Political Sentiment and Innovation: Evidence from Patenters

Joseph Engelberg
UC San Diego

Runjing Lu
U. of Alberta

William Mullins
UC San Diego

Richard Townsend
UC San Diego & NBER[*]

Preliminary
First draft: March 23, 2022
This draft: July 29, 2022

Abstract

We document political sentiment effects on inventors in the US. Democrat patenters are more likely to patent (relative to Republicans) after the election of Barack Obama but less likely to patent following the election of Donald Trump. These effects are 2-3 times as strong among active partisans (those that vote and donate), are present even within firms over time, and are detectable up to six years post election. We also find a large drop in patenting by immigrant inventors (relative to non-immigrants) following the election of Trump. Finally, we show partisan concentration by technology class and firm. For example, Republicans outnumber Democrats 3-to-1 in weapons patenting, but are outnumbered by Democrats 5-to-1 at Google.

Keywords: Patents, Partisanship, Productivity

JEL Classification Numbers: O31, J24, M5, D72

[*]Engelberg, jengelberg@ucsd.edu; Lu, runjing1@ualberta.ca; Mullins, wmullins@ucsd.edu; Townsend, rrtownsend@ucsd.edu.

1. Introduction

Rising political partisanship has turned major U.S. elections into life-changing events. Partisans who experience election losses report sharp decreases in economic expectations and subjective well-being (e.g., Mian et al. 2021, Di Tella and MacCulloch 2005). Moreover, this partisan gap is growing, with Mian et al. (2021) finding a four-fold increase in the explanatory power of political party for economic expectations over the last 20 years. This paper asks whether Americans bring these feelings to work: do party-changing elections affect worker productivity?

Changes in partisan sentiment could affect both workers' willingness and their ability to be productive. First, workers who become less *optimistic* about the economy, and who share in the rents created by their labor, may exert less effort after their party loses because they anticipate a lower return. Second, because mood affects productivity (Banerjee and Mullainathan 2008, Oswald et al. 2015), workers who become less *happy* as the result of an election loss may experience a decline their productive capacity. Regardless of the mechanism, political cycles coupled with increasing partisanship may have important downstream effects on productivity.

The individuals that we study in this paper are innovative workers who produce patents. These workers provide an advantageous and important setting for several reasons. First, detailed measures of their productive output are directly observable via the USPTO patent database. Second, innovative workers' income is tied to the success of their patents (Kline et al. 2019), which allows for economic expectations to naturally feed back into their productivity decisions. Finally, their productive output is of direct interest, as it constitutes a critical component of long-run economic growth (Solow 1956, Romer 1990, Aghion and Howitt 1992, Mokyr 1992).[1]

We find a significant productivity effect on patents produced around the 2008 and 2016 elections of Barack Obama and Donald Trump. Our analysis compares party-identified *individual patenters* in the same *geographic area or firm* before versus after the 2008 and 2016 presidential elections. To do this, we match 380,000 inventors to a database of all registered voters in the U.S. in order to obtain each patenter's political affiliation (Republican, Democrat or Independent). We also use individual data on patenter voting and donation behavior to

[1] A recent literature links declining innovative productivity (Kortum 1997, Jones 2009) with declining growth rates in economies at the technological frontier (e.g., Cowen 2011, Gordon 2016), underscoring the importance of understanding the patent production function.

assess the intensity of their partisanship.

We first examine Republicans' and Democrats' patenting probability after removing the yearly average by technology class. The two groups' likelihood of patenting is indistinguishable in the two years before each election, as well as during the election year and even in the first year post-election (Figure 1). However, by the second year post-election clear partisan trends emerge, with the winning side's patenting probability rising above the pre-period mean and the losing side's probability falling below it.

Figure 1 shows simple group averages in event time. We next use a yearly difference-in-differences event study approach and continue to find an *increase* in productivity for individual Democratic patenters (relative to Republicans) after the 2008 election, but a relative *decline* in productivity after the 2016 election. Specifically, Democratic inventors' annual likelihood of patenting is 2% of the mean higher than that of Republicans by the third year after the 2008 election (see Figure 2). However, by the third year after the 2016 election, their relative productivity drops by 3.8% of the mean. There are no discernible pretrends before each election. Aggregating over both periods, the effects amount to a partisan shift of at least 12,000 new patent applications.

To sharpen the evidence that it is the *political orientation* of inventors that has a causal effect on productivity, we examine active partisans. Specifically, we use the voting and donation history of each inventor to separate an active partisan from a less-committed one. The intuition is straightforward: an individual who is more involved in political elections will be more affected by a regime-switch than someone who is not. If this is true, we should find stronger effects among the set of politically active patenters.

This is precisely what we find. Defining politically active patenters as those with an above-median history of voting in past elections, we estimate that active Democrats' annual probability of patenting is 4.3% higher than that of Republicans following the 2008 election, while that of inactive Democrats is only 0.8% higher (see Figure 3). For the 2016 election, the corresponding relative differences are negative 4.7% for politically active Democratic patenters and negative 3.5% for inactive ones. A similar pattern emerges when we use inventors' individual donation histories to capture political activeness. Moreover, the partisan productivity effect is long-lasting, with detectable effects for six years after the 2008 election.

One potential concern is that the effect we document could be driven by policy changes at the geographic or industry level. For example, following the election of Donald Trump, government policy may have become more favorable to sectors with more Republicans (e.g., oil and gas) and less friendly towards sectors with more Democrats (e.g., renewable energy). Consequently, we might see a shift in patenting in response to such policy changes even if the willingness and ability of workers to innovate is unchanged. One can imagine similar policy changes targeting political geographies.

To address this issue, we include a variety of fixed effects in our regression specifications to absorb individual characteristics, as well as time-varying patterns in patenting across geographies and technologies. In one of our most stringent specifications, we include person fixed effects to estimate effects using within-person variation over time. The results are generally robust across a variety of specifications and always robust when considering politically active patenters. For example, in a specification with person fixed effects, the average treatment effect for active Democratic patenters is 2.66% of the mean in the three years following the 2008 election and -2.96% in the three years following the 2016 election. For inactive Democratic patenters, the corresponding numbers are 0.88% and -0.04% and statistically insignificant.

In our most demanding specification, we consider the subset of patenters that work for firms (86% of our sample) and include firm-by-time fixed effects. That is, we compare the differential patenting activity of Republicans and Democrats working *at the same firm* and *at the same time* through political regime changes. Even among this subset, our main finding holds: active Democrats increase their patenting activity relative to Republicans following the 2008 election, and decrease it after the 2016 election. Because firms tend to specialize in technologies, firm-by-time fixed effects are, arguably, a more precise control than industry, which should further mitigate concerns that our main result is driven by policy changes at the industry level.

As more direct evidence of a political sentiment channel, we examine survey microdata from Gallup around the 2008 election.[2] While Gallup does not separately identify patenters, when we split respondents by characteristics most associated with them (i.e., college-educated and professional), we find large swings along party lines in both optimism about the economy and mood among well-educated and professional Democrats following the 2008 election. For example, the share of Democrats with a graduate degree saying that the U.S. economy was improving increased by about 50 percentage points from 2008 to 2009, in contrast to the Republican share,

[2] There is insufficient data to do this for the 2016 election.

which remained roughly unchanged.

We then explore patent citations. If there are political sentiment effects tied to economic optimism, we would expect that patenters aligned with the losing side would focus their efforts only on the most promising ideas – which would be robust to the poor economic conditions they anticipate. We find evidence consistent with this hypothesis. Specifically, patents produced by Democrats shortly after the election of Barack Obama have fewer citations (compared to Republicans) while those produced after the election of Donald Trump have relatively more citations.

As further evidence of politically-induced sentiment effects surrounding election outcomes, we also examine *immigrant* patenters. First, we find that immigrant patenters are substantially more likely to patent than non-immigrants, consistent with the evidence in Bernstein et al. (2018), which underscores the critical role immigrants play in innovation. Second, we examine immigrant patenting around both the 2008 and 2016 elections. Immigration was a key campaign issue during the 2016 election, and then-candidate Trump offered both rhetoric and policy proposals which alienated many immigrants. Following Bernstein et al. (2018), we identify immigrants by the age at which they received their social security numbers. We find a sharp decrease (of around 5% of the mean) in the patenting likelihood of immigrant inventors after the 2016 election but no effect after the 2008 election. Because these immigrants are also citizens, this effect is unlikely to come from a change in policy following the 2016 election, as policies targeting citizens by national origin are illegal.

Our results imply that the interaction of partisanship and the political cycle may have important consequences for innovation. In particular, if certain technology classes tend to be dominated by inventors of one party, then the development of these technologies could be accelerated or delayed by partisan productivity effects. Indeed, we find multiple technology classes and large firms which appear to display assortative matching by political affiliation. For example, Republicans outnumber Democrats 3-to-1 in weapons patenting, but are outnumbered by Democrats 5-to-1 at Google. Moreover, the segregation of Republican and Democratic inventors – both at the firm and at the technology class level – has been increasing since 2015.

This paper is at the intersection of two growing literatures: the determinants of innovation and the effects of partisanship. Most of the innovation literature takes a "top-down" view, in which firms invest in innovation based on expected profits and employees simply execute their plans. Accordingly, most of the work in this area has focused on firm-level and market-level drivers of innovative output (see, for example, Harhoff (1999), Aghion et al. (2005), Lerner et al. (2011), Manso (2011), Aghion et al. (2013), Ferreira et al. (2014), Seru (2014), Bernstein (2015)). In contrast, our findings highlight a "bottom-up" view of innovation, wherein innovative workers are not merely interchangeable parts, but themselves play an important role. Specifically, we explore whether political sentiment shocks to workers affect their innovative output. Our work is similar in spirit to Bernstein et al. (2021b), who explore the effects of worker-level financial shocks on innovation.

Our paper also contributes to the new literature on the economic effects of partisanship. To date, part of the literature has focused on decisions taken by households (Dahl et al., 2022, Meeuwis et al., 2022, Cookson et al., 2020, Cullen et al., 2021, Bernstein et al., 2021a, McCartney et al., 2021) and firms (Colonnelli et al., 2022, Engelberg et al., 2022, Fos et al., 2021). Other papers have focused on how financial professionals' forecasts are impacted by their partisan identity (Kempf and Tsoutsoura, 2021, Dagostino et al., 2020), consistent with survey evidence that partisanship affects perceptions of the economy (Bartels, 2002, Evans and Andersen, 2006, Mian et al., 2021). Our paper is the first to examine partisan effects on worker productivity. While we document these effects for a uniquely important class of workers for which we can directly observe their output, it is likely that our effects would apply across the U.S. workforce, especially among those who are active partisans.

The paper proceeds as follows. Section 2 describes the data and sample, section 3 the empirical strategy and results, and section 4 concludes.

2. Data and Sample

2.1 Patent Data

We measure individual productivity via patenting output. We obtain patent data directly from the United States Patent and Trademark Office (USPTO). These data cover all patent applications and grants published from 2001 through 2020. For most of our analysis we focus on patent applications rather than patent grants to measure productivity. We do this to minimize truncation issues at the end of our sample period stemming from the lag between an application and a grant.[3] As is standard in the literature, we limit attention to utility patents and exclude design patents from our analysis. The USPTO provides information on: the date a patent was applied for and ultimately granted (if applicable); the individuals credited as the patent's inventors; the firm to which the patent was originally assigned; other patents cited as prior work; and the technology class that the patent falls under.

A challenge that the data presents is that it lacks consistent identifiers for both patent inventors and firms: they are identified primarily by their names, which may not be unique. In addition, even for the same firm or individual, there is often slight variation in how their name is listed due to differing conventions or recording errors. Therefore, we create inventor and firm identifiers for our sample using the methodology of Balsmeier et al. (2015).

2.2 Voter Data

We obtain data on the universe of registered voters (including their partisan affiliation) as of October 2020 from L2, a non-partisan data provider used by political groups and academics (e.g., Allcott et al., 2020, Billings et al., 2020, Bernstein et al., 2021a). For 34 states (and for DC), L2 assigns political affiliation using self-reported voter registration. For the remaining 16 states, L2 infers party identification using a variety of data sources, including voter participation in primaries, demographics, exit polling, and commercial lifestyle data.[4] 42% of inventors in our sample reside in these states.[5]

Among registered voters, we identify those who are more politically active in two ways. First, we use voting history data.[6] In this case, for each election, we define individuals as politically active if they have voted in more than their party's median share of general and

[3]Even for applications there is some truncation, as there is a lag of approximately 18 months between when a patent is applied for and when the USPTO publishes the patent application. Thus, approximately half of 2019 applications are missing from our sample.

[4]L2's data is subject to repeated testing by political campaigns in the field, supporting their claims of high accuracy. Brown and Enos (2021) validates the partisan classifications.

[5]These 16 states are: Alabama, Georgia, Hawaii, Illinois, Indiana, Michigan, Minnesota, Missouri, Montana, North Dakota, Ohio, South Carolina, Texas, Vermont, Virginia, Washington. L2's party inference varies according to data availability in each state. For example, in states like Illinois, Indiana and Texas, where the state provides voter participation in party primaries, L2 uses participation in these primaries to infer political party. However, in states like Minnesota, Missouri and Montana, where states provide no information that indicates likely party affiliation, L2 models each voter's party based on characteristics it collects independently.

[6]We use the 2020 voter roll and party affiliations because earlier versions of the data do not contain voting history, which is needed to construct our main activeness measure. We examine robustness to using the 2014 voter roll (the earliest available data) in section 3.2.

primary elections that they were eligible for in the recent past (2000-2008 for the 2008 election; 2008-2016 for the 2016 election).[7]

The second way that we identify politically active individuals is by using data on political donations. The Federal Election Commission (FEC) records individuals' donations in excess of $200 per election cycle and L2 has linked these data to their voter registrations. We define inventors as politically active around the 2016 election if they made a political donation by 2016. For the 2008 election, we define inventors as politically active if they donated by 2014 (as far back as the L2 data go). If donation status as of 2014 or 2016 is unavailable for an individual, we use donation status as of 2020 instead. Around 9% of inventors in our sample are politically active under this donation-based measure, which means we have only limited statistical power in specifications with many fixed effects (such as firm fixed effects). As a result, we use voting history as our main political activeness measure.

Finally, L2 provides voters' addresses and a suite of demographic variables, such as voters' birth year, gender, race/ethnicity, and education level. We include these demographic variables, fully interacted, as controls in our main specifications.

2.3 Sample Construction

We match the names in the voter database to the names of patenters in the USPTO database by name and address using an iterative algorithm. Specifically, we first match by name and state. A patenter is coded as matched to a voter if the patenter matches one and only one voter in the L2 database. For the remaining unmatched patenters, we next match by name and county, followed by name and city. This matching procedure yields roughly 1.2 million patenter-voter matches. We further require patenters to be between the ages of 18 and 70 during our sample period (2005 - 2019). To capture career inventors, we restrict our sample to those who submitted at least one granted patent before the pre-period in our analyses (4-10 years before an election event). For example, we only include patenters who submitted at least one subsequently granted patent between 2006 and 2012 for the 2016 election. The resulting sample is a patenter-year panel with 230,000 to 245,000 individual inventors per year.

[7] Median voting propensities are 54% for Democrats and 50% for Republicans for the 2008 election, and 54% for both parties for the 2016 election. We exclude all consolidated general elections, which combine local and general elections and occur in odd years.

2.4 Descriptive Statistics

Table 1 reports summary statistics about our sample. Recall from section 2.3, our sample is the set of patenters surrounding the 2008 and 2016 elections. Table 1 combines the samples from both elections, and a disaggregated version is reported in Appendix Table A1.

Approximately half the sample are Republicans (52%) and half are Democrats (48%). Moreover, consistent with the innovation literature our sample is disproportionately male (89%), college educated (84%), and has patents assigned to their firm (86%). Comparing Democrats and Republicans, there are a few notable differences. For example, among Democrats the sample is 15% female, while among Republicans it is only 8%. Similarly, 90% of Republican inventors are white compared to 75% among Democrats.

