred from the assignee names.

Table A.4: **Differences between Democrat and Republican Inventors**

	Republicans mean (sd) (1)	Democrats mean (sd) (2)	Difference (p-value) (3)
Female	0.049(0.216)	0.122(0.328)	0.058***(0.000)
Age	51.093(11.166)	50.576(11.131)	-0.887**(0.027)
Log Zipcode Income	11.411(0.419)	11.571(0.450)	-0.005(0.584)
White	0.231(0.421)	0.113(0.316)	-0.018**(0.018)
Research	0.027(0.163)	0.080(0.271)	0.038***(0.000)
Non-Corp Assignee	0.018(0.132)	0.012(0.109)	-0.001(0.469)
Health technology	0.110(0.313)	0.163(0.369)	0.032***(0.001)

Notes. The sample includes all the USPTO inventors merged with NY and FL voters register microdata. The regressions control for issue year and county fixed effects; s.e. are clustered at the county level. The "Difference" column reports the estimated differences between Democrats and Republicans. Standard deviations and p-values are reported in round brackets.

[42]This includes governments and individual assignees.

A.6. Robustness checks

In this Section, we perform some robustness checks of Equation (1). Including either the log of the zipcode income or city fixed effects or restricting the sample to New York does not change the coefficients for the Democrat dummy. Note that using the zipcode income as a proxy for individual income is widespread in the literature (see, for instance, Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey and Wernerfelt (2022)).

Income

Data on median zipcode family income come from the Missouri Census Data Center. They include several indicators from the 2017-2021 American Community Survey.

Table A.5: **Party Affiliation and Direction of Innovation, control for Income**

	Green	Adaptation to Climate Change	Weapon	Dirty	Female Health	Male Health
Democrat	0.0015***	0.0013**	-0.0028***	-0.0012***	0.0038**	0.0012
	[0.0004]	[0.0005]	[0.0009]	[0.0004]	[0.0015]	[0.0012]
Other	0.0013**	0.0003	-0.0015	-0.0008*	0.0022*	0.0003
	[0.0006]	[0.0006]	[0.0010]	[0.0004]	[0.0013]	[0.0012]
Log Zipcode Income	-0.0002	-0.0009	-0.0023*	-0.0003	0.0033**	0.0015
	[0.0009]	[0.0019]	[0.0013]	[0.0005]	[0.0014]	[0.0024]
Observations	334,521	334,521	334,521	334,521	334,521	334,521
Patents	228,355	228,355	228,355	228,355	228,355	228,355
Inventors	65,250	65,250	65,250	65,250	65,250	65,250
% of Dem.	0.350	0.350	0.350	0.350	0.350	0.350
$\mathbb{E}(LHS)$ for Rep.	0.005	0.006	0.009	0.004	0.013	0.017
Effect Size %	28.697	21.821	-32.442	-31.321	28.895	7.285
Patent Year FE	✓	✓	✓	✓	✓	✓
County FEs	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Section FE	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓

City FE

Table A.6: **Party Affiliation and Direction of Innovation, control for city FE**

	Green	Adaptation to Climate Change	Weapon	Dirty	Female Health	Male Health
Democrat	0.0017***	0.0016***	-0.0029***	-0.0011***	0.0036**	0.0009
	[0.0005]	[0.0005]	[0.0009]	[0.0004]	[0.0014]	[0.0012]
Other	0.0016***	0.0004	-0.0014	-0.0007	0.0022*	0.0001
	[0.0006]	[0.0006]	[0.0011]	[0.0004]	[0.0012]	[0.0012]
Observations	334,387	334,387	334,387	334,387	334,387	334,387
Patents	228,245	228,245	228,245	228,245	228,245	228,245
Inventors	65,117	65,117	65,117	65,117	65,117	65,117
% of Dem.	0.350	0.350	0.350	0.350	0.350	0.350
$\mathbb{E}(LHS)$ for Rep.	0.005	0.006	0.009	0.004	0.013	0.017
Effect Size %	32.049	26.565	-32.679	-29.918	27.611	5.604
Patent Year FE	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Section FE	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓

