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EVIDENCE FROM PATENTERS

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ABSTRACT

We document political sentiment effects on US inventors. Democratic inventors are more likely to patent (relative to Republicans) after the 2008 election of Obama but less likely after the 2016 election of Trump. These effects are 2-3 times as strong among politically active partisans and are present even within firms over time. Patenting by immigrant inventors (relative to non-immigrants) also falls following Trump's election. Finally, we show partisan concentration by technology class and firm. This concentration aggregates up to more patenting in Democrat-dominated technologies (e.g., Biotechnology) compared to Republican-dominated technologies (e.g., Weapons) following the 2008 election of Obama.

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1. Introduction

U.S. presidential elections have turned into life-changing events. Voters whose candidate lost the election report sharp decreases in their economic expectations and subjective well-being (e.g., Mian, Sufi, and Khoshkhou, 2021, Di Tella and MacCulloch, 2005). For example, Republicans went from being one standard deviation less optimistic than Democrats immediately before the 2016 election to a standard deviation more optimistic in the first quarter of 2017.[1] This paper asks whether Americans bring these feelings and expectations to work: do party-changing elections affect worker productivity?

Election-driven changes in 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, Proto, and Sgroi, 2015), workers who become less *happy* as the result of an election loss may experience a decline in their productive capacity. Regardless of the mechanism, political cycles coupled with increasing partisanship may have important downstream effects on productivity.

We focus on innovative workers who produce patents. These workers are particularly important because the productivity of U.S. based patenters is a major driver of technological innovation, thus constituting a critical determinant of long-run economic growth (Romer, 1990, Aghion and Howitt, 1992, Mokyr, 1992, Kogan, Papanikolaou, Seru, and Stoffman, 2017, Bloom, Jones, Van Reenen, and Webb, 2020, Liu and Ma, 2022), international competitiveness (Hombert and Matray, 2018), and startup activity (Farre-Mensa, Hegde, and Ljungqvist, 2020).[2] These workers also provide an advantageous setting to examine the effects of political sentiment on worker productivity for two reasons. First, their productive output is directly observable via the USPTO patent database. Second, innovative workers' income is tied to the success of their patents (Kline, Petkova, Williams, and Zidar, 2019), which allows for economic expectations to

[1] Source: Bloomberg Consumer Comfort Index, standard deviation calculated from June 1990 through October 2016.

[2] A series of papers links sharply declining innovative productivity (e.g., Kortum, 1997, Jones, 2009, Bloom, Jones, Van Reenen, and Webb, 2020) 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.

naturally feed back into their productivity decisions.

We investigate productivity effects on patenters around the party-changing presidential elections of 2008 (Barack Obama) and 2016 (Donald Trump). First, we compare party-identified *individual patenters* in the same geographic area or firm before vs. after each election. 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).

Second, we examine the productivity response of immigrant patenters around these elections. Immigrants are not only vitally important to U.S. innovation (Hunt and Gauthier-Loiselle, 2010, Bernstein, Diamond, McQuade, and Pousada, 2021a), but also were a key campaign issue in the 2016 election, making them a natural demographic subgroup to be affected by its outcome.

We begin the analysis by exploring whether party-changing elections affect the relative productivity of individuals who identify with the winning or losing side. Specifically, we 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 group averages over time. When we use a difference-in-differences event study approach, we continue to find an *increase* in productivity for 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.

To sharpen the evidence that it is the *political orientation* of inventors that has a causal effect on productivity, we examine politically active inventors. 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 by the third year after 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. Even when we include person fixed effects to focus on within-person variation over time, the results are generally robust across a variety of specifications and always robust among politically active patenters. For example, in a specification with person, technology-by-time, and state-by-time fixed effects, the average treatment effect for politically active Democratic patenters is 2.6% of the mean in the three years following the 2008 election and -3.0% in the three years following the 2016 election. For inactive Democratic patenters, the corresponding numbers are 0.7% and -0.1% and statistically insignificant.

In our most demanding specification, we consider the subset of patenters affiliated with 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 technology, which should further mitigate concerns that our main result is driven by policy changes that target specific industries or technologies.

As more direct evidence of a political sentiment channel, we examine survey microdata from Gallup around the 2008 election. While Gallup does not separately identify patenters, when we split respondents by characteristics most associated with them (i.e., those with a graduate degree or professionals), we find large swings along party lines in both optimism about the economy and mood following the 2008 election.

To further explore whether our results are consistent with a political sentiment channel, we examine the effect of party-changing elections on the *quality* of the patents produced by Democrats and Republicans. If there are political sentiment effects tied to economic optimism, we would expect patenters aligned with the losing side to focus their efforts only on the most promising ideas, which would be robust to the poor economic conditions they expect. Thus, while their likelihood of patenting would decline, the average quality of submitted patents should increase. We generally 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.

Next, we investigate the aggregate implications of the individual-level productivity effects we have documented. If, following an election, some inventors become less productive and some become more productive, it is possible that these effects offset in the aggregate. However, to the extent that certain technologies or firms are heavily skewed toward one party, offsetting effects will not occur. For example, if Technology X was populated by only Republican inventors and those inventors became less productive following Obama's election in 2008, then we would expect Technology X to lag in its rate of progress following 2008. Motivated by this observation, we examine the extent of political segregation in our setting.

We find evidence of significant political segregation among patenters both across firms and across technological areas (Figure 7). Specifically, the dissimilarity index (measuring segregation) increased by 10% or more for technologies starting around 2016, with a similar pattern among firms. As an illustration of this phenomenon, Republicans outnumber Democrats 3-to-1 in weapons patenting, but are outnumbered by Democrats 5-to-1 at Google. Moreover, we find increasing segregation among patenting teams, which are critical to knowledge production (Jaravel, Petkova, and Bell, 2018). Beginning in 2004, we show a strong downward trend in patent applications from mixed-party teams (i.e., teams with both Democrats and Republicans). The likelihood of a mixed team submitting a patent fell by 14% from 2004 to 2019.

Given the evidence of political segregation among patenters, we would expect partisan sentiment shocks to have aggregate effects on technological progress. To directly examine this we study technology-level patenting patterns around the 2008 election.[3] We find that Democrat-dominated technologies display a steadily increasing innovative advantage relative to Republican technologies following the election, with no discernible difference beforehand. Specifically, Democratic technology subclasses have one standard deviation more granted patents than Republican ones in 2010, with the difference growing to 1.5 standard deviations by 2015.

In our final analysis, we compare the productivity of immigrants vs. non-immigrants. First, we find that immigrant patenters are two to three percentage points (around 12% of the mean) more likely to patent in a given year than non-immigrant patenters, consistent with the evidence in Bernstein, Diamond, McQuade, and Pousada (2021a). This underscores the critical role immigrants play in U.S. innovation. Second, we examine immigrant patenting around the 2016 election. Immigration was a central campaign issue during the 2016 election, and then-candidate Trump offered both rhetoric and policy proposals which alienated many immigrants.

In general, we find larger election effects on productivity for immigrants than we found for partisans. Specifically, we estimate that immigrants (compared to non-immigrants) are 3.1% of the mean less likely to patent in our baseline specification and 3.2% less likely in our most stringent specification with person fixed effects. For non-white immigrants, the corresponding effect sizes are -3.7% and -2.5%. Asian immigrants make up the largest immigrant group among patenters (52.7% of immigrant patenters) and have the largest effects of -4.7% and -3.4%, respectively. Because these immigrants are also citizens, this effect is unlikely to come from a change in policy following the 2016 election, as policies cannot target citizens by country of birth.[4] Moreover, the effect on immigrant inventors is independent of the effect on Republican and Democratic ones.

[3]For this exercise we focus on granted patents as these are the innovations that matter for technological progress, and on the 2008 election because our data ends in 2020, making the data on granted patents following the 2016 election too sparse.

[4]We find no effects among any immigrant groups around the 2008 election, where immigration was not a major issue for voters (Pew, 2009).

Our immigration analysis illustrates the fact that election effects on worker productivity can extend beyond Republicans and Democrats to demographic subgroups who are a campaign focus. For example, African Americans were a key demographic in the election of Barack Obama in 2008 (Pew, 2008), and political scientists expect women to be a critical subgroup following the Supreme Court decision in Dobbs v. Jackson Women's Health Organization (TargetSmart, 2022). The evidence here suggests election outcomes can drive sentiment in these key groups, leading to predictable changes in their productivity.

This paper is at the intersection of three growing literatures: the determinants of innovation, the effects of partisanship on real outcomes, and the role of immigrants in innovation. 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, Manso 2011, Nanda and Rhodes-Kropf 2013, Bernstein 2015, Krieger, Li, and Papanikolaou 2022, Bena and Simintzi 2022). In contrast, our findings highlight a "bottom-up" view of innovation, wherein innovative workers are not interchangeable parts, but instead play an important role as individuals. Specifically, we explore whether political sentiment shocks to workers affect their innovative output and team formation. In this sense our work is similar in spirit to Bernstein, McQuade, and Townsend (2021b) and Babina, Bernstein, and Mezzanotti (2022), who explore the effects of financial shocks on worker-level innovation.

Second, 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, Lu, and Mullins, 2022, Meeuwis, Parker, Schoar, and Simester, 2022, Cookson, Engelberg, and Mullins, 2020, Cullen, Turner, and Washington, 2021, Bernstein, Billings, Gustafson, and Lewis, 2022, McCartney, Orellana-Li, and Zhang, 2021) and firms (Colonnelli, Neto, and Teso, 2022, Engelberg, Guzman, Lu, and Mullins, 2022, Fos, Kempf, and Tsoutsoura, 2021). Other papers have focused on how financial professionals' forecasts are impacted by their partisan identity (Kempf and Tsoutsoura, 2021, Dagostino, Gao, and Ma, 2020), consistent with survey evidence that partisanship affects perceptions of the economy (Bartels, 2002, Evans and Andersen, 2006, Mian, Sufi, and Khoshkhou, 2021). To our knowledge, 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 observe a major output measure, it is likely that our effects would apply across the U.S. workforce, especially among those who are active partisans.

Finally, our paper adds to the growing literature on immigrants and innovation (e.g., Kerr and Lincoln, 2010, Hunt and Gauthier-Loiselle, 2010, Moser, Voena, and Waldinger, 2014, Ganguli, 2015, Akcigit, Grigsby, and Nicholas, 2017, Moser, Parsa, and San, 2020, Terry, Chaney, Burchardi, Tarquinio, and Hassan, 2023). Much of this literature highlights the critical role immigrants play in innovation; for example, Bernstein, Diamond, McQuade, and Pousada (2021a) find that approximately 30% of US adjusted patent citations since 1976 are attributable to immigrants. Because immigrants are a critical cog in the wheel of innovation, understanding shocks that affect their productivity is important.

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. Patent applications have two additional advantages relative to grants: (i) applications appear sooner than grants, allowing us to better match the event to its response and (ii) they measure innovative *effort* rather than quality. 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 along with the zip code of their residence; the firm to which the patent was originally assigned (if applicable); other patents cited as prior work; and the technology area that the patent falls under.

We define a patent's technology class based on its primary Cooperative Patent Classification (CPC) code. The U.S. switched to classifying patents using the CPC scheme at the start of

2015. For patents granted before 2015, we obtain a CPC classification from the USPTO's back-filled classifications (using the CPC Master Classification File for U.S. Patent Grants).

A challenge that the data presents is that it lacks consistent identifiers for 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 can be 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 following Balsmeier et al. (2015). Our procedure is detailed in Appendix A.

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, Braghieri, Eichmeyer, and Gentzkow, 2020, Brown and Enos, 2021, Billings, Chyn, and Haggag, 2021, Bernstein, Billings, Gustafson, and Lewis, 2022, Spenkuch, Teso, and Xu, 2021). 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.[5] 42% of inventors in our sample reside in these states.[6]

Among registered voters, we identify those who are more politically active in two ways. First, we use voting history data.[7] 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 primary elections, out of all the elections that they were eligible for in the recent past (2000-2008 for the 2008 election; 2008-2016 for the 2016 election).[8]

[5] L2's data is subject to repeated testing by political campaigns in the field. Academic work has also verified the accuracy of voter file partisanship measures: Bernstein, Billings, Gustafson, and Lewis (2022) validates the accuracy of L2 partisanship by comparing 2012 partisanship in state files to 2018 L2 data; Brown and Enos (2021) runs a survey to verify L2 partisanship; Pew (2018) compares voter file data to Pew national survey microdata.

[6] 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 where the state records voter participation in party primaries (e.g., Illinois, Indiana, Texas), 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 individual's party based on characteristics it collects.

[7] 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.

[8] Median voting propensities are 54% for Democrats and 50% for Republicans for the 2008 election, and

The second way that we identify politically active individuals is by using data on political donations. The Federal Election Commission (FEC) records individuals' cumulative 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-time fixed effects). As a result, we use voting history as our main political activeness measure.

Finally, L2 provides voters' addresses and demographic variables, such as birth year, gender, race/ethnicity, and education level. We include these demographic variables, fully interacted, as controls in our main specifications.[9]

2.3 Immigration Data

Our data on immigrants comes from Infutor, a commercial consumer identification provider. Their data includes social security numbers (SSNs) and year of birth for 187 million individuals who received their U.S. SSNs before the early 2000s. Following the procedure in Bernstein, Diamond, McQuade, and Pousada (2021a), we use the first 5 digits of an individual's SSN to identify the year in which a number was assigned, and then use each person's year of birth to determine the age at which they received their SSN. An individual is classified as an immigrant if they were 21 or older when they received their SSN because native born citizens receive them at earlier ages.[10] Using this approach, we identify approximately 23.5 million immigrants (12.6% of individuals in the Infutor data with SSN and birthyear information).

54% for both parties for the 2016 election. We exclude consolidated general elections, which combine local and general elections and occur in odd years.

[9]Birth year and gender are from voter registration forms. Education is imputed by L2. In some states voters report their race as part of their voter registration, but in others L2 infers race data. Bernstein, Billings, Gustafson, and Lewis (2022) validates the L2 race data using HMDA; Pew (2018) finds high accuracy on race for commercial voter registration data by matching to their national panel survey microdata.

[10]Bernstein, Diamond, McQuade, and Pousada (2021a) provides extensive validation tests for this method of determining immigrant status. Infutor only has SSNs assigned before 2012 but this is recent enough that it excludes few of the patenters of interest.

2.4 Sample Construction

To construct our sample of registered voters who are also patenters, 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 patenters, 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).[11] For example, we only include patenters who submitted at least one subsequently granted patent between 2006 and 2012 for the 2016 election. For our main analysis we focus on Democrats and Republicans; the resulting sample is a patenter-year panel with 224,000 to 235,000 individual inventors per year.

For our sample of immigrant and native patenters, we match the names in the Infutor database to the names of patenters in the USPTO database following the same iterative algorithm as above. The procedure returns approximately 1.2 million matches, 15.2% of which we identify as immigrants, with the rest native-born. We further require these matched patenters to appear in L2 and satisfy the age and patenting history requirements laid out above. The resulting sample is a patenter-year panel with 221,000 to 227,000 individual inventors per year.[12]

2.5 Descriptive Statistics

Table 1 reports statistics from our sample of Democrats and Republicans (Panel A) and immigrants and natives (Panel B).

Recall from section 2.4 that our voter sample is composed of registered voters who are also patenters around the 2008 and 2016 elections. Table 1 combines the samples from both elections, and a disaggregated version is reported in Appendix Tables A1 and A2.

[11] We assign patenters to their modal firm in this period, as the firms they work for in later periods may be endogenous to the effects we examine.

[12] Note that this sample includes registered Independents, in addition to Democrats and Republicans.

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

The annual likelihood of an inventor patenting is 18.1% (first column). The number is slightly higher for Democrats (19.6%) than Republicans (16.6%). While patenting likelihood is relatively stable across most individual characteristics, this is not true for firm affiliation: inventors affiliated with a firm are much more likely in any given year to file for a patent (20%) than those who are not (6%).