The annual likelihood of an inventor patenting is 18.0%. The number is slightly higher for Democrats (19.3%) than Republicans (16.8%). While patenting probability is relatively stable across most individual characteristics, this is not true for firm affiliation: inventors affiliated with a firm are much more likely to file for a patent (20%) than those who are not (6%).

2.5 Partisan Segregation by Technology and Firm

The following sections provide evidence that the productivity of inventors changes around elections along party lines. However, *where* these effects occur will depend on the distribution of partisans across firms and technologies. Here we examine this distribution by looking at all patenters in the USPTO data.

Table 2 documents which technologies and firms disproportionately engage patenters associated with one of the two main political parties between 2001 and 2019. Panel A classifies patenters according to the broadest possible technology group (section), while Panel B deploys a finer classification (class). These panels document substantial political heterogeneity across technologies. For example, in Biochemistry there are 41.6 percentage points more Democrat patenters than Republican ones. Organic Chemistry, Nanotechnology and Combinatorial Technology also heavily favor Democrat patenters. However, in the Weapons technology class Republican patenters outnumber Democrat ones by 45.3 percentage points. Ammunition, Construction and Hydraulic Engineering also heavily favor Republican patenters. In addition, there are technology subclasses that show no meaningful partisan differences, such as sports, apparel and sugar technology.

Panel C presents a similar exercise for the top ten publicly traded firms with over 1,000 patenters. Google, Yahoo and Microsoft all have at least 65 percentage points more Democrat than Republican patenters, while Halliburton, Kimberly Clark and Caterpillar have are Republican-leaning by over 35 percentage points. Firms with an equal share of Republican and Democrat patenters include Chevron, Proctor & Gamble and Verizon.

To examine how clustering has evolved over time, we construct an isolation index for technology subclass (or firm) j in year t following (White, 1986):

$$S_t = \frac{\sum_{j \in J} \frac{rep_{jt}}{rep_t} \times \frac{rep_{jt}}{total_{jt}} - \frac{rep_t}{total_t}}{1 - \frac{rep_t}{total_t}} \tag{1}$$

where rep_{jt} is the number of Republican patenters in technology subclass (or firm) j in year t; $total_{jt}$ the total number of patenters in j in year t; rep_t the number of all Republican patenters in year t; and $total_t$ the number of all Republican and Democrat patenters in year t. The isolation index captures the extent to which Republican patenters disproportionately cluster in a technology or firm with other Republican patenters.[8] An isolation index of one represents the maximum level of segregation, meaning that Republican (Democrat) patenters only patent in technology subclasses or work in firms where 100% of patenters are Republicans (Democrats).

Figure 4 plots the isolation indices by year, separately by technology subclass and by firm. Firms are approximately twice as segregated by partisanship as technology subclasses, consistent with the evidence in Fos et al. (2021) and Colonnelli et al. (2022) of partisan assortative matching at firms in the US and Brazil. Starting in 2015 there is evidence of growing patenter segregation over time, both across firms and technologies.

[8] S_t can also be re-written as the patenter-weighted average Republican exposure of Republicans minus the average Republican exposure of Democrats:

$$S_t = \sum_{j \in J} \frac{rep_{jt}}{rep_t} \times \frac{rep_{jt}}{total_{jt}} - \sum_{j \in J} \frac{dem_{jt}}{dem_t} \times \frac{dem_{jt}}{total_{jt}} \tag{2}$$

3. Empirical Strategy and Results

3.1 Election event study

Our first approach is a difference-in-differences (DID) event study design contrasting individuals of different political parties, within the same geographic area and industry, around presidential elections. We estimate the following regression:

$$\mathrm{Y}_{it} = \sum_{\tau=-3,\tau\neq-1}^{3} \beta_\tau 1\{EventYear_t = \tau\} \times Dem_i + \gamma Dem_i + \delta' \mathbf{X_i} + \alpha_{zip(i)} + \alpha_{industry(i),t} + \epsilon_{it} \quad (3)$$

where Y_{it} is an indicator for individual i submitting a patent application in year t. Event time t indexes the number of years relative to the elections we examine (2008 and 2016). We define $t = 0$ as the year of a presidential election (2008 and 2016) and omit $t = -1$ as the reference period. We focus our attention on years -3 through $+3$ to include only one presidential election in each regression. Our treatment variable is Dem_i, which equals one if individual i is a Democrat and zero if they are Republican (see section 2.2 for definitions of partisanship). We include inventor zip code fixed effects $\alpha_{zip(i)}$ and industry-by-year fixed effects $\alpha_{industry(i),t}$ to control for average patenting activity in a zip code and industry-specific time trends in patenting. We define a patenter's industry as the technology class in which they most frequently patented during the years preceding our sample window.[9] We also control for individual characteristics $\mathbf{X_i}$, which are full interactions between gender, education, race/ethnicity, and age group bins. To allow for arbitrary cross-inventor correlation by geographic area, we cluster standard errors by zip code.

A key assumption of the difference-in-differences methodology is that patenting trends between Democrat and Republican inventors (within the same zip code and the same industry) would have been parallel in the absence of a presidential election. In this case, the β_τ vector in equation 3 identifies the causal impact of an election on the relative productivity of Democrat inventors. As we will show, this parallel trends assumption appears to hold.

Figure 1 plots the probability of submitting a patent, separately for Democrat and Republican inventors, after removing yearly technology class averages. The top panels plot these

[9] Specifically, a patenter is assigned the industry in which they submitted the most applications in years $t-10$ to $t-4$, counting only granted patents.

probabilities at a quarterly frequency for the 2008 and 2016 elections, while the bottom panels do so yearly, which reduces the impact of noise in the data. For both elections, the figure shows pre-trends for Republican and Democrat inventors that are parallel and largely overlapping. After the election we see divergence in the expected directions. For 2008, Democrat inventors appear to increase their rate of patenting relative to Republicans (and to the pre-period) starting six quarters after the election, while in 2016 the divergence begins around four quarters after, with Republicans patenting at higher rates.

In Figure 2, we plot the β_τ coefficients from equation 3, capturing how the 2008 and 2016 elections changed the likelihood of patenting for Democrats relative to Republicans. There are no pre-trends leading up to both elections, but we observe large and statistically significant effects in years two and three post-election. It makes sense that the effect only shows up with a lag, as patent applications are likely a lagging measure of innovative activity—there is likely some time between when projects are initiated and when they generate patent applications. Following the election of President Obama in 2008, we observe a relative increase in Democrats' annual patenting probability, converging to approximately 2% of the mean by year three. Extrapolating across all U.S. inventors, this increases the difference between Republican and Democrat patents by at least 5,400.[10] In contrast, following the 2016 election, Democrats' patenting probability decreased by 3.8% of the mean relative to Republicans by year three. This change corresponds to at least 10,000 patents. Regression coefficients are reported in Appendix Table A2.

To sharpen the evidence that it is the *political orientation* of inventors that has a causal effect on productivity, we examine the active partisans described in section 2.2. Specifically, we use the voting and donation history of each inventor to separate an active partisan from a less-committed one. Shifts in political power should have a stronger impact on the productivity

[10] To obtain the extrapolation for the three-year period after an election, we sum coefficients on $Dem \times 1$ through $Dem \times 3$ in Table A2 column (1) and divide the sum by 100. Finally, we multiply the sum by one third of the number of inventors in the USPTO database between 2001 and 2019 (2.3 million), assuming for simplicity that one third of U.S. patenters are Democrat, Republican, or non-partisans. The aggregations that follow are calculated similarly.

of politically active inventors. To test the hypothesis, we estimate the following model:

$$\begin{aligned} \mathrm{Y}_{it} = &\sum_{t=-3}^{3} \beta_{1,t} Active\ Dem_i + \sum_{t=-3}^{3} \beta_{2,t} Inactive\ Dem_i + \gamma_1 Active\ Dem_i \\ &+ \gamma_2 Inactive\ Dem_i + \delta' \mathbf{X_i} + \alpha_{zip(i)} + \alpha_{industry(i),t} + \epsilon_{it} \end{aligned} \tag{4}$$

where $Active\ Dem_i$ ($Inactive\ Dem_i$) equals one if individual i is a politically (in)active Democrat, and zero otherwise. Republicans as a whole are the comparison group. All specifications and variable definitions follow those in equation (3).

We first define political activeness using inventors' voting histories. Under this definition, politically active inventors are those who voted in an above-median number of general and primary elections in the preceding two election cycles for which they were eligible to vote (see section 2.2 for details). Figure 3 panel (a) shows that, compared to Republican inventors, politically active Democrats increase their annual patenting likelihood by 4.3% of the mean by the third year following the 2008 election while their inactive counterparts increase by only 0.8%. Following the 2016 election, panel (b) shows an analogous decrease of 4.7% of the mean for politically active Democrats and 3.5% for their inactive counterparts by year three. Appendix Table A3 reports the regression results.

We also use inventors' donation histories to define politically active inventors as those who made political donations recorded by the FEC (see section 2.2 for details), a subset made up of 9% of the inventors in our sample. The contrast between politically active Democrats and their inactive counterparts is even starker using this measure, consistent with donors being even more politically engaged than active voters defined using voting history.

Figure 3 panel (c) shows that, compared to Republican inventors, actively donating Democrats increase their annual patenting likelihood by 4.3% of the mean by the third year following the 2008 election, compared to 1.8% for inactive Democrats. Similarly, panel (d) shows that actively donating Democrats decrease their annual patenting likelihood by 5.3% of the mean compared to 3.6% for inactive Democrats following the 2016 election. Regression results are reported in Appendix Table A4.

3.2 Difference-in-differences analysis

To summarize the DID event study coefficients into an average treatment effect over the years following each election, we estimate the following:

$$\mathrm{Y}_{it} = \beta Dem_i \times Post_t + \gamma Dem_i + \delta' \mathbf{X_i} + \alpha_{zip(i)} + \alpha_{industry(i),t} + \epsilon_{it} \tag{5}$$

where Y_{it} is individual i's patent activity in year t. Similar to equation 3, we focus our attention on the three years before and the three years after party-switching presidential elections. We exclude the election year to avoid potential anticipation effects. The variable $Post_t$ is one for the three years following the election year, and zero otherwise. In our basic specification, we include zip code fixed effects $\alpha_{zip(i)}$ and industry-by-time fixed effects $\alpha_{industry(i),t}$, corresponding to those in the prior event study. In more demanding specifications, we add individual fixed effects α_i, geographic area-by-time fixed effects $\alpha_{geo(i),t}$, or firm-by-time fixed effects $\alpha_{firm(i),t}$. The geographic fixed effects include state, county, and zip code. By including these additional fixed effects, we can further absorb time-invariant inventor traits that matter for patenting and time-varying patent activity within a fine geographic area or even within a firm. All remaining specifications and variable definitions are the same as in equation 3.

Our coefficient of interest is β, which identifies the impact of presidential elections on the patent activity among Democrats relative to Republicans living in the same area, patenting in the same industry, or working in the same firm in the years following party-changing presidential elections.

Table 3 reports the estimates from equation 5. We include increasingly stringent fixed effects moving from column (1) to column (8). Consistent with the patterns revealed by the DID event study, coefficients on $Dem_i \times Post_t$ are almost always significantly positive for the 2008 election and significantly negative for the 2016 election. Column (6), which includes zip code, state-by-time, and industry-by-time fixed effects, produce point estimates of 0.28 and -0.25 for the 2008 and 2016 elections, respectively. In other words, Democrat patenters are 0.28 percentage points more likely than their Republican counterparts to submit patent applications in a given year following the election of President Obama but 0.25 percentage points less likely following the election of President Trump. This is a sizeable effect, representing 1.4% and 1.1% of the sample means for the 2008 and the 2016 elections, respectively. Aggregating across the U.S., this amounts to a shift in the partisan gap of at least 12,000 patents over both post-election periods.[11] To check whether these changes in patenting productivity around elections occur within individual inventors, we further include individual fixed effects in columns (7) and (8). We find similar results, although the point estimates become noisier for 2016. As we discuss next, we find strong within-individual effects once we focus specifically on politically active partisans.

As before, we also we compare the changes among regular partisans to *politically active* partisans. Specifically, we estimate the following model:

$$\begin{aligned} \mathrm{Y}_{it} = {} & \beta_1 Active\ Dem_i \times Post_t + \beta_2 Inactive\ Dem_i \times Post_t + \gamma_1 Active\ Dem_i \\ & + \gamma_2 Inactive\ Dem_i + \delta' \mathbf{X_i} + \alpha_{zip(i)} + \alpha_{industry(i),t} + \epsilon_{it} \end{aligned} \tag{6}$$

where $Active\ Dem_i$ ($inactive\ Dem_i$) equals one if individual i is a politically (in)active Democrat, and zero otherwise. Republicans are the comparison group. All specifications and variable definitions follow those in equation 5.

Table 4 reports the estimates using voting history to define the intensity of partisanship. Across all specifications, active voter Democrats experience a significant increase in patent likelihood compared to Republicans following the 2008 election, while inactive Democrats do not. In column (6), which includes zip code, state-by-time, and industry-by-time fixed effects, active voter Democrats are 0.52 percentage points less likely to submit patent applications in a given year compared to Republicans after the 2008 election, which is three times larger than the effect size among inactive Democrats (p value < 0.1). An analogous decrease in patent likelihood also appears after the 2016 election. In column (6), the relative decrease in annual patent likelihood among active voter Democrats is 0.4 percentage points while it is only 0.16 percentage points among inactive Democrats. Back-of-the-envelopment calculations suggest that this corresponds to a shift in the partisan gap of at least 10,000 patents among politically active inventors and 3,300 among inactive inventors across the U.S. over both post-election

[11] To obtain the extrapolation for the three-year post-election period, we multiply the coefficient on $Dem \times Post$ in column (6) by three, divide it by 100, and multiply it by one third of the number of inventors in the USPTO database between 2001 and 2019 (2.3 million). The reported number is the sum of the extrapolation for the 2008 and 2016 elections.

periods.[12] In columns (7) and (8), we also include individual fixed effects. In this case, the point estimates remain strongly significant and, in fact, become larger in magnitude for 2016.

The contrast between politically active and non-active partisans becomes sharper when we define activeness using donation history in Appendix Table A5. We find that donor Democrats are 0.77 percentage points and 1.11 percentage points less likely to submit patent applications compared to Republicans following the 2008 and the 2016 elections, respectively, in column (6). By contrast, the relative change among non-donating Democrats is only a third and a tenth of the aforementioned effects. The difference in effect sizes between donor and non-donor Democrats is significant in almost all specifications. Again, these results remain similar with individual fixed-effects in columns (7) and (8).

In Figure 5 we extend the estimation horizon to seven years after the 2008 election (i.e., through 2015) in order to evaluate the persistence of effects. Panel (a) shows that the effect for Democrats relative to Republicans declines starting in post-election year four, with the point estimate returning to zero by year seven. Panels (b) and (c) separate active from inactive Democrats using the voting and donation measures, respectively. In contrast to the average effect which pools both active and inactive partisans, the productivity impact of the election for *active* voters persists for at least six years post election. The productivity of active *donors* also displays a dip in productivity in presidential election years (2008 and 2012), suggesting that this subset of voters is especially sensitive to the uncertainty of election outcomes.

