Drawing Partisan Lines in Innovation: Political Polarization and U.S. Inventor Collaboration

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[Preliminary; Please Do Not Circulate]

Abstract

Innovation collaboration in the United States has become increasingly partisan over the past decade. Using merged inventor and voter registration data, we document an abrupt and substantial decrease in inter-party collaboration among patent inventors after the 2016 presidential election. Our analysis reveals that Democratic inventors in counties with higher Republican vote shares in 2016 became less likely to collaborate with Republican inventors afterward. This decline is driven by both inventor reallocation across technology fields, geographic space, and companies, as well as a reduction in their intrinsic willingness to collaborate. As a result, the quality of collaboration networks among Democratic inventors is adversely affected. Collectively, our findings highlight a crucial connection between polarization in the local political environment and declines in inter-party collaboration.

Keywords: Patents, Partisanship, Elections

JEL Codes: O31, D72, J24

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1 Introduction

”Not my president!” an American colleague, a Democrat, exclaimed when asked about Trump shortly after his unexpected victory in the 2016 election. The phrase soon became a rallying cry at mass protests across the country, capturing the sense of alienation and outrage among many Democrats. This outburst of emotion signaled not just opposition to a single leader, but the culmination of a decades-long erosion of cross-party empathy in American political life.

Trump’s victory in 2016 thus marked a defining moment in the long-run intensification of partisan polarization in the United States. In the 1970s, Americans generally held moderate political views, and their feelings toward opposing parties were not particularly hostile (Haidt and Hetherington, 2012; Iyengar, Sood and Lelkes, 2012). Partisan politics rarely intruded into interpersonal relationships. Today, partisan identity influences nearly every aspect of American life—from brand preferences to moral worldviews, and most critically, which relatives one can still talk to and who they consider a friend or collaborator. A 2016 Pew Research Center survey revealed unprecedented levels of mutual hostility between voters from both parties: for the first time since surveys began in 1992, majorities in both parties expressed not only unfavorable but very unfavorable views of the opposing party.[1] This marked a sharp increase from just two years earlier and set the stage for an accelerating spiral of partisan polarization and division that continues to this day.

While numerous studies have explored the impact of political polarization—intensified by the 2016 election—on economic and household decisions of partisan voters, including stock market trading and retirement investments (Addoum and Kumar, 2016; Cookson, Engelberg and Mullins, 2020; Meeuwis et al., 2022), entrepreneurship and employment

[1]Democrats overwhelmingly saw Republicans as ”closed-minded” (70%), while Republicans viewed Democrats as ”immoral” (47%), ”lazy” (46%) and ”dishonest” (45%), Pew Research Center, “Partisanship and Political Animosity in 2016,” https://www.pewresearch.org/politics/2016/06/22/partisanship-and-political-animosity-in-2016/.

decisions (Colonnelli, Neto and Teso, 2022; Engelberg et al., 2022), patent invention (Engelberg et al., 2025), and fertility decision (Dahl, Lu and Mullins, 2022), far less scholarly attention has been devoted to understanding how political polarization affects interpersonal collaboration, particularly in the realm of innovation and patent invention.

Understanding the effects of polarization on collaborative innovation is particularly important because collaboration has increasingly supplanted individual efforts in knowledge production over the past century (Azoulay, Graff Zivin and Wang, 2010; Wuchty, Jones and Uzzi, 2007), and diversity in team composition is often found to improve research productivity (e.g. Agrawal, Goldfarb and Teodoridis, 2016; Borjas and Doran, 2015; Freeman and Huang, 2015). Although ideology is not intrinsically tied to inventive ability, inventors affiliated with different parties often specialize in different technological domains (Engelberg et al., 2025). Inter-party collaboration can therefore recombine distinct knowledge bases and spur more novel, high-impact ideas (e.g. Dahlin and Behrens, 2005; Fleming, 2001; Weitzman, 1998). Indeed, our data shows that inter-party teams constitute only 14% of all collaborative patents filed by partisan inventors in the pre-2016 period, yet their patents receive, on average, 2.37 more forward citations than other collaborative patents, representing a 17.3% increase over the baseline mean of 13.72 citations. If rising polarization deters collaboration across party lines, it will diminish the very diversity that drives breakthrough innovation, with adverse consequences for long-run economic growth.

This study investigates how political polarization surrounding the 2016 presidential election affected inter-party collaboration among patent inventors and the resulting quality of collaboration networks among partisan inventors. We combine inventor data from PatentView with voter registration records from L2 and leverage geographic variation in local political environments to identify causal effects. Our difference-in-differences (DiD) design compares collaboration patterns of Democratic and Republican inventors across counties with varying Republican vote shares in 2016, using the divisive presidential election as a natural experiment. We hypothesize that the divisive nature of the 2016 presidential election, interacting with more polarized local political environments, may adversely affect inventors' willingness to collaborate across party lines.

Our empirical analysis reveals three key findings. First, political polarization negatively impacts inter-party collaboration among inventors, particularly for Democrats. Using the share of collaborative patents with inventors from opposing parties as the outcome variable, our DiD analysis shows that Democratic inventors in counties with higher Republican vote shares are significantly less likely to collaborate with Republican inventors following the 2016 election. In contrast, we do not observe a significant effect on Republican inventors. Our triple-differences (TD) analysis further indicates a notable divergence in the willingness to collaborate across party lines between Democratic and Republican inventors in more Republican-leaning counties.

Second, the decline of inter-party collaboration can only partially be explained by the switch of research focus, geographic locations, and employers of the democratic inventors. After controlling for technology classes of invention, locations of filing, and companies of the inventors at the inventor-patent level, we still find that Democratic inventors in counties with higher Republican vote shares are significantly less likely to cooperate with Republican inventors conditional on patent filings, suggesting a more polarized political environment indeed directly reduced the intrinsic willingness of Democratic inventors to collaborate with the opposite party.

Third, erosion in inter-party collaboration is economically costly. After the 2016 presidential election, Democratic inventors more exposed to Republican-leaning environments filed fewer patents and shifted toward collaborators with non-partisan or third-party backgrounds to compensate for lost ties to Republican inventors. However, this substitution fell short: using a novel measure of collaborator quality, we document a significant and persistent decline in the quality of these inventors' collaboration networks.

This research makes two primary contributions. First, our research contributes to the growing literature on political polarization in the United States and its economic implications. Recent studies have documented increasing partisan divisions across multiple dimensions of American society (Allcott and Gentzkow, 2017; Autor et al., 2020; Bertrand and Kamenica, 2018; Boxell, Gentzkow and Shapiro, 2024; Dimock and Wike, 2020; Gentzkow, 2016). For corporations, research has revealed partisan influences on credit ratings, syndicated lending, and executive team composition (Dagostino, Gao and Ma, 2023; Fos, Kempf and Tsoutsoura, 2022; Kempf and Tsoutsoura, 2021); for households, studies consistently show that partisan affiliation shapes economic optimism around elections (Bartels, 2002; Evans and Andersen, 2006).

While the literature presents mixed evidence on whether partisan sentiment affects consumer spending (Benhabib and Spiegel, 2019; Gerber and Huber, 2009; Gillitzer and Prasad, 2018; McGrath et al., 2017; Mian, Sufi and Khoshkhou, 2023), recent research documents substantial partisan effects on other economic behaviors. Engelberg et al. (2022, 2025) find that Democrats exhibit lower rates of business formation during Republican administrations and reduced patent innovation after 2016. Similarly, Dahl, Lu and Mullins (2022) document significantly lower birth rates in Democratic-leaning counties following the 2016 election. We extend this literature by examining how political polarization affects interpersonal collaboration in patent invention—a domain where cooperation is particularly valuable and intensive. Beyond the macro-level shock of the 2016 election, we demonstrate that local political environment, measured by partisan vote share, significantly influences Democratic inventors' willingness to engage in inter-party collaboration.