NY subsample

Table A.7: **Party Affiliation and Direction of Innovation, NY-only sample**

	Green	Adaptation to Climate Change	Weapon	Dirty	Female Health	Male Health
Democrat	0.0014***	0.0014**	-0.0019**	-0.0013***	0.0029*	0.0018
	[0.0004]	[0.0006]	[0.0008]	[0.0004]	[0.0016]	[0.0012]
Other	0.0011	0.0003	-0.0011	-0.0009*	0.0004	0.0005
	[0.0007]	[0.0007]	[0.0007]	[0.0005]	[0.0011]	[0.0011]
Observations	266,102	266,102	266,102	266,102	266,102	266,102
Patents	174,900	174,900	174,900	174,900	174,900	174,900
Inventors	44,371	44,371	44,371	44,371	44,371	44,371
% of Dem.	0.371	0.371	0.371	0.371	0.371	0.371
$\mathbb{E}(LHS)$ for Rep.	0.004	0.004	0.005	0.004	0.011	0.013
Effect Size %	32.715	33.492	-34.051	-35.192	25.822	13.486
Patent Year FE	✓	✓	✓	✓	✓	✓
County FEs	✓	✓	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓	✓	✓
Section FE	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓

Between Firms

Table A.8: **Party Shares and Direction of Innovation, assignee-level analysis**

	Green Words	Adaptation to Climate Change	Weapon	Dirty	Female Health	Male Health
	(1)	(2)	(3)	(4)	(5)	(6)
Share of Democrats	0.0027**	0.0067***	-0.0041**	-0.0004	0.0077***	0.0032
	[0.0013]	[0.0018]	[0.0017]	[0.0005]	[0.0027]	[0.0028]
Share of Others	0.0029	0.0027	-0.0003	-0.0025***	0.0009	-0.0017
	[0.0039]	[0.0045]	[0.0036]	[0.0007]	[0.0051]	[0.0059]
Observations	42,495	42,495	42,495	42,495	42,495	42,495
Assignees	14,702	14,702	14,702	14,702	14,702	14,702
% of Dem.	0.318	0.318	0.318	0.318	0.318	0.318
$\mathbb{E}(LHS)$	0.009	0.014	0.011	0.002	0.030	0.033
Effect Size %	29.847	49.111	-36.445	-18.315	25.124	9.769
Year FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Section Controls	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓

Notes. The sample includes all the matched assignees that are not individuals. The unit of observation is the assignee-state-year. The regressions control for issue year and state fixed effects; s.e. are clustered at the assignee level. The "Share of Democrats" is the share of Democrat inventors over the total number of inventors in each assignee-state-year. Similarly for the "Share of Others". Also, all the outcomes are measured as shares of that category over the total number of patents filed in each assignee-state-year.

Within Firms

Table A.9: **Party Affiliation and Direction of Innovation, within firms**

	Green Words	Adaptation to Climate Change	Weapon	Dirty	Female Health	Male Health
	(1)	(2)	(3)	(4)	(5)	(6)
Democrat	0.0005	-0.0001	-0.0003	-0.0001	0.0005	0.0007
	[0.0005]	[0.0005]	[0.0004]	[0.0003]	[0.0012]	[0.0014]
Other	0.0002	0.0000	0.0002	0.0002	-0.0005	0.0005
	[0.0004]	[0.0007]	[0.0005]	[0.0003]	[0.0010]	[0.0011]
Observations	247,873	247,873	247,873	247,873	247,873	247,873
Patents	152,143	152,143	152,143	152,143	152,143	152,143
Inventors	34,897	34,897	34,897	34,897	34,897	34,897
% of Dem.	0.371	0.371	0.371	0.371	0.371	0.371
$\mathbb{E}(LHS)$	0.005	0.004	0.003	0.003	0.011	0.012
Effect Size %	3.855	-0.446	-2.507	-0.675	3.993	5.512
Patent Year FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
County $\times$ Year FE	✓	✓	✓	✓	✓	✓
Assignee FE	✓	✓	✓	✓	✓	✓
Section FE	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓

Notes. The unit of observation of an inventor-patent. The sample includes all the USPTO inventors merged with NY and FL voters register microdata. The regression specification controls for county-by-year FEs, section FEs, assignee FEs, age, and gender. The sample is restricted to firms with at least 5 Democrats and 5 Republicans. Results are invariant to changes in this cutoff.