So far, we have focused on inventors who appear in the 2020 voter roll and used their party registrations as of 2020, which are ex-post relative to the presidential elections we study. To evaluate the importance of using ex-post party affiliations in this context, we re-estimate equations 5 and 6 for the 2016 election using patenters who appear in the 2014 voter roll and their party affiliations as of 2014, which are the earliest available from our data provider. Appendix Table A6 presents the results. Panel A shows coefficients that are very similar across all eight columns to those for the 2016 election in Table 3. Panel B shows similar, but slightly larger effects than those in Table A5 for politically active inventors using the donation-based

[12]This calculation further assumes that half of the patenters in each party are active voters, e.g., that one sixth of patenters are active voter Democrats. To obtain the extrapolation, we multiply the coefficient on *Active Dem* $\times$ *Post* (or *Inactive Dem* $\times$ *Post*) in column (6) by three, divide it by 100, and multiply it by one sixth of the number of U.S. inventors to obtain the value for the three-year period after an election. The reported number is the sum of both elections.

measure.[13] These results lend credence to the use of the 2020 voter file in our setting.

Summarizing, politically engaged inventors drive the patenting effects we document. Moreover, these effects for politically active patenters appear to persist over time. The difference-in-differences framework we employ estimates *relative* effects. These may be driven by a decrease in productivity among those aligned with the losing side, an increase in productivity among those aligned with the winning party, or both. Regardless of which of these possibilities is correct, our results imply that political partisanship may have aggregate consequences for innovation. In particular, given that certain technology classes tend to be dominated by inventors of one party, the development of whole technologies could be accelerated or delayed by partisan productivity effects. Moreover, such distortions could also spill over into other, complementary technologies, even if they are are not dominated by one party (Liu and Ma, 2022).

3.3 Examining channels: political sentiment versus others

Our preferred explanation for the productivity patterns we have documented is that shifts in political power generate changes in political sentiment along party lines.

Policy channel

An alternative explanation is that regime switches lead to policy changes favoring industries or geographic areas that are aligned with the party in power. To test whether actual or expected policy is driving our findings, we examine patenting within industry and geography, because policies are typically targeted at these levels. We also examine patenting *within firms*, as Government favor could manifest as preferential funding or contract awards to specific firms. If policy is the dominant driver, effects should not be present *within* industry, geography, or firm.

The interaction of industry (125 technology classes) and time is already included in our main tables, so Table 5 adds *firm* × *post* fixed effects. This means we are comparing Republican to Democrat inventors within the same firms across a political regime change. Column (1) which adds firm × post fixed effects to our main specification (i.e., to column 4 in Table 4) shows that coefficients for the 2008 election are almost identical, while those for the 2016 election

[13] We cannot generate a similar test for the 2008 election because we do not have access to voter rolls before 2008. In addition, the 2014 data does not contain voting history, so we cannot replicate the heterogeneity result by voting activeness.

are statistically significant, albeit smaller. However, including firm fixed effects demands a lot of the data. Specifically, for our main coefficients to be properly estimated under firm fixed effects, we need enough observations within each combination of party affiliation and political activeness within a firm. Therefore, in columns (2) through (5), we restrict the sample to firms with at least one, two, four and eight patenters in each combination of party and activeness, respectively. Results for both elections become very similar to those without firm fixed effects.

In Appendix Table A7, we replicate these results using our alternative activeness definition based on political donations. Estimating partisan effects among donors under firm fixed effects substantially reduces precision, as only 9% of inventors are donors. Nonetheless, results are broadly consistent with the corresponding table without firm fixed effects (Appendix Table A5) for the 2008 election and are very similar for 2016.

In Appendix Table A8, we add finer geography-by-time fixed effects to capture any geographically targeted policy. Specifically, we add either county × post or zipcode × post fixed effects in place of the state × post fixed effects we include in our baseline specification. Results are broadly consistent with Table 4 and Appendix Table A5, and the results for the 2008 election even survive zipcode × post fixed effects, although it is somewhat implausible that policy would be targeted to such small units.

In summary, we compare the patenting activity through political regime changes of Republicans and Democrats patenting in the *same industry at the same time*, and living in the *same area at the same time*, or working at the *same firm at the same time*.[14] The fact that our results appear within industries, firms, and geographies suggests that policy is not the main driver of the productivity effects we document.

Political sentiment channel

Absent a policy channel, the most likely explanation for our results is that Democrat and Republican patenters experience changes in political sentiment around party-changing elections, which in turn affects their productivity. Such changes in sentiment could take two forms. First, following an election, those politically aligned with the losing side may become more pessimistic about economic conditions relative to those on the winning side (Bartels 2002, Evans and

[14]We do not control for firm×post and geography×post fixed effects simultaneously, because they are largely co-linear.

Andersen 2006, Mian et al. 2021, Engelberg et al. 2022). Because patenters have been shown to capture significant rents from their inventions (Kline et al. 2019), declines in their economic optimism may then lead them to exert less effort, in anticipation of lower returns to that effort. Second, those aligned with the losing side may become less happy as a result (Di Tella and MacCulloch 2005). Such declines in happiness or general mood may lead patenters to experience a decline in their productivity (Banerjee and Mullainathan 2008, Oswald et al. 2015). These two forms of political sentiment – economic optimism and mood – are closely related and difficult to distinguish empirically. They are also not mutually exclusive. Our goal is not to determine which is the primary driver of our results, but rather to show that our results are most consistent with some type of political sentiment effect on productivity.

We begin by examining whether survey evidence supports either form of the political sentiment channel. To do so, we utilize the Gallup U.S. Daily Survey. Gallup elicits the views of 1,000 U.S. adults daily from 2008 to 2013 and 500 adults a day from 2013 to 2016 on topics related to the economy, politics and their well-being. Importantly, respondents identify their political party (38% of respondents are Democrats and 37% are Republicans). Although the survey does not identify respondents as patenters, we know whether they have a graduate degree (19% of respondents) and whether they are professional workers (16%), which we will use as proxy variables for patenters.

In Figure 6, we plot the percentage of respondents choosing "Getting better" to the question "Right now, do you think that economic conditions in this country, as a whole, are getting better or getting worse?" Panel (a) presents the percentage separately for respondents with and without a graduate degree, while panel (b) presents it for professional workers and non-professional workers. Both panels show that the optimism among Democrats who have patenter-like qualities rises sharply after the 2008 presidential election and falls markedly after the 2016 election, while the optimism of well-educated and professional Republicans exhibits the opposite pattern.[15] Interestingly, patenter-like Democrats respond much more strongly to the election results than other Democrats, while patenter-like Republicans respond similarly to other Republicans.

While Figure 6 indicates that beliefs about the economy follow party lines it is also possible

[15]Note that the survey does not ask for respondents' occupation after the first quarter of 2017, so panel (b) stops after that.

that general mood does as well. We find some evidence for this in Figure 7 which plots the average responses to questions about mood. These are "Did you experience the feeling of *worry* yesterday" (Panels a and c) and "Did you experience the feeling of *enjoyment* during a lot of the day yesterday?" (Panels b and d). As was true for responses to the question about economic optimism, Democrat respondents react more positively (with lower worry and greater reported enjoyment) than Republicans to the 2008 election result. However, after 2012 the series become more volatile because the Gallup sample size falls by half, making a general pattern difficult to ascertain.

These plots provide suggestive evidence that partisans with qualities shared by patenters change both their economic optimism and general mood following party-switching presidential elections.

To further explore whether our results are consistent with a political sentiment channel, we also examine the effect of party-changing elections on the *quality* of the patents produced by Democrat and Republican patenters. If there are political sentiment effects tied to economic optimism, we would expect that patenters aligned with the losing side would focus their efforts only on the most promising ideas – which would be robust to the poor economic conditions they expect. Thus, while the likelihood of patenting would decline, the average quality of any submitted patents should increase. In contrast, if there are political sentiment effects tied to general mood, we might expect to see a decrease in both the likelihood of patenting and its quality on the losing side. A patenter experiencing a fall in productive ability due to a decline in mood might both be less able to execute on ideas in general and to generate good ideas.

Following the patent literature, we proxy for the quality of patenters' output using the number of citations their patents receive from other patents. For patents submitted surrounding the 2008 and 2016 elections, we examine their cumulative citations by 2020.[16] We measure citations using three metrics: raw citations (the number of cumulative cites), scaled citations (the number of cumulative cites divided by the average cites within the patent's technology class and grant year), and standardized citations (the number of cumulative cites standardized by the average and standard deviation of the cites within the patent's technology class and grant year). We then average the citations across all patents an inventor submitted in a year

[16]The cumulative citations is based on cites *after* a patent is granted. Patent applications that are rejected or have not been granted by 2020 will have zero citations.

and re-estimate equation 5. However, this regression sample is conditional on patent activity, i.e., for each year only inventors who submitted patents in that year are included.

Table 6 column (1) indicates that patents submitted by Democrat inventors following the 2008 election accumulate *fewer* cites (6% of the mean) than patents submitted by Republican inventors living in the same area and working in the same technology class at the same time. In contrast, patents submitted by Democrat inventors following the 2016 election accumulate *more* cites (14% of the mean) than those by their Republican counterparts. The same holds true, albeit with more statistical noise, when we examine scaled and standardized citations, which further account for the variation in citations across technology classes and grant years.

Overall, this evidence from citations is consistent with political sentiment effects mainly driven not by mood, but by economic optimism. When Democrat patenters become economically optimistic after Obama's election they become more likely to patent, but these are of lower average quality, reflecting a lower selectivity of which projects to pursue. When Democrat patenters become economically pessimistic after Trump's election, they produce fewer, but better quality patents, reflecting an increasing selectivity of projects.

3.4 Evidence of sentiment from Immigrant Patenters

Thus far we have argued that Republican patenters display positive sentiment effects when a Republican president is elected, while the opposite holds for Democrats. However, in the 2016 election another class of voters was differentially exposed to sentiment effects – immigrants – as a result of candidate Trump's proposed policies and charged rhetoric surrounding immigration (LA Times 2019, Dahl et al. 2022). According to Holbrook and Park (2018), immigrant voters supported Clinton (relative to Trump) by 34%, higher than for any previous election. With this in mind, we identify immigrant voters in our data using the approach of Bernstein et al. (2018).[17]

In Table 7, we reproduce Table 3 but rather than having an indicator for Democrat-registered

[17] Using data from Infutor, a commercial consumer identification dataset, we identify immigrants using the first 5 digits of their social security numbers (SSN) which pin down the state and approximate year in which each individual's SSN was assigned until mid 2011. Following Bernstein et al. (2018) we classify an individual as an immigrant if they were 21 or older when they received their SSN; native born citizens receive them at earlier ages. To assign immigrant status to patenters in our sample, we match patenters to individuals in Infutor by name and address using the same iterative algorithm used to match patenters to voter registration data. To the extent that we mis-classify patenters' immigrant status, our estimates will be biased towards zero.

patenters, we now have an indicator for whether a patenter is an immigrant. Critically, because all voters – whether they were originally immigrants or not – are U.S. citizens, any observed effects we find among this group are unlikely to come from a policy channel, because it is illegal to target groups based on country of origin under the Civil Rights Act of 1964. The positive coefficients on the immigrant indicator in both the 2008 and 2016 election specifications indicate that immigrant entrepreneurs are on average more productive than non-immigrants, at around 8-10% of the mean, consistent with Bernstein et al. (2018).

Turning to effects around the elections, Table 7 finds no differential changes in patenting likelihood between immigrants and non-immigrants after the election of President Obama (panel A) but a strong relative decrease among immigrants after the election of President Trump (Panel B), consistent with the sentiment hypothesis. Moreover, the relative decrease among immigrant patenters is larger than the decrease among Democrats (see Table 4). Specifically, the coefficient of -1.689 on *Immigrant* × *Post* in column (1) represents a relative decrease in patenting likelihood of immigrants equal to -7.3% of the mean. After deploying the same fixed effects as in Table 4, the effect size stays between -6% and -4.5% of the mean in columns (2) through (8).

Appendix Table A9 further investigates whether it is Democrat or Republican immigrants who drive the productivity response to the Trump election by interacting *Immigrant* × *Post* with party affiliation. In our sample, 37% of immigrant patenters with political registrations are Democrats, 22% are Republicans and 41% are Independents. The table suggests that *Democrat* immigrants respond most strongly to the election, with an effect size of -8.9% of the mean in column (1) compared to an effect size of -4% among immigrant Republicans.

We view this evidence on immigrant patenters' productivity as important for two reasons. First, Bernstein et al. (2018) shows that immigrant inventors play a critical and outsized role in U.S. innovation. We corroborate this around the 2008 and 2016 elections, and document that a political event – the 2016 election – materially disrupted their innovative activity. Given the important contributions of this group, it is critical to understand any potential impact of political rhetoric regarding immigration on their productivity. Second, showing that immigrants respond to political regime change in a way predicted by the sentiment hypothesis provides further support to the interpretation of our original evidence. Specifically, sentiment changes around elections manifest as important changes in innovator productivity.

4. Conclusion

Political affiliation has become an increasingly important part of American identity (Dias and Lelkes, 2021) and predictive of a wide range of beliefs and behaviors (Pew, 2017). This paper documents an effect of political identity on worker productivity: when workers' political party wins a party-changing presidential election, they become relatively more productive while the losers become relatively less productive.

While we find this effect among patenters – where we can measure their productivity via the number of patents that they produce – many unanswered questions remain. For example, if the productivity declines we document after a political loss are manifestations of reduced effort following increased pessimism, we would expect declines in productivity regardless of occupation. Is this the case? Or are there some occupations whose productivity is particularly vulnerable to political regime changes?

In addition, as Americans have become increasingly partisan (Pew, 2017), there is some evidence that their workplaces are becoming increasingly politically homogeneous (Colonnelli et al., 2022, Fos et al., 2021). We find the same pattern among patenters. This suggests that, over time, we should see larger productivity effects that aggregate to the firm and technology levels. We leave these questions to future research.

References

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and innovation: An inverted-u relationship. *Quarterly Journal of Economics*, 120(2):701–728.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica: Journal of the Econometric Society*, pages 323–351.

Aghion, P., Van Reenen, J., and Zingales, L. (2013). Innovation and institutional ownership. *American Economic Review*, 103(1):277–304.

Allcott, H., Braghieri, L., Eichmeyer, S., and Gentzkow, M. (2020). The welfare effects of social media. *American Economic Review*, 110(3):629–76.

Balsmeier, B., Chavosh, A., Li, G.-C., Fierro, G., Johnson, K., Kaulagi, A., O'Reagan, D., Yeh, B., and Fleming, L. (2015). Automated disambiguation of us patent grants and applications. *Working paper*.

Banerjee, A. V. and Mullainathan, S. (2008). Limited attention and income distribution. *American Economic Review*, 98(2):489–93.

Bartels, L. M. (2002). Beyond the running tally: Partisan bias in political perceptions. *Political Behavior*, 24(2):117–150.

Bernstein, A., Billings, S. B., Gustafson, M., and Lewis, R. (2021a). Partisan residential sorting on climate change risk. *Working Paper*.

Bernstein, S. (2015). Does going public affect innovation?. *Journal of Finance*, 70(4):1365–1403.

Bernstein, S., Diamond, R., McQuade, T., and Pousada, B. (2018). The contribution of high-skilled immigrants to innovation in the united states. *Working Paper*, 3748:202019–20.

Bernstein, S., McQuade, T., and Townsend, R. R. (2021b). Do household wealth shocks affect productivity? evidence from innovative workers during the great recession. *Journal of Finance*, 76(1):57–111.

Billings, S. B., Chyn, E., and Haggag, K. (2020). The long-run effects of school racial diversity on political identity. *NBER WP*.

Brown, J. R. and Enos, R. D. (2021). The measurement of partisan sorting for 180 million voters. *Nature Human Behaviour*, pages 1–11.

Colonnelli, E., Neto, V. P., and Teso, E. (2022). Politics at work. *NBER Working Paper*.

Cookson, J. A., Engelberg, J. E., and Mullins, W. (2020). Does partisanship shape investor beliefs? Evidence from the COVID-19 pandemic. *Review of Asset Pricing Studies*, 10(4):863–893.

Cowen, T. (2011). *The Great Stagnation: How America ate all the low-hanging fruit of modern history, got sick, and will (eventually) feel better*. Penguin.