Panel B describes summary statistics comparing immigrant to native born patenters. Across all 15 characteristics we report in this panel, immigrants have a materially higher probability of submitting a patent in our sample period than natives. Immigrants are also more likely to be female (14% for immigrants vs. 9% for natives) and Hispanic (7% for immigrants vs. 3% for natives), but the largest differences appear for the Asian share: 53% of immigrant patenters are Asian compared to 5% for natives. Finally, immigrants are more likely to be Democrats (37% vs. 34% for natives) and less likely to be Republicans (21% vs. 42% for natives), making it important to distinguish a partisan election effect from an immigrant one; in the Appendix we show that these results are robust to controlling for each other.

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:

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

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 inventor industry-by-year fixed effects $\alpha_{industry(i),t}$ to control for average patenting activity in a zip code (Ganguli, Lin, and Reynolds 2020) and time-varying industry-specific average patenting. We define a patenter's industry as the technology class in which they most frequently patented during the years preceding our sample window.[13] We also control for individual characteristics $\mathbf{X_{it}}$, which are all pairwise 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 DID event study methodology is that patenting trends for Democratic and Republican inventors (within the same zip code and the same industry-year) would have been parallel in the absence of a presidential election. In this case, the β_τ vector in equation 1 identifies the causal impact of an election outcome on the productivity of Democratic vs. Republican inventors.

Starting with the raw data, Figure 1 plots the probability of submitting a patent, separately for Democratic and Republican inventors, after removing yearly technology class averages. The top panels plot these 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 parallel pre-trends for Republican and Democratic inventors that are largely overlapping. After the election we see divergence in the expected directions. For 2008, Democratic inventors appear to increase their likelihood of submitting a patent application 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 Republican patent applications appearing at higher rates.

[13] 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.

In Figure 2, we plot the estimated β_τ coefficients from equation 1, 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 either election, 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, i.e., there is 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. In contrast, following the 2016 election, Democrats' patenting probability decreased by 3.8% of the mean relative to Republicans by year three.

To sharpen the evidence that it is the *political orientation* of inventors that has a causal effect on productivity, we examine politically active partisans (see section 2.2 for definitions). Specifically, we use the voting and donation history of each inventor to distinguish an active partisan from a less-committed one. Shifts in political power should have a stronger impact on the productivity of politically active inventors. To test the hypothesis, we estimate the following model:

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

where $Active\ Dem_i$ ($Inactive\ Dem_i$) equals one if individual i is a politically (in)active Democrat, and zero otherwise. Republicans are the omitted group. All specifications and variable definitions otherwise follow those in equation (1).

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. 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.

We also use inventors' donation histories to define politically active inventors as those who made political donations recorded by the FEC, a subset made up of 9% of the inventors in our sample. The contrast between politically active Democrats and their inactive counterparts is similar using this measure. Figure 3 panel (c) shows that, compared to Republican inventors, donor 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 donor Democrats decrease their annual patenting likelihood by 5.3% of the mean compared to 3.6% for inactive Democrats following the 2016 election.

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:

$$\mathrm{Y}_{it} = \beta Dem_i \times Post_t + \gamma Dem_i + \delta' \mathbf{X_{it}} + \alpha_{zip(i)} + \alpha_{industry(i),t} + \epsilon_{it} \quad (3)$$

where Y_{it} is individual i's patent activity in year t. Similar to equation 1, we focus 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 $\times$ post fixed effects $\alpha_{industry(i),t}$. In more demanding specifications, we add individual fixed effects α_i, geographic area $\times$ post fixed effects $\alpha_{geo(i),t}$, or firm $\times$ post 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 1.

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

Table 2 reports the estimates from equation 3. 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 positive and generally statistically significant for the 2008 election and negative for the 2016 election. Column (6), which includes zip code, state $\times$ post, and industry $\times$post fixed effects, reports point estimates of 0.28 and -0.25 for the 2008 and 2016 elections, respectively. In other words, Democratic 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. 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 with weaker statistical significance for 2016. As we discuss next, we find strong within-individual effects once we focus on politically active partisans.

As before, we also examine the changes among *politically active* vs. less committed partisans. Specifically, we estimate the following model:

$$\begin{aligned} \mathrm{Y}_{it} = {} & \beta_1 \textit{Active Dem}_i \times \textit{Post}_t + \beta_2 \textit{Inactive Dem}_i \times \textit{Post}_t + \gamma_1 \textit{Active Dem}_i \\ & + \gamma_2 \textit{Inactive Dem}_i + \delta' \mathbf{X_{it}} + \alpha_{zip(i)} + \alpha_{industry(i),t} + \epsilon_{it} \end{aligned} \tag{4}$$

where $\textit{Active Dem}_i$ ($\textit{Inactive Dem}_i$) equals one if individual i is a politically (in)active Democrat, and zero otherwise. Republicans are the omitted group. All variable definitions follow those in equation 3.

Table 3 reports the estimates using voting history to define the intensity of partisanship. Across all specifications, active voter Democrats experience a significant increase in patenting likelihood relative to Republicans following the 2008 election, while inactive Democrats do not. In column (6), which includes zip code, state $\times$ post, and industry $\times$ post 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 four times larger than the effect size among inactive Democrats. 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. In columns (7) and (8), we add 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 even sharper when we define activeness using donation history in Appendix Table A6. We find that donor Democrats are 0.77 percentage points more likely 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 4 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 may be 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 3 and 4 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 A7 presents the results. Panel A shows coefficients that are very similar across all eight columns to those for the 2016 election in Table 2. Panel B shows similar, but slightly larger effects than those in Table A6 for politically active inventors using the donation-based measure.[14] These results lend credence to the use of the 2020 voter file in our setting.

[14]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

Summarizing, politically engaged inventors drive the patenting effects we document. Moreover, these effects for politically active patenters appear to persist over time. The DID 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.

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* across political regime changes, as government favor could manifest as preferential funding or contract awards to specific firms. If policy is the dominant driver, effects should disappear *within* industry, geography, or firm.

The interaction of industry (125 technology classes) and time is already included in our main tables, so Table 4 adds *firm* $\times$ *post* fixed effects to our main specification (i.e., Table 3 column 4). This means we are comparing Republican to Democratic inventors within the same firms across a political regime change. Table 4 column (1) shows that coefficients for the 2008 election are almost identical, while those for the 2016 election 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.

by voting activeness.

In Appendix Table A8, 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. Nevertheless, results are broadly consistent with the corresponding table without firm fixed effects (Appendix Table A6) for the 2008 election and are very similar for 2016.

In Appendix Table A9, 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 3 and Appendix Table A6, 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*.[15] 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 Democratic 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 Andersen 2006, Mian, Sufi, and Khoshkhou 2021, Dahl, Lu, and Mullins 2022, Engelberg, Guzman, Lu, and Mullins 2022). Because patenters have been shown to capture significant rents from their inventions (Kline, Petkova, Williams, and Zidar 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

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

to experience a decline in their productivity (Banerjee and Mullainathan 2008, Oswald, Proto, and Sgroi 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 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 2016 on topics related to the economy, politics and their well-being. Importantly, respondents identify their political party (38% are Democrats and 37% are Republicans). Although the survey does not identify patenters, we know whether respondents have a graduate degree and whether they are professional workers, which we will use as proxy variables for patenters.

In Figure 5, we plot the difference in the share of Democratic and Republican respondents ("Dem minus Rep") choosing "Getting better" in response 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 characteristics rises sharply after the 2008 presidential election and falls markedly after the 2016 election, relative to well-educated and professional Republicans.

While Figure 5 indicates that beliefs about the economy follow party lines, it is possible that general mood also does. We find some evidence for this in Figure 6 which plots the average "Dem minus Rep" difference in response to questions about mood. These are "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). As was true for economic optimism, Democrats' mood reacts more positively to the 2008 election outcome (with lower worry and greater enjoyment) relative to Republicans. However, after 2012 the series become more volatile (as the questions were asked of a lower share of respondents), making a general pattern harder to ascertain.

These plots provide suggestive evidence that patenter-like partisans 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 examine the effect of party-changing elections on the *quality* of the patents produced by Democrats and Republicans. If there are political sentiment effects tied to economic optimism, patenters aligned with the losing side may focus their efforts only on the most promising ideas – which would be robust to the poor economic conditions they expect. Thus, while their likelihood of patenting would decline, the average quality of submitted patents should increase. In contrast, if there are political sentiment effects tied to general mood, we would expect to see a decrease in both the likelihood and quality of patenting on the losing side. This is because patenters aligned with the losing party might be less able to both execute on ideas 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 forward citations by 2020.[16] We measure citations using three metrics: the number of forward cites, scaled citations (the number of forward cites divided by the average number of cites within the patent's technology class and grant year), and normalized citations (the number of forward cites subtracting the average and dividing by the 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 and re-estimate equation 3. Note that this regression sample is conditional on patent activity, i.e., for each year only inventors who submitted patents in that year are included.

Table 5 column (1) indicates that patents submitted by Democrats following the 2008 election accumulate *fewer* cites (6% of the mean) than patents submitted by Republicans living in the same area and working in the same technology class at the same time. In contrast, patents submitted by Democrats following the 2016 election accumulate *more* cites (14% of the mean) than those by their Republican counterparts. The same holds true, albeit with substantially more statistical noise, when we examine scaled and normalized citations, which further account for the variation in citations across technologies and grant years.

Overall, this evidence from citations is consistent with political sentiment effects mainly driven by economic optimism (rather than mood effects). When Democratic patenters become

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

economically optimistic after Obama's election they become more likely to patent, but these appear to be of lower average quality, reflecting a lower selectivity of which projects to pursue. When Democratic patenters become economically pessimistic after Trump's election, they produce fewer, but better quality patents, reflecting higher project selectivity.

3.4 Political Segregation and aggregate effects

Thus far, we have shown that election outcomes affect the productivity of partisan patenters. Here we consider whether these individual-level effects aggregate up to the technology or firm levels. If some inventors become less productive while others become more productive following an election, it is possible that the individual-level effects offset in the aggregate. However, if certain technologies or firms are disproportionately Democrat or Republican, the effects will not cancel out. For this reason, we investigate whether there is political segregation across firms and technologies.

Table 6 documents which technologies and firms disproportionately employ patenters registered as either Republicans or Democrats. Panel A classifies patenters according to the broadest possible technology group (nine "sections"), while panel B deploys a finer classification (125 "classes"). These panels document substantial political segregation across technologies. For example, in Biochemistry there are 41.6 percentage points more Democratic patenters than Republican ones. Organic Chemistry, Nanotechnology and Combinatorial Technology also heavily favor Democratic patenters. However, in the Weapons technology class, Republican patenters outnumber Democratic ones by 45.3 percentage points. Ammunition, Construction and Hydraulic Engineering also heavily favor Republican patenters. In addition, there are technology classes that show no meaningful partisan differences, such as Dyes, Sports and Apparel.

Panel C presents a similar exercise for the top ten publicly traded firms with over 1,000 party-identified patenters. Google, Yahoo and Microsoft all have at least 65 percentage points more Democratic than Republican patenters, while Halliburton, Kimberly Clark and Caterpillar are Republican-leaning by over 35 percentage points. These rankings are consistent with Silicon Valley firms being Democratic (FiveThirtyEight, 2016) and defense/weapons firms skewing Republican, such as Halliburton where former Republican Vice President Dick Cheney served as Chairman and CEO. In summary, we find substantial political clustering in the cross-section of firms and technologies.

Consistent with evidence from U.S. C-suites (Fos, Kempf, and Tsoutsoura, 2021) we find increasing segregation in the time series. For each year we construct two standard measures of segregation: the isolation and dissimilarity indices, at the technology subclass or the firm level.[17] The isolation index captures the extent to which Republican patenters disproportionately cluster in a technology or firm with other Republican patenters. An isolation index of one represents the maximum level of segregation, meaning that partisans patenters only patent in technology subclasses or work in firms where 100% of patenters match their partisanship. The dissimilarity index instead captures the share of one group of partisans that would have to be moved to produce an unsegregated distribution.

Figure 7 panels (a) and (b) plot the isolation and dissimilarity indices. These indices provide similar evidence of increasing political segregation. For example, while relatively flat before 2016, the subclass-level dissimilarity index increased by over 10% by the end of the sample, with a similar pattern for the firm-level index.

Panel (c) examines segregation at the *team* level, because teamwork plays a central role in the creation of patents (Jaravel et al., 2018). Specifically, it plots the probability of mixed-party teams applying for a patent in each year relative to the probability in the base year 2004, controlling for zip code and technology class fixed effects as well as team characteristics.[18] As an additional control we include the predicted annual likelihood of forming a mixed-party team with N members in each technological subclass ("subclass control") or across the US ("US control)," by calculating the share of mixed party teams that result from randomly picking N patenters within the subclass or across the US. The likelihood of a mixed team submitting a patent fell steadily from 36% in 2004 to 31% in 2019. After controls, the decrease becomes

[17] We calculate isolation index and dissimilarity index in year t following White (1986) and Cutler, Glaeser, and Vigdor (1999), respectively:

$$Isolation_t = \frac{\sum_{j \in J} \frac{Rep_{jt}}{Rep_t} \times \frac{Rep_{jt}}{total_{jt}} - \frac{Rep_t}{total_t}}{1 - \frac{Rep_t}{total_t}} \tag{5}$$

$$Dissimilarity_t = \frac{1}{2} \sum_{j \in J} \left| \frac{Rep_{jt}}{Rep_t} - \frac{Dem_{jt}}{Dem_j} \right| \tag{6}$$

where Rep_{jt} (Dem_{jt}) is the number of Republican (Democractic) patenters in technology subclass or firm j in year t; $total_{jt}$ the total number of patenters in j in year t; Rep_t (Dem_t) the number of all Republican (Democratic) patenters in year t; and $total_t$ the number of all Republican and Democratic patenters in year t.

[18] The team characteristics are team size, sex, education, race and age group; all as a share of the team.

3 percentage points, or 8% of the 2004 level. Panel (d) shows the same pattern as in panel (c) using patent grants. These segregation patterns may be due to sorting of partisans into increasingly segregated firms (as suggested by panels a and b), or by sorting into homogeneous teams *within the same firm*. Controlling for the predicted probability of a mixed team within a firm (the triangle-dashed line in panel d) indicates that there has only been a moderate increase in sorting within the same firm. Thus, most of the decline in mixed teams is driven by across-firm sorting.[19]

Given political segregation at the team, firm and technology levels, shocks to political sentiment (e.g., from an election outcome) should have effects on the innovative activity of entire sectors. As an example, if Republicans, who are disproportionately clustered in the Weapons subclass, become pessimistic after the 2008 election, this effect should aggregate to less innovative activity in Weapons relative to Biochemistry, where Democrats outnumber Republicans by more than 2:1. While the political segregation we have shown implies post-election effects at the technology level, it is nonetheless of interest to explore them empirically. However, we caution that aggregate analysis does not allow us to address the endogeneity concern that policy may directly affect investment in technologies, which we address in our individual analysis (with firm-time and technology-time fixed effects and individual measures of partisan intensity).

Figure 8 examines whether Democratic technologies register more granted patents relative to Republican technologies following the 2008 election. We focus on granted patents as these are the innovations that matter for technological progress, and on the 2008 election because our data ends in 2020, making the data on granted patents following the 2016 election too sparse. Panels (a) and (b) present evidence for technology subclasses, while (c) and (d) focus on classes. Panels (a) and (c) display the annual difference in the number of patent grants between Democratic and Republican technologies, while panels (b) and (d) present the difference in the standardized number (subtracting the mean and dividing by the standard deviation). All four panels tell the same story: innovative activity in Democratic technologies steadily increased relative to Republican ones following the 2008 election, with no discernable pre-trends. Subclasses are more politically segregated, generating larger effect sizes and tighter confidence intervals compared to the class-level evidence, which is not statistically significant. For example, in panel (b) we

[19] We are able to control for within-firm probability of mixed teams for patent grants, but not applications, because grants have much better assignee (firm) information.

see Democratic subclasses experience a standard deviation increase in patenting relative to Republican ones by 2010, while it takes until 2015 to reach this point estimate at the class-level in panel (d).