Second, this study contributes to the literature on the role of collaboration and diversity in innovation. As the nature of innovation evolves and the search for new ideas becomes increasingly challenging (Bloom et al., 2020; Jones, 2009, 2010), collaboration is becoming more prevalent and essential in today's innovation landscape (Azoulay, Graff Zivin and Wang, 2010; Wuchty, Jones and Uzzi, 2007). Collaborating with individuals from diverse backgrounds can yield significant benefits (Agrawal and Goldfarb, 2008; Agrawal, Goldfarb and Teodoridis, 2016; Borjas and Doran, 2015; Freeman and Huang, 2015; Moser, Voena and Waldinger, 2014), while severing ties with highly productive collaborators can have detrimental effects on an inventor's innovation productivity (Azoulay, Graff Zivin and Wang, 2010; Jaravel, Petkova and Bell, 2018). Our findings reveal a previously undocumented dimension of diversity, namely political ideology, that matters for innovation outcomes. We show that political polarization creates barriers to valuable cross-party collaborations.

The U.S. innovation system has historically benefited from the free flow of ideas and collaboration across geographic, institutional, and demographic boundaries. If political polarization continues to intensify and erode cross-party collaboration, it may undermine the innovation productivity of U.S. inventors and threaten America's competitive advantage in technological development. More broadly, our results suggest that political polarization may affect other forms of professional collaboration beyond patent invention, warranting further investigation into how partisan divisions shape labor market matching, entrepreneurial partnerships, and organizational team formation.

2 Data and Empirical Strategy

2.1 Data

2.1.1 Voter Registration Data from L2

We obtained comprehensive U.S. voter registration data from L2, a proprietary nonpartisan data vendor widely used in academic research (e.g. Allcott et al., 2020; Billings, Chyn and Haggag, 2021; Bernstein et al., 2022; Engelberg et al., 2025; Spenkuch, Teso and Xu, 2023). Our dataset spans 2010 to 2022 and pools multiple waves of L2 releases to maximize temporal coverage and matching rates with inventor data. L2 typically releases two to three updated voter registration files annually. For each individual, we construct a time-invariant party affiliation based on the party label appearing most frequently across all observed years. This approach is justified by the very low rate of party switching among registered voters: Engelberg et al. (2022) estimate that only 1.8% of voters change their partisan registration in a given year.

L2's methodology for determining political affiliation varies across states. In 37 states, political affiliation is determined directly through voters' self-identification on registration forms. In 6 states where partisan or presidential primary voting information is intermittently available,[2] L2 models party affiliation based on the most recent even-year primary in which a voter cast a partisan vote. In the remaining 9 states where voters do not self-identify party affiliation,[3] L2 uses Bayesian analysis to predict party affiliation based on demographic data, exit polling, and commercial lifestyle information. We constructed variables for inventors' political identifications using this political affiliation data.

2.1.2 US Patent Data from USPTO

We obtain patent inventor data from the *PatentsView* database, which provides detailed information on patent applications and grants filed with the United States Patent and Trademark Office (USPTO). Our sample includes all utility patents granted between 2000 and 2020. For each patent, we collect comprehensive information on its inventors, including their locations (country, latitude and longitude, state, and county if in the U.S.), gender,[4] application filing dates, Cooperative Patent Classification (CPC) codes, and both forward and backward citations. For the purpose of this study, we restrict our analysis to patents with at least one inventor based in the U.S.

To identify partisan inventors, we match disambiguated inventor names and addresses

[2]These states include Illinois, Michigan, South Carolina, Texas, Virginia, and Washington DC.

[3]These states include Alabama, Georgia, Hawaii, Indiana, Minnesota, Missouri, Montana, North Dakota, and Vermont.

[4]Inventor gender is assigned by a gender attribution algorithm of the USPTO.

from *PatentsView* with L2 voter records using an iterative algorithm adapted from Engelberg et al. (2025).[5] Our matching process begins with unique name-state combinations across both databases. For unmatched cases, we refine the search using unique name-city combinations, then name-county combinations, and finally unique names alone.

This procedure yields approximately 406,477 inventor-voter matches, comprising 130,566 Democrats, 108,747 Republicans, 158,054 Independents, and 9,110 affiliated with other parties. These numbers are comparable to the matching results in Engelberg et al. (2025). Together, the matched inventors in our sample account for 43.34% of all U.S. inventors in our sample who patented between 2010 and 2020. The unmatched inventors are likely to be unregistered voters, non-U.S. citizens ineligible to vote, or individuals with non-unique name–location identifiers. These cases are unlikely to systematically bias our empirical results.

2.1.3 County-level Vote Outcomes

We obtain county-level presidential vote outcomes for 2008 and 2016 from Autor et al. (2020), who compiled the data using Dave Leip's Atlas of US Elections (Leip, 2017). Our primary measure is the Republican two-party vote share in the 2016 presidential election. Additionally, we compile county-level demographic characteristics from the same source, including manufacturing employment share, college attainment rate, and age and racial distributions.

Figure A1 in Appendix shows that both the distribution of county-level Republican vote shares and their changes from 2008 shifted markedly rightward in 2016. Following Autor et al. (2020) and Dahl, Lu and Mullins (2022), we use county-level Republican vote share in 2016 as a proxy for local political polarization. The divisive nature of Trump's candidacy and presidency makes this measure particularly well-suited for capturing the intensity of partisan tensions across local environments during this period.

[5] We modify their approach by using the full cross-sectional sample of voter registration records from 2010 to 2020 to maximize the matching rate.

2.2 Variable Construction

We categorize each inventor matched to L2 voter records as Democratic, Republican, or non-partisan/other parties. For each patent-inventor pair ij (where i denotes the inventor and j denotes the patent), we define mutually exclusive indicator variables based on the political composition of all inventors in patent j when inventor i is Democratic or Republican:

1. *Sole*: Inventor i is the sole inventor of patent j;
2. *Intra-party*: At least one co-inventor shares inventor i's party affiliation, with no inventors from the opposite party;
3. *Inter-party*: At least one co-inventor belongs to the opposite party of inventor i;
4. *Other*: All co-inventors are non-partisan or affiliated with other parties.

Next, we aggregate the number of patents from the patent-by-inventor level to inventor-by-year observations. For each inventor-year unit it, we calculate the total number of patents filed by inventor i in year t (N_{it}), as well as the counts of inter-party patents. Our main outcome variable is the share of inter-party patents in inventor i's portfolio from year t:

$$s_{it}^{Inter} = \frac{\sum_{k=1}^{N_{it}} \mathbb{1}(Inter\text{-}party_{ik} = 1)}{N_{it}}.$$

Similarly, we compute the shares of sole, intra-party, and other patents. These measures are conditional on positive patent filings in the given inventor-year observation.

Table A1 in Appendix reports summary statistics for Democratic and Republican inventors. Democratic inventors produce more patents on average, both in simple counts and citation-weighted terms, but are less likely to collaborate across party lines. Demographically, Democratic inventors include higher proportions of women and minorities.

2.3 Empirical Strategy

We employ both difference-in-differences (DiD) and triple-differences (TD) designs at the inventor-year level to assess the impact of political polarization on inter-party collaboration among inventors. Our key explanatory variable is the Republican two-party vote share in each county during the 2016 presidential election, which proxies for local intensity of political polarization. We hypothesize that higher Republican vote shares reduce inventors' willingness to collaborate across party lines, particularly for Democratic inventors.

Difference-in-Differences Specification. Our baseline DiD specification is:

$$y_{it} = \beta Rep\_Share_{c(i)} \times Post16_t + \alpha_i + \lambda_t + \epsilon_{it}, \tag{1}$$

where i denotes each Democratic or Republican inventor and t denotes each year from 2010 to 2020. In the main regression, the dependent variable y_{it} is the share of inter-party patents in inventor i's portfolio in year t. $Rep\_Share_{c(i)}$ is the Republican vote share in county $c(i)$, where inventor i is registered to vote in the 2016 presidential election. $Post16_t$ equals 1 for $t \geq 2016$ and 0 otherwise. We control for inventor fixed effects α_i and year fixed effects λ_t. We also extend the regression model to account for time-varying effects of inventor characteristics, county characteristics, and state-specific time trends.