Cullen, J. B., Turner, N., and Washington, E. L. (2021). Political alignment, attitudes toward government and tax evasion. *American Economic Journal: Economic Policy*.

Dagostino, R., Gao, J., and Ma, P. (2020). Partisanship in loan pricing. *Working Paper*.

Dahl, G., Lu, R., and Mullins, W. (2022). Partisan fertility and presidential elections. *American Economic Review: Insights*.

Di Tella, R. and MacCulloch, R. (2005). Partisan social happiness. *The Review of Economic Studies*, 72(2):367–393.

Dias, N. and Lelkes, Y. (2021). The nature of affective polarization: Disentangling policy disagreement from partisan identity. *American Journal of Political Science*.

Engelberg, J., Guzman, J., Lu, R., and Mullins, W. (2022). Partisan entrepreneurship. *Working Paper*.

Evans, G. and Andersen, R. (2006). The political conditioning of economic perceptions. *The Journal of Politics*, 68(1):194–207.

Ferreira, D., Manso, G., and Silva, A. C. (2014). Incentives to innovate and the decision to go public or private. *Review of Financial Studies*, 27(1):256–300.

Fos, V., Kempf, E., and Tsoutsoura, M. (2021). The political polarization of US firms. *Working Paper*.

Gordon, R. J. (2016). *The rise and fall of American growth*. Princeton University Press.

Harhoff, D. (1999). Firm formation and regional spillovers-evidence from germany. *Economics of Innovation and New Technology*, 8(1-2):27–55.

Holbrook, T. M. and Park, S. Y. (2018). The immigrant voter. *Working Paper*.

Jones, B. F. (2009). The burden of knowledge and the "death of the renaissance man": Is innovation getting harder? *The Review of Economic Studies*, 76(1):283–317.

Kempf, E. and Tsoutsoura, M. (2021). Partisan professionals: Evidence from credit rating analysts. *Journal of Finance*.

Kline, P., Petkova, N., Williams, H., and Zidar, O. (2019). Who profits from patents? rent-sharing at innovative firms. *The Quarterly Journal of Economics*, 134(3):1343–1404.

Kortum, S. S. (1997). Research, patenting, and technological change. *Econometrica: Journal of the Econometric Society*, pages 1389–1419.

LA Times (2019). As Trump seeks reelection, immigrant voters stand in his path. https://www.latimes.com/politics/story/2019-10-23/trump-attacks-immigrants-new-naturalized-citizen-voter-registration (accessed June 21, 2022).

Lerner, J., Sorensen, M., and Strömberg, P. (2011). Private equity and long-run investment: The case of innovation. *The Journal of Finance*, 66(2):445–477.

Liu, E. and Ma, S. (2022). Innovation networks and r&d allocation. *Working Paper*.

Manso, G. (2011). Motivating innovation. *Journal of Finance*, 66(5):1823–1860.

McCartney, W. B., Orellana-Li, J., and Zhang, C. (2021). Political polarization affects households' financial decisions, evidence from home sales. *Working Paper*.

Meeuwis, M., Parker, J. A., Schoar, A., and Simester, D. I. (2022). Belief disagreement and portfolio choice. *Journal of Finance*.

Mian, A. R., Sufi, A., and Khoshkhou, N. (2021). Partisan bias, economic expectations, and household spending. *The Review of Economics and Statistics*.

Mokyr, J. (1992). *The lever of riches: Technological creativity and economic progress*. Oxford University Press.

Oswald, A. J., Proto, E., and Sgroi, D. (2015). Happiness and productivity. *Journal of Labor Economics*, 33(4):789–822.

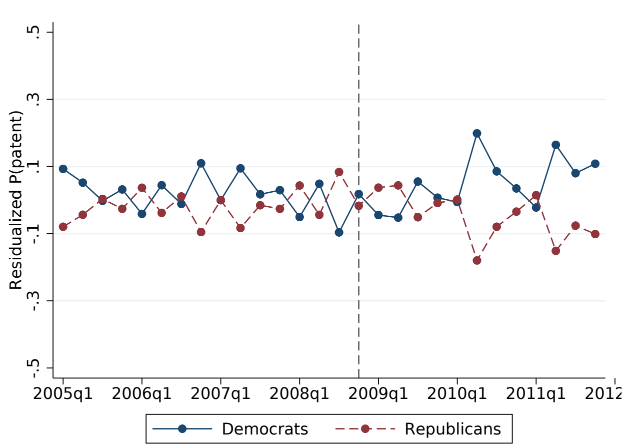
Pew (2017). The partisan divide on political values grows even wider. *Pew Research Center*.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2):S71–S102.

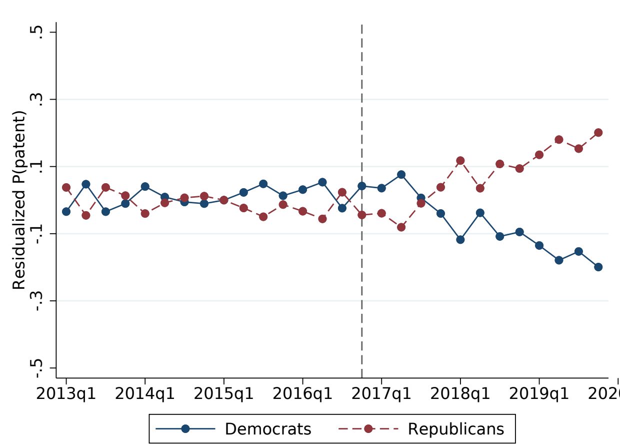
Seru, A. (2014). Firm boundaries matter: Evidence from conglomerates and R&D activity. *Journal of Financial Economics*, 111(2):381–405.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1):65–94.

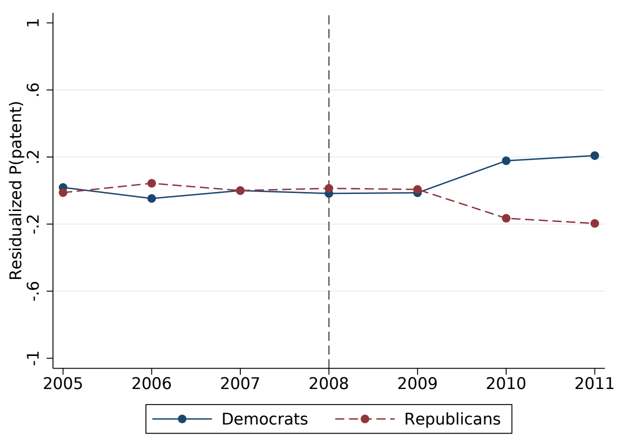
White, M. J. (1986). Segregation and diversity measures in population distribution. *Population index*, pages 198–221.



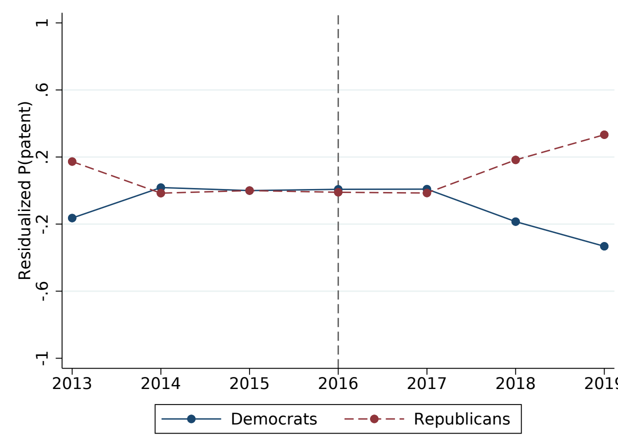
(a) 2008 election, quarterly



(b) 2016 election, quarterly



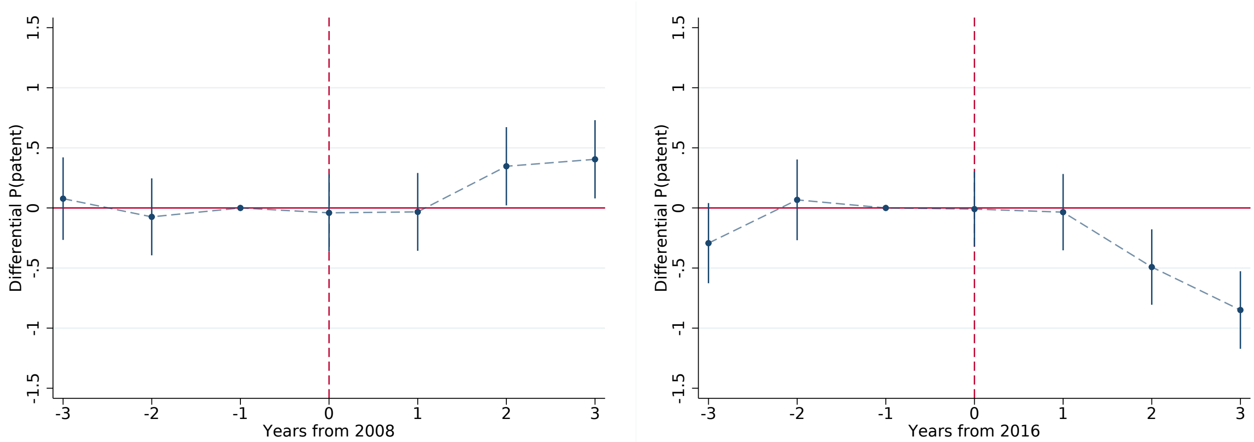
(c) 2008 election, annual



(d) 2016 election, annual

Figure 1: Residualized Probability of Submitting a Patent
Democrat versus Republican Inventors

Note: This figure plots the residualized probability of submitting a patent for Democrat and Republican inventors, at annual and quarterly frequencies. Residualized probability is the residual obtained from regressing the raw probability on technology class-by-year fixed effects. Units are in percentage points. Levels are normalized to 2007q1 and 2015q1 in panels (a) and (b), and to 2007 and 2015 in panels (c) and (d), respectively.

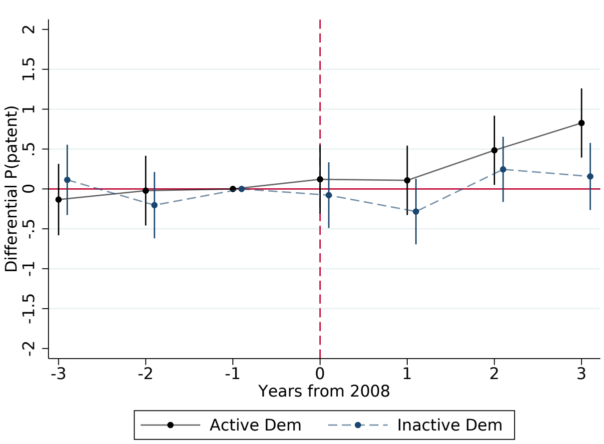


(a) 2008 election

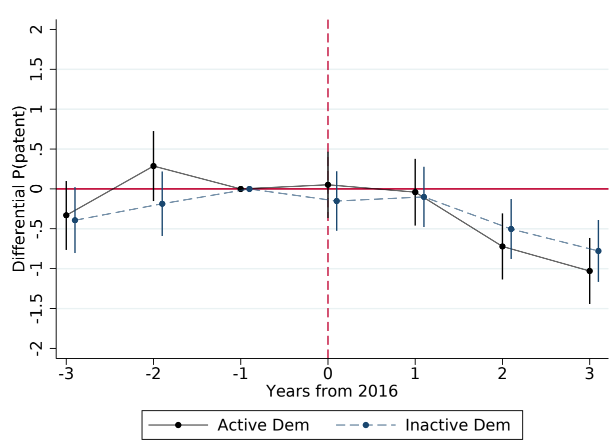
(b) 2016 election

Figure 2: Political Mismatch and the Probability of Submitting a Patent
Democrat versus Republican Inventors

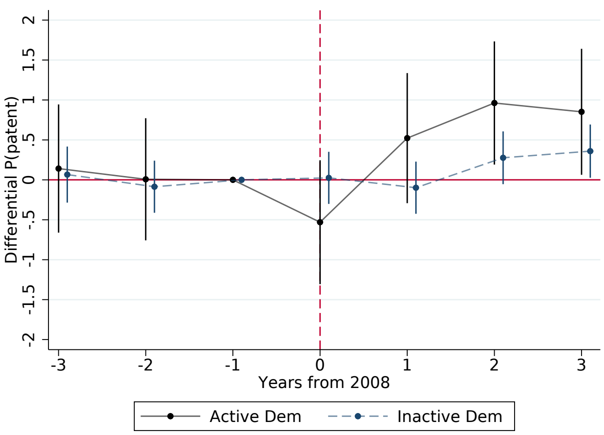
Note: This figure plots the annual probability of submitting a patent for Democrat inventors relative to Republican inventors. Units are in percentage points and the omitted group is Republican inventors. Event time 0 refers to the year of a presidential election. Event time -1 is the omitted period. All regressions control for zip code fixed effects, technology class × event fixed effects, and fully interacted voter characteristics (gender, education, age groups, race). Standard errors are clustered by zip code; we report 90% confidence intervals. Regression results are reported in Table A2.



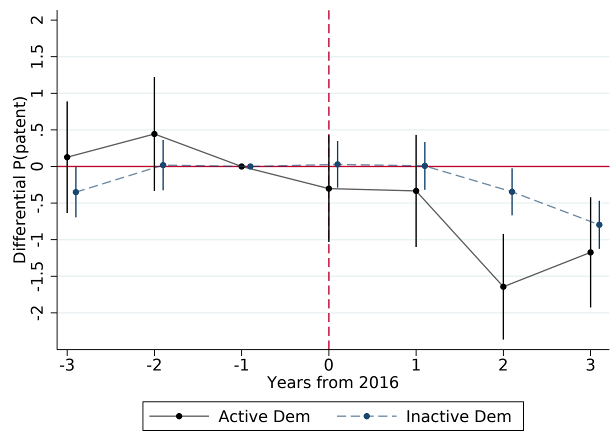
(a) 2008 election, by voting activeness



(b) 2016 election, by voting activeness



(c) 2008 election, by donation activeness



(d) 2016 election, by donation activeness

Figure 3: Political Mismatch and the Probability of Submitting a Patent
Democrat versus Republican Inventors *by Political Activeness*

Note: This figure plots the annual probability of submitting a patent for active versus inactive Democrat inventors relative to Republican inventors. Units are in percentage points and the omitted group is Republican. In panels A and B, *Active Dem* is one for active Democrat based on voting history and zero for others; *Inactive Dem* is one for inactive Democrats based on voting history and zero for others. In panels C and D, *Active Dem* is one for active Democrat based on FEC donation history and zero for others; *Inactive Dem* is one for inactive Democrats based on FEC donation history and zero for others. See section 2.2 for definitions of partisanship and activeness. Event year 0 is the year of a presidential election, year -1 is omitted. All regressions control for zip code fixed effects, technology class × event fixed effects, and fully interacted voter characteristics (gender, education, age groups, race). Standard errors are clustered by zip code; we report 90% confidence intervals. Regression results for panels (a) and (b) are reported in Table A3 and those for panels (c) and (d) are reported in Table A4.