Appendix Table A10 presents DID estimates corresponding to the subclass-level analysis in panels (a) and (b) using various definitions of Republican and Democratic technologies. Columns (1)-(2) compare technologies above vs. below median (as in the panels), columns (3)-(4) compare top vs. bottom tercile, and columns (5)-(6) compare quartiles. Results are very similar across comparisons. In the three years following the 2008 election, Democratic subclasses on average submitted 42 (or a standard deviation) more patent applications that are eventually granted relative to Republican subclasses in each year. Aggregating across all subclasses, the effect amounts to a difference of nearly 10,600 (=42×504/2) patent grants per year or 4.5% of annual total patent grants in the U.S. during our sample period.

3.5 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 also differentially exposed to sentiment effects – immigrants – as a result of candidate Trump's proposed policies and 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 turn to study the difference in patenting activity between immigrant and native-born voters around the 2016 election.[20] Critically, all voters – including the immigrant patenters we examine – are U.S. citizens. Hence, any observed effects we find among this group are unlikely to come from a pure policy channel because it is illegal to target citizens based on country of origin.

Evidence regarding immigrant inventors' productivity is important for two reasons. First, Bernstein, Diamond, McQuade, and Pousada (2021a) and Terry, Chaney, Burchardi, Tarquinio, and Hassan (2023) show that immigrant inventors play a critical and outsized role in U.S. innovation. Given the important contributions of this group, understanding any potential

[20]We also analyze the 2008 election as a placebo exercise, given that immigration was not a major election issue in 2008.

impact of political rhetoric regarding immigration on their productivity is of direct interest to policymakers. Second, showing that immigrants respond to political regime change in a way predicted by the sentiment hypothesis would provide further support to the interpretation of our evidence on Democratic vs. Republican patenters. Specifically, sentiment changes around elections manifest as important changes in inventor productivity.

With this in mind, we estimate the following models, similar to equations 1 and 3:

$$\begin{aligned} \mathrm{Y}_{it} = & \sum_{\tau=-3,\tau\neq-1}^{3} \beta_\tau 1\{EventYear_t = \tau\} \times Immigrant_i + \gamma Immigrant_i + \delta' \mathbf{X_{it}} \\ & + \alpha_{zip(i),race(i)} + \alpha_{industry(i),race(i),t} + \epsilon_{it} \end{aligned} \tag{7}$$

$$\mathrm{Y}_{it} = \beta Immigrant_i \times Post_t + \gamma Immigrant_i + \delta' \mathbf{X_{it}} + \alpha_{zip(i),race(i)} + \alpha_{industry(i),race(i),t} + \epsilon_{it} \tag{8}$$

where we replace Dem_i with $Immigrant_i$, which equals one if a voter is identified as an immigrant, and zero if native born. We identify immigrants in our data following Bernstein et al. (2021a).[21] The sample is all registered voters (not only Democrats and Republicans) who submitted at least one granted patent before the pre-period in our analyses *and* are matched to a record with a valid SSN in Infutor. Native-born inventors are the comparison group. Given race-specific trends in patenting in the U.S., we ensure comparability between immigrants and native-born individuals by interacting fixed effects with indicators for racial groupings (whites, non-whites, Asians) or estimating within each group. All other specifications and variable definitions follow those in equations 1 and 3.

A key identifying assumption for our analysis is that patenting trends between immigrant and native born individuals (of the same race and in the same zip code and industry) would have been parallel in the absence of the 2016 election. In this case, the β_τ vector and β in equations 7 and 8 identify the causal impact of the election on the relative productivity of immigrant inventors.

Figure 9 plots the probability of submitting a patent, separately for immigrant and native-

[21] Using data from Infutor, a commercial consumer identification dataset, we identify immigrants using the first five 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. 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.

born inventors, after removing yearly race-specific technology class averages. Panel (a) presents these probabilities at a quarterly frequency while panel (b) does so yearly. This figure shows parallel pre-trends for immigrant and native-born inventors; the trends only start to diverge after the election. Specifically, immigrant inventors decrease their rate of patenting relative to native-born individuals (and to the pre-period) starting four quarters after the election of Trump. Figure 10 further shows that pre-trends are parallel for each racial group. Overall, our evidence suggests that the parallel trends assumption hold in the current setting.

In Figure 11, we plot the β_τ coefficients from equation 7, capturing how the 2016 elections changed the likelihood of patenting for immigrant relative to native-born inventors. We observe no pre-trends leading up to the election but large and statistically significant effects in years two and three after the election across all races. Specifically, following Trump's election, immigrants' likelihood of patenting decreased by 3.2 - 4.2% of the mean relative to native born inventors by year three. Regression coefficients are reported in Appendix Table A11.

In Table 7, we reproduce Table 2 panel (b) while replacing the indicator for Democrats ("Dem") with an indicator for immigrants ("Immigrant"). Coefficients on *Immigrant* are positive in all specifications, indicating that immigrant inventors are on average 10 - 12% of the mean more productive than non-immigrants.

Turning to effects of the 2016 election, we find a strong decrease in patenting likelihood among immigrant relative to native-born inventors after the election, consistent with the sentiment hypothesis. Moreover, the relative decrease among immigrants is larger than the relative decrease among Democrats (see Table 2). Specifically, the coefficient of -0.853 on *Immigrant*$\times$*Post* in column (1) represents a relative decrease in patenting probability of immigrants equal to 3.7% of the mean. After deploying the same fixed effects as in Table 2, the effect size stays between 2.7% and 3.8% of the mean in columns (2) through (8).[22]

Table 8 further examines heterogeneity in the immigrant effects across races. While immigrants of all races experience a decrease in patenting likelihood compared to native born individuals, non-whites – especially Asians – respond more strongly than whites. Columns (1)-(3) show that the relative drop in immigrant patenting in the three years post election is 2.7% of the mean among whites while 3.7% among non-whites and 4.7% among Asians. Columns

[22]In Appendix Table A12 we study the immigrant effects of the 2008 election and find no differential changes in patenting likelihood between immigrants and non-immigrants after the election.

(4)-(6) include individual fixed effects to absorb person-level time-invariant heterogeneity. Even under this specification, the estimated magnitudes are essentially unchanged. The immigrant effects for non-whites and Asians persist even when we compare immigrant and native-born inventors *in the same firm* around the election (columns 8-9).

In our sample, 37% of immigrant patenters are Democrats and 22% are Republicans while the rest are Independents (see Table 1 panel B). To investigate whether the immigrant effects are driven by Democrats' and Republicans' differential response to Trump's electoral victory, we add $Dem \times Post$ and $Rep \times Post$ in Appendix Tables A13 and A14. Coefficients on $Immigrant \times Post$ change only slightly, indicating that the immigrant effect is distinct from the partisan effect.[23]

We also explore whether the patents created by immigrants vs. non-immigrants around the 2016 election have more citations, analogous to the investigation in Table 5. Recall in that table we found suggestive evidence of relatively more (less) citations for the patents of the losing (winning) group following an election outcome, consistent with the political sentiment hypothesis. Here we find similar – albeit weak – evidence in Appendix Table A16 when examining the number of patent citations for immigrants vs. non-immigrants.

Finally, Table 9 demonstrates substantial clustering of immigrants within firms and technologies, implying that shocks to the productivity of immigrant inventors could have implications for technological progress in aggregate. For example, at Qualcomm the share of immigrant patenters in our sample stands at around 40%, compared to 7% at Lockheed Martin. Similarly, the share in Nanotechnology is 25% compared to 7% in Construction.

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 those on the losing side become relatively less productive.

While we find this effect among patenters – where we can measure productivity via the number of patents they produce – many unanswered questions remain. For example, if the

[23]The partisan effect is also largely unchanged when we control for $Immigrant \times Post$ (see Table A15).

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 growing concern that workplaces may become politically homogeneous. We find a pattern of increasing political homogeneity among patenters and that this aggregates to effects on the rate of progress across technologies. If current polarization trends continue, we should see even larger aggregate productivity effects following election outcomes or other shocks to political sentiment.

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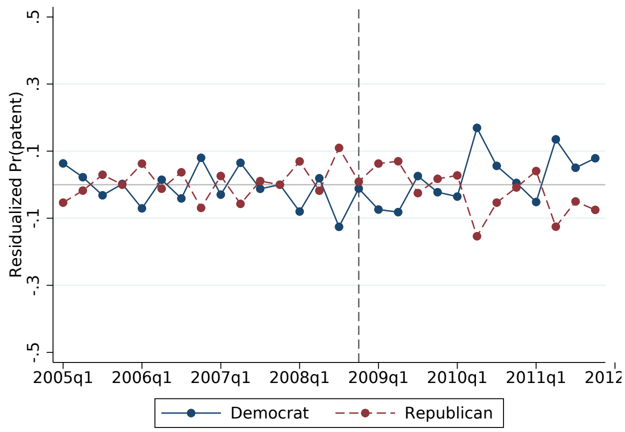
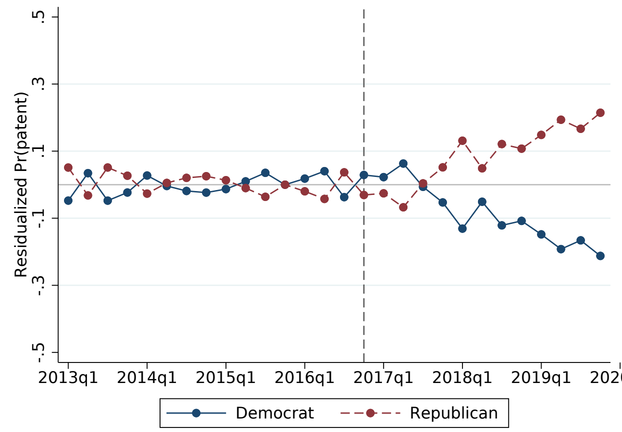
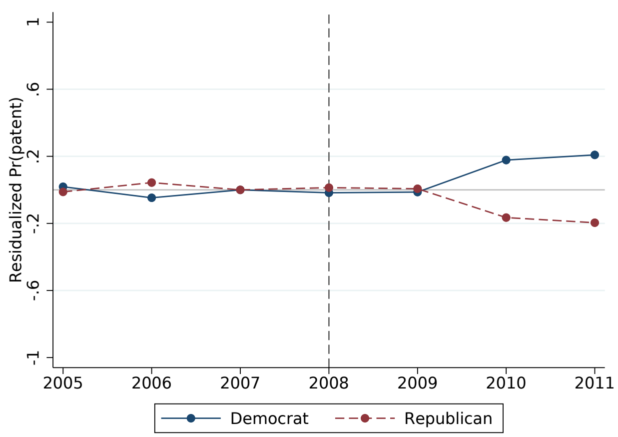


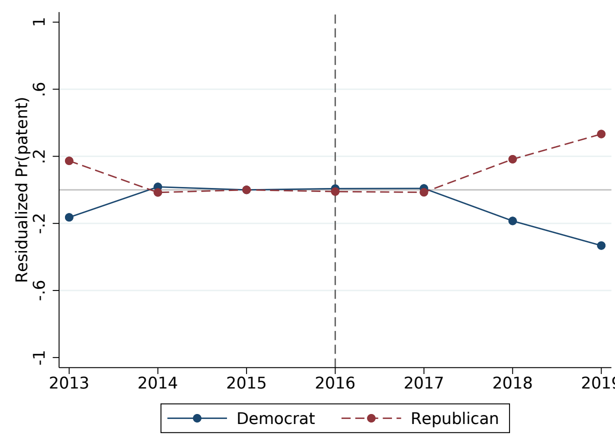
(a) 2008 election, quarterly



(b) 2016 election, quarterly



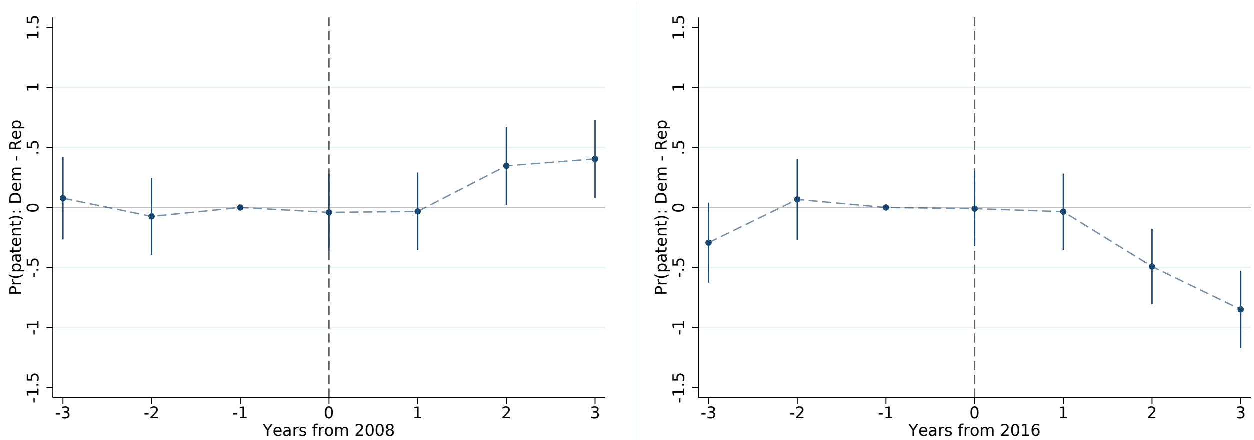
(c) 2008 election, annual



(d) 2016 election, annual

Figure 1: Residualized Probability of Submitting a Patent Application
Democrat vs. Republican Inventors

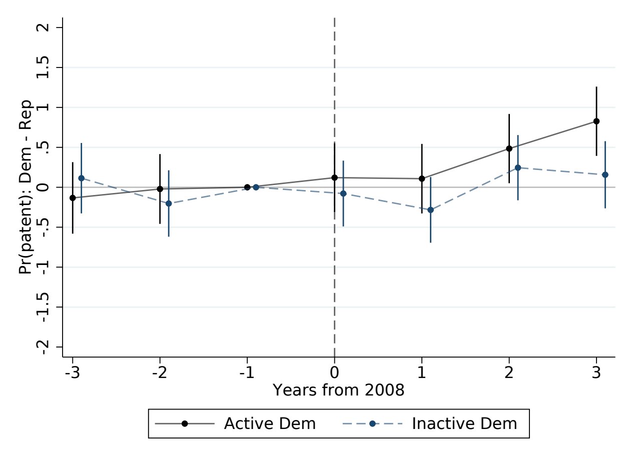
Note: This figure plots the (residualized) probability of submitting a patent application for Democrat and Republican inventors, at annual and quarterly frequencies. Residualized probability is the residual obtained from regressing the raw probability on technology class-by-year fixed effects. Units are in percentage points. Levels are normalized to 2007q4 and 2015q4 in panels (a) and (b), and to 2007 and 2015 in panels (c) and (d), respectively.