We estimate Equation 1 separately for Democratic and Republican inventors. The coefficient β captures the differential changes in inter-party collaboration after 2016 across counties with varying Republican vote shares.

To examine the dynamic effects, we estimate an event-study variant of Specification 1, using 2015, one year before the 2016 presidential election, as the base year:

$$y_{it} = \sum_{k=2010}^{2020} \beta_k Rep\_Share_{c(i)} \times \mathbb{1}(t = k) + \alpha_i + \lambda_t + \epsilon_{it}, \tag{2}$$

Triple-Differences Specification. To directly compare Democratic and Republican inventors' responses to local polarization, we pool both groups and estimate:

$$\begin{aligned} y_{it} = &\phi Dem_i \times Rep\_Share_{c(i)} \times Post16_t + \psi Rep\_Share_{c(i)} \times Post16_t \\ &+ \alpha_i + \lambda_{p(i)t} + \epsilon_{it}, \end{aligned} \tag{3}$$

where Dem_i equals to 1 for Democratic inventor and 0 for Republican if inventor i is Democratic and zero otherwise, and $p(i)$ is the party affiliation of inventor i. The coefficient ϕ on the triple interaction terms among Dem_i, $Rep\_Share_{c(i)}$, and $Post16_t$ measures how the difference in inter-party collaboration between Democratic and Republican inventors changed after 2016 as a function of county Republican vote share. We include party-by-year fixed effects $\lambda_{p(i)t}$, which absorb the interaction of $Dem_i \times Post16_t$, and control for party-specific time trends.

The event-study variant of the TD specification is:

$$\begin{aligned} y_{it} = &\sum_{k=2010}^{2020} \phi_k Dem_i \times Rep\_Share_{c(i)} \times \mathbb{1}(t = k) + \sum_{k=2010}^{2020} \psi_k Rep\_Share_{c(i)} \times \mathbb{1}(t = k) \\ &+ \alpha_i + \lambda_{p(i)t} + \epsilon_{it}, \end{aligned} \tag{4}$$

Our identification relies on two assumptions. First, absent the 2016 election shock, inter-party collaboration trends would have been parallel across counties with different Republican vote shares (DiD) and between Democratic and Republican inventors in those counties (TD). Second, county-level Republican vote shares capture pre-existing local polarization that interacted with the national election shock, rather than being endogenous to inventor collaboration patterns. We provide evidence supporting these assumptions through event-study and robustness checks.

3 Findings

3.1 2016 Presidential Election and inter-party Collaboration

3.1.1 Graphical Evidence

Panel A of Figure 1 illustrates the time trends in the average inter-party patent shares for Democratic and Republican inventors, as well as the mean difference between them. Several observations emerge from this figure. First, in 2010, Republican inventors had a higher average share of inter-party patents compared to Democratic inventors, possibly due to lower innovation productivity and greater reliance on collaborators from the opposite party. Second, prior to 2016, the average inter-party patent shares among Republican inventors remained stable, while Democratic inventors experienced a downward trend. Third, and most importantly, both groups saw immediate and sharp declines in inter-party patent shares during the 2016 presidential election, with no recovery to pre-election levels by 2020. Lastly, the mean difference continuously declined over the sample period (even after the 2016 presidential election), indicating that Democratic inventors became progressively less likely to collaborate with opposite-party inventors compared to their Republican counterparts.

[Figure 1]

Panel B of Figure 1 plots the β_k and ϕ_k coefficients (and their 95% confidence intervals) from Equations 2 and 4, capturing the dynamic effects on inter-party collaboration during the 2016 election. The DiD estimates in Figures B1 and B2 show no signs of pre-existing trends in inter-party collaboration for Democratic or Republican inventors across counties, despite modest fluctuations in the Republican sample. Following the 2016 election, we observe a persistent decline in the event study coefficients for the Democratic inventor sample until 2020, while those for the sample of Republican inventors remain unchanged. Figure B3 demonstrates that the difference in effects on Democratic versus

Republican inventors consistently turns negative post-election.

3.1.2 Baseline Estimates

Table 1 presents regression estimates from equations 1 and 3. Columns 1-3 (4-6) focus exclusively on Democratic (Republican) inventors to perform a DiD analysis (Specification 1), while Columns 7-9 include both Democratic and Republican inventors for a TD analysis (Specification 3). Columns 1, 4, and 7 control for inventor and year fixed effects only; Columns 2, 5, and 8 additionally include inventor characteristics (*ex ante* main CPC class,[6] gender, age and age squared, minority status, and postgraduate indicator) interacted with year dummies; Columns 3, 6, and 9 add *ex ante* county characteristics (manufacturing employment share, female population share, college-educated worker share, minority population share) and state-specific time trends. Standard errors are two-way clustered at the registered county and inventor CPC class levels.

[Table 1]

The interaction term $\%Rep.vote \times Post16$ is negative and statistically significant in Columns 1-3, ranging from -0.0322 to -0.0547, while insignificant in Columns 3-4 and positively significant in Column 6 (0.0408). This indicates that local vote shares for Donald Trump in 2016 had a significant negative impact on Democratic inventors' inter-party collaboration. Conversely, Republican vote shares positively affected Republican inventors' willingness to collaborate across party lines when accounting for other county characteristics. The economic magnitude is substantial for Democratic inventors: a shift in Republican vote share from the 25th to 75th percentile among U.S. counties (20.9%) leads to a 1.14 percentage point decrease in inter-party patent share, approximately 5.45% of the sample average. This explains around 27.5% to 40.1% of the sudden decrease in inter-party patent shares among Democratic inventors during the 2016 election presented in

[6] The *ex ante* main CPC technology class is defined as the class in which the inventor filed most patent applications during 2010-2015.

Panel A of Figure 1.

TD estimates in Columns 7 and 9 highlight contrasting effects on inter-party collaboration between Democratic and Republican inventors, showing a gap of -0.0608 to -0.0514. The estimate in Column 7 translates to a -1.07 percentage point decrease in the relative likelihood of inter-party collaboration among Democratic inventors from a shift in Republican vote share from the 25th to the 75th percentile across U.S. counties. These findings suggest that local political polarization substantially contributed to the drop in inter-party collaboration, particularly among Democratic inventors.

In Table A2, we further show that declines in inter-party collaboration among Democratic inventors are accompanied by reductions in their innovation output, measured by both simple and citation-weighted patent counts. This aligns with the findings in Engelberg et al. (2025) and implies the potential detrimental consequences of less collaboration across party lines.

3.1.3 Robustness Tests

Table A3 presents three sets of robustness tests to validate our findings. Panel A uses an alternative treatment variable, designated as Republican-leaning, defined as 1 if a county's Republican Party vote share exceeds the sample median in the 2008 presidential election (Engelberg et al., 2022). This approach addresses concerns regarding continuous treatment variables in a DiD design (Callaway, Goodman-Bacon and Sant'Anna, 2024). Our results remain robust with the Republican-leaning indicator.

Our measure of political polarization using Republican vote shares may capture inherent local voter coalitions. However, anecdotal evidence suggests Trump's campaign attracted unconventional Republican voters. Following Dahl, Lu and Mullins (2022), Panel B employs county-level changes in Republican vote shares between 2008 and 2016 as an alternative treatment variable to capture changes in ”floating” voter preferences. The estimates are consistent with our baseline.

Finally, we weight the regressions by the number of patent applications filed by each inventor in a given year in Panel C. The key estimates remain statistically significant and similar to unweighted ones, indicating effects are not concentrated among less productive inventors but extend to more productive ones, suggesting a sizable aggregated effect on inter-party collaboration.