A.7. DIME Bonica (2019)

As a robustness check and validation exercise, we use the political contribution data, obtained from Stanford's Database on Ideology, Money in Politics, and Elections (DIME) database, which contains all the political contributions from individuals and organizations between 1979 and 2016. Adam Bonica gently provided the rest of the data up to 2018. The DIME data contain information on the contributors' names, city of residence, employers, occupations, the amount donated, and the recipient committee, and, importantly, the political affiliation of the committee. Following Fos, Kempf and Tsoutsoura (2022), we use the cumulative donation amount to a party to infer the party affiliation.

We prefer voter registration data to campaign contribution data for twofold reasons. First, the measure of political affiliation is more precise in the voter data, while with DIME it is constructed indirectly by summing up the contributions. Additionally, political contributions can be affected by many other factors besides political ideology. For instance, there is evidence that CEOs can influence their employees' contributions (Babenko, Fedaseyeu and Zhang, 2019)). Or, individuals use political contributions to exert their influence in politics. Hence, overall, voter registrations are a more reliable indicator of individuals' political ideology compared to their political contributions, as suggested in Fos, Kempf and Tsoutsoura (2022). Also, individuals donate to committees that cannot be linked to any party or give an equal amount of dollars to different parties, thereby creating a lot of noise in this measure. Second, the matched contributor-inventor sample is clearly a non-random sample of the population of US inventors. For example, inventors who donate could be those with stronger political preferences. Thus, the external validity of the results is more limited when using this sample, compared to the matched voter-inventor sample. We use a similar matching procedure to the one described above, the only difference is that we can screen out "wrong" matches using the occupation of the donors. We manually select a list of occupations not related to innovation, e.g., bankers, nurses, educators etc. Another difference is that we do not have information on donors' age, so we cannot restrict the sample to inventors aged between 22 and 89 as we do with the voter data.

The results for the matched campaign contributor-inventor sample are displayed in Table A.10. They are very close to those described in Section 4. The main difference consists of the coefficient for the Democrat dummy in the regression using "dirty" as the outcome variable, which becomes statistically insignificant. This may be related to the fact that political affiliation is noisier in the contribution data, and that it captures not only ideology but also investment and influence-seeking motives. Also, inventors who are contributors are a selected sample of inventors, differently from inventors who are registered voters, as it is possible to see from the party distribution. Conditional on having the residence in either FL or NY, there are 45% Democrat and 20% Republican inventors in the matched DIME dataset, while 35% and 32% in the matched voter dataset, respectively. This is in line with Fos, Kempf and Tsoutsoura (2022), who argue that Republican executives are more hidden compared to Democrat executives as they make campaign contributions that are not directly linked to the Republican party.

Nevertheless, as DIME data span all US states for a fairly long time series, we are able to match many more inventors and patents. This allows us to run separate regressions for the subset of inventors working in a research-oriented organization, as displayed in Table A.11. As these inventors have more discretion on the direction of their job, the fact that results still hold alleviates concerns related to demand-side factors. If all the results present in Section 4 were explained by the demand for these kinds of patents then we should not observe similar patterns for research inventors.

Note that since campaign donors are around 0.5% of the total population, we match a few inventors for every county-year pair or every city. This prevents us from adding county-by-year or city fixed effects, differently from what we do in our main analysis of the voters' data.