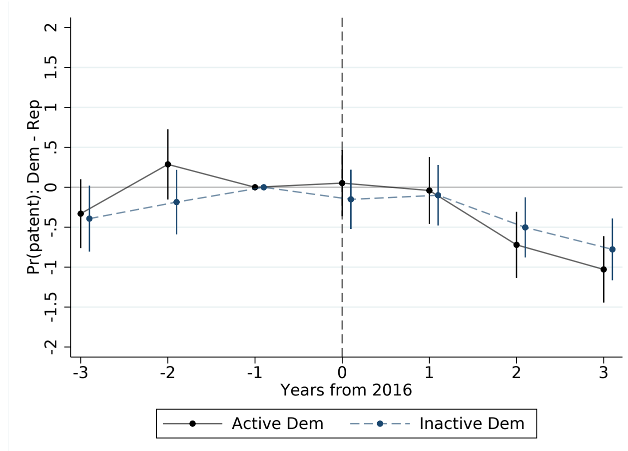
(a) 2008 election **(b)** 2016 election

Figure 2: Political Mismatch and the Probability of Submitting a Patent Application
Democrat vs. Republican Inventors

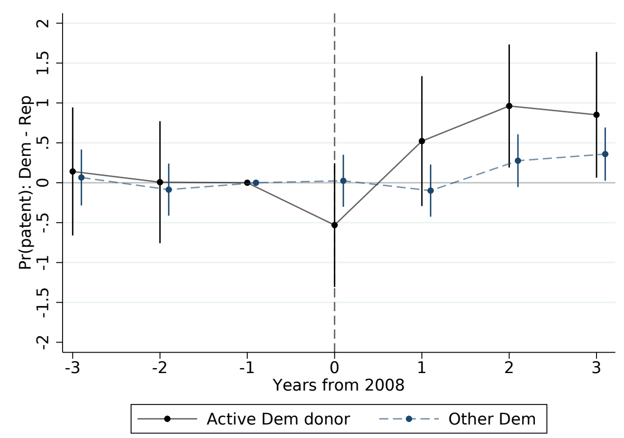
Note: This figure plots the estimated annual probability of submitting a patent application for Democrat inventors relative to Republican inventors around the 2008 and 2016 elections. Units are in percentage points and the omitted group is Republican inventors. Event time 0 refers to the year of a presidential election. Event time -1 is the omitted period. All regressions control for zip code fixed effects, technology class $\times$ event-year fixed effects and fully interacted voter characteristics (gender, education, age groups, race). Standard errors clustered by zip code; 90% confidence intervals. Regression results are reported in Table A3.



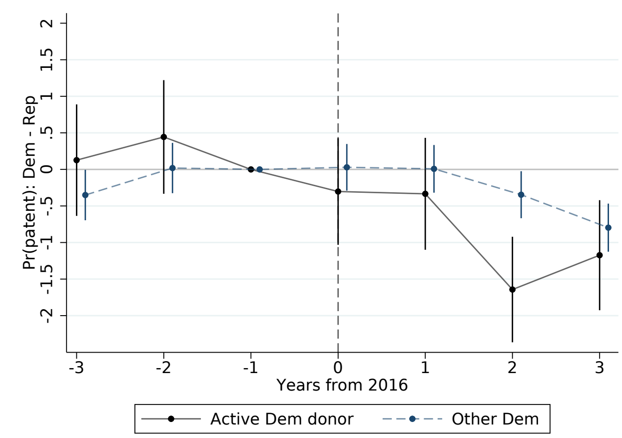
(a) 2008 election, by voting activeness



(b) 2016 election, by voting activeness



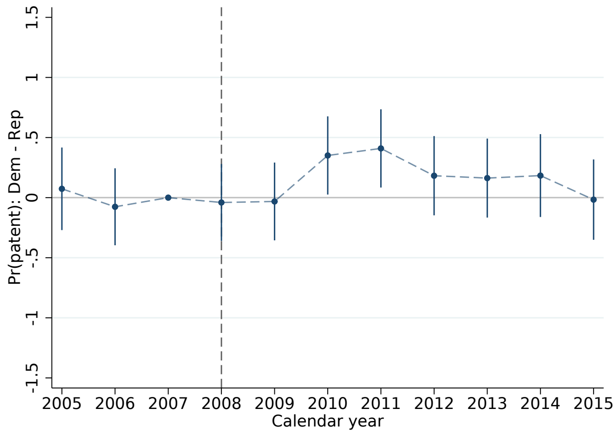
(c) 2008 election, by donation activeness



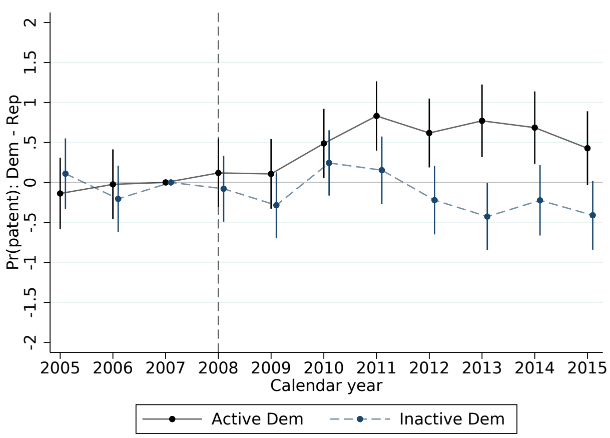
(d) 2016 election, by donation activeness

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

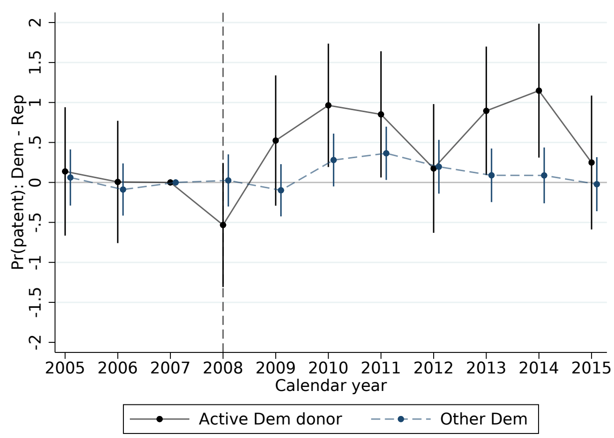
Note: This figure plots the estimated annual probability of submitting a patent application for active and inactive Democrat inventors, both relative to Republican inventors. Units are in percentage points and the omitted group is Republican. In panels (a) and (b), *Active Dem* is one for active Democrats (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 and Inactive Democrats are defined using FEC donation history instead. 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 clustered by zip code; 90% confidence intervals. Regression results for panels (a) and (b) are reported in Table A4 and those for panels (c) and (d) are reported in Table A5.



(a) Democrats vs. Republicans



(b) Active and inactive voters
Democrats vs. Republicans

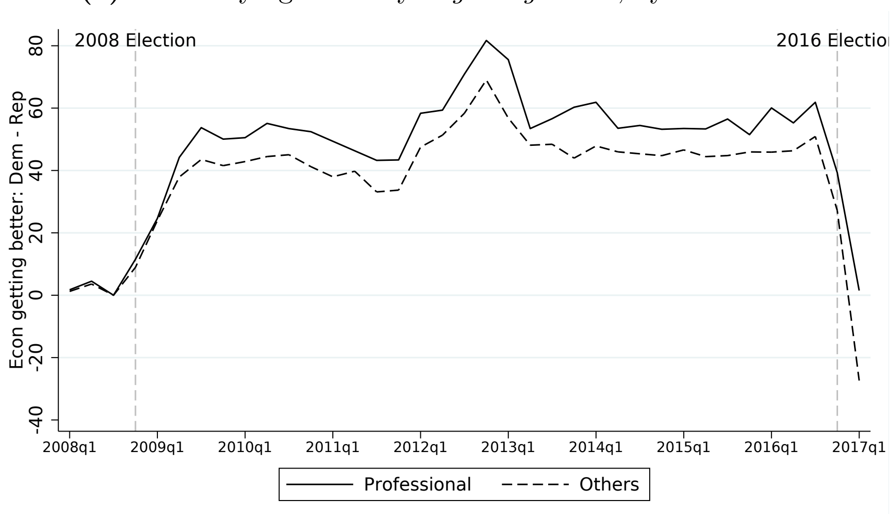


(c) Active and inactive donors
Democrats vs. Republicans

Figure 4: Political Mismatch and the Probability of Submitting a Patent Application
Democrat vs. 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. Our data does not allow us to do this for the 2016 election. See Figures 2 and 3 for details.

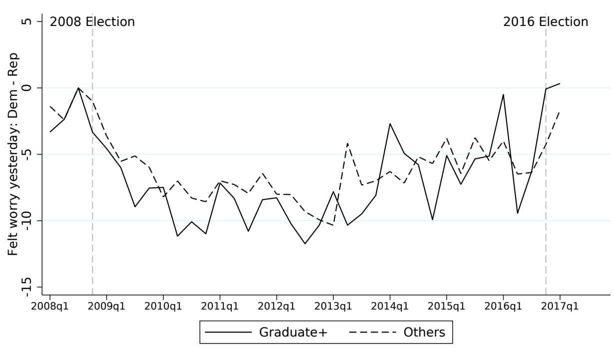
(a) Share saying economy is *getting better*, by education



(b) Share saying economy is *getting better*, by occupation

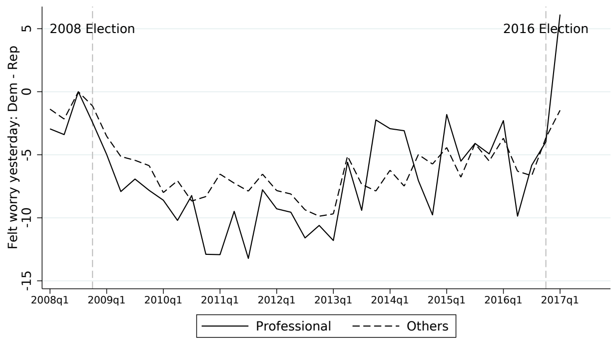
Figure 5: Optimism about National Economy: the Gallup U.S. Daily Survey by Education and Occupation

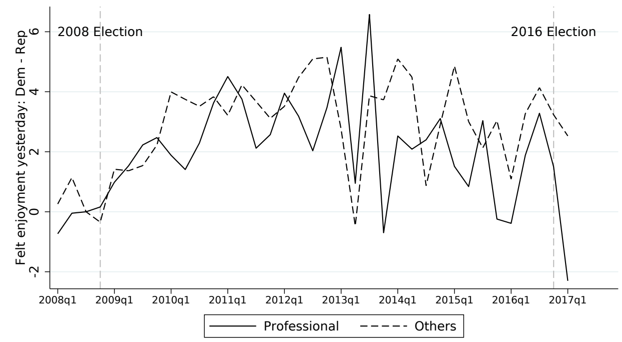
Note: This figure plots the difference in the share of Democratic and Republican respondents ("Dem minus Rep") answering "Getting better" to the question "Right now, do you think that economic conditions in this country, as a whole, are getting better or getting worse?" in the Gallup U.S. Daily Survey. 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).



(a) *Qs: Worry yesterday*, by education

(b) *Qs: Enjoyment yesterday*, by education



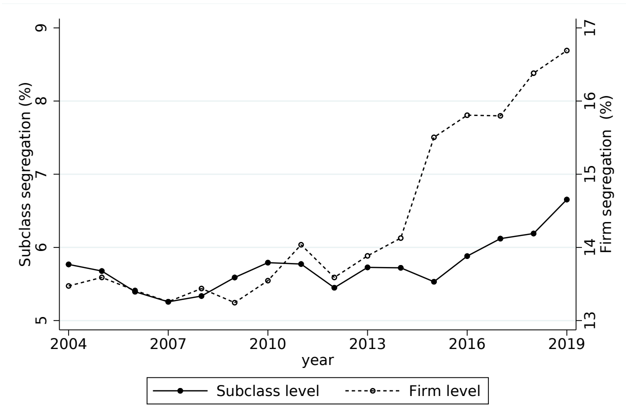


(c) *Qs: Worry yesterday*, by occupation

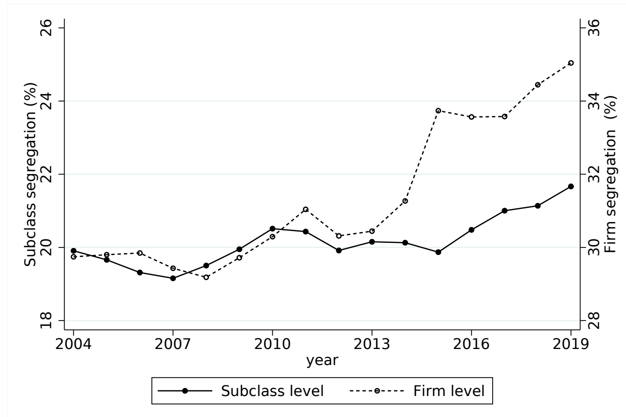
(d) *Qs: Enjoyment yesterday*, by occupation

Figure 6: Mood: the Gallup U.S. Daily Survey by Education or Occupation

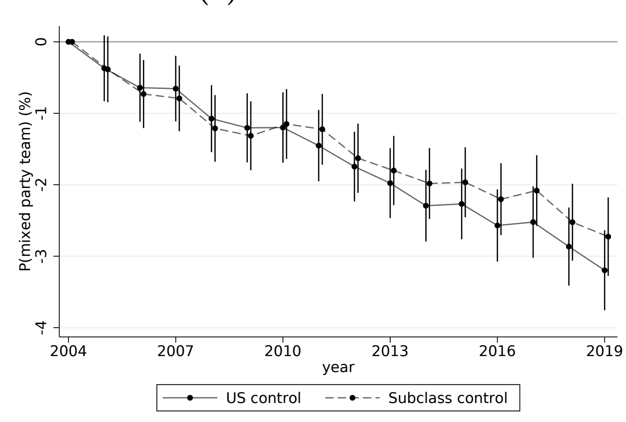
Note: This figure plots the difference in the share of Democratic and Republican respondents ("Dem minus Rep") answering "Yes" to the questions "Did you experience the feeling of *worry* during a lot of the day yesterday?" (panels a and c) and "Did you experience the feeling of *enjoyment* during a lot 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) split respondents by education 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).



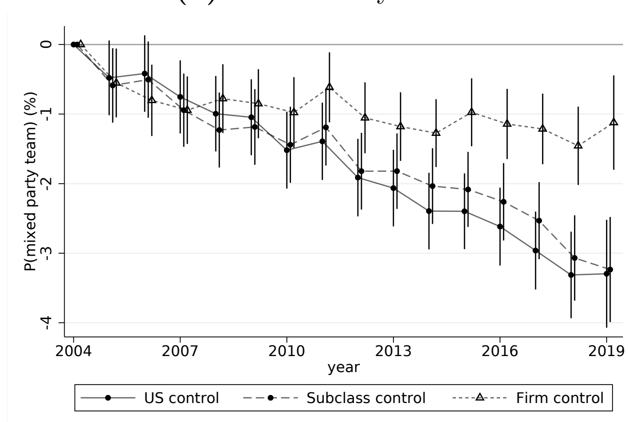
(a) Isolation index



(b) Dissimilarity index



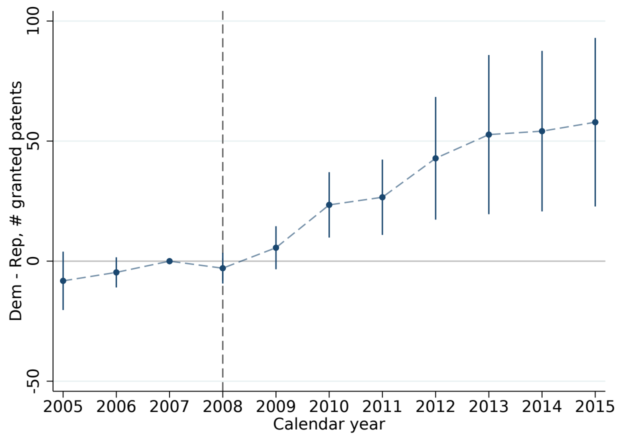
(c) Prob. mixed-party application teams



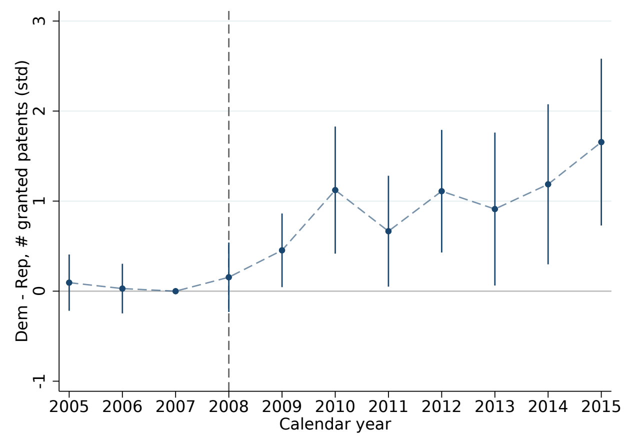
(d) Prob. mixed-party grant teams

Figure 7: Partisan Affiliation and Clustering by Technology, Firm, or Team

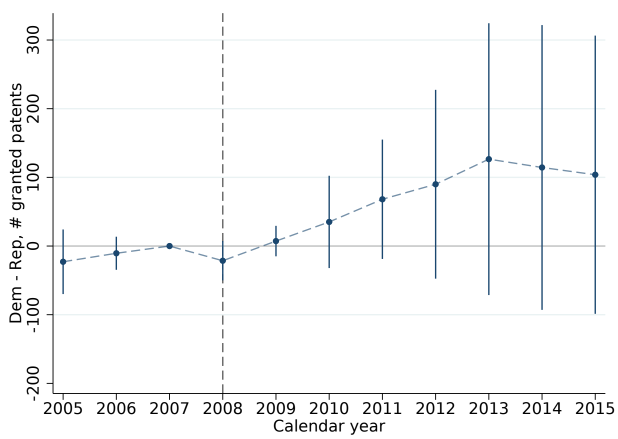
Note: This figure plots inventors' segregation along party lines by technology subclass, firm or team over time. Panel (a) plots the isolation index (White 1986) and panel (b) the dissimilarity index (Cutler, Glaeser, and Vigdor 1999) for technology subclasses and firms. Only technology subclasses and firms with more than 10 Republican or Democratic inventors in a year are included. Panels (c) and (d) plot the probability of mixed-party teams (and 90 percent confidence intervals) relative to 2004, using USPTO patent application data and grant data, respectively. Both panels control for zip code fixed effects, technology class fixed effects, and team characteristics (i.e., team size, fraction of men, fraction of college educated, fraction of a certain race, fraction in a certain age group). Different lines in each panel result from different controls used in predicting the likelihood of forming a mixed-party team: *US control*, *subclass control*, and *firm control* refer to the likelihood of forming a mixed-party team by randomly picking N inventors (team size) in the US, in a technological subclass, and in a firm, respectively. Panel (c) does not show results for *firm control* because a large fraction of patent applications lack firm information. Standard errors are clustered by zip code. Units are in percentage points.