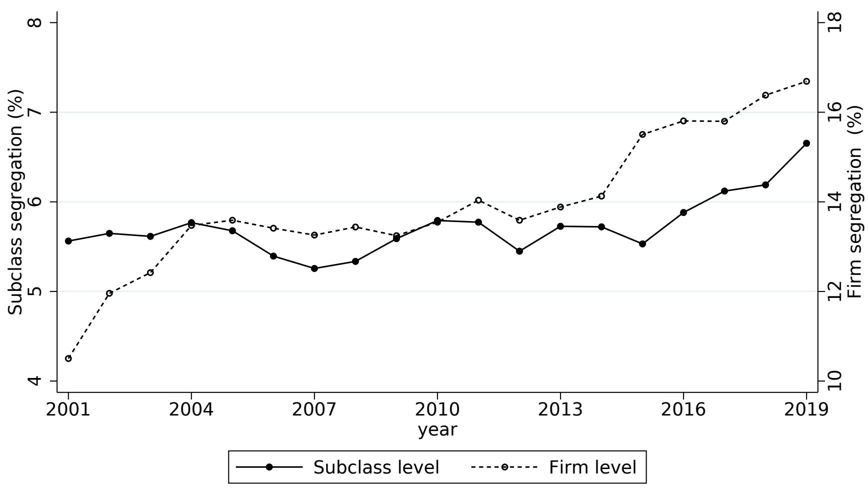
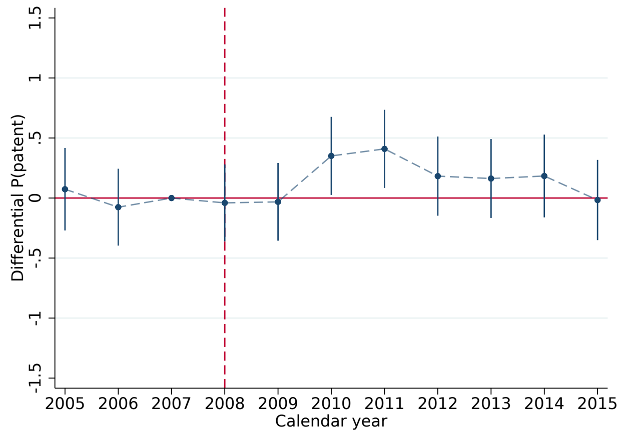
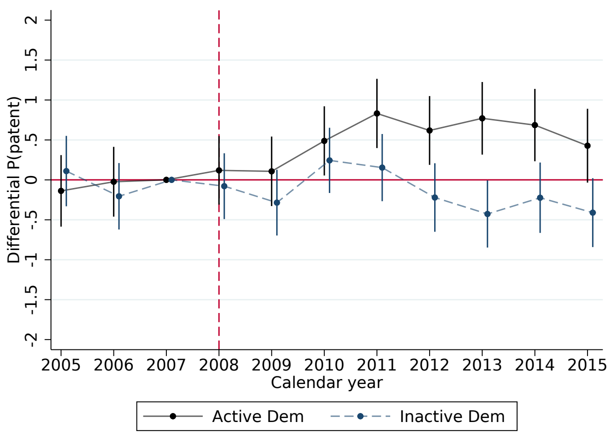


Figure 4: Party Affiliation and Clustering by Technology or Firm over time

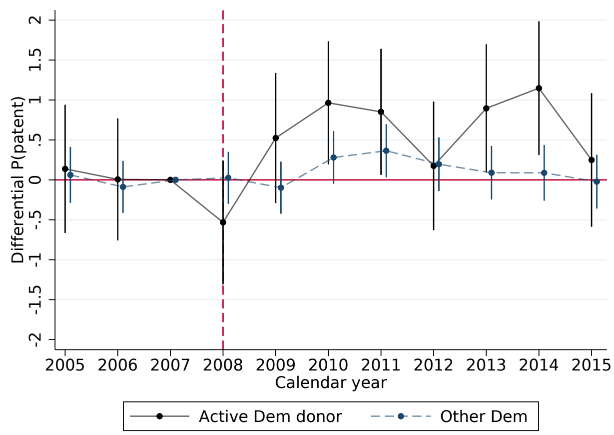
Note: This figure plots a measure of patenters' segregation along party lines by technology and by firm over time. Specifically, the panel plots the isolation index (White, 1986) for technology subclasses and firms. Only technology subclasses and firms with more than 10 Republican or Democratic patenters in a year are included. Units are in percentage points.



(a) Dems vs Reps



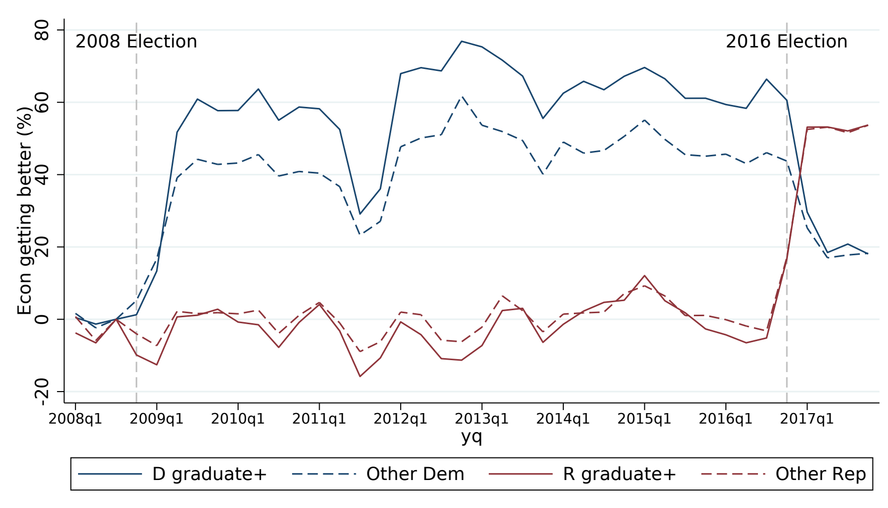
(b) Active and inactive voter Dems vs Reps



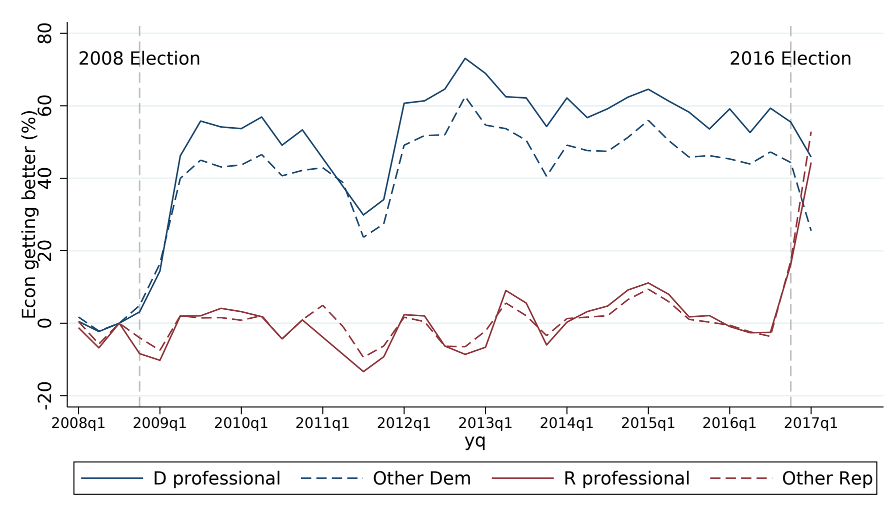
(c) Active and inactive donor Dems vs Reps

Figure 5: Political Mismatch and the Probability of Submitting a Patent
Democrat versus Republican Inventors (Longer Horizon)

Note: This figure extends Figure 2 panel (a) and Figure 3 panels (a) and (c) to seven quarters after the quarter of the 2008 election. Data constraints mean that we cannot do this for the 2016 election. See Figures 2 and 3 for details.



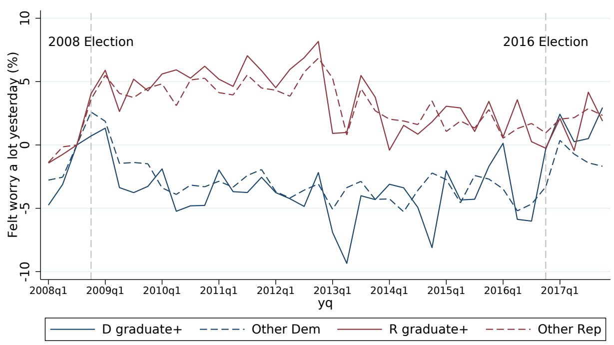
(a) By education



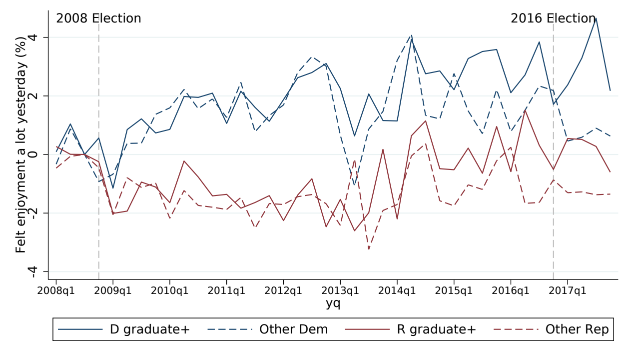
(b) By occupation

Figure 6: Optimism about National Economy: the Gallup U.S. Daily Survey by Education (or Occupation) and Party Affiliation

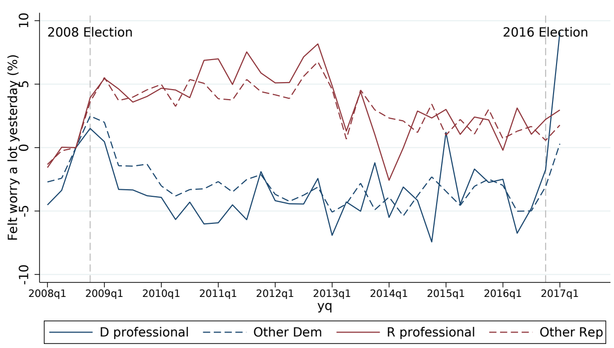
Note: This figure plots the fraction of respondents choosing ”Getting better” to the question “Right now, do you think that economic conditions in this country, as a whole, are getting better or getting worse?” in the Gallup U.S. Daily Survey. Values are normalized to their 2008 Q3 levels and units are in percentage points. Panel (a) plots the response by education level and panel (b) by occupation. “Graduate+” refers to respondents who self-identify as having a graduate or higher degree. “Professional” refers to respondents who self-identify as professional workers (lawyer, doctor, scientist, teacher, engineer, nurse, accountant, computer programmer, architect, investment banker, stock brokerage, marketing, musician, artist). Starting in 2017 Q2 the survey does not ask the national economy question and about respondents’ occupation at the same time, so panel (b) stops in 2017 Q1.



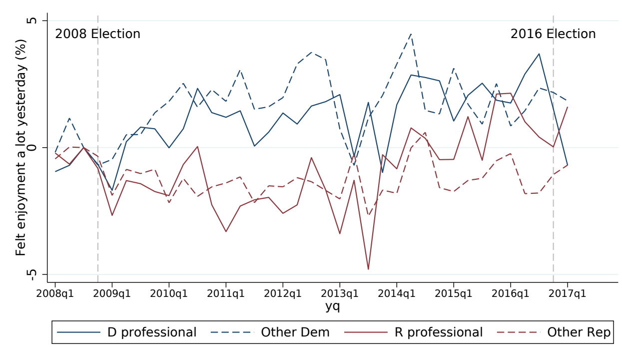
(a) Worry yesterday by education



(b) Enjoyment yesterday by education



(c) Worry yesterday by occupation



(d) Enjoyment yesterday by occupation

Figure 7: Mood: the Gallup U.S. Daily Survey by Education (or Occupation) and Party Affiliation

Note: This figure plots the fraction of respondents answering "Yes" to the questions "Did you experience the feeling of *worry* during a lot of the day yesterday?" (panels a and c) and "Did you experience the feeling of *enjoyment* during a lot of the day yesterday?" (panels b and d) in the Gallup U.S. Daily Survey. Values are normalized to their 2008 Q3 levels, and units are in percentage points. Panels (a) and (b) plot the percentage by education level and panels (c) and (d) by occupation. "Graduate+" refers to respondents who self-identify as having a graduate or higher degree. "Professional" refers to respondents who self-identify as professional workers (lawyer, doctor, scientist, teacher, engineer, nurse, accountant, computer programmer, architect, investment banker, stock brokerage, marketing, musician, artist).

Table 1: Annual Pr(submitting a patent conditional on characteristics) and Sample composition

	Full sample			Democrat			Republican		
	Probability (pp)			Probability (pp)			Probability (pp)		
	Mean	SD	%Sample	Mean	SD	%Sample	Mean	SD	%Sample
All	18.02	38.43	100	19.33	39.49	100	16.79	37.38	100
Male	18.44	38.78	88.79	19.97	39.97	85.41	17.13	37.67	91.95
Female	14.64	35.35	11.21	15.62	36.31	14.59	12.98	33.61	8.05
College+	18.74	39.02	84.18	20.17	40.12	85.67	17.47	37.97	82.90
High school–	14.88	35.59	15.82	15.95	36.61	14.33	14.11	34.81	17.10
White	17.70	38.17	82.96	19.32	39.48	74.78	16.50	37.11	90.32
Black	12.41	32.97	2.96	12.20	32.73	5.76	14.84	35.55	0.45
Hispanic	16.11	36.76	3.75	17.15	37.70	5.03	14.28	34.99	2.60
Asian	21.05	40.77	10.32	21.34	40.97	14.43	20.48	40.36	6.63
Age 18-29	12.83	33.44	7.08	12.78	33.39	8.84	12.89	33.51	5.44
Age 30-39	20.58	40.43	17.53	21.58	41.14	18.81	19.51	39.63	16.33
Age 40-49	20.20	40.15	29.57	21.80	41.29	28.59	18.80	39.07	30.48
Age 50-59	17.98	38.40	28.74	19.75	39.81	27.39	16.47	37.09	30.01
Age 60-70	13.82	34.52	17.08	15.26	35.96	16.37	12.59	33.17	17.75
W/ firm	19.92	39.94	86.33	21.03	40.75	88.58	18.83	39.09	84.24
W/o firm	6.03	23.81	13.67	6.20	24.11	11.42	5.92	23.60	15.76
N patenter×year		6,755,327			3,260,841			3,494,486	
N patenter		379,305			183,122			196,183	
N state		51			51			51	

Note: This table reports summary statistics for our main sample (see section 2 for more details). The outcome is the average annual probability of submitting a patent conditional on patenters' characteristics. The *%Sample* column displays the fraction of patenters with each characteristic in the sample. All units are in percentage points. Columns (1)-(3), (4)-(6) and (7)-(9) are calculated based on both Democrats and Republicans, Democrats alone, and Republicans alone, respectively (see section 2.2 for definition of partisanship). *Male* is an indicator for being male, *College+* (*High school–*) is an indicator for having a college or higher degree (having a completed high school or lower), *Age xx-yy* is an indicator for being between xx and yy years old, and *W/ firm* (*W/o firm*) is an indicator for a patenter being affiliated with a firm (or not). 51 "states" corresponds to 50 states plus DC.