3.1.4 Extensions

i. Heterogeneous Effects by Inventor Characteristics

To explore heterogeneous effects, we categorize our sample into pairwise comparisons contrasting: female and male inventors, young inventors (under 40 years old in 2016) and older inventors (40 years and older), minority inventors (African American, Asian American, and Hispanic) and non-minority inventors (non-Hispanic white), inventors with post-graduate degrees and those without, as well as inventors who previously donated to affiliated parties and those who did not.

Table A4 presents TD estimates based on specification 3 for each subgroup. Columns 1 and 2 indicate the partisan divergence in innovation collaboration is slightly more pronounced among male inventors. Columns 3 and 4 present larger point estimates for young inventors compared to older inventors, with both groups showing statistically significant estimates. These findings align with Boxell, Gentzkow and Shapiro (2017), which reports increased polarization among male and young voters during the 2016 election.

Columns 5 and 6 exhibit estimates of similar magnitudes for white and minority inventors, with only the former statistically significant. Better-educated inventors, particularly those with post-graduate degrees, exhibit more pronounced shifts in inter-party collaboration behaviors, as in Columns 7 and 8. Lastly, Columns 9 and 10 reveal greater effects among inventors who previously donated to political campaigns, suggesting reductions in inter-party collaboration among Democratic inventors are likely driven by political factors.

ii. Who Do Democratic Inventors Choose to Collaborate With Instead?

We have shown that Democratic inventors in more polarized counties collaborate less with Republican inventors following the 2016 election. However, it remains unclear with whom they choose to collaborate instead or whether they work independently. Table A5 comprehensively examines how other patent types of Democratic and Republican inventors are affected, following the baseline specifications 1 and 3. It shows, rather than collaborating with same-party inventors or working alone, Democratic inventors increasingly collaborate with non-partisan or third-party inventors.

iii. The 2008 Presidential Election

We explore whether our findings apply to the 2008 presidential election, during which Democratic candidate Barack Obama won with a significant margin. We conduct a similar analysis to examine how 2008 Republican vote shares affect Democratic and Republican inventors' willingness to collaborate across party lines.[7] Table A6 shows positive or insignificant effects of local Republican vote shares on inter-party collaboration among Democratic inventors, and negative or insignificant effects among Republican inventors. Moreover, Democratic inventors in counties with higher Republican vote shares are more likely to collaborate with Republican inventors compared to Republican counterparts in TD regressions. These results suggest fundamental differences between the 2008 and 2016 elections — the 2016 election appears more divisive and substantially inhibits partisan inventors' willingness to collaborate across party lines in communities dominated by opposite party supporters, while the 2008 election encourages such collaboration.

3.2 Channels

This section explores and tests possible channels for the negative impact of local political polarization on inter-party collaboration among Democratic inventors. We propose two non-mutually exclusive hypotheses to guide our empirical analysis: inventor reallocation

[7] Sample used for this extension is restricted to years between 2002 and 2012.

and collaborative disengagement.

Inventors, as high-skilled workers, are notably mobile across geographic locations and employers (e.g. Fallick, Fleischman and Rebitzer, 2006; Kerr et al., 2017). Political factors, particularly those related to recent polarization, significantly influence their migration choices (e.g. Nelson and Witko, 2022). Democratic inventors in Republican counties can choose to relocate to areas where their political affiliation is more common, switch to technology classes dominated by like-minded inventors (Engelberg et al., 2025), or leave companies where they are politically misaligned (Fos, Kempf and Tsoutsoura, 2022). Such politically-driven reallocation may disrupt interactions with opposite-party peers, reducing inter-party collaboration among Democratic inventors.

Hypothesis 1 *Democratic inventors in counties with higher Republican vote shares are more likely to switch their research focus, geographic location, and company.*

To test this hypothesis, we examine the effect of county-level 2016 Republican vote shares on the likelihood of Democratic or Republican inventors changing their technology focuses, locations, and companies. We use the CPC technology class to represent each inventor's technology focus, the Census Core-Based Statistical Area (CBSA) code for location,[8] and the PERMCO public company code for the employer.[9] We define the main CPC technology fields, CBSAs, and company for each inventor before and after 2016 as those appearing most frequently in the inventor's patent filings during the respective periods (2010-2015 and 2016-2020). We then construct dummy variables, $\mathbb{1}$(change_CPC = 1), $\mathbb{1}$(change_CBSA = 1), $\mathbb{1}$(change_PERMCO = 1), indicating whether the inventor experienced a change in technology focus, location, or company after 2016.[10] We conduct

[8] The crosswalk between county and CBSA codes is retrieved from the NBER Public Use Data Archive, Census Core-Based Statistical Area (CBSA) to Federal Information Processing Series (FIPS) County Crosswalk. We use CBSA codes instead of county codes because county codes reported in patent filings frequently change and may not reflect major migration decisions.

[9] We use the extended KPSS crosswalk between patents and public firms (Kogan et al., 2017).

[10] Due to incomplete mapping between patents and companies, we also consider changing from a non-public company to a public company, or vice versa, as a change of company.

cross-sectional regressions to determine if Democratic inventors in have a higher probability of experiencing these changes when exposed to more polarized environments.

[Table 2]

Panel A of Table 2 presents the regression estimates. We find that Democratic inventors in counties with higher Republican vote shares show a greater likelihood of changing their main CPC technology classes and CBSAs after 2016 (the estimate for changing PERMCO is positive but statistically insignificant, possibly due to incomplete mapping between patents and companies). In contrast, Republican inventors in these counties do not significantly alter their CBSA or company choices, while having a higher probability of changing main CPC classes as well. In the pooled sample of Democratic and Republican inventors, Democratic inventors exhibit a significantly higher likelihood of changing CPC classes, CBSAs, and PERMCO IDs than Republican inventors. These findings support Hypothesis 1, indicating a more active politically-driven reallocation of Democratic inventors following the 2016 election.

Collaborative Disengagement. — Extensive laboratory and field experiments demonstrate that social identity influences cooperative behavior (see Charness and Chen (2020) for a review). Political identity, especially in the context of polarization, significantly affects cooperativeness between opposing factions (Dimant, 2024). Beyond inventor reallocation, a more polarized political environment may directly reduce the intrinsic willingness of Democratic inventors to collaborate with the opposite party:

Hypothesis 2 *Conditional on patent filing, Democratic inventors in counties with higher Republican vote shares are less likely to cooperate with Republican inventors within technology classes, locations, and companies.*

To test Hypothesis 2, we conduct regression analysis similar to 1 at the patent-inventor level, controlling for the technology class, CBSA, and PERMCO ID associated with each patent filing, all interacted with year dummies, to absorb the potential impact of inventor reallocation. We also include forward citations as a measure of patent quality.

Panel B of Table 2 shows that when a Democratic inventor participates in a patent application, her likelihood of collaborating with opposing-party inventors significantly decreases in counties with higher Republican vote shares. Conversely, the point estimates for Republican inventors are significantly positive, suggesting a relatively higher probability of inter-party collaboration among them in these counties.[11] Estimates from the pooled sample reveal a significant divergence in the propensity for inter-party collaboration between Democratic and Republican inventors, with Democratic inventors being less likely to collaborate across party lines than Republican inventors.

It is important to note that these effects cannot be attributed to inventor reallocation, as they are conditional on the CPC class, location, company of each patent application. Our back-of-envelope calculations suggest that moving the Republican vote share from the 25th to the 75th percentile corresponds to a reduction of approximately 0.798 percentage points in the probability of inter-party collaboration among Democratic inventors in each patent application. This accounts for around 70% of the implied magnitude of the baseline estimate (1.14 percentage points), while the remaining 30% might be attributed to inventor reallocation.