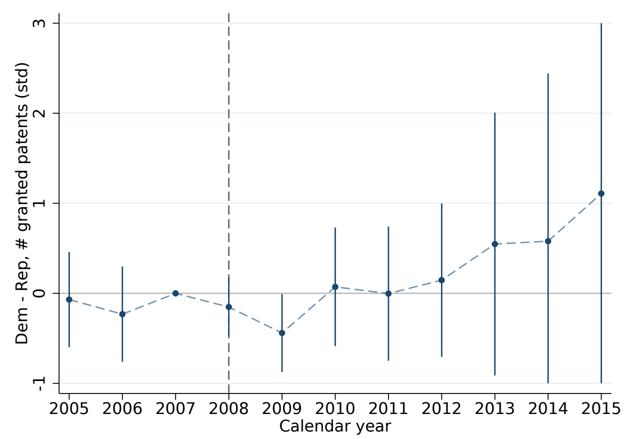
(a) Subclass-level granted patents



(b) Subclass-level granted patents (std)



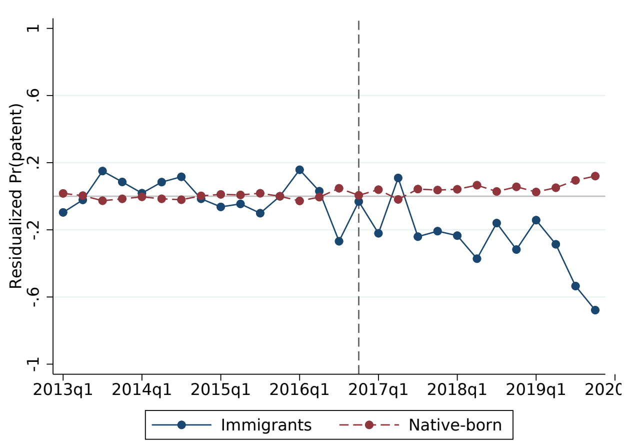
(c) Class-level granted patents



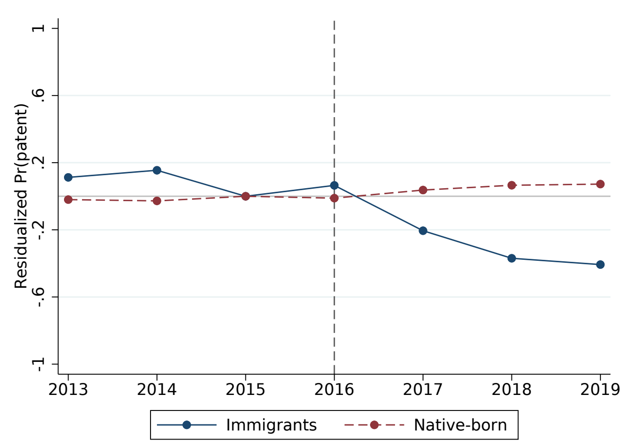
(d) Class-level granted patents (std)

Figure 8: Political Mismatch and Number of Granted Patents by Technology Class and Subclass

Note: This figure plots estimates of the effect of political alignment on the number of granted patents at the technology (sub)class-level around the 2008 presidential election. In this figure we assign a granted patent to its application year. Democratic technologies are those with an above-median share of Democrats among all inventors actively patenting in the 10 through 4 years preceding the 2008 election. Republican technologies are similarly defined. Only technologies with at least eight actively patenting inventors before the election are assigned a partisan leaning. The outcome for panel (a) is the number of eventually-granted patents submitted in each subclass each year. The outcome in panel (b) standardizes by the pre-election subclass mean and standard deviation. Panels (c) and (d) repeat the exercise at the class level. Specifications follow Table 4 panel (a) while controlling for technology subclass (or class) fixed effects and class (or section)-by-year fixed effects. 90% confidence intervals; standard errors clustered by subclass (or class).



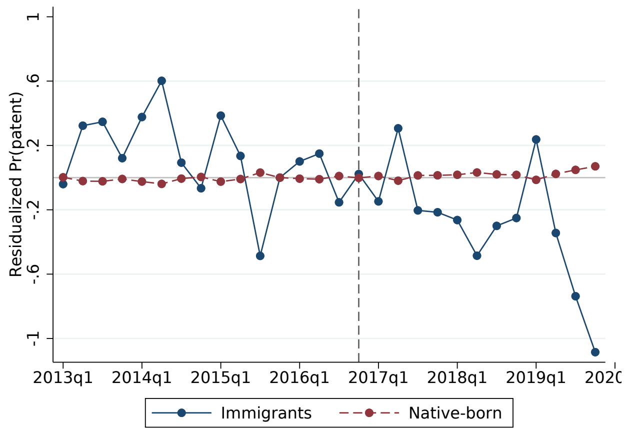
(a) Quarter



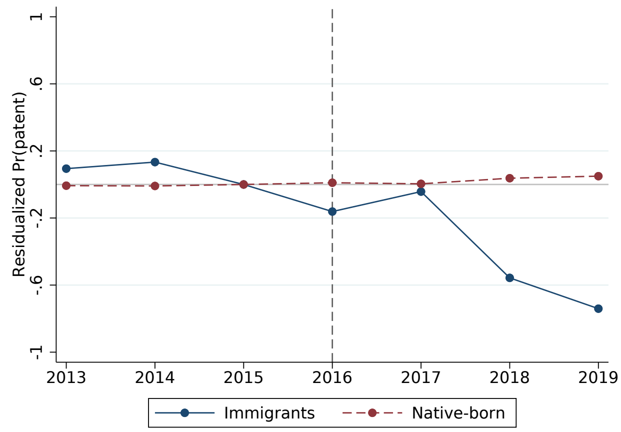
(b) Annual

Figure 9: Residualized Probability of Submitting a Patent Application
Immigrant vs. Native-Born Inventors

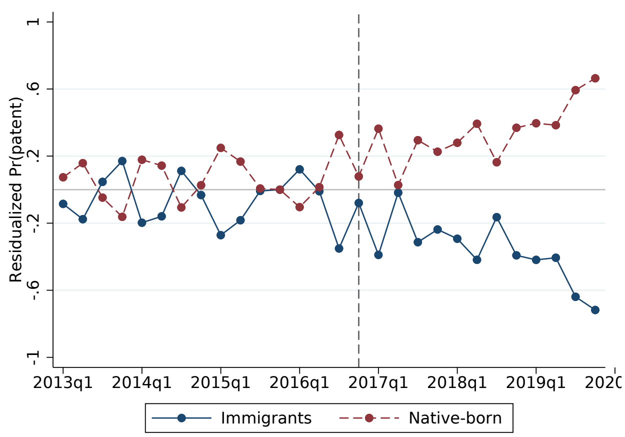
Note: This figure plots the (residualized) probability of submitting a patent application for immigrant and native-born inventors. We exclude inventors with unknown race for comparability with later figures. Residualized probability is the residual obtained from regressing the raw probability on technology class-by-year-by-race fixed effects. Units are in percentage points. Levels are normalized to 2015q4 in panel (a) and 2015 in panel (b).



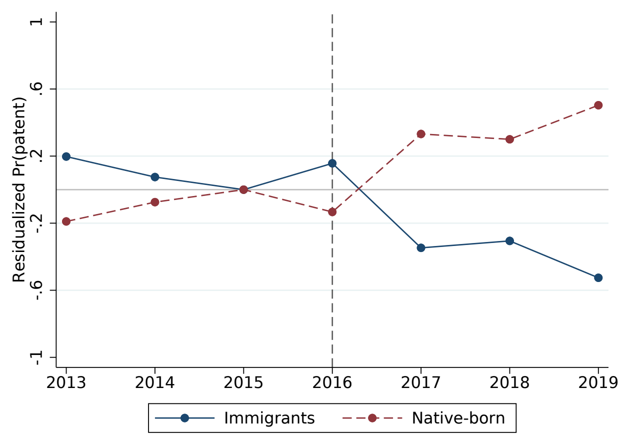
(a) White, quarterly



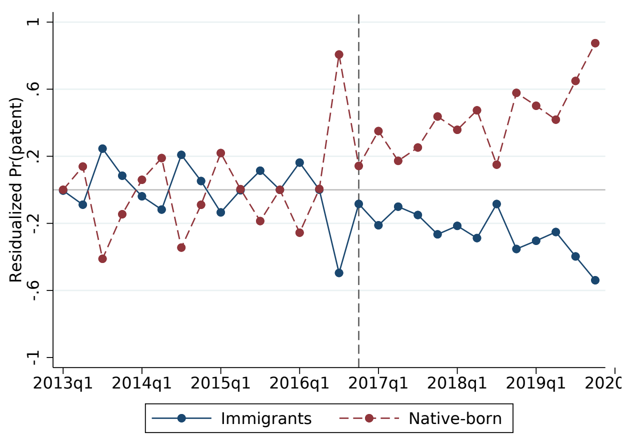
(b) White, annual



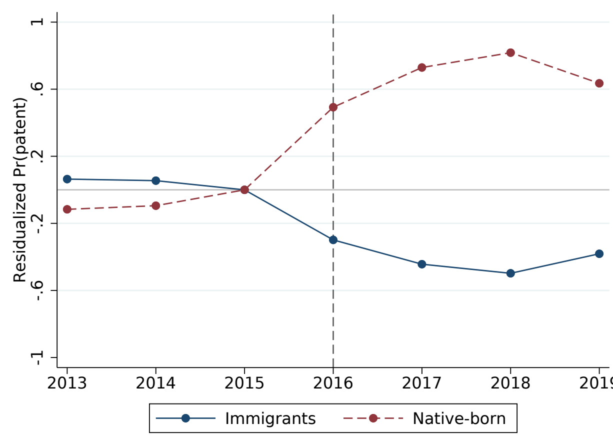
(c) Non-white, quarterly



(d) Non-white, annual



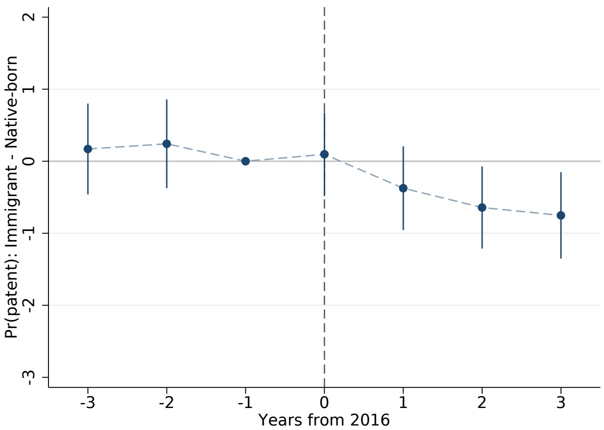
(e) Asian, quarterly



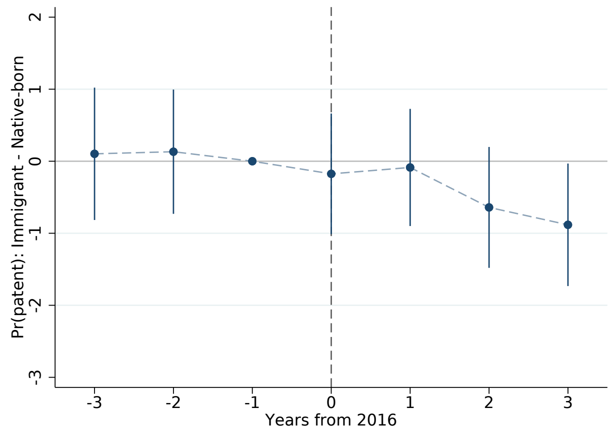
(f) Asian, annual

Figure 10: Residualized Probability of Submitting a Patent Application (2016) *by Race* Immigrant vs. Native-Born Inventors

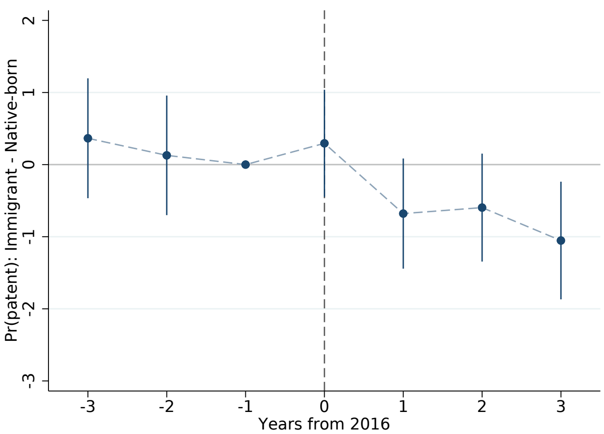
Note: This figure plots the (residualized) probability of submitting a patent application for immigrant and native-born inventors. Residualized probability is the residual obtained from regressing the raw probability on technology class-by-year fixed effects. Units are in percentage points. Levels are normalized to 2015q4 in panels (a), (c), (e) and 2015 in panels (b), (d), (f).



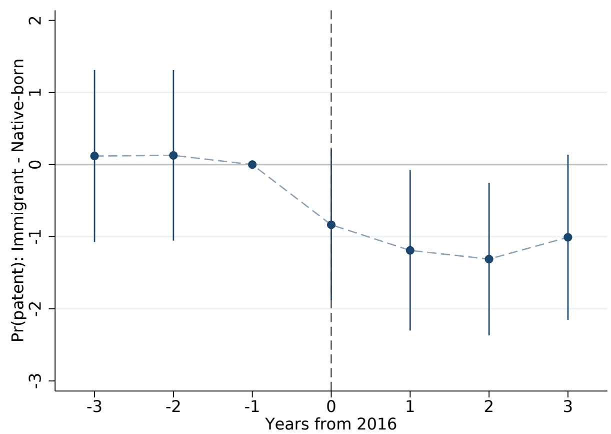
(a) All races



(b) White



(c) Non-white



(d) Asian

Figure 11: Probability of Submitting a Patent Application (2016)
Immigrant vs. Native-Born Inventors

Note: This figure plots the estimated annual probability of submitting a patent application for immigrant inventors relative to non-immigrant inventors around the 2016 election. The sample consists of USPTO inventors who are matched to both the voter roll (L2) and Infutor, and non-immigrant inventors are the omitted category. Panels (b), (c) and (d) focus on White, non-White, and Asian inventor subgroups, respectively. Event time 0 refers to the year of a presidential election. Event time -1 is the omitted period. All regressions control for zip code (× race) fixed effects, technology class (× race) × event fixed effects, and fully interacted voter characteristics (gender, education, age groups, race). Standard errors clustered by zip code; 90% confidence intervals. Units are in percentage points. Coefficients are reported in Table A11.