Table 2: Party Concentration by Technology and by Firm

Democrat-leaning		Republican-leaning		No lean	
Name	%Dem-Rep	Name	%Dem-Rep	Name	%Dem-Rep
Panel A: By technology section					
Chemistry; Metallurgy	18.9	Fixed Constructions	-33.9	Human Necessities	1.2
Physics	15.0	Mech. Eng.; Lighting; Heating; Weapons; Blasting	-23.1		
Electricity	11.0	Performing Operations; Transporting	-15.9		
		Textiles; Paper	-15.0		
Panel B: By technology class					
Combinatorial Technology	47.5	Weapons	-45.3	Dyes; Paints; Polishes; Natural Resins	0.0
Biochemistry; Alcohol; Vinegar; Genetic Eng.	41.6	Ammunition; Blasting	-42.2	Hand or Travelling Articles	0.1
Organic Chemistry	36.6	Construction of Roads, Railways, or Bridges	-41.5	Signalling	0.3
Nanotechnology	29.8	Hydraulic Engineering; Foundations; Soil Shifting	-39.5	Sports; Games; Amusements	-0.5
Musical Instruments; Acoustics	27.6	Saddlery; Upholstery	-37.8	Machines or Engines for Liquids	-0.6
Information And Communication Technology	21.8	Earth Drilling; Mining	-37.3	Sugar Industry	-0.7
Computing; Calculating; Counting	21.2	Presses	-36.5	Controlling; Regulating	-0.8
Electric Communication Technique	19.8	Crushing, Pulverising, or Disintegrating; Prep. of Grain	-35.1	Wearing Apparel	0.9
Microstructural Technology	18.8	Butchering; Meat Treatment; Processing Poultry or Fish	-35.0	Organic Macromolecular Compounds	1.4
Crystal Growth	18.0	Making Articles of Paper	-34.8	Checking-Devices	-1.4
Panel C: By firm					
Google Inc.	70.4	Halliburton Energy Services Inc.	-39.3	Dow Global Tech LLC	0.9
Yahoo Inc.	65.6	Baker Hughes Inc.	-38.9	Chevron USA Inc.	-1.3
Microsoft Corp.	65.2	Kimberly Clark Worldwide Inc.	-36.9	GM Global Tech Operations LLC	2.0
Genentech Inc.	63.7	Caterpillar Inc.	-34.6	United Tech Corp.	-2.8
Apple Inc.	60.0	Illinois Tool Works Inc.	-33.8	The Procter & Gamble Co	-2.9
Oracle Int Corp.	44.4	3M Innovative Properties Co	-31.0	Verizon Patent & Licensing Inc	3.9
Merck & Co Inc.	39.0	Delphi Tech Inc.	-29.2	Dell Prod LP	-4.8
Sun Microsystems Inc.	35.6	Micron Tech Inc.	-28.5	Bank of America Corp.	-4.8
Cisco Tech Inc.	33.3	Honeywell Int Inc.	-23.7	Motorola Inc.	5.3
Qualcomm Inc.	32.3	Lockheed Martin Corp.	-21.3	Boston Sci Scimed Inc.	-7.3

Note: This table reports the difference in the shares of Democrat and Republican patenters among partisans by technology section, by technology class, or by firm using USPTO patent applications submitted between 2001 and 2019. Panel A reports the difference for each *technology section* in our sample. Panel B reports the difference for the ten *technology classes* with the greatest difference (i) between Democrat and Republican shares ("Democrat-leaning"), (ii) between Republican and Democrat shares ("Republican-leaning") and (iii) between the ten with the least difference ("No lean"); panel C does the same for the ten publicly traded *firms* (with >1,000 patenters in the USPTO data) in the three "lean" categories.

Table 3: Political Mismatch and Patent Application Likelihood - DID: Democrat versus Republican Inventors

	(1) P(patent)	(2) P(patent)	(3) P(patent)	(4) P(patent)	(5) P(patent)	(6) P(patent)	(7) P(patent)	(8) P(patent)
Panel A: 2008 election								
Dem×Post	0.055	0.068	0.226*	0.236*	0.268**	0.279**	0.306**	0.336**
	(0.131)	(0.130)	(0.134)	(0.134)	(0.131)	(0.131)	(0.135)	(0.132)
Dem	2.539***	2.310***	1.666***	1.580***	1.645***	1.558***		
	(0.148)	(0.154)	(0.145)	(0.152)	(0.146)	(0.152)		
Effect as %mean	.28	.34	1.14	1.19	1.35	1.41	1.55	1.7
Observations	1,307,930	1,309,566	1,307,612	1,309,242	1,307,612	1,309,242	1,309,242	1,309,242
R-squared	0.032	0.063	0.049	0.078	0.049	0.078	0.484	0.485
Outcome mean	19.69	19.69	19.69	19.69	19.69	19.69	19.69	19.69
N cluster (zip)	18,549	18,562	18,548	18,561	18,548	18,561	18,561	18,561
Panel B: 2016 election								
Dem×Post	-0.540***	-0.531***	-0.377***	-0.375***	-0.253**	-0.247*	-0.243*	-0.135
	(0.128)	(0.128)	(0.126)	(0.126)	(0.129)	(0.129)	(0.126)	(0.130)
Dem	2.507***	2.141***	1.915***	1.678***	1.856***	1.616***		
	(0.154)	(0.160)	(0.152)	(0.158)	(0.152)	(0.159)		
Effect as %mean	-2.45	-2.41	-1.71	-1.7	-1.15	-1.12	-1.1	-.61
Observations	1,356,239	1,358,125	1,355,588	1,357,474	1,355,588	1,357,474	1,357,474	1,357,474
R-squared	0.030	0.059	0.047	0.075	0.047	0.075	0.501	0.501
Outcome mean	22.13	22.12	22.13	22.12	22.13	22.12	22.12	22.12
N cluster (zip)	17,651	17,665	17,649	17,663	17,649	17,663	17,663	17,663
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	N	Y	N	Y	N	N	N
Zip FE	N	Y	N	Y	N	Y	N	N
Person FE	N	N	N	N	N	N	Y	Y
State×Post FE	Y	Y	N	N	Y	Y	N	Y
Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: The table compares the likelihood of submitting a patent between Democrat and Republican inventors in the same area in the years before and after the 2008 and 2016 presidential elections. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Dem* is one for Democrats and zero for Republicans (see section 2.2 for definition of partisanship). *Post* is one for the first through third years after a presidential election. For example, for the 2016 election, *Post* refers to 2017, 2018, and 2019. The year of a presidential election is excluded from the regression. Demographic controls correspond to fully interacted inventor characteristics (i.e., gender, education, age groups, race) and are included in all regressions. Standard errors are clustered by zip code.

Table 4: Political Mismatch and Patent Application Likelihood - DID: Democrat versus Republican Inventors *by Voting Activeness*

	(1) P(patent)	(2) P(patent)	(3) P(patent)	(4) P(patent)	(5) P(patent)	(6) P(patent)	(7) P(patent)	(8) P(patent)
Panel A: 2008 election								
Active Dem×Post	0.289*	0.288*	0.521***	0.520***	0.521***	0.523***	0.511***	0.485***
	(0.173)	(0.173)	(0.173)	(0.172)	(0.175)	(0.174)	(0.173)	(0.175)
Inactive Dem×Post	-0.088	-0.074	0.055	0.069	0.115	0.129	0.145	0.206
	(0.166)	(0.166)	(0.169)	(0.169)	(0.167)	(0.167)	(0.169)	(0.167)
Active Dem	2.415***	2.069***	1.414***	1.235***	1.414***	1.232***		
	(0.197)	(0.205)	(0.193)	(0.201)	(0.195)	(0.202)		
Inactive Dem	2.514***	2.332***	1.797***	1.733***	1.767***	1.703***		
	(0.184)	(0.192)	(0.182)	(0.191)	(0.181)	(0.190)		
Active effect as %mean	1.48	1.48	2.68	2.67	2.68	2.69	2.63	2.49
Inactive effect as %mean	-.46	-.39	.28	.35	.59	.66	.74	1.06
p value	.061	.071	.018	.022	.044	.05	.061	.164
Observations	1,175,393	1,176,774	1,175,111	1,176,486	1,175,111	1,176,486	1,176,486	1,176,486
R-squared	0.032	0.064	0.049	0.079	0.049	0.079	0.480	0.481
Outcome mean	19.39	19.39	19.39	19.39	19.39	19.39	19.39	19.39
N cluster (zip)	17,979	17,991	17,976	17,988	17,976	17,988	17,988	17,988
Panel B: 2016 election								
Active Dem×Post	-0.715***	-0.724***	-0.550***	-0.565***	-0.389**	-0.396**	-0.658***	-0.526***
	(0.169)	(0.169)	(0.166)	(0.166)	(0.170)	(0.170)	(0.167)	(0.172)
Inactive Dem×Post	-0.437***	-0.415***	-0.274*	-0.260*	-0.178	-0.161	-0.029	0.060
	(0.151)	(0.151)	(0.149)	(0.149)	(0.152)	(0.152)	(0.150)	(0.153)
Active Dem	2.863***	2.423***	2.235***	1.950***	2.158***	1.869***		
	(0.198)	(0.205)	(0.195)	(0.202)	(0.196)	(0.203)		
Inactive Dem	2.284***	1.970***	1.735***	1.528***	1.689***	1.480***		
	(0.185)	(0.192)	(0.182)	(0.189)	(0.183)	(0.190)		
Active effect as %mean	-3.25	-3.29	-2.5	-2.57	-1.77	-1.8	-2.99	-2.39
Inactive effect as %mean	-1.99	-1.89	-1.25	-1.19	-.81	-.73	-.13	.27
p value	.131	.092	.126	.091	.252	.2	0	.001
Observations	1,298,758	1,300,559	1,298,128	1,299,929	1,298,128	1,299,929	1,299,929	1,299,929
R-squared	0.031	0.060	0.048	0.076	0.048	0.076	0.500	0.500
Outcome mean	22.05	22.04	22.05	22.04	22.05	22.04	22.04	22.04
N cluster (zip)	17,455	17,469	17,453	17,467	17,453	17,467	17,467	17,467
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	N	Y	N	Y	N	N	N
Zip FE	N	Y	N	Y	N	Y	N	N
Person FE	N	N	N	N	N	N	Y	Y
State×Post FE	Y	Y	N	N	Y	Y	N	Y
Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: The table compares the likelihood of submitting a patent between Democrat and Republican inventors in the same area in the years before and after the 2008 and 2016 presidential elections. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Active Dem* is one for active Democrat based on voting history and zero for others; *Inactive Dem* is one for inactive Democrats based on voting history and zero for others (see section 2.2 for definition of partisanship). *Post* is one for the first through third years after a presidential election. For example, for the 2016 election, *Post* refers to 2017, 2018, and 2019. The year of a presidential election is excluded from the regression. Demographic controls correspond to fully interacted inventor characteristics (i.e., gender, education, age groups, race) and are included in all regressions. Standard errors are clustered by zip code.

Table 5: Political Mismatch and Patent Application Likelihood - DID *within Firm*: Democrat versus Republican Inventors *by Voting Activeness*

	(1) Inventors w/ firm	(2) Num≥1	(3) Num≥2	(4) Num≥4	(5) Num≥8
Panel A: 2008 election					
Active Dem×Post	0.5628***	0.4706**	0.5113**	0.4153*	0.4815*
	(0.2092)	(0.2315)	(0.2395)	(0.2516)	(0.2706)
Inactive Dem×Post	0.0509	-0.1995	-0.1180	-0.0544	0.0610
	(0.2040)	(0.2251)	(0.2359)	(0.2491)	(0.2662)
Active Dem	1.2426***	1.5552***	1.5980***	1.6913***	1.7139***
	(0.2360)	(0.2633)	(0.2775)	(0.2931)	(0.3149)
Inactive Dem	1.7172***	2.0620***	1.9430***	1.9017***	1.8751***
	(0.2269)	(0.2509)	(0.2654)	(0.2845)	(0.3028)
Active effect as %mean	2.59	2.02	2.2	1.79	2.06
Inactive effect as %mean	.23	-.86	-.51	-.24	.26
p value	.027	.009	.019	.097	.167
Observations	1,007,287	688,764	628,185	564,889	495,915
R-squared	0.200	0.129	0.123	0.121	0.121
Outcome mean	21.697	23.225	23.202	23.172	23.291
N cluster (zip)	16,215	13,499	12,919	12,299	11,458
Panel B: 2016 election					
Active Dem×Post	-0.3512*	-0.4833**	-0.5749***	-0.6089***	-0.6708***
	(0.1933)	(0.2105)	(0.2197)	(0.2336)	(0.2466)
Inactive Dem×Post	-0.1218	-0.2127	-0.2363	-0.2165	-0.1979
	(0.1792)	(0.1979)	(0.2072)	(0.2191)	(0.2326)
Active Dem	1.6934***	1.9708***	2.0990***	2.1972***	2.2960***
	(0.2364)	(0.2635)	(0.2737)	(0.2894)	(0.3067)
Inactive Dem	1.0930***	1.1502***	1.1707***	1.1386***	1.1147***
	(0.2196)	(0.2446)	(0.2565)	(0.2733)	(0.2950)
Active effect as %mean	-1.48	-1.95	-2.32	-2.45	-2.71
Inactive effect as %mean	-.52	-.86	-.95	-.87	-.8
p value	.262	.23	.15	.111	.066
Observations	1,159,878	814,722	746,028	677,514	596,597
R-squared	0.204	0.128	0.122	0.119	0.117
Outcome mean	23.848	24.875	24.886	24.918	24.771
N cluster (zip)	16,215	13,588	12,998	12,403	11,640
Demographics	Y	Y	Y	Y	Y
Zip FE	Y	Y	Y	Y	Y
Class×Post FE	Y	Y	Y	Y	Y
Firm×Post FE	Y	Y	Y	Y	Y

Note: The table compares the likelihood of submitting a patent between Democrat and Republican inventors in the same firm in the years before and after the 2008 and 2016 presidential elections. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Active Dem* is one for active Democrat based on voting history and zero for others; *Inactive Dem* is one for inactive Democrats based on voting history and zero for others (see section 2.2 for definition of partisanship). *Post* is one for the first through third years after a presidential election. For example, for the 2016 election, *Post* refers to 2017, 2018, and 2019. The year of a presidential election is excluded from the regression. column (1) include inventors affiliated with a firm, and columns (2) through (5) further restrict the firms to have at least a certain number of inventors of each type of party and activeness. All regressions control for zip code, technology class×post, and firm×post fixed effects as well as demographics (i.e., fully interacted inventor gender, education, age group, and race). Standard errors are clustered by zip code.

Table 6: Political Mismatch and Patent Citations:
Democrat versus Republican Inventors

VARIABLES	(1) Raw cite	(2) Raw cite	(3) Scaled cite	(4) Scaled cite	(5) Std. cite	(6) Std. cite
Panel A: 2008 election						
Dem×Post	-0.595**	-0.335	-0.053*	-0.047	-0.020**	-0.017*
	(0.274)	(0.290)	(0.032)	(0.032)	(0.010)	(0.010)
Dem	0.126	0.010	0.056**	0.053**	0.021**	0.020**
	(0.315)	(0.316)	(0.024)	(0.023)	(0.008)	(0.008)
Effect as %mean	-5.51	-3.1	-4.13	-3.65	-18.27	-15.44
Observations	216,685	216,685	216,684	216,684	216,682	216,682
R-squared	0.153	0.154	0.103	0.104	0.107	0.108
Outcome mean	10.79	10.79	1.28	1.28	.11	.11
N cluster (zip)	12,834	12,834	12,834	12,834	12,834	12,834
Panel B: 2016 election						
Dem×Post	0.289**	0.355***	0.088*	0.085*	0.009	0.015*
	(0.113)	(0.118)	(0.047)	(0.050)	(0.008)	(0.009)
Dem	-0.277**	-0.298***	-0.053	-0.052	-0.008	-0.010
	(0.111)	(0.114)	(0.033)	(0.034)	(0.007)	(0.007)
Effect as %mean	13.79	16.93	7.98	7.76	26.22	47.27
Observations	235,347	235,347	235,307	235,307	235,307	235,307
R-squared	0.137	0.141	0.083	0.084	0.094	0.094
Outcome mean	2.09	2.09	1.1	1.1	.03	.03
N cluster (zip)	12,658	12,658	12,657	12,657	12,657	12,657
Demographics	Y	Y	Y	Y	Y	Y
Zip FE	Y	Y	Y	Y	Y	Y
Class×Post FE	Y	Y	Y	Y	Y	Y
State×Post FE	N	Y	N	Y	N	Y

Note: The table compares patent citation between Democrat and Republican inventors in the same zip code in the years before and after the 2008 and 2016 presidential elections. The outcome in columns (1) through (3) (and columns (4) through (6)) is an inventor's average citation across their patents submitted in a year, average scaled citation (i.e., citation divided by the mean citation within technology class and grant year), and average standardized citation (i.e., citation less mean and divided by standard deviation of citation within technology class and grant year), respectively. *Dem* is one for Democrats and zero for Republicans (see section 2.2 for definition of partisanship). *Post* is one for the first through third years after a presidential election. For example, for the 2016 election, *Post* refers to 2017, 2018, and 2019. The year of a presidential election is excluded from the regression. Demographic controls correspond to fully interacted inventor characteristics (i.e., gender, education, age groups, race) and are included in all regressions. Standard errors are clustered by zip code.