3.3 Quality of Collaboration Networks

What are the economic implications of the decline in inter-party collaboration? Notably, Figure A2 in Appendix shows that inter-party patents systematically receive more forward citations than intra-party patents, suggesting that political diversity correlates with higher innovation quality in collaborative research. Furthermore, when researchers are separated from their previous collaborators due to political factors, it can be costly

[11] Another interpretation is that Republican inventors reduce inter-party collaboration in counties with higher Democratic vote shares.

to search for and form collaborative partnerships with new and suitable collaborators. Therefore, a direct byproduct of the decline in inter-party collaboration might be impaired collaboration networks.

We introduce a novel measure of collaborator quality that is independent of the inventor's own innovation quality. Specifically, we compute the average forward citations received by patents filed by an inventor's collaborators in the previous five years, excluding patents filed jointly with the inventor herself. This measure of collaborator quality for inventor i in year t can be expressed as follows:

$$CQ_{it} = \frac{1}{|\Phi_{it}|} \sum_{k \in \Phi_{it}} \sum_{\tau = t-5}^{t-1} \sum_{j \in \Omega_{k\tau} \setminus \Omega_{ik\tau}} cit_j, \tag{5}$$

where Φ_{it} is the set of collaborators of inventor i in year t, $\Omega_{k\tau}$ is the set of patents filed by inventor k in year τ, and $\Omega_{ik\tau}$ is the set of patents filed jointly by inventors i and k in year τ. cit_j represents the number of forward citations received by patent j. Conceptually, CQ_{it} is independent of inventor i's own quality and increases when inventor i collaborates with more productive inventors who have received a higher number of citations in previous years. Given that CQ_{it} is highly right-skewed, we apply the inverse-hyperbolic-sine (IHS) transformation and winsorize the variable at the 99th percentile by filing years.

[Table 3]

We re-estimate equations 1 and 3 by substituting the outcome variable with the measured collaborator quality in Table 3. The results in Columns 1-3 indicate a significant decline in collaborator quality among Democratic inventors following the 2016 election in counties with higher Republican vote shares, even after controlling for inventor and county characteristics: an increase in Republican vote share from the 25th to the 75th percentile among U.S. counties (20.9%) leads to a 4.54% to 6.88% decrease in collaborator quality for Democratic inventors. In contrast, the impact on Republican inventors' collaborator quality is minimal, as shown in Columns 4-6. When comparing the differential effects on Democratic and Republican inventors, the estimates in Columns 7-9 suggest a dispersion of 6.29% to 7.42% in collaboration quality resulting from a 25th to 75th percentile shift in Republican vote shares.[12] The results imply that the declined inter-party collaboration among partisan inventors may lead to long-run costs in the form of reduced innovation quality due to interruptions in collaboration networks.

4 Concluding Remarks

This study documents that political polarization since 2016 has led to less collaboration across party lines, which may harm innovation and long-term growth in the United States. We first document a decline in inter-party collaboration among US inventors, especially during the 2016 presidential election. Using Republican vote share in each county as a proxy for political polarization, we find that Democratic inventors become significantly less willing to collaborate with Republican inventors when they reside in counties with higher Republican vote shares. In contrast, we do not find similar effects on Republican inventors. The decline in inter-party collaboration among Democratic inventors is driven by their reallocation among technology focuses, geographical locations, and companies, as well as reductions in their intrinsic willingness to collaborate. This harms Democratic inventors' innovation productivity, reducing their patent filings and diminishing the quality of their collaboration networks.

Our study highlights a new channel of economic cost associated with political polarization: reduced collaboration among inventors. As teamwork becomes increasingly vital in today's knowledge production, a decline in inter-party collaboration may have

[12] Figure A3, which presents the dynamic effects, suggests that the negative impact on collaboration quality persists until the end of the sample period. This may be due to the high search costs associated with forming new collaboration relationships.

significant implications for the United States' leadership in innovation and its long-term economic growth. Our findings also suggest that it is particularly important to consider the role of political identity in shaping collaboration networks in the design of innovation policies.

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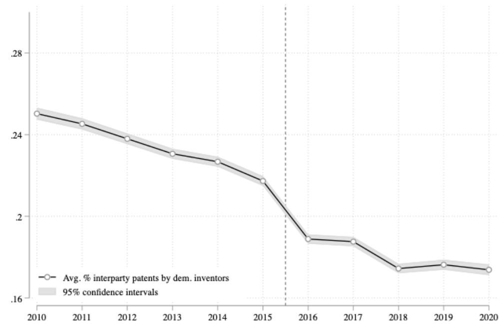
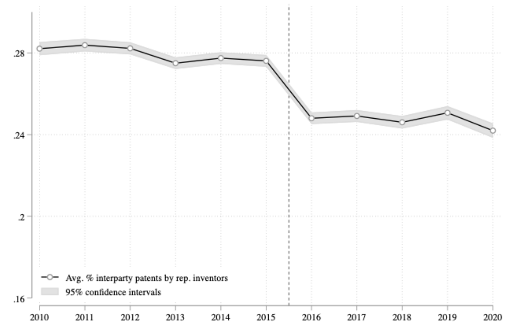
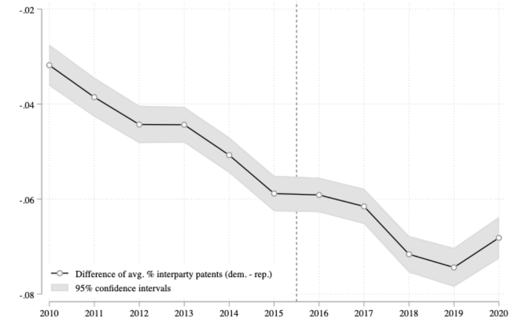
Figure 1: 2016 Presidential Election and Inter-party Collaboration:
Time Trends and Event Study Estimates



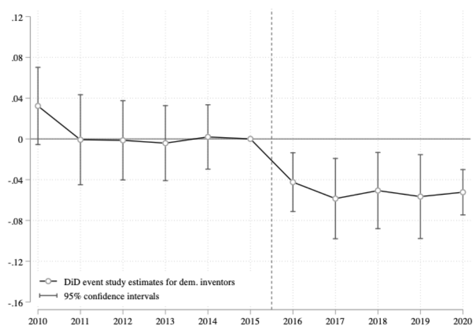
Panel A1. Democratic Inventors



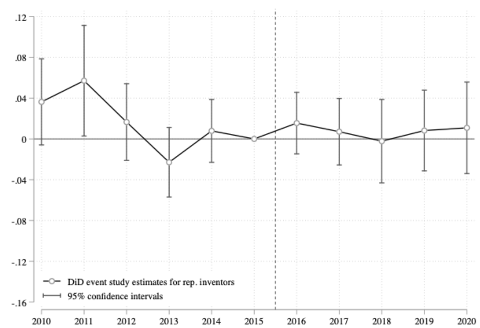
Panel A2. Republican Inventors



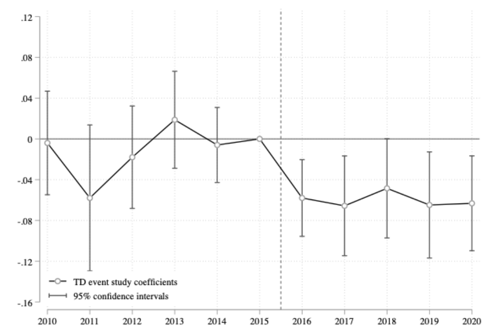
Panel A3. Differences



Panel B1. Democratic Inventors



Panel B2. Republican Inventors



Panel B3. TD Estimates

Note: This figure plots the average shares of inter-party patents by Democratic and Republican inventors and the mean difference between the two in Panel A, and the estimated event study coefficients from the DiD specification 1 and the TD specification 3 and their 95 percent confidence intervals in Panel B. The share of inter-party patents is calculated by dividing the number of inter-party patent applications by the total number of patent applications an inventor filed in a given year.