Table 1: Sample statistics

	Mean	SD	%Sample	Mean	SD	%Sample	Mean	SD	%Sample
Panel A: Democrat vs. Republican patenters									
	Full sample			Democrats			Republicans		
	Pr(patent) in pp			Pr(patent) in pp			Pr(patent) in pp		
All	18.07	38.48	100	19.60	39.70	100	16.64	37.24	100
Male	18.50	38.83	88.72	20.25	40.19	85.33	16.97	37.54	91.90
Female	14.74	35.45	11.28	15.83	36.51	14.67	12.89	33.51	8.10
College+	18.82	39.09	84.24	20.46	40.34	85.72	17.35	37.87	82.95
High school–	14.53	35.24	15.76	15.79	36.46	14.28	13.61	34.29	17.05
White	17.61	38.09	82.84	19.42	39.56	74.62	16.26	36.90	90.28
Black	11.99	32.48	2.99	11.80	32.26	5.79	14.15	34.86	0.45
Hispanic	16.43	37.05	3.78	17.61	38.09	5.08	14.34	35.05	2.60
Asian	21.94	41.39	10.40	22.37	41.67	14.52	21.10	40.80	6.67
Age 18-29	16.05	36.71	5.08	16	36.66	6.60	16.14	36.79	3.64
Age 30-39	22.26	41.60	14.76	23.28	42.26	16.48	21.05	40.77	13.14
Age 40-49	20.22	40.17	28.61	21.89	41.35	27.84	18.74	39.02	29.33
Age 50-59	17.53	38.02	31.59	19.34	39.50	29.87	15.99	36.66	33.20
Age 60-70	13.29	33.94	19.97	14.77	35.48	19.21	11.99	32.48	20.68
With a firm	20.02	40.02	86.44	21.36	40.98	88.66	18.71	39	84.35
Without a firm	5.65	23.09	13.56	5.90	23.56	11.34	5.49	22.77	15.65
N patenters × year		5,291,640			2,562,831			2,728,809	
N patenters		375,857			181,673			194,184	
N states		51			51			51	
Panel B: Immigrant vs. native born patenters									
	Full sample			Immigrants			Native-born		
	Pr(patent) in pp			Pr(patent) in pp			Pr(patent) in pp		
All	18.96	39.20	100	22.91	42.03	100	18.34	38.70	100
Democrat	20.20	40.15	34.26	23.59	42.45	37.31	19.62	39.71	33.79
Republican	17.15	37.69	39.28	20.38	40.28	21.47	16.89	37.47	42.04
Male	19.35	39.51	90.03	23.37	42.32	85.61	18.77	39.04	90.72
Female	15.39	36.09	9.97	20.20	40.15	14.39	14.23	34.94	9.28
College+	19.80	39.85	84.50	23.82	42.60	88.80	19.14	39.34	83.83
High school–	15.12	35.82	15.50	19.55	39.66	11.20	14.64	35.35	16.17
White	18.43	38.77	83.37	21.88	41.34	38.76	18.21	38.59	89.78
Black	12.08	32.59	2.25	14.85	35.56	1.73	11.79	32.25	2.32
Hispanic	17.34	37.86	3.57	19.68	39.76	6.53	16.64	37.24	3.15
Asian	23.10	42.15	10.81	24.01	42.72	52.98	21.62	41.17	4.74
Age 18-29	16.69	37.29	3.86	18.13	38.52	3.10	16.52	37.14	3.98
Age 30-39	23.01	42.09	13.39	24.89	43.24	11.75	22.75	41.92	13.65
Age 40-49	21.40	41.01	29.75	25.67	43.68	31.82	20.68	40.50	29.43
Age 50-59	18.45	38.79	32.97	23.01	42.09	33.33	17.73	38.19	32.92
Age 60-70	13.91	34.60	20.03	17.94	38.37	20	13.28	33.94	20.03
With a firm	20.92	40.67	87.16	24.29	42.88	91.83	20.37	40.27	86.43
Without a firm	5.64	23.07	12.84	7.48	26.30	8.17	5.47	22.74	13.57
N patenters × year		5,047,813			677,629			4,370,184	
N patenters		357,496			48,372			309,124	
N states		51			51			51	

Note: This table reports summary statistics for our main samples between 2005 and 2019 for the Democrat vs. Republican comparison (panel A) and for the immigrant vs. native born comparison (panel B); see section 2 for details. The first, fourth and seventh columns display the the average annual probability of submitting a patent, conditional on the patenter characteristic in each row. The SD column displays the corresponding sample standard deviation. The *%Sample* column displays the fraction of patenters with each characteristic in the sample. All units are in percentage points (pp). Panel A columns (1)-(3), (4)-(6) and (7)-(9) are calculated based on both Democrats and Republicans, only Democrats, and only Republicans, respectively. Panel B columns (1)-(3), (4)-(6) and (7)-(9) are calculated based on both immigrants and native-born, only immigrants, and only native-born, respectively, including Democrats, Republicans, and inventors of other parties. *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 *With a firm* (*Without a firm*) is an indicator for a patenter being affiliated with a firm (or not). 51 "states" corresponds to 50 states plus DC.

Table 2: Election DID analysis: Democratic vs. 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^2	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 clusters (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^2	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 clusters (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
Technology Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: This table reports estimates from difference in differences (DID) analyses comparing the likelihood of a Democratic inventor applying for a patent relative to a Republican one around the 2008 and 2016 presidential elections. The outcome is an indicator for applying for a patent, 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. Demographic controls correspond to fully interacted inventor characteristics (i.e., gender, education, age groups, race) and are included in all regressions. Standard errors in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table 3: Election DID analysis: Democratic vs. 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^2	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 clusters (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^2	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 clusters (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
Technology Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: This table reports estimates from difference in differences (DID) analyses comparing the likelihood of politically active and inactive Democratic inventors applying for a patent relative to Republicans around the 2008 and 2016 presidential elections. The outcome is an indicator for submitting a patent application, and units are in percentage points. *Active Dem* is one for a politically active Democrat based on voting history and zero otherwise; *Inactive Dem* is one for politically inactive Democrats based on voting history and zero otherwise (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 in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table 4: *Within Firm* Election DID analysis: Democratic vs. Republican Inventors
By Voting Activeness

	(1) Within firm	(2) group size≥1	(3) group size≥2	(4) # group size≥4	(5) # group size≥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^2	0.200	0.129	0.123	0.121	0.121
Outcome mean	21.697	23.225	23.202	23.172	23.291
N clusters (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^2	0.204	0.128	0.122	0.119	0.117
Outcome mean	23.848	24.875	24.886	24.918	24.771
N clusters (zip)	16,215	13,588	12,998	12,403	11,640
Demographics	Y	Y	Y	Y	Y
Zip FE	Y	Y	Y	Y	Y
Technology Class×Post FE	Y	Y	Y	Y	Y
Firm×Post FE	Y	Y	Y	Y	Y

Note: This table reports estimates from difference in differences (DID) analyses comparing the likelihood of Democratic inventors applying for a patent relative to Republicans *in the same firm* around the 2008 and 2016 presidential elections. The outcome is an indicator for submitting a patent application, and units are in percentage points. *Active Dem* is one for politically active Democrats (based on voting history) and zero otherwise; *Inactive Dem* is one for politically inactive Democrats (based on voting history) and zero otherwise (see section 2.2 for definition of partisanship). *Post* is one for the first through third years after a presidential election; presidential election years are excluded. Column (1) includes all inventors in our sample affiliated with a firm, and columns (2) through (5) further restrict the firms to have a minimum number of inventors of each type of party and activeness. For example, for a firm's inventors to be in the sample, column (2) requires the firm have at least 1 inventor in each combination of Republican/Democrat × Active/Inactive. 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 in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table 5: Election DID analysis: Democratic vs. Republican Inventors
Patent Citations

VARIABLES	(1) # Citations	(2) # Citations	(3) Scaled #	(4) Scaled #	(5) Normalized #	(6) Normalized #
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	-	-
Observations	216,685	216,685	216,684	216,684	216,682	216,682
R^2	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 clusters (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	-	-
Observations	235,347	235,347	235,307	235,307	235,307	235,307
R^2	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 clusters (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
Technology Class×Post FE	Y	Y	Y	Y	Y	Y
State×Post FE	N	Y	N	Y	N	Y

Note: The table reports estimates from difference in differences (DID) analyses comparing the number of patent citations to Democrat and Republican inventors' patents around the 2008 and 2016 presidential elections. The outcomes in columns (1)-(2), columns (3)-(4), and columns (5)-(6) are, respectively, (i) an inventor's average number of citations across the patents they submitted in each year (# Citations), (ii) the average number divided by the technology class and grant year mean (Scaled), and (iii) the average number after subtracting the mean and dividing by the standard deviation of the technology class and grant year (Normalized). *Dem* is one for Democrats and zero for Republicans. *Post* is one for the first through third years after a presidential election. 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 in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table 6: 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; Beer; Spirits; Wine; Vinegar and etc	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 inventors 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 inventors in our sample in each of the three "lean" categories.

Table 7: Election DID analysis: Immigrant vs. Native-Born Inventors

VARIABLES	(1) P(patent)	(2) P(patent)	(3) P(patent)	(4) P(patent)	(5) P(patent)	(6) P(patent)	(7) P(patent)	(8) P(patent)
Immigrant×Post	-0.853***	-0.888***	-0.659***	-0.713***	-0.631***	-0.684***	-0.781***	-0.747***
	(0.235)	(0.235)	(0.236)	(0.236)	(0.237)	(0.237)	(0.234)	(0.234)
Immigrant	2.834***	2.696***	2.353***	2.295***	2.339***	2.281***		
	(0.278)	(0.300)	(0.270)	(0.293)	(0.270)	(0.293)		
Dem	1.401***	1.187***	1.135***	0.992***	1.135***	0.991***		
	(0.183)	(0.198)	(0.181)	(0.195)	(0.181)	(0.195)		
Rep	-0.550***	-0.442**	-0.268	-0.230	-0.268	-0.231		
	(0.186)	(0.199)	(0.182)	(0.196)	(0.182)	(0.196)		
Effect as %mean	-3.68	-3.83	-2.84	-3.08	-2.73	-2.95	-3.37	-3.22
Observations	1,145,144	1,146,557	1,144,667	1,146,080	1,144,667	1,146,080	1,146,080	1,146,080
R^2	0.038	0.093	0.057	0.111	0.057	0.111	0.505	0.505
Outcome mean	23.206	23.201	23.207	23.202	23.207	23.202	23.202	23.202
N clusters (zip)	16,762	16,775	16,761	16,774	16,761	16,774	16,774	16,774
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
Person	N	N	N	N	N	N	Y	Y
County×Race FE	Y	N	Y	N	Y	N	N	N
Zip×Race FE	N	Y	N	Y	N	Y	N	N
State×Race×Post FE	Y	Y	N	N	Y	Y	N	Y
Technology Class×Race×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: The table reports estimates from a difference in differences (DID) analysis comparing the likelihood that an immigrant inventor applies for a patent relative to a non-immigrant one around the 2016 presidential election. The outcome is an indicator for submitting a patent application, and units are in percentage points. The sample consists of all inventors matched to the voter rolls who are identified as either immigrants or native-born, thus all are US citizens. *Immigrant* is one for immigrant inventors and zero for native-born inventors. *Post* is one for the first through third years after a presidential election, i.e., 2017, 2018, and 2019. The year of a presidential election (2016) is excluded from the regression. All regressions control for fully interacted voter demographic characteristics (i.e., gender, education, age groups, race). Standard errors in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table 8: Election DID analysis: Immigrant vs. Native-Born Inventors
by Race

VARIABLES	(1) White	(2) Non-white	(3) Asian	(4) White	(5) Non-white	(6) Asian	(7) White	(8) Non-white	(9) Asian
Immigrant×Post	-0.611*	-0.917***	-1.252***	-0.687**	-0.917***	-1.359***	-0.309	-0.654*	-0.940*
	(0.336)	(0.305)	(0.434)	(0.337)	(0.304)	(0.428)	(0.395)	(0.389)	(0.547)
Immigrant	2.434***	1.798***	2.353***				2.919***	1.690***	1.840***
	(0.388)	(0.398)	(0.574)				(0.441)	(0.459)	(0.620)
Dem	0.962***	0.841**	0.940*				0.952***	0.662	0.934
	(0.221)	(0.378)	(0.513)				(0.259)	(0.451)	(0.578)
Rep	-0.177	-0.770	-0.843				0.035	-1.448**	-0.949
	(0.214)	(0.473)	(0.666)				(0.253)	(0.601)	(0.785)
Effect as %mean	-2.69	-3.7	-4.68	-3.02	-3.7	-5.08	-1.26	-2.48	-3.41
Observations	898,874	247,206	133,865	898,874	247,206	133,865	806,239	225,628	127,035
R^2	0.089	0.120	0.123	0.500	0.518	0.520	0.230	0.277	0.285
Outcome mean	22.762	24.799	26.77	22.762	24.799	26.77	24.579	26.392	27.58
N clusters (zip)	16115	7231	3900	16115	7231	3900	14927	6625	3718
Demographics	Y	Y	Y	Y	Y	Y	Y	Y	Y
Person	N	N	N	Y	Y	Y	N	N	N
Zip FE	Y	Y	Y	N	N	N	Y	Y	Y
State×Post FE	N	N	N	Y	Y	Y	N	N	N
Technology Class×Post FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm×Post	N	N	N	N	N	N	Y	Y	Y

Note: The table reports estimates from a difference in differences (DID) analysis comparing the likelihood that an immigrant inventor in a specific racial group submits a patent application relative to a non-immigrant inventor of the same race around the 2016 presidential election. The outcome is an indicator for submitting a patent application, and units are in percentage points. Columns (1), (4), (7) consists of white inventors only (either immigrant or native-born); columns (2), (5), (8) non-white inventors; and columns (3), (6), (9) Asian inventors. *Immigrant* is one for immigrant inventors of a specific race and zero for native-born inventors. *Post* is one for the first through third years after a presidential election, i.e., 2017, 2018, and 2019. The year of a presidential election (2016) is excluded from the regression. All regressions control for fully interacted voter characteristics (i.e., gender, education, age groups, race). Standard errors in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table 9: Immigrant Concentration by Technology and by Firm

Highest share of immigrants		Lowest share of immigrants	
Name	% Immigrant	Name	% Immigrant
Panel A: By technology section			
Chemistry; Metallurgy	20	Fixed Constructions	9.1
Electricity	18	Mech. Eng.; Lighting; Heating; Weapons; Blasting	9.9
Physics	16	Performing Operations; Transporting	10.5
Textiles; Paper	13.7	Human Necessities	12.8
Panel B: By technology class			
Crystal Growth	24.5	Skins; Hides; Pelts; Leather	5.8
Organic Chemistry	24.2	Weapons	6.2
Nanotechnology	23.9	Doors, Windows, Shutters, or Roller Blinds; Ladders	6.2
Basic Electronic Circuitry	23.6	Headwear	6.4
Biochemistry; Beer; Spirits; Wine; Vinegar and etc	22.3	Separating Solids From Solids; Sorting	6.8
Generating or Transmitting Mechanical Vibrations	21.6	Hoisting; Lifting; Hauling	7
Coating Metallic Material	21.3	Ammunition; Blasting	7.1
Information Storage	20.8	Construction Of Roads, Railways, or Bridges	7.2
Inorganic Chemistry	20.5	Locks; Keys; Window or Door Fittings; Safes	7.4
Coating Metallic Material	20.2	Writing or Drawing Implements; Bureau Accessories	7.5
Panel C: By firm			
Qualcomm Inc.	39.6	Lockheed Martin Corp.	6.7
Cisco Tech Inc.	37.5	Caterpillar Inc.	7.9
Oracle Int Corp.	36.3	Raytheon Co.	8
Applied Materials Inc.	33.4	Eastman Kodak Co.	8
Intel Corp.	28.8	Medtronic Inc.	8.3
Texas Instr Inc.	24.5	The Boeing Co.	9
Microsoft Corp.	23.6	3M Innovative Properties Co.	9
Sony Corp.	22.4	United Tech Corp.	9.1
Motorola Inc.	19.4	Xerox Corp.	10.6
Abbott Lab	18.7	Honeywell Int Inc.	12.3

Note: This table reports the sample share of immigrants by technology section, by technology class, or by firm using USPTO patent applications submitted between 2001 and 2019. Panel A reports the share for each *technology section* in our sample. Panel B reports the share for the ten *technology classes* with the highest share in columns (1) and (2), and the ten with the lowest share in columns (3) and (4); panel C does the same for the ten publicly traded *firms* with >1,000 inventors in our sample with the highest share in columns (1) and (2), and the ten with the lowest share in columns (3) and (4).