Table A.10: **Political Affiliation and Direction of Innovation, DIME sample**

	Green	Adaptation to Climate Change	Weapon	Dirty	Female Health	Male Health
Panel A: Full Sample						
Democrat	0.0012***	0.0020***	-0.0035***	-0.0001	0.0022**	-0.0002
	[0.0005]	[0.0007]	[0.0006]	[0.0003]	[0.0011]	[0.0011]
Other	0.0010**	0.0007	-0.0009	0.0000	0.0012	0.0010
	[0.0004]	[0.0008]	[0.0006]	[0.0003]	[0.0011]	[0.0012]
Observations	1096275	1096275	1096275	1096275	1096275	1096275
Patents	916,609	916,609	916,609	916,609	916,609	916,609
Inventors	211,635	211,635	211,635	211,635	211,635	211,635
Share of Dem.	0.463	0.463	0.463	0.463	0.463	0.463
$\mathbb{E}(LHS)$ for Rep.	0.007	0.010	0.011	0.004	0.024	0.029
Effect Size %	17.999	20.433	-33.080	-2.916	9.111	-0.845
Patent Year FEs	✓	✓	✓	✓	✓	✓
County FEs	✓	✓	✓	✓	✓	✓
Section FEs	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Panel B: Male Sample						
Democrat					0.0021*	-0.0001
					[0.0011]	[0.0011]
Other					0.0011	0.0014
					[0.0011]	[0.0012]
Observations					1017336	1017336
Patents					863,435	863,435
Inventors					192,597	192,597
% of Dem.					0.449	0.449
$\mathbb{E}(LHS)$ for Rep.					0.023	0.028
Effect Size %					9.036	-0.205
Patent Year FEs					✓	✓
County FEs					✓	✓
Section FEs					✓	✓
Log Income					✓	✓

Table A.11: **Political Affiliation and Direction of Innovation, DIME research sample**

	Green	Adaptation to Climate Change	Weapon	Dirty	Female Health	Male Health
Panel A: Full Sample						
Democrat	0.0028*	0.0053*	0.0001	0.0002	0.0124***	-0.0119**
	[0.0016]	[0.0032]	[0.0007]	[0.0003]	[0.0041]	[0.0052]
Other	0.0019	0.0007	0.0011	0.0001	0.0053	-0.0049
	[0.0017]	[0.0040]	[0.0011]	[0.0003]	[0.0048]	[0.0055]
Observations	109,415	109,415	109,415	109,415	109,415	109,415
Patents	85,083	85,083	85,083	85,083	85,083	85,083
Inventors	26,853	26,853	26,853	26,853	26,853	26,853
Share of Dem.	0.578	0.578	0.578	0.578	0.578	0.578
$\mathbb{E}(LHS)$ for Rep.	0.007	0.019	0.002	0.001	0.064	0.086
Effect Size %	37.972	27.352	3.882	32.037	19.311	-13.819
Patent Year FEs	✓	✓	✓	✓	✓	✓
County FEs	✓	✓	✓	✓	✓	✓
Section FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Panel B: Male Sample						
Democrat					0.0129***	-0.0128**
					[0.0042]	[0.0054]
Other					0.0070	-0.0056
					[0.0046]	[0.0056]
Observations					98,620	98,620
Patents					78,340	78,340
Inventors					23,479	23,479
% of Dem.					0.559	0.559
$\mathbb{E}(LHS)$ for Rep.					0.061	0.087
Effect Size %					21.034	-14.726
Patent Year FEs					✓	✓
County FEs					✓	✓
Section FEs					✓	✓
Log Income					✓	✓

A.8. Model Extension

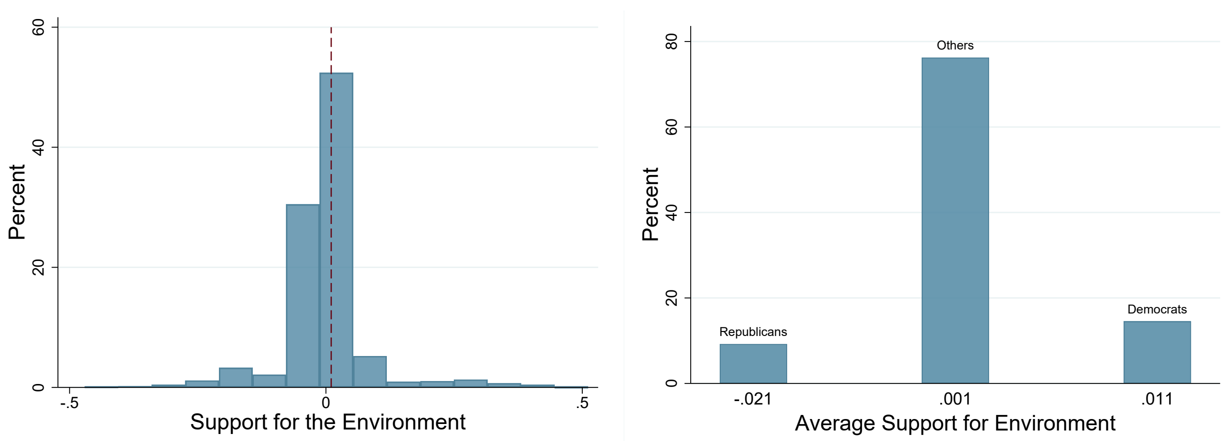
A.8.1. Evidence on the distribution of ideology across workers