Table 1: Effect of Local Republican Vote Shares on Inter-party Patent Collaboration

Dependent variable: % inter-party patents	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Rep. vote × Post16	-0.0547***	-0.0421***	-0.0322**	-0.00327	0.00429	0.0408**	-0.00327	0.0101	0.0341**
	(0.00925)	(0.00826)	(0.0131)	(0.0115)	(0.0140)	(0.0205)	(0.0115)	(0.0128)	(0.0171)
% Rep. vote × Post16 × Dem.							-0.0514***	-0.0581***	-0.0608***
							(0.0137)	(0.0124)	(0.0110)
Sample	Dem.	Dem.	Dem.	Rep.	Rep.	Rep.	Dem. + Rep.	Dem. + Rep.	Dem. + Rep.
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Party-affiliation×year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
(Inventor Charateristics)×year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
(County charateristics)×year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State-specific time trend	No	No	Yes	No	No	Yes	No	No	Yes
Outcome mean	0.209	0.209	0.209	0.266	0.266	0.266	0.233	0.233	0.233
Observations	267,192	245,819	245,819	194,370	178,840	178,840	461,562	424,729	424,729

Note: This table reports the estimated effect of county-level Republican vote shares in the 2016 presidential election on the share of inter-party patents filed by Democratic and Republican inventors, following specifications 1 and 3. The sample is at the inventor-year level; it covers Democratic inventors in Columns 1-3, Republican inventors in Columns 4-6, and all Democratic or Republican inventors in Columns 7-9. The dependent variable is the share of inter-party patent applications in all patent applications filed by an inventor in a given year. Columns 1, 4, and 7 control for inventor and (party-affiliation by) year fixed effects. Columns 2, 5, and 8 include inventor characteristics (gender, age, age squared, main CPC class, minority indicator, and postgraduate indicator) interacted with year dummies. Columns 3, 6, 9 include county characteristics (manufacturing employment share, female population share, college-educated worker share, minority population share) interacted with year dummies, and state-specific time trends. Heteroskedasticity-consistent standard errors are two-way clustered by county and inventor's main CPC class. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Inventor Reallocation and Collaborative Disengagement Channels

Panel A. Inventor reallocation

	$\mathbb{1}$(change_CPC = 1)			$\mathbb{1}$(change_CBSA = 1)			$\mathbb{1}$(change_PERMCO = 1)		
	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)	(8a)	(9a)
% Rep. vote	0.136***	0.0831**	0.0626	0.0628***	-0.000434	-0.0138	0.0352	-0.0176	-0.0473
	(0.0500)	(0.0404)	(0.0458)	(0.0213)	(0.0228)	(0.0185)	(0.0648)	(0.0698)	(0.0625)
% Rep. vote × Dem.			0.0881**			0.0843***			0.0888**
			(0.0431)			(0.0272)			(0.0380)
Sample	Dem.	Rep.	Dem. + Rep.	Dem.	Rep.	Dem. + Rep.	Dem.	Rep.	Dem. + Rep.
Controls and FEs	Gender, age, age^2, minority, postgrad, state FE								
Outcome mean	0.339	0.362	0.349	0.215	0.181	0.200	0.474	0.474	0.474
Observations	38,229	28,267	66,499	38,370	28,212	66,586	24,920	16,092	41,017

Panel B. Collaborative disengagement

	$\mathbb{1}$(bipartisan = 1)		
	(1b)	(2b)	(3b)
% Rep. vote × Post16	-0.0382**	0.0410**	0.0400***
	(0.0152)	(0.0162)	(0.0121)
% Rep. vote × Post16 × Dem.			-0.0739***
			(0.0158)
Sample	Dem.	Rep.	Dem. + Rep.
Controls and FEs	Inventor FE, forward citations, CPC subclass-year FE, CBSA-year FE, PERMCO-year FE		
Outcome mean	0.186	0.265	0.217
Observations	540,421	323,926	869,655

Note: This table presents evidence for the two proposed channels: inventor reallocation and collaborative disengagement. Panel A reports the estimated effect of county-level Republican vote shares in the 2016 presidential election on an inventor's probability of changing her main CPC class, CBSA, or PERMCO after the 2016 presidential election. The sample is at the inventor level; it covers Democratic inventors in Columns 1a, 4a, and 7a, Republican inventors in Columns 2a, 5a, and 8a, and all Democratic or Republican inventors in Columns 3a, 6a, and 9a. The dependent variable is an indicator variable that equals one if the inventor's main CPC class is different before and after 2016 (and zero otherwise) in Columns 1a-3a, an indicator variable that equals one if the inventor's main CBSA code is different before and after 2016 (and zero otherwise) in Columns 4a-6a, and an indicator variable that equals one if the inventor's main PERMCO is different before and after 2016 (and zero otherwise) in Columns 7a-9a. Panel B reports the estimated effect of county-level Republican vote shares in the 2016 presidential election on the conditional probability of a filed patent being inter-party. The sample is at the inventor-patent level; it covers Democratic inventor-patent pairs in Column 1b, Republican inventor-patent pairs in Column 2b, and all Democratic or Republican inventor-patent pairs in Columns 3b. All columns control for inventor fixed effects, forward citations, patent CPC subclass by year fixed effects, patent CBSA by year fixed effects, and patent PERMCO by year fixed effects. Heteroskedasticity-consistent standard errors are two-way clustered by county and inventor's main CPC class in both panels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

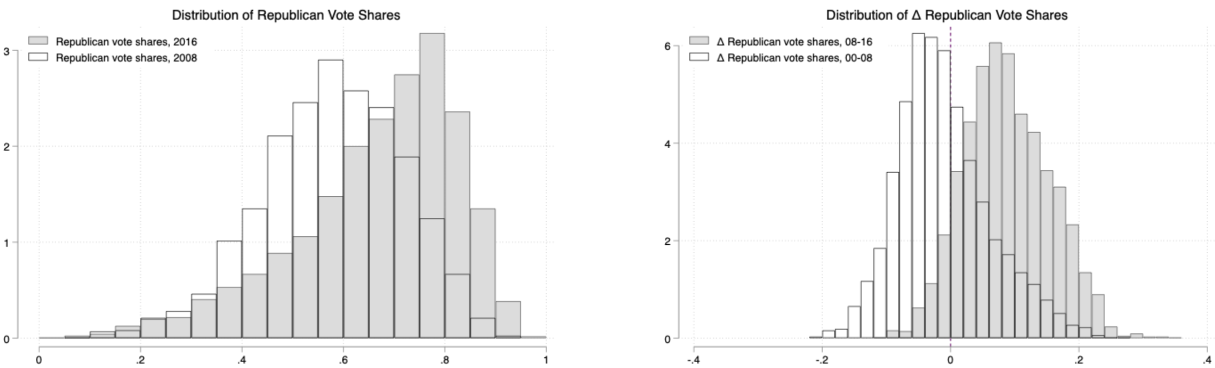
Table 3: Effect of Local Republican Vote Shares on Collaboration Quality

Dependent variable: collaborative quality	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Rep. vote × Post16	-0.329***	-0.217***	-0.317***	0.0269	0.0139	-0.00356	0.0269	0.0506	0.0153
	(0.0975)	(0.0824)	(0.112)	(0.0804)	(0.110)	(0.148)	(0.0804)	(0.0997)	(0.0897)
% Rep. vote × Post16 × Dem.							-0.355***	-0.301***	-0.315***
							(0.0923)	(0.112)	(0.0683)
Sample	Dem.	Dem.	Dem.	Rep.	Rep.	Rep.	Dem. + Rep.	Dem. + Rep.	Dem. + Rep.
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Party-affiliation×year FE	Yes	No	No	Yes	No	No	Yes	No	No
(Inventor Charateristics)×year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
(County charateristics)×year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State-specific time trend	No	No	Yes	No	No	Yes	No	No	Yes
Outcome mean	3.689	3.689	3.689	3.331	3.331	3.331	3.539	3.539	3.539
Observations	260,240	240,172	240,172	182,566	168,443	168,443	442,806	408,708	408,708