Appendix for
Political Sentiment and Innovation: Evidence from Patenters

A. USPTO Name Disambiguation

Assignee Name Disambiguation

- We collect all patent grants and applications with non-missing assignees corresponding to firms (asgtype=2 or asgtype=3).
- We standardize all assignee names using the name standardization algorithm developed by the NBER patent data project. This replaces different variations of common words with one standardized version and also standardizes capitalization, punctuation, etc. (https://sites.google.com/site/patentdataproject/)
  - The NBER name standardization algorithm creates a standardized name and also a stem name (which excludes words like "Incorporated," "LLC," etc.).
- We also standardize and parse assignee location names (into city, state, country) by running them through the Google geocode API.
- Initial assignee IDs are then generated based on the standardized assignee names (assignee_id). That is, two patents assigned to assignees with the exact same standardized name are given the same value of assignee_id.
- These initial assignee IDs are then "smoothed" (i.e. multiple values of assignee_id are combined into one) several times based on alternative ID variables containing further disambiguating information.
- This smoothing process is recursive, such that if any two values of assignee_id are linked by an alternative ID (either directly or indirectly), they are combined. For example, two patents with assignee_id=104 and assignee_id=2007 may be linked by the same alternative ID (e.g. alt_id=57). And two different patents with assignee_id=2007 and assignee_id=9782 may also be linked by the same alternative ID (e.g., alt_id=3450). In this case, after smoothing based on alt_id, all patents that had assignee_id=104 or assignee_id=2007 or assignee_id=9782 would now have assignee_id=104.
- Note that the alternative IDs do not need to be non-missing for all observations. Nonetheless, an alternative ID may end up changing assignee_id, even for observations for which

the alternative ID is missing. o In the example above, there may be an observation with assignee_id==9782 and alt_id missing. Nonetheless, after smoothing, assignee_id would change to 104 for that observation.

- The alternative IDs used for smoothing are as follows, with all variables required to be non-missing:

  1. The assignee ID developed by the NBER patent project for granted patents from 1976-2006. https://sites.google.com/site/patentdataproject/
  2. Tuples based on assignee stem name and assignee city
  3. Tuples based on assignee short name (first 4 non-white space characters, excluding "THE"), inventor first name, inventor last name, inventor city, and assignee city The assignee name cannot contain the "UNIV"
  4. Tuples based on assignee acronym (first letters of each word in stem name), inventor first name, inventor last name, inventor city, and assignee city The assignee acronym must be at least 3 characters long The assignee name cannot contain the "UNIV"
  5. Tuples based on assignee stem name, patent application number, and patent application date This links assignees from a patent application to assignees from a subsequent patent grant

<u>Inventor Name Disambiguation</u>

- Inventor names are disambiguated using a similar methodology to assignee names.

- We collect all patent grants and applications with non-missing inventors.

- We standardize and parse inventor names

  - We take the first "word" in the name to be their first name and the last "word" in the name to be the last name (where words are separated by white space), except for certain exceptions where the last two words are consider a middle name (e.g., last names beginning with the word "AL," "DA," "DE," "DEL," "DELLA," "DER," "DI," "DU," "EL," etc.).

  - All other words in between the first and last are considered middle names o In some cases we only observe middle initials or no middle name/initial information.

- We standardize and parse inventor locations using the google geocode API..

- Initial inventor IDs are then generated based on the following tuples, with missing values treated as values.

  - First name, middle names (all), middle initials (all), last name, inventor city, assignee_id

- These initial inventor IDs are then smoothed based on the following tuples. Missing values treated as values for tuple 1, and all variables are required to be non-missing for tuples 2-11.

  1. First name, middle names (all), middle initials (all), last name, inventor city, technology section
  2. First name, middle initial (first), last name, inventor city, assignee_id,
  3. First name, middle initial (first), last name, inventor city, technology section
  4. First name, middle name (first), last name, inventor location
  5. First name, middle name (first), last name, technology section, inventor country
  6. First name, middle initials (all), last name, inventor city
  7. First name, middle initials (all), last name, technology section, inventory country
  8. First name, last name, application number, application date
  9. First name, application number, application date, inventor sequence number
  10. Last name, application number, application date, inventor sequence number
  11. First name, middle names (all), last name

Table A1: Summary Statistics by Election – Democrats vs. Republicans

	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	21.53	41.10	100	17.90	38.34	100
Male	20.11	40.08	90.20	22.31	41.63	87.02	18.29	38.66	93.01
Female	14.97	35.68	9.80	16.31	36.95	12.98	12.78	33.39	6.99
College+	20.61	40.45	83.56	22.66	41.86	85.15	18.85	39.11	82.25
High school–	15.18	35.88	16.44	16.69	37.29	14.85	14.13	34.84	17.75
White	19.12	39.33	84.81	21.38	41	77.10	17.50	38	91.36
Black	12.55	33.13	3.03	12.30	32.84	6.03	15.25	35.95	0.48
Hispanic	17.10	37.65	3.33	18.71	39	4.50	14.49	35.20	2.34
Asian	24.59	43.06	8.83	25.39	43.52	12.37	23.13	42.17	5.82
Age 18-29	17.96	38.38	3.32	17.64	38.12	4.26	18.43	38.78	2.50
Age 30-39	22.68	41.88	14.63	24.20	42.83	15.29	21.22	40.89	14.04
Age 40-49	21.14	40.83	34.17	23.37	42.32	32.92	19.32	39.48	35.27
Age 50-59	19.21	39.39	31.26	21.30	40.95	31.48	17.34	37.86	31.07
Age 60-70	14.79	35.50	16.61	16.70	37.29	16.05	13.22	33.87	17.11
With a firm	22.06	41.46	86.72	23.80	42.59	88.71	20.45	40.34	84.96
Without a firm	3.58	18.57	13.28	3.71	18.91	11.29	3.49	18.35	15.04
N patenters×year		1,528,849			715,811			813,038	
N patenters		223,685			104,729			118,956	
N states		51			51			51	
Panel B: 2016 election									
All	22.13	41.51	100	23.73	42.54	100	20.48	40.35	100
Male	22.70	41.89	88.73	24.55	43.04	85.57	20.94	40.69	91.97
Female	17.58	38.06	11.27	18.87	39.13	14.43	15.19	35.89	8.03
College+	22.82	41.96	85.82	24.50	43.01	87.14	21.18	40.86	84.58
High school–	18.35	38.71	14.18	19.72	39.79	12.86	17.28	37.81	15.42
White	21.69	41.21	81.50	23.62	42.47	73.59	20.12	40.09	89.30
Black	15.21	35.92	2.60	14.88	35.59	4.82	19.03	39.26	0.41
Hispanic	19.93	39.95	3.93	21.20	40.87	5.23	17.48	37.98	2.65
Asian	25.50	43.59	11.97	25.92	43.82	16.36	24.63	43.09	7.64
Age 18-29	19.78	39.84	2.76	19.84	39.88	3.67	19.67	39.75	1.82
Age 30-39	25.27	43.45	12.27	26.18	43.96	14.51	23.91	42.65	9.98
Age 40-49	24.04	42.73	26.69	25.34	43.50	27.20	22.65	41.85	26.16
Age 50-59	22.32	41.64	34.62	24.33	42.91	31.72	20.57	40.42	37.60
Age 60-70	18.33	38.70	23.66	20.06	40.05	22.90	16.68	37.28	24.45
With a firm	23.84	42.61	90.16	25.22	43.43	91.96	22.38	41.68	88.31
Without a firm	6.38	24.45	9.84	6.73	25.05	8.04	6.14	24.01	11.69
N patenters×year		1,585,778			802,319			783,459	
N patenters		234,796			118,620			116,176	
N states		51			51			51	

Note: This table reports sample statistics for Democrats and Republicans separately for the 2008 and 2016 elections, spanning 2005-2011 and 2013-2019, respectively. See note to Table 1 for variable definitions.

Table A2: Summary Statistics by Election – Immigrant vs. Native-born patenters

	Full sample			Immigrants			Native-born		
	Probability (pp)			Probability (pp)			Probability (pp)		
	Mean	SD	%Sample	Mean	SD	%Sample	Mean	SD	%Sample
Panel A: 2008 election									
All	20.87	40.64	100	26.16	43.95	100	20.07	40.05	100
Democrat	22.48	41.74	34.49	26.94	44.36	37.63	21.73	41.24	34.02
Republican	18.67	38.97	40.34	23.22	42.23	22.54	18.31	38.67	43.05
Male	21.33	40.96	90.79	26.68	44.23	86.87	20.55	40.41	91.39
Female	16.43	37.05	9.21	22.72	41.90	13.13	14.96	35.67	8.61
College+	21.96	41.40	84.06	27.25	44.52	88.62	21.10	40.81	83.37
High school–	16.08	36.73	15.94	21.19	40.87	11.38	15.54	36.23	16.63
White	20.22	40.17	84.59	24.86	43.22	41.76	19.92	39.94	90.63
Black	12.99	33.62	2.28	17.22	37.76	1.76	12.54	33.12	2.35
Hispanic	18.62	38.92	3.26	21.87	41.34	6.30	17.59	38.08	2.83
Asian	26.43	44.10	9.88	27.70	44.75	50.18	24.28	42.88	4.19
Age 18-29	18.51	38.84	3.28	20.87	40.64	2.96	18.19	38.57	3.33
Age 30-39	24.32	42.90	14.85	28.36	45.08	13.51	23.77	42.56	15.06
Age 40-49	22.51	41.77	35.19	28.51	45.15	36.85	21.55	41.11	34.94
Age 50-59	20.26	40.19	31.09	25.94	43.83	30	19.43	39.56	31.26
Age 60-70	15.63	36.31	15.59	20.50	40.37	16.69	14.82	35.53	15.42
With a firm	23.27	42.26	87.73	27.85	44.83	92.39	22.53	41.78	87.02
Without a firm	3.74	18.97	12.27	5.56	22.92	7.61	3.57	18.56	12.98
N patenter×year		1,550,740			204,946			1,345,794	
N patenter		226,516			30,114			196,402	
N state		51			51			51	
Panel B: 2016 election									
All	23.26	42.25	100	26.76	44.27	100	22.67	41.87	100
Democrat	24.60	43.07	34.86	27.53	44.67	37.63	24.06	42.74	34.39
Republican	21.25	40.91	37.34	23.98	42.70	19.87	21.02	40.74	40.30
Male	23.73	42.55	90.46	27.28	44.54	85.80	23.17	42.19	91.25
Female	18.76	39.04	9.54	23.57	42.45	14.20	17.44	37.95	8.75
College+	24.01	42.71	86.10	27.60	44.70	89.62	23.36	42.31	85.50
High school–	19.21	39.39	13.90	24.02	42.72	10.38	18.62	38.93	14.50
White	22.75	41.92	82.23	26.35	44.05	36.54	22.52	41.77	89.41
Black	15.65	36.34	1.89	17.58	38.07	1.53	15.42	36.11	1.95
Hispanic	21.39	41	3.65	23.36	42.31	6.31	20.78	40.57	3.23
Asian	26.79	44.28	12.24	27.49	44.65	55.62	25.65	43.67	5.41
Age 18-29	20.67	40.49	2.18	22.88	42.01	2.07	20.31	40.23	2.20
Age 30-39	26.27	44.01	8.89	27.61	44.71	5.45	26.14	43.94	9.47
Age 40-49	25.64	43.66	27.18	28.25	45.02	27.79	25.18	43.41	27.07
Age 50-59	23.54	42.42	37.27	27.74	44.77	40.40	22.76	41.93	36.74
Age 60-70	19.33	39.49	24.49	23.55	42.43	24.29	18.62	38.93	24.52
With a firm	24.93	43.26	90.94	27.89	44.85	94.08	24.41	42.96	90.41
Without a firm	6.48	24.61	9.06	8.79	28.31	5.92	6.23	24.18	9.59
N patenters×year		1,494,618			216,531			1,278,087	
N patenters		221,224			32,120			189,104	
N states		51			51			51	

Note: This table reports sample statistics for immigrant and native-born inventors separately for the 2008 and 2016 elections, spanning 2005-2011 and 2013-2019, respectively. See note to Table 1 for variable definitions.

Table A3: Election Event Study: Democratic vs. 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^2	0.077	0.075
Outcome mean	19.602	22.126
N clusters (zip)	18,561	17,663
Demographics	Y	Y
Zip code FE	Y	Y
Technology Class×event FE	Y	Y

Note: This table reports the coefficients in Figure 2. The table reports estimates from a difference in differences event-study analysis comparing the likelihood that a Democrat inventor submits a patent application relative to a Republican one around the 2008 and 2016 presidential elections. The outcome is an indicator for submitting a patent application, 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 in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table A4: Election Event Study: Democratic vs. 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^2	0.078	0.077
Outcome mean	19.299	22.04
N clusters (zip)	17,988	17,467
Demographics	Y	Y
Zip code FE	Y	Y
Technology Class×Event FE	Y	Y

Note: This table reports the coefficients in Figure 3 panels (a) and (b). The table reports estimates from a difference in differences event-study analysis comparing the likelihood that a Democrat inventor submits a patent application relative to a Republican one around the 2008 and 2016 presidential elections. The outcome is an indicator for submitting a patent application, and units are in percentage points. *Active Dem* is one for politically active Democrats (based on voting history) and zero for others; *Inactive Dem* is one for politically inactive Democrats (based on voting history), and zero for others. 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 in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table A5: Election Event Study: Democratic vs. 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^2	0.077	0.076
Outcome mean	19.602	22.126
N clusters (zip)	18,561	17,663
Demographics	Y	Y
Zip code FE	Y	Y
Technology Class×Event FE	Y	Y

Note: This table reports the coefficients in Figure 3 panels (c) and (d). The table reports estimates from a difference in differences event-study analysis comparing the likelihood that a Democrat inventor submits a patent application relative to a Republican one around the 2008 and 2016 presidential elections. The outcome is an indicator for submitting a patent application, and units are in percentage points. *Active Dem* is one for politically active Democrats (based on FEC donation history) and zero for others; *Inactive Dem* is one for politically inactive Democrats (based on FEC donation history), and zero for others. 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 in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table A6: Election DID analysis: Democratic vs. 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^2	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 clusters (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^2	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 clusters (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
Technology Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: This is a variant of Table 3 where political activeness is measured using FEC donation data. *** 1%, ** 5%, * 10% significance level.

Table A7: 2016 Election DID analysis: Democratic vs. Republican Inventors
Inventor Partisanship from the *2014 Voter Roll*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	P(patent)	P(patent)	P(patent)	P(patent)	P(patent)	P(patent)	P(patent)	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^2	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 clusters (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^2	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 clusters (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
Technology Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: Panels A and B in this table replicate Table 2 panel B and Table A6 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 3 panel B. *** 1%, ** 5%, * 10% significance level.