Table 7: Political Mismatch and Patent Application Likelihood - DID: Immigrants versus Non-immigrants

	(1) P(patent)	(2) P(patent)	(3) P(patent)	(4) P(patent)	(5) P(patent)	(6) P(patent)	(7) P(patent)	(8) P(patent)
Panel A: 2008 election								
Immigrant×Post	-0.224	-0.290	0.257	0.193	0.102	0.040	0.236	0.097
	(0.318)	(0.318)	(0.322)	(0.322)	(0.321)	(0.321)	(0.329)	(0.327)
Immigrant	5.288***	4.744***	4.276***	3.869***	4.354***	3.946***		
	(0.379)	(0.388)	(0.373)	(0.381)	(0.369)	(0.379)		
Effect as %mean	-1.07	-1.38	1.22	.91	.48	.18	1.11	.46
Observations	746,575	747,573	746,389	747,387	746,389	747,387	747,387	747,387
R-squared	0.037	0.078	0.055	0.094	0.055	0.094	0.481	0.481
Outcome mean	21.09	21.1	21.09	21.1	21.09	21.1	21.1	21.1
N cluster (zip)	151,66	151,78	151,63	151,75	151,63	151,75	151,75	151,75
Panel B: 2016 election								
Immigrant×Post	-1.689***	-1.692***	-1.340***	-1.357***	-1.239***	-1.255***	-1.172***	-1.080***
	(0.310)	(0.311)	(0.309)	(0.309)	(0.311)	(0.311)	(0.310)	(0.312)
Immigrant	4.290***	4.029***	3.729***	3.550***	3.679***	3.499***		
	(0.377)	(0.385)	(0.368)	(0.376)	(0.370)	(0.378)		
Effect as %mean	-7.28	-7.3	-5.78	-5.85	-5.34	-5.41	-5.06	-4.66
Observations	700,021	701,091	699,744	700,814	699,744	700,814	700,814	700,814
R-squared	0.034	0.077	0.052	0.094	0.052	0.094	0.501	0.501
Outcome mean	23.21	23.2	23.21	23.2	23.21	23.2	23.2	23.2
N cluster	141,79	141,89	141,79	141,89	141,79	141,89	141,89	141,89
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	N	Y	N	Y	N	N	N
Zip FE	N	Y	N	Y	N	Y	N	N
Person FE	N	N	N	N	N	N	Y	Y
State×Post FE	Y	Y	N	N	Y	Y	N	Y
Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: The table compares the likelihood of submitting a patent for immigrant versus non-immigrant inventors in the same area in the years before versus the years after the 2008 and 2016 presidential elections. Regression specifications follow those in Table 3. The sample consists of Democratic and Republican patenters who are matched to Infutor. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Immigrant* is an indicator for inventors who are categorized as immigrants using age of first SSN (or ITIN number) following the procedure in Bernstein et al. (2018). *Post* is one for the first through third years after a presidential election. For example, for the 2016 election, *Post* refers to 2017, 2018, and 2019. The year of a presidential election is excluded from the regression. Demographic controls correspond to fully interacted inventor characteristics (i.e., gender, education, age groups, race) and are included in all regressions. Standard errors are clustered by zip code.

Appendix for "Political Sentiment and Innovation: Evidence from Patenters"[1]

[1]Citation format: Joseph Engelberg, Runjing Lu, William Mullins and Richard Townsend, Appendix for "Political Sentiment and Innovation: Evidence from Patenters" 2022, Working Paper.

Table A1: Summary Statistics by Election

	Full sample			Democrat			Republican		
	Probability (pp)			Probability (pp)			Probability (pp)		
	Mean	SD	%Sample	Mean	SD	%Sample	Mean	SD	%Sample
Panel A: 2008 election									
All	19.60	39.70	100	21.27	40.92	100	18.12	38.52	100
Male	20.10	40.08	90.08	22.04	41.45	86.88	18.50	38.83	92.92
Female	15.02	35.72	9.92	16.19	36.84	13.12	13.08	33.72	7.08
College+	20.57	40.42	83.72	22.41	41.70	85.29	19.00	39.23	82.42
High school–	15.64	36.32	16.28	16.87	37.45	14.71	14.78	35.49	17.58
White	19.23	39.41	84.61	21.23	40.90	76.83	17.78	38.23	91.27
Black	12.77	33.38	3.06	12.45	33.02	6.07	16.23	36.87	0.48
Hispanic	17.22	37.75	3.38	18.51	38.84	4.57	15.08	35.78	2.36
Asian	23.66	42.50	8.95	24.38	42.94	12.54	22.36	41.66	5.88
Age 18-29	20.10	40.07	3.74	19.43	39.57	4.66	21.03	40.75	2.93
Age 30-39	24.79	43.18	13.15	25.76	43.73	13.68	23.86	42.62	12.68
Age 40-49	22.33	41.64	29.63	24.23	42.85	28.98	20.71	40.52	30.20
Age 50-59	18.72	39.01	32.58	20.78	40.57	32.05	16.96	37.52	33.05
Age 60-70	13.75	34.43	20.90	15.33	36.02	20.63	12.38	32.94	21.14
W/ firm	21.81	41.29	86.87	23.30	42.28	88.86	20.42	40.32	85.11
W/o firm	4.99	21.77	13.13	5.08	21.95	11.14	4.93	21.65	14.89
N patenter×year		4,015,445			1,885,593			2,129,852	
N patenter		228,250			107,114			121,136	
N state		51			51			51	
Panel B: 2016 election									
All	24.03	42.73	100	25.14	43.38	100	22.92	42.03	100
Male	24.59	43.06	88.97	25.91	43.81	85.82	23.36	42.31	92.14
Female	19.52	39.63	11.03	20.49	40.37	14.18	17.75	38.21	7.86
College+	24.73	43.14	85.66	25.94	43.83	86.99	23.57	42.44	84.41
High school–	21.19	40.86	14.34	22.21	41.57	13.01	20.39	40.29	15.59
White	23.89	42.64	81.91	25.38	43.52	74.13	22.70	41.89	89.44
Black	18.55	38.87	2.55	18.27	38.64	4.75	21.72	41.24	0.41
Hispanic	21.36	40.99	3.83	22.40	41.69	5.08	19.42	39.56	2.63
Asian	25.89	43.80	11.71	25.91	43.81	16.04	25.84	43.78	7.52
Age 18-29	13.61	34.29	8.76	13.71	34.39	10.59	13.46	34.13	6.92
Age 30-39	23.77	42.57	20.28	24.66	43.10	21.60	22.76	41.93	18.95
Age 40-49	26.35	44.06	30.23	27.83	44.82	29.12	24.97	43.28	31.35
Age 50-59	25.93	43.83	26.69	27.85	44.83	25.23	24.19	42.82	28.16
Age 60-70	22.31	41.64	14.04	24.01	42.71	13.46	20.74	40.55	14.62
W/ firm	25.77	43.73	89.90	26.60	44.19	91.78	24.89	43.24	88.01
W/o firm	8.61	28.04	10.10	8.86	28.42	8.22	8.43	27.78	11.99
N patenter×year		4,425,794			2,221,865			2,203,929	
N patenter		244,792			123,078			121,714	
N state		51			51			51	

Note: This table reports summary statistics for regression samples for the 2008 and 2016 elections separately. See note to Table 1 for variable definitions.

Table A2: Political Mismatch and Patent Application - Election Event Study: Democrat versus Republican Inventors

VARIABLES	(1) 2008	(2) 2016
Dem×-3	0.0775	-0.2929
	(0.2087)	(0.2027)
Dem×-2	-0.0740	0.0674
	(0.1946)	(0.2042)
Dem×0	-0.0406	-0.0094
	(0.1947)	(0.1894)
Dem×1	-0.0327	-0.0349
	(0.1967)	(0.1931)
Dem×2	0.3470*	-0.4917***
	(0.1978)	(0.1907)
Dem×3	0.4048**	-0.8493***
	(0.1979)	(0.1961)
Dem	1.5700***	1.7377***
	(0.1900)	(0.1939)
Observations	1,528,168	1,584,826
R-squared	0.077	0.075
Outcome mean	19.602	22.126
Demographics	Y	Y
Zip code FE	Y	Y
Class×event FE	Y	Y
N cluster (zip)	18,561	17,663

Note: The table compares the likelihood of submitting a patent between Democrat and Republican inventors in the same zip code in the years before and after the 2008 and 2016 presidential elections. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Dem* is one for Democrats and zero for Republicans (see section 2.2 for definition of partisanship). Event time 0 refers to the year of a presidential election. Event time -1 is the omitted period. All regressions control for zip code fixed effects, technology class×event fixed effects, and fully interacted inventor characteristics (i.e., gender, education, age groups, race). Standard errors are clustered by zip code.

Table A3: Political Mismatch and Patent Application Likelihood - Election Event Study: Democrat versus Republican Inventors *by Voting Activeness*

VARIABLES	(1) 2008	(2) 2016
Active Dem×-3	-0.1331	-0.3305
	(0.2722)	(0.2623)
Active Dem×-2	-0.0213	0.2870
	(0.2657)	(0.2675)
Active Dem×0	0.1208	0.0525
	(0.2611)	(0.2521)
Active Dem×1	0.1079	-0.0400
	(0.2646)	(0.2545)
Active Dem×2	0.4846*	-0.7207***
	(0.2635)	(0.2515)
Active Dem×3	0.8267***	-1.0282***
	(0.2636)	(0.2526)
Inactive Dem×-3	0.1139	-0.3924
	(0.2679)	(0.2512)
Inactive Dem×-2	-0.2030	-0.1855
	(0.2528)	(0.2457)
Inactive Dem×0	-0.0780	-0.1512
	(0.2504)	(0.2259)
Inactive Dem×1	-0.2831	-0.0997
	(0.2500)	(0.2303)
Inactive Dem×2	0.2455	-0.5020**
	(0.2483)	(0.2288)
Inactive Dem×3	0.1568	-0.7773***
	(0.2556)	(0.2353)
Active Dem	1.3226***	1.9213***
	(0.2543)	(0.2512)
Inactive Dem	1.7258***	1.7241***
	(0.2350)	(0.2330)
Observations	1,373,385	1,517,796
R-squared	0.078	0.077
Outcome mean	19.299	22.04
Demographics	Y	Y
Zip code FE	Y	Y
Class×Event FE	Y	Y
N cluster (zip)	17,988	17,467

Note: The table compares the likelihood of submitting a patent between Democrat and Republican inventors in the same zip code in the years before and after the 2008 and 2016 presidential elections. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Active Dem* is one for active Democrat based on voting history and zero for others; *Inactive Dem* is one for inactive Democrats based on voting history and zero for others (see section 2.2 for definition of partisanship). Event time 0 refers to the year of a presidential election. Event time -1 is the omitted period. All regressions control for zip code fixed effects, technology class×event fixed effects, and fully interacted inventor characteristics (i.e., gender, education, age groups, race). Standard errors are clustered by zip code.

Table A4: Political Mismatch and Patent Application Likelihood - Election Event Study: Democrat versus Republican Inventors *by Donation Activeness*

VARIABLES	(1) 2008	(2) 2016
Active Dem×-3	0.1414	0.1269
	(0.4880)	(0.4635)
Active Dem×-2	0.0070	0.4440
	(0.4648)	(0.4724)
Active Dem×0	-0.5304	-0.3022
	(0.4716)	(0.4435)
Active Dem×1	0.5222	-0.3338
	(0.4951)	(0.4654)
Active Dem×2	0.9622**	-1.6431***
	(0.4689)	(0.4389)
Active Dem×3	0.8519*	-1.1735**
	(0.4795)	(0.4576)
Inactive Dem×-3	0.0657	-0.3504*
	(0.2133)	(0.2097)
Inactive Dem×-2	-0.0862	0.0188
	(0.1983)	(0.2091)
Inactive Dem×0	0.0248	0.0290
	(0.1983)	(0.1937)
Inactive Dem×1	-0.0986	0.0078
	(0.1985)	(0.1982)
Inactive Dem×2	0.2763	-0.3462*
	(0.2009)	(0.1955)
Inactive Dem×3	0.3594*	-0.7966***
	(0.2026)	(0.1999)
Active Dem	4.8625***	4.7108***
	(0.4318)	(0.4326)
Inactive Dem	1.1855***	1.4067***
	(0.1935)	(0.1972)
Observations	1,528,168	1,584,826
R-squared	0.077	0.076
Outcome mean	19.602	22.126
Demographics	Y	Y
Zip code FE	Y	Y
Class×Event FE	Y	Y
N cluster (zip)	18561	17663

Note: The table compares the likelihood of submitting a patent between Democrat and Republican inventors in the same zip code in the years before and after the 2008 and 2016 presidential elections. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Active Dem* is one for active Democrat based on FEC donation history and zero for others; *Inactive Dem* is one for inactive Democrats based on FEC donation history and zero for others (see section 2.2 for definition of partisanship). Event time 0 refers to the year of a presidential election. Event time -1 is the omitted period. All regressions control for zip code fixed effects, technology class×event fixed effects, and fully interacted inventor characteristics (i.e., gender, education, age groups, race). Standard errors are clustered by zip code.

Table A5: Political Mismatch and Patent Application Likelihood - DID: Democrat versus Republican Inventors *by Donation Activeness*

	(1) P(patent)	(2) P(patent)	(3) P(patent)	(4) P(patent)	(5) P(patent)	(6) P(patent)	(7) P(patent)	(8) P(patent)
Panel A: 2008 election								
Active Dem×Post	0.459	0.481	0.710**	0.723**	0.755**	0.768**	0.646**	0.669**
	(0.314)	(0.313)	(0.321)	(0.320)	(0.314)	(0.313)	(0.321)	(0.314)
Inactive Dem×Post	0.019	0.027	0.177	0.183	0.220	0.228*	0.262*	0.295**
	(0.134)	(0.133)	(0.136)	(0.136)	(0.134)	(0.134)	(0.137)	(0.135)
Active Dem	6.961***	5.896***	5.659***	4.889***	5.636***	4.866***		
	(0.331)	(0.343)	(0.330)	(0.340)	(0.330)	(0.339)		
Inactive Dem	1.979***	1.881***	1.174***	1.192***	1.152***	1.169***		
	(0.151)	(0.158)	(0.148)	(0.155)	(0.149)	(0.156)		
Active effect as %mean	2.33	2.44	3.6	3.67	3.83	3.9	3.27	3.39
Inactive effect as %mean	.09	.13	.89	.93	1.11	1.15	1.33	1.49
p value	.16	.147	.091	.087	.088	.084	.225	.233
Observations	1,307,930	1,309,566	1,307,612	1,309,242	1,307,612	1,309,242	1,309,242	1,309,242
R-squared	0.033	0.063	0.050	0.078	0.050	0.078	0.484	0.485
Outcome mean	19.69	19.69	19.69	19.69	19.69	19.69	19.69	19.69
N cluster (zip)	18,549	18,562	18,548	18,561	18,548	18,561	18,561	18,561
Panel B: 2016 election								
Active Dem×Post	-1.569***	-1.601***	-1.186***	-1.222***	-1.079***	-1.108***	-1.391***	-1.308***
	(0.296)	(0.295)	(0.295)	(0.295)	(0.297)	(0.296)	(0.294)	(0.296)
Inactive Dem×Post	-0.399***	-0.390***	-0.262**	-0.260**	-0.140	-0.134	-0.106	0.000
	(0.132)	(0.132)	(0.129)	(0.129)	(0.133)	(0.133)	(0.130)	(0.134)
Active Dem	6.539***	5.432***	5.832***	4.965***	5.780***	4.910***		
	(0.344)	(0.352)	(0.344)	(0.352)	(0.344)	(0.352)		
Inactive Dem	2.024***	1.764***	1.453***	1.306***	1.395***	1.245***		
	(0.157)	(0.163)	(0.154)	(0.160)	(0.154)	(0.161)		
Active effect as %mean	-7.1	-7.24	-5.36	-5.53	-4.88	-5.01	-6.29	-5.92
Inactive effect as %mean	-1.81	-1.77	-1.19	-1.18	-.64	-.61	-.48	0
p value	0	0	.001	.001	.001	.001	0	0
Observations	1,356,239	1,358,125	1,355,588	1,357,474	1,355,588	1,357,474	1,357,474	1,357,474
R-squared	0.031	0.059	0.048	0.075	0.048	0.075	0.501	0.501
Outcome mean	22.13	22.12	22.13	22.12	22.13	22.12	22.12	22.12
N cluster (zip)	17,651	17,665	17,649	17,663	17,649	17,663	17,663	17,663
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	N	Y	N	Y	N	N	N
Zip FE	N	Y	N	Y	N	Y	N	N
Person	N	N	N	N	N	N	Y	Y
State×Post FE	Y	Y	N	N	Y	Y	N	Y
Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: The table compares the likelihood of submitting a patent between Democrat and Republican inventors in the same area in the years before and after the 2008 and 2016 presidential elections. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Active Dem* is one for active Democrat based on FEC donation history and zero for others; *Inactive Dem* is one for inactive Democrats based on FEC donation history and zero for others (see section 2.2 for definition of partisanship). *Post* is one for the first through third years after a presidential election. For example, for the 2016 election, *Post* refers to 2017, 2018, and 2019. The year of a presidential election is excluded from the regression. Demographic controls correspond to fully interacted inventor characteristics (i.e., gender, education, age groups, race) and are included in all regressions. Standard errors are clustered by zip code.