Note: This table reports the estimated effect of county-level Republican vote shares in the 2016 presidential election on the quality of collaboration networks of Democratic and Republican inventors, following specification 1 and 3. The dependent variable is collaborator quality (CQ_{it}) constructed following Equation 5. Columns 1, 4, and 7 control for inventor and (party-affiliation by) year fixed effects. Columns 2, 5, and 8 include inventor characteristics (gender, age, age squared, main CPC class, minority indicator, and postgraduate indicator) interacted with year dummies. Columns 3, 6, 9 include county characteristics (manufacturing employment share, female population share, college-educated worker share, minority population share) interacted with year dummies, and state-specific time trends. Heteroskedasticity-consistent standard errors are two-way clustered by county and inventor's main CPC class. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

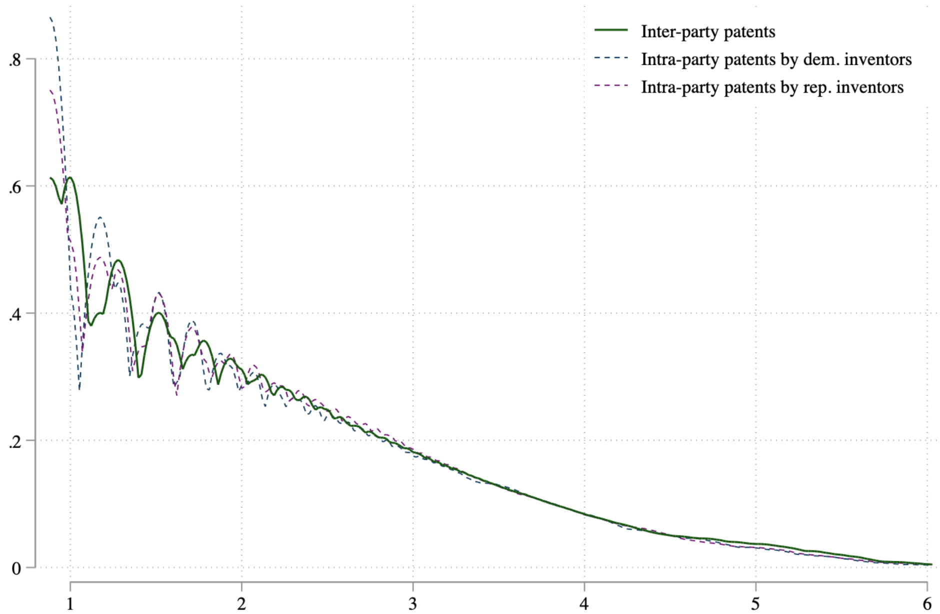
A Additional Figures and Tables

Figure A1: Distribution of Republican Vote Shares Across US Counties



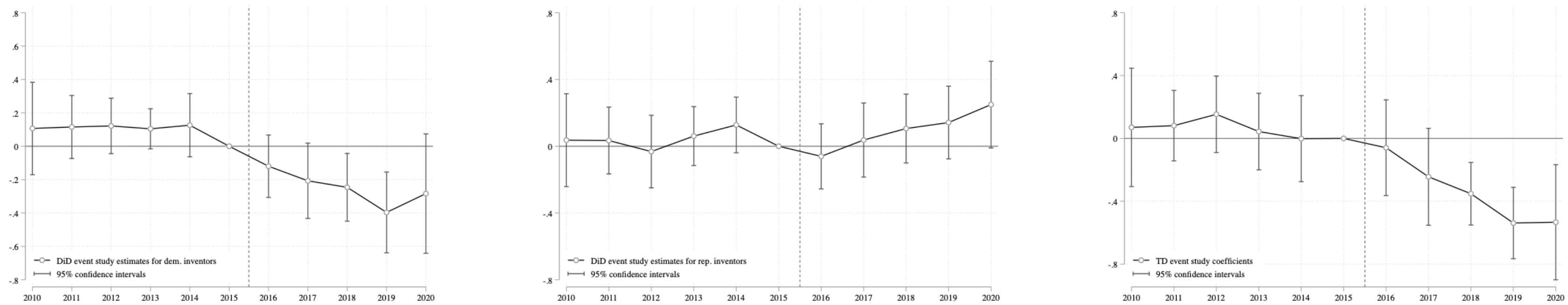
Note: This figure plots the distribution of Republican vote shares and their eight-year changes across U.S. counties during the 2008 and 2016 presidential elections. Panel A displays the distribution of Republican vote shares, with the gray bars representing the shares in 2016 and the white bars representing those in 2008. Panel B displays the distribution of changes in Republican vote shares, with the gray bars representing the changes from 2000 to 2008 and the white bars representing those from 2008 to 2016.

Figure A2: Density of Citations by Patents' Political Categories



Note: This figure plots the kernel density of IHS-transformed citations received by intra-party patents among Democratic inventors, intra-party patents among Republican inventors, and inter-party patents.

Figure A3: Event Study Estimates (Collaborator Quality)



Democratic Inventors — Republican Inventors — TD Estimates

Note: This figure plots the estimated event study coefficients from the DiD specification 1 and the TD specification 3 and their 95 percent confidence. The dependent variable is collaborator quality (CQ_{it}) constructed following Equation 5. Heteroskedasticity-consistent standard errors are two-way clustered by county and inventor's main CPC class.

Table A1: Summary Statistics

Panel A. Democratic Inventors (N = 322,525)					
Variables	Mean	Std.Dev.	p25	p50	p75
All patents	1.956	2.962	1	1	2
All patents (citation-weighted)	14.58	190.4	0	2	7
Sole patents	0.101	0.287	0	0	0
Collaborative patents with Dem. only	0.301	0.428	0	0	0.750
Collaborative patents with Rep. only	0.118	0.303	0	0	0
Collaborative patents with non-partisan only	0.389	0.454	0	0	1
Inter-party patents	0.209	0.383	0	0	0.200
Intra-party patents	0.301	0.428	0	0	0.750
Age (by 2015)	45.19	14.81	34	45	56
Gender (Female = 1)	0.142	0.349	0	0	0
Minority	0.336	0.472	0	0	1
Post-graduate degree	0.249	0.432	0	0	0

Panel B. Republican Inventors (N = 244,202)					
Variables	Mean	Std.Dev.	p25	p50	p75
All patents	1.658	1.749	1	1	2
All patents (citation-weighted)	11.90	133.2	0	1	6
Sole patents	0.148	0.341	0	0	0
Collaborative patents with Dem. only	0.176	0.360	0	0	0
Collaborative patents with Rep. only	0.215	0.391	0	0	0.200
Collaborative patents with non-partisan only	0.372	0.457	0	0	1
Inter-party patents	0.266	0.420	0	0	0.500
Intra-party patents	0.215	0.391	0	0	0.200
Age (by 2015)	49.25	13.65	40	50	58
Gender (Female = 1)	0.0794	0.270	0	0	0
Minority	0.162	0.369	0	0	0
Post-graduate degree	0.254	0.435	0	0	1

Note: This table presents summary statistics for the innovation outcomes and characteristics of inventor-year observations in our sample. Panel A includes data for Democratic inventors, Panel B for Republican inventors.