What is the distribution of ρ (the ideological match) across workers? To answer this question, we proxy individual ρ with individual beliefs over a given polarized topic, and we turn to the data. Using GSS data for 1974 to 2022, we plot the distribution of attitudes toward the environment residualized by demographic characteristics.

The left panel shows the distribution across all respondents. The dotted red line corresponds to the median. Looking at the distribution to the right of the median, we obtain the distribution of ρ for environmental technologies in the support $[0, \rho_{max}]$.[43] Those closer to the red line are individuals for whom the ideological match is low. Moving to the right, individuals become more and more ideological. The plot suggests that a large share of individuals have ρ_i close to 0, while a residual portion of individuals is distributed to the right. This distribution seems therefore somehow close to the one in example 2.

In the right panel, we show support for the environment pooled into three bins: those who are strongly Republicans, strongly Democrats, and all others. This is helpful as in the main econometric analysis we observe only these three political groups, rather than the specific attitudes and beliefs towards a polarized topic. This distribution maps nicely the bimodal example described below where θ maps the fraction of strongly Dem and $1-\theta$ maps the fraction in the Other category.[44]

Figure A.3: Distribution of *support for the environment* among GSS respondents



Notes. In both graphs, the measure of being supportive toward the environment has been residualized by sex, age, race, education, income, region FEs, year FEs, and work status FEs.

[43]For simplicity, for the moment we do not consider values of $\rho < 0$.
[44]For simplicity, we do not factor in comparisons with Republicans.

A.8.2. Example: Bimodal pdf

Consistent with the empirical evidence on the distribution of ρ, we assume that the distribution of the ideological match is bimodal. A share of workers θ derives utility from working for the ideological firm (firm 2). The remaining share $(1-\theta)$ derives no utility from it. In other words,

$$\rho_i = \begin{cases} \psi & \text{for } 0 < \theta < 1 \\ 0 & \text{for } 1-\theta \end{cases} \tag{A.1}$$

Therefore,

$$u_{i,2} = \begin{cases} w_2 + \psi & \text{for } 0 < \theta < 1 \\ w_2 & \text{for } 1-\theta \end{cases} \tag{A.2}$$

L_1 and L_2 are pinned down by the wage levels (w_1, w_2):

- If $w_1 < w_2$: everyone works for firm 2.
- If $w_1 = w_2$: θ workers choose firm 2 (the "ideological" workers). The remaining $1-\theta$ workers are indifferent between firm 1 and firm 2, and split equally among the two. Therefore, any $\theta \leq L_2 < 1$ can be sustained.
- If $w_2 < w_1 \leq w_2 + \psi$: $L_2 = \theta$ (the "ideological" workers) and $L_1 = 1-\theta$.
- If $w_1 > w_2 + \psi$: everyone works for firm 1.

ψ represents the ideological distance between ideological workers and neutral workers. When the economy becomes more polarized, ψ increases.[45] Any subsidy $s < \psi$ will not shift any additional worker from firm 1 to firm 2.

How should governments design policies to incentivize innovation (and research) in specific technologies (e.g., solar panels)? Using this stylized model it is possible to see that, in order to subsidize *polarized* technologies, it might be important to take into account: i.) share of ideological workers in the economy, ii.) the overall polarization around a given technology. Even though the world is less bimodal than this example – this may still partly explain why the elasticity of science is so low, and it may inform the design of policies to subsidize innovation. This example shows that the degree of polarization and the share of ideological inventors may be important factors to take into account in the design of these policies. Other predictions of the model are that higher taxation might be needed to switch away from technologies like weapons.

[45] In this model, we assume that the share of ideological workers (θ) is independent of the polarization on a given technology.

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