Table A6: Political Mismatch and Patent Application Likelihood:
Patenter partisanship defined using the *2014 Voter Roll*

	(1) P(patent)	(2) P(patent)	(3) P(patent)	(4) P(patent)	(5) P(patent)	(6) P(patent)	(7) P(patent)	(8) P(patent)
Panel A: 2016 election pooled								
Dem×Post	-0.554***	-0.544***	-0.382***	-0.376***	-0.306**	-0.300**	-0.284*	-0.215
	(0.144)	(0.144)	(0.145)	(0.145)	(0.146)	(0.146)	(0.145)	(0.147)
Dem	1.871***	1.687***	1.285***	1.216***	1.249***	1.180***		
	(0.170)	(0.179)	(0.167)	(0.177)	(0.167)	(0.177)		
Effect as %mean	-2.61	-2.56	-1.8	-1.77	-1.44	-1.41	-1.34	-1.01
Observations	1,072,720	1,072,733	1,072,229	1,072,242	1,072,229	1,072,242	1,072,242	1,072,242
R-squared	0.033	0.065	0.050	0.081	0.050	0.081	0.499	0.499
Outcome mean	21.28	21.28	21.28	21.28	21.28	21.28	21.28	21.28
N cluster (zip)	16,356	16,359	16,354	16,357	16,354	16,357	16,357	16,357
Panel B: 2016 election by donation								
Active Dem×Post	-2.075***	-2.106***	-1.585***	-1.630***	-1.502***	-1.545***	-1.556***	-1.488***
	(0.570)	(0.568)	(0.571)	(0.570)	(0.571)	(0.570)	(0.570)	(0.571)
Inactive Dem×Post	-0.485***	-0.475***	-0.325**	-0.319**	-0.252*	-0.245*	-0.233	-0.166
	(0.145)	(0.145)	(0.145)	(0.145)	(0.147)	(0.147)	(0.146)	(0.148)
Active Dem	6.744***	5.813***	5.756***	5.095***	5.716***	5.055***		
	(0.637)	(0.649)	(0.638)	(0.649)	(0.639)	(0.650)		
Inactive Dem	1.675***	1.530***	1.108***	1.070***	1.073***	1.035***		
	(0.171)	(0.181)	(0.168)	(0.178)	(0.168)	(0.178)		
Active effect as %mean	-9.75	-9.9	-7.45	-7.66	-7.06	-7.26	-7.31	-6.99
Inactive effect as %mean	-2.28	-2.24	-1.53	-1.51	-1.19	-1.16	-1.1	-.78
p value	.005	.004	.026	.021	.027	.021	.019	.02
Observations	1,072,720	1,072,733	1,072,229	1,072,242	1,072,229	1,072,242	1,072,242	1,072,242
R-squared	0.033	0.065	0.050	0.081	0.050	0.081	0.499	0.499
Outcome mean	21.28	21.28	21.28	21.28	21.28	21.28	21.28	21.28
N cluster (zip)	16,356	16,359	16,354	16,357	16,354	16,357	16,357	16,357
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	N	Y	N	Y	N	N	N
Zip FE	N	Y	N	Y	N	Y	N	N
Person FE	N	N	N	N	N	N	Y	Y
State×Post FE	Y	Y	N	N	Y	Y	N	Y
Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: Panels A and B in this table replicate Table 3 panel B and Table A5 panel B, respectively, but using the 2014 voter roll and patenters' party as of 2014. All specifications mirror those in the corresponding tables. We do not have voting history for the 2014 voter roll, and so cannot replicate Table 4 panel B.

Table A7: Political Mismatch and Patent Application Likelihood - DID *within Firm*: Democrat versus Republican Inventors *by Donation Activeness*

	(1) Inventors w/ firm	(2) Num≥1	(3) Num≥2	(4) Num≥4	(5) Num≥8
Panel A: 2008 election					
Active Dem×Post	0.5196	0.4639	0.2392	0.3484	0.3372
	(0.3552)	(0.4174)	(0.4585)	(0.5225)	(0.5789)
Inactive Dem×Post	0.2238	0.1010	0.0561	-0.0399	0.0477
	(0.1660)	(0.2059)	(0.2217)	(0.2451)	(0.2686)
Active Dem	4.9462***	5.3159***	5.3850***	5.5677***	5.3247***
	(0.3906)	(0.4863)	(0.5307)	(0.5933)	(0.6530)
Inactive Dem	1.1525***	1.4186***	1.5032***	1.6457***	1.6990***
	(0.1850)	(0.2353)	(0.2561)	(0.2865)	(0.3241)
Active effect as %mean	2.35	1.93	.99	1.45	1.4
Inactive effect as %mean	1.01	.42	.23	-.17	.19
p value	.397	.38	.685	.455	.614
Observations	1,121,576	626,039	527,668	434,021	351,000
R-squared	0.197	0.124	0.125	0.124	0.125
Outcome mean	22.024	23.952	23.993	23.873	23.989
N cluster (zip)	16,824	12,903	11,888	10,739	9,401
Panel B: 2016 election					
Active Dem×Post	-0.9075***	-1.1283***	-1.3264***	-1.6154***	-1.2282**
	(0.3268)	(0.3987)	(0.4437)	(0.4958)	(0.5466)
Inactive Dem×Post	-0.0676	-0.0681	-0.1322	-0.0445	0.0778
	(0.1568)	(0.1973)	(0.2142)	(0.2356)	(0.2623)
Active Dem	4.6363***	5.1000***	5.4373***	5.7485***	5.9455***
	(0.3913)	(0.4909)	(0.5376)	(0.5943)	(0.6718)
Inactive Dem	0.9055***	0.8928***	0.8812***	1.0421***	1.2101***
	(0.1888)	(0.2388)	(0.2606)	(0.2908)	(0.3293)
Active effect as %mean	-3.8	-4.51	-5.33	-6.51	-4.98
Inactive effect as %mean	-.29	-.28	-.54	-.18	.31
p value	.01	.008	.007	.001	.015
Observations	1,212,645	678,190	572,110	469,185	379,393
R-squared	0.202	0.120	0.119	0.120	0.121
Outcome mean	23.916	25.028	24.901	24.821	24.685
N cluster (zip)	16,417	12,356	11,350	10,254	9,103
Demographics	Y	Y	Y	Y	Y
Zip code FE	Y	Y	Y	Y	Y
Class×Post FE	Y	Y	Y	Y	Y
Firm×Post FE	Y	Y	Y	Y	Y

Note: The table compares the likelihood of submitting a patent between Democrat and Republican inventors in the same firm in the years before and after the 2008 and 2016 presidential elections. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Active Dem* is one for active Democrat based on FEC donation history and zero for others; *Inactive Dem* is one for inactive Democrats based on FEC donation history and zero for others (see section 2.2 for definition of partisanship). *Post* is one for the first through third years after a presidential election. For example, for the 2016 election, *Post* refers to 2017, 2018, and 2019. The year of a presidential election is excluded from the regression. column (1) include inventors affiliated with a firm, and columns (2) through (5) further restrict the firms to have at least a certain number of inventors of each type of party and activeness. All regressions control for zip code, technology class×post, and firm×post fixed effects as well as fully interacted inventor characteristics (i.e., gender, education, age groups, race). Standard errors are clustered by zip code.

Table A8: Political Mismatch and Patent Application Likelihood - DID: *Finer* Geography-by-Time Fixed Effects

VARIABLES	(1) Active voter	(2) Active voter	(3) Donor voter	(4) Donor voter
Panel A: 2008 election				
Active Dem×Post	0.542***	0.472**	0.822***	0.672**
	(0.180)	(0.193)	(0.317)	(0.327)
Inactive Dem×Post	0.169	0.201	0.253*	0.238
	(0.169)	(0.181)	(0.138)	(0.149)
Active Dem	1.405***	1.262***	5.605***	4.917***
	(0.197)	(0.207)	(0.331)	(0.342)
Inactive Dem	1.740***	1.669***	1.136***	1.167***
	(0.183)	(0.194)	(0.150)	(0.160)
Active effect as %mean	2.79	2.43	4.17	3.4
Inactive effect as %mean	.87	1.03	1.28	1.2
p value	.067	.204	.069	.178
Observations	1,175,111	1,176,486	1,307,612	1,309,242
R-squared	0.051	0.089	0.051	0.087
Outcome mean	19.39	19.39	19.69	19.69
N cluster (zip)	17976	17988	18548	18561
Panel B: 2016 election				
Active Dem×Post	-0.300*	-0.289	-0.976***	-0.937***
	(0.172)	(0.183)	(0.301)	(0.315)
Inactive Dem×Post	-0.107	-0.116	-0.065	-0.064
	(0.155)	(0.165)	(0.136)	(0.145)
Active Dem	2.116***	1.819***	5.731***	4.834***
	(0.197)	(0.206)	(0.346)	(0.358)
Inactive Dem	1.655***	1.461***	1.359***	1.212***
	(0.184)	(0.193)	(0.156)	(0.164)
Active effect as %mean	-1.36	-1.32	-4.41	-4.24
Inactive effect as %mean	-.49	-.53	-.3	-.29
p value	.294	.362	.002	.004
Observations	1,298,128	1,299,929	1,355,588	1,357,474
R-squared	0.049	0.084	0.049	0.083
Outcome mean	22.05	22.04	22.13	22.12
N cluster (zip)	17453	17467	17649	17663
Demographics	Y	Y	Y	Y
County×Post FE	Y	N	Y	N
Zip×Post FE	N	Y	N	Y
Class×Post FE	Y	Y	Y	Y

Note: The table provides robustness checks for our main results: columns (1)-(4) for Table 4 and columns (5)-(8) Table A5. All specifications mirror columns (5)-(6) in the two tables except for the more stringent geography-by-time fixed effects in the current table.

Table A9: Political Mismatch and Patent Application Likelihood - DID: Immigrants versus Non-immigrants *by Party Registration*

	(1) P(patent)	(2) P(patent)	(3) P(patent)	(4) P(patent)	(5) P(patent)	(6) P(patent)	(7) P(patent)	(8) P(patent)
Panel A: 2008 election								
Immigrant Dem×Post	-0.269	-0.337	0.280	0.209	0.135	0.068	0.287	0.157
	(0.393)	(0.393)	(0.396)	(0.397)	(0.397)	(0.397)	(0.401)	(0.400)
Immigrant Rep×Post	-0.187	-0.236	0.177	0.131	0.002	-0.043	0.135	-0.020
	(0.503)	(0.503)	(0.508)	(0.508)	(0.505)	(0.505)	(0.514)	(0.511)
Immigrant Dem	5.981***	5.304***	4.749***	4.271***	4.822***	4.342***		
	(0.465)	(0.474)	(0.457)	(0.466)	(0.453)	(0.463)		
Immigrant Rep	3.955***	3.652***	3.368***	3.087***	3.457***	3.176***		
	(0.547)	(0.562)	(0.536)	(0.552)	(0.536)	(0.552)		
Dem effect as %mean	-1.28	-1.6	1.32	.99	.64	.32	1.36	.74
Rep effect as %mean	-.89	-1.12	.83	.62	.01	-.21	.63	-.1
Observations	746,575	747,573	746,389	747,387	746,389	747,387	747,387	747,387
R-squared	0.037	0.079	0.055	0.094	0.055	0.094	0.481	0.481
Outcome mean	21.09	21.1	21.09	21.1	21.09	21.1	21.1	21.1
N cluster (zip)	151,66	151,78	151,63	151,75	151,63	151,75	151,75	151,75
Panel B: 2016 election								
Immigrant Dem×Post	-2.065***	-2.063***	-1.629***	-1.645***	-1.527***	-1.539***	-1.383***	-1.284***
	(0.372)	(0.372)	(0.372)	(0.371)	(0.373)	(0.373)	(0.370)	(0.372)
Immigrant Rep×Post	-0.927*	-0.927*	-0.762	-0.765	-0.666	-0.674	-0.707	-0.631
	(0.480)	(0.480)	(0.474)	(0.473)	(0.475)	(0.475)	(0.472)	(0.473)
Immigrant Dem	5.073***	4.672***	4.376***	4.077***	4.325***	4.023***		
	(0.443)	(0.454)	(0.434)	(0.445)	(0.436)	(0.447)		
Immigrant Rep	2.588***	2.616***	2.326***	2.398***	2.278***	2.353***		
	(0.560)	(0.570)	(0.548)	(0.559)	(0.548)	(0.560)		
Dem effect as %mean	-8.9	-8.89	-7.02	-7.09	-6.58	-6.64	-5.96	-5.54
Rep effect as %mean	-4	-4	-3.29	-3.3	-2.87	-2.91	-3.05	-2.72
Observations	700,021	701,091	699,744	700,814	699,744	700,814	700,814	700,814
R-squared	0.034	0.077	0.052	0.094	0.052	0.094	0.501	0.501
Outcome mean	23.21	23.2	23.21	23.2	23.21	23.2	23.2	23.2
N cluster (zip)	141,79	141,89	141,79	141,89	141,79	141,89	141,89	141,89
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	N	Y	N	Y	N	N	N
Zip FE	N	Y	N	Y	N	Y	N	N
Person FE	N	N	N	N	N	N	Y	Y
State×Post FE	Y	Y	N	N	Y	Y	N	Y
Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: The table compares the likelihood of submitting a patent between Democratic and Republican immigrant versus non-immigrant inventors in the same area in the years before and after the 2008 and 2016 presidential elections. The sample consists of Democratic and Republican inventors who are matched to Infutor. The outcome is the likelihood of submitting a patent in a year, and units are in percentage points. *Immigrant* is one for inventors who are categorized as immigrant using age of first ssn and ITIN number (Bernstein et al., 2018) and zero for non-immigrants. *Dem* is one for Democrats and zero for Republicans (see section 2.2 for definition of partisanship). *Post* is one for the first through third years after a presidential election. For example, for the 2016 election, *Post* refers to 2017, 2018, and 2019. The year of a presidential election is excluded from the regression. Demographic controls correspond to fully interacted inventor characteristics (i.e., gender, education, age groups, race) and are included in all regressions. Standard errors are clustered by zip code.