Table A2: Effect on Total Patent Filings

Dependent variables	# patents			# patents, citation-weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
% Rep. vote × Post16	-0.342***	0.0914**	0.0914**	-0.429***	0.116*	0.116*
	(0.0400)	(0.0406)	(0.0406)	(0.152)	(0.0611)	(0.0651)
% Rep. vote × Post16 × Dem.			-0.433***			-0.546***
			(0.0579)			(0.0873)
Model	PPML					
Sample	Dem.	Rep.	Dem. + Rep.	Dem.	Rep.	Dem. + Rep.
Outcome mean	0.557	0.469	0.512	2.518	2.032	2.300
Observations	991087	806120	1797207	774057	621792	1395849

Note: This table reports the estimated effect of county-level Republican vote shares in the 2016 presidential election on the total number of patent filings of Democratic and Republican inventors, following specifications 1 and 3. The sample is at the inventor-year level; it covers Democratic inventors in Columns 1 and 4, Republican inventors in Columns 2 and 5, and all Democratic or Republican inventors in Columns 3 and 6. The dependent variable in Columns 1-3 is the number of patent applications; and in Columns 4-6, the citation-weighted patent application counts. All columns are estimated using Poisson Pseudo Maximum Likelihood (PPML) models and include inventor and year fixed effects. Heteroskedasticity-consistent standard errors are two-way clustered by county and inventor's main CPC class. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Robustness Tests

Panel A. Alternative Treatment (Republican-leaning)			
	(1a)	(2a)	(3a)
Rep-leaning × Post16	-0.0267***	0.00287	0.00287
	(0.00687)	(0.00710)	(0.00710)
Rep-leaning × Post16 × Dem.			-0.0295***
			(0.00905)
Panel B. Alternative Treatment (Δ % Rep. Vote)			
	(1b)	(2b)	(3b)
Δ % Rep. vote × Post16	-0.174***	-0.00863	-0.00863
	(0.0276)	(0.0274)	(0.0274)
Δ % Rep. vote × Post16 × Dem.			-0.166***
			(0.0389)
Panel C. # Patent-Weighted Estimates			
	(1c)	(2c)	(3c)
% Rep. vote × Post16	-0.0516***	0.0120	0.0120
	(0.0130)	(0.0107)	(0.0107)
% Rep. vote × Post16 × Dem.			-0.0636***
			(0.0117)
Sample	Dem.	Rep.	Dem. + Rep.
Observations	267192	194370	461562

Note: This table reports the estimated coefficients from the robustness checks. The dependent variable is the share of inter-party patent applications in all patent applications of an inventor in a given year. All Columns include inventor and year fixed effects. Panel A replaces the treatment variable by an indicator of Republican-leaning. Panel B replaces the treatment variables by the changes of Republican vote shares between the 2016 and 2008 presidential elections. Panel C weights the regressions by the number of patent applications filed by an inventor in a given year. Heteroskedasticity-consistent standard errors are two-way clustered by county and inventor's main CPC class. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: (Extension I) Heterogeneity Analysis: Inventor Characteristics

Dependent variable: % inter-party patents										
Characteristics	*Gender*		*Age*		*Race*		*Education*		*Donation*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% Rep. vote × Post16	0.00783	-0.00298	-0.000859	-0.00379	0.00499	-0.00583	0.0188	-0.0101	0.0653	-0.00670
	(0.0461)	(0.0145)	(0.0134)	(0.0135)	(0.0301)	(0.0119)	(0.0351)	(0.00757)	(0.0619)	(0.0115)
% Rep. vote × Post16 × Dem.	-0.0409	-0.0548***	-0.0635**	-0.0424**	-0.0477	-0.0512***	-0.0834**	-0.0418***	-0.136*	-0.0470***
	(0.0469)	(0.0175)	(0.0251)	(0.0178)	(0.0313)	(0.0195)	(0.0344)	(0.0140)	(0.0772)	(0.0140)
Sample	Female	Male	< 40	≥ 40	Minority	Non-minority	Grad school	< Grad school	Donor	Non-donor
Outcome mean	0.248	0.231	0.223	0.238	0.217	0.239	0.238	0.232	”0.201”	0.235
Observations	46,185	413,641	119,041	340,895	119,928	339,990	119,290	340,671	26,684	433,141

Note: This table reports the TD estimates of Equation 3 for pairwise subsamples of inventors. The sample is at the inventor-year level and covers both Democratic and Republican inventors. The sample is divided by gender in Columns 1 and 2 (Column 1: female, Column 2: male), by age in Columns 3 and 4 (Column 3: age < 40, Column 4: age ≥ 40), by race in Columns 5 and 6 (Column 5: minority, Column 6: non-minority), by education in Columns 7 and 8 (Column 7: with master's degrees or above, Column 8: otherwise), and by *ex ante* donation status (Column 9: donated before 2016; Column 10: otherwise). All columns include inventor and year fixed effects. Heteroskedasticity-consistent standard errors are two-way clustered by county and inventor's main CPC class. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: (Extensions II) Effect on Other Types of Patent Filings

Dependent variables	% intraparty patents			% other collaborative patents			% sole patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Rep. vote × Post16	-0.00731	-0.0122	-0.0122	0.0571***	0.00829	0.00829	0.00490	0.00720	0.00720
	(0.0143)	(0.00935)	(0.00935)	(0.0135)	(0.0164)	(0.0164)	(0.00549)	(0.00764)	(0.00764)
% Rep. vote × Post16 × Dem.			0.00491			0.0488***			-0.00230
			(0.0141)			(0.00996)			(0.00829)
Sample	Dem.	Rep.	Dem. + Rep.	Dem.	Rep.	Dem. + Rep.	Dem.	Rep.	Dem. + Rep.
Outcome mean	0.301	0.215	0.264	0.389	0.372	0.382	0.101	0.148	0.121
Observations	267192	194370	461562	267192	194370	461562	267192	194370	461562

Note: This table reports the estimated effect of county-level Republican vote shares in the 2016 presidential election on other types of patent filings of Democratic and Republican inventors, following specifications 1 and 3. The sample is at the inventor-year level; it covers Democratic inventors in Columns 1, 4, and 7, Republican inventors in Columns 2, 5, and 8, and all Democratic or Republican inventors in Columns 3, 6, and 9. The dependent variable in Columns 1-3 is the share of intra-party patents; in Columns 4-6, the share of collaborative patents with non-partisan or third-party inventors; and in Columns 7-9, the share of sole patents. All columns include inventor and year fixed effects. Heteroskedasticity-consistent standard errors are two-way clustered by county and inventor's main CPC class. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: (Extensions III) Effect of 2008 Presidential Election

Dependent variable: % inter-party patents	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% Rep. vote × Post08	0.0254*	0.00549	0.0179	-0.0362**	-0.0439**	-0.0297	-0.0362**	-0.0473***	-0.0319
	(0.0144)	(0.0143)	(0.0179)	(0.0170)	(0.0173)	(0.0273)	(0.0170)	(0.0178)	(0.0219)
% Rep. vote × Post08 × Dem.							0.0617**	0.0605**	0.0481*
							(0.0255)	(0.0239)	(0.0247)
Sample	Dem.	Dem.	Dem.	Rep.	Rep.	Rep.	Dem. + Rep.	Dem. + Rep.	Dem. + Rep.
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Party-affiliation×year FE	Yes	No	No	Yes	No	No	Yes	No	No
(Inventor Charateristics)×year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
(County charateristics)×year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State-specific time trend	No	No	Yes	No	No	Yes	No	No	Yes
Outcome mean	0.220	0.220	0.220	0.252	0.252	0.252	0.235	0.235	0.235
Observations	172378	159702	159702	146725	136643	136643	319103	296452	296452

Note: This table reports the estimated effect of county-level Republican vote shares in the 2008 presidential election on the share of inter-party patents filed by Democratic and Republican inventors, following specifications 1 and 3. The sample is at the inventor-year level; it covers Democratic inventors in Columns 1-3, Republican inventors in Columns 4-6, and all Democratic or Republican inventors in Columns 7-9. The dependent variable is the share of inter-party patent applications in all patent applications filed by an inventor in a given year. Columns 1, 4, and 7 control for inventor and (party-affiliation by) year fixed effects. Columns 2, 5, and 8 include inventor characteristics (gender, age, age squared, main CPC class, minority indicator, and postgraduate indicator) interacted with year dummies. Columns 3, 6, 9 include county characteristics (manufacturing employment share, female population share, college-educated worker share, minority population share) interacted with year dummies, and state-specific time trends. Heteroskedasticity-consistent standard errors are two-way clustered by county and inventor's main CPC class. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.