Table A8: *Within Firm* Election DID analysis: Democratic vs. 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^2	0.197	0.124	0.125	0.124	0.125
Outcome mean	22.024	23.952	23.993	23.873	23.989
N clusters (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^2	0.202	0.120	0.119	0.120	0.121
Outcome mean	23.916	25.028	24.901	24.821	24.685
N clusters (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
Technology Class×Post FE	Y	Y	Y	Y	Y
Firm×Post FE	Y	Y	Y	Y	Y

Note: This is a variant of Table 4 measuring political activeness using FEC donation history rather than voting. *** 1%, ** 5%, * 10% significance level.

Table A9: Election DID analysis: Democratic vs. Republican Inventors
More granular Geography × 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^2	0.051	0.089	0.051	0.087
Outcome mean	19.39	19.39	19.69	19.69
N clusters (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^2	0.049	0.084	0.049	0.083
Outcome mean	22.05	22.04	22.13	22.12
N clusters (zip)	17453	17467	17649	17663
Demographics	Y	Y	Y	Y
County×Post FE	Y	N	Y	N
Zip×Post FE	N	Y	N	Y
Technology Class×Post FE	Y	Y	Y	Y

Note: The table shows the robustness of our main results to using more granular geography × time fixed effects: columns (1) and (2) for Table 3 and columns (3) and (4) for Table A6. Specifications mirror columns (5) and (6) in the two original tables, but replace State × Post fixed effects with County × Post or Zip × Post fixed effects. *** 1%, ** 5%, * 10% significance level.

Table A10: Political Mismatch and the Number of Granted Patents: Democratic versus Republican *Technologies*

	(1)	(2)	(3)	(4)	(5)	(6)
	Median split		Top vs. bottom tercile		Top vs. bottom quartile	
	Grant	Std. grant	Grant	Std. grant	Grant	Std. grant
Dem×Post	41.891***	0.974***	42.071***	0.926**	48.084*	0.796**
	(13.479)	(0.360)	(15.682)	(0.442)	(25.159)	(0.364)
Effect as %mean	18.72	-	17.84	-	19.43	-
Observations	5,040	5,040	3,950	3,950	2,900	2,900
R^2	0.959	0.556	0.958	0.553	0.956	0.575
Outcome mean	223.76	.344	235.79	.412	247.4	.38
N clusters (subclass)	504	504	395	395	290	290
Subclass FE	Y	Y	Y	Y	Y	Y
Technology Class×Post FE	Y	Y	Y	Y	Y	Y

Note: This table shows the robustness of the main result in Figure 8 panels (a) and (b) using differing definitions of Democratic and Republican technology subclasses. The table compares the number of granted patents in Democratic vs. Republican technology subclasses submitted in the years around the 2008 presidential election. Democratic technology subclasses are those whose share of Democrats among all inventors actively patenting in the pre-pre-period (i.e., years 10 through 4 before the 2008 election) exceeds a certain threshold: columns (1)-(2) use sample median, (3)-(4) the 66th percentile, and (5)-(6) the 75th percentile. Only subclasses with at least eight actively patenting patenters before the election are assigned a partisan leaning. The outcome in columns (1), (3), and (5) is the number of eventually granted patents submitted in each subclass each year; the outcome in columns (2), (4), and (6) is the number subtracting the pre-election subclass mean and then dividing by the standard deviation. All regressions control for subclass fixed effects and class-by-year fixed effects. Standard errors in parentheses are clustered by subclass. *** 1%, ** 5%, * 10% significance level.

Table A11: 2016 Election Event Study: Immigrant vs. Native-Born Inventors

VARIABLES	(1) All races	(2) White	(3) Non-white	(4) Asian
Immigrant×-3	0.170	0.103	0.365	0.119
	(0.383)	(0.559)	(0.505)	(0.725)
Immigrant×-2	0.242	0.132	0.128	0.128
	(0.374)	(0.524)	(0.504)	(0.719)
Immigrant×0	0.096	-0.175	0.295	-0.834
	(0.353)	(0.509)	(0.452)	(0.635)
Immigrant×1	-0.374	-0.086	-0.679	-1.190*
	(0.353)	(0.494)	(0.464)	(0.676)
Immigrant×2	-0.642*	-0.641	-0.596	-1.310**
	(0.347)	(0.510)	(0.455)	(0.643)
Immigrant×3	-0.752**	-0.883*	-1.053**	-1.008
	(0.365)	(0.517)	(0.496)	(0.696)
Immigrant	2.078***	2.333***	1.535***	2.117***
	(0.345)	(0.481)	(0.452)	(0.656)
Dem	0.920***	0.865***	0.842**	0.849
	(0.193)	(0.219)	(0.383)	(0.526)
Rep	-0.306	-0.255	-0.901*	-0.963
	(0.194)	(0.212)	(0.473)	(0.665)
Observations	1,338,085	1,049,533	288,552	156,234
R^2	0.112	0.090	0.121	0.125
Outcome mean	23.193	22.749	24.804	26.788
N clusters (zip)	16,774	16,115	7,231	3,900
Zip(×Race) FE	Y	Y	Y	Y
Technology Class(×Race)×Event FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y

Note: This table reports the coefficients in Figure 11. The table reports the annual probability of submitting a patent for immigrant inventors relative to non-immigrant inventors around the 2016 election. Units are in percentage. The sample consists of USPTO inventors who are matched to both L2 and Infutor, and the omitted group is non-immigrant inventors; columns (1)-(4) focus on all, White, non-White, and Asian inventors, respectively. Event time 0 refers to the year of a presidential election. Event time -1 is the omitted period. All regressions also control for fully interacted voter demographic characteristics (gender, education, age groups, race). Standard errors in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table A12: 2008 Election DID analysis: Immigrant vs. Native-Born Inventors

VARIABLES	(1) P(patent)	(2) P(patent)	(3) P(patent)	(4) P(patent)	(5) P(patent)	(6) P(patent)	(7) P(patent)	(8) P(patent)
Immigrant×Post	-0.020	-0.076	0.143	0.105	0.114	0.078	-0.023	-0.055
	(0.241)	(0.241)	(0.240)	(0.241)	(0.241)	(0.242)	(0.241)	(0.242)
Immigrant	3.730***	3.327***	2.954***	2.701***	2.968***	2.715***		
	(0.261)	(0.281)	(0.253)	(0.273)	(0.253)	(0.273)		
Dem	1.295***	1.125***	0.857***	0.738***	0.857***	0.738***		
	(0.179)	(0.193)	(0.176)	(0.190)	(0.176)	(0.190)		
Rep	-1.097***	-1.032***	-0.730***	-0.750***	-0.730***	-0.751***		
	(0.172)	(0.184)	(0.167)	(0.180)	(0.167)	(0.180)		
Effect as %mean	-.1	-.37	.68	.5	.54	.37	-.12	-.27
Observations	1,185,676	1,187,051	1,185,370	1,186,745	1,185,370	1,186,745	1,186,745	1,186,745
R^2	0.040	0.095	0.060	0.111	0.060	0.112	0.486	0.486
Outcome mean	20.889	20.892	20.886	20.889	20.886	20.889	20.889	20.889
N clusters (county)	17,837	17,850	17,837	17,850	17,837	17,850	17,850	17,850
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
Person	N	N	N	N	N	N	Y	Y
County×Race FE	Y	N	Y	N	Y	N	N	N
Zip×Race FE	N	Y	N	Y	N	Y	N	N
State×Race×Post FE	Y	Y	N	N	Y	Y	N	Y
Technology Class×Race×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: This is the 2008 version of Table 7 (which is for 2016). The table reports estimates from a difference in differences (DID) analysis comparing the likelihood that an immigrant inventor applies for a patent relative to a non-immigrant one around the 2008 presidential election. The outcome is an indicator for submitting a patent application, and units are in percentage points. The sample consists of all inventors matched to the voter rolls who are identified as either immigrants or native-born, thus all are US citizens. *Immigrant* is one for immigrant inventors and zero for native-born inventors. *Post* is one for the first through third years after a presidential election. The year of a presidential election (2008) is excluded from the regression. All regressions control for fully interacted voter demographic characteristics (i.e., gender, education, age groups, race). Standard errors in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table A13: 2016 Election DID analysis: Immigrant vs. Native-Born Inventors Controlling for *Party* × *Post*

VARIABLES	(1) P(patent)	(2) P(patent)	(3) P(patent)	(4) P(patent)	(5) P(patent)	(6) P(patent)	(7) P(patent)	(8) P(patent)
Immigrant×Post	-0.832***	-0.871***	-0.649***	-1.213***	-0.626***	-0.681***	-0.785***	-0.910***
	(0.236)	(0.236)	(0.236)	(0.210)	(0.237)	(0.237)	(0.234)	(0.214)
Immigrant	2.824***	2.687***	2.348***	2.514***	2.337***	2.280***		
	(0.278)	(0.300)	(0.270)	(0.264)	(0.270)	(0.293)		
Dem×Post	-0.396**	-0.435**	-0.319*	-0.313*	-0.289	-0.333*	-0.415**	-0.349*
	(0.184)	(0.184)	(0.179)	(0.176)	(0.185)	(0.185)	(0.178)	(0.181)
Dem	1.595***	1.399***	1.291***	1.151***	1.276***	1.154***		
	(0.211)	(0.223)	(0.208)	(0.211)	(0.208)	(0.220)		
Rep×Post	0.257	0.223	0.105	0.171	0.116	0.085	-0.027	-0.035
	(0.181)	(0.181)	(0.174)	(0.172)	(0.182)	(0.182)	(0.174)	(0.180)
Rep	-0.674***	-0.550**	-0.318	-0.386*	-0.324	-0.271		
	(0.213)	(0.225)	(0.208)	(0.214)	(0.209)	(0.221)		
Effect as %mean	-3.59	-3.76	-2.8	-5.23	-2.7	-2.94	-3.39	-3.93
Observations	1,145,144	1,146,557	1,144,667	1,146,080	1,144,667	1,146,080	1,146,080	1,146,080
R^2	0.038	0.093	0.057	0.081	0.057	0.111	0.505	0.505
Outcome mean	23.206	23.201	23.207	23.202	23.207	23.202	23.202	23.202
N clusters (zip)	16,762	16,775	16,761	16,774	16,761	16,774	16,774	16,774
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
Person	N	N	N	N	N	N	Y	Y
County×Race FE	Y	N	Y	N	Y	N	N	N
Zip×Race FE	N	Y	N	Y	N	Y	N	N
State×Race×Post FE	Y	Y	N	N	Y	Y	N	Y
Technology Class×Race×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: The table reports the results of a robustness test for Table 7 by additionally controlling for *Dem* × *Post* and *Rep* × *Post*. All regression samples, specifications, and variable definitions mirror those Table 7. Standard errors in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table A14: 2016 Election DID analysis: Immigrant vs. Native-Born Inventors *by Race* Controlling for *Party* × *Post*

VARIABLES	(1) White	(2) Non-white	(3) Asian	(4) White	(5) Non-white	(6) Asian	(7) White	(8) Non-white	(9) Asian
Immigrant×Post	-0.584*	-0.920***	-1.239***	-0.687**	-0.909***	-1.316***	-0.306	-0.647*	-0.930*
	(0.337)	(0.309)	(0.433)	(0.338)	(0.307)	(0.427)	(0.395)	(0.391)	(0.548)
Immigrant	2.421***	1.799***	2.347***				2.917***	1.687***	1.835***
	(0.388)	(0.400)	(0.576)				(0.441)	(0.461)	(0.623)
Dem×Post	-0.391*	-0.123	0.033	-0.479**	-0.029	0.181	-0.385	0.005	0.099
	(0.208)	(0.334)	(0.463)	(0.214)	(0.350)	(0.476)	(0.248)	(0.429)	(0.563)
Dem	1.153***	0.902**	0.924				1.140***	0.659	0.885
	(0.248)	(0.430)	(0.589)				(0.289)	(0.522)	(0.696)
Rep×Post	0.059	0.216	0.304	-0.113	0.197	0.640	-0.070	0.140	0.042
	(0.192)	(0.413)	(0.574)	(0.201)	(0.430)	(0.622)	(0.236)	(0.539)	(0.724)
Rep	-0.205	-0.875	-0.992				0.070	-1.516**	-0.970
	(0.239)	(0.537)	(0.756)				(0.282)	(0.685)	(0.900)
Effect as %mean	-2.57	-3.71	-4.63	-3.02	-3.67	-4.92	-1.25	-2.46	-3.38
Observations	898,874	247,206	133,865	898,874	247,206	133,865	806,239	225,628	127,035
R^2	0.089	0.120	0.123	0.500	0.518	0.520	0.230	0.277	0.285
Outcome mean	22.762	24.799	26.77	22.762	24.799	26.77	24.579	26.392	27.58
N clusters (zip)	16115	7231	3900	16115	7231	3900	14927	6625	3718
Demographics	Y	Y	Y	Y	Y	Y	Y	Y	Y
Person	N	N	N	Y	Y	Y	N	N	N
Zip FE	Y	Y	Y	N	N	N	Y	Y	Y
State×Post FE	N	N	N	Y	Y	Y	N	N	N
Technology Class×Post FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm×Post	N	N	N	N	N	N	Y	Y	Y

Note: The table reports the results of a robustness test for Table 8 by additionally controlling for *Dem* × *Post* and *Rep* × *Post*. All regression samples, specifications, and variable definitions mirror those Table 8. Standard errors in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table A15: Election DID analysis: Democratic vs. Republican Inventors Controlling for *Immigrant* × *Post*

	(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	0.066	0.080	0.219*	0.230*	0.267**	0.279**	0.293**	0.331**
	(0.130)	(0.130)	(0.133)	(0.133)	(0.131)	(0.131)	(0.134)	(0.132)
Dem	2.442***	2.219***	1.600***	1.517***	1.576***	1.492***		
	(0.147)	(0.154)	(0.145)	(0.152)	(0.145)	(0.152)		
Immigrant×Post	-0.130	-0.166	0.231	0.193	0.109	0.072	0.239	0.122
	(0.254)	(0.254)	(0.258)	(0.258)	(0.256)	(0.256)	(0.262)	(0.259)
Immigrant	3.508***	3.226***	2.783***	2.547***	2.845***	2.609***		
	(0.288)	(0.295)	(0.282)	(0.289)	(0.281)	(0.288)		
Mi immigrant×Post	-0.010	-0.016	0.065	0.057	-0.016	-0.022	0.254*	0.171
	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.137)	(0.138)
Mi immigrant	-3.169***	-3.200***	-3.071***	-3.119***	-3.031***	-3.078***		
	(0.155)	(0.160)	(0.152)	(0.158)	(0.153)	(0.158)		
Effect as %mean	.33	.4	1.11	1.16	1.35	1.41	1.48	1.67
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^2	0.034	0.064	0.050	0.079	0.051	0.079	0.484	0.485
Outcome mean	19.69	19.69	19.69	19.69	19.69	19.69	19.69	19.69
N clusters (zip)	18,549	18,562	18,548	18,561	18,548	18,561	18,561	18,561
Panel B: 2016 election								
Dem×Post	-0.496***	-0.489***	-0.345***	-0.346***	-0.227*	-0.222*	-0.253**	-0.141
	(0.128)	(0.128)	(0.126)	(0.126)	(0.129)	(0.130)	(0.127)	(0.131)
Dem	2.467***	2.101***	1.891***	1.652***	1.834***	1.593***		
	(0.154)	(0.161)	(0.152)	(0.158)	(0.152)	(0.159)		
Immigrant×Post	-1.149***	-1.143***	-0.908***	-0.907***	-0.856***	-0.859***	-0.696***	-0.670***
	(0.253)	(0.253)	(0.252)	(0.252)	(0.253)	(0.253)	(0.255)	(0.256)
Immigrant	2.563***	2.430***	2.205***	2.099***	2.178***	2.074***		
	(0.291)	(0.294)	(0.285)	(0.288)	(0.285)	(0.288)		
Mi immigrant×Post	0.308**	0.341**	0.311**	0.337**	0.317**	0.342***	0.743***	0.739***
	(0.133)	(0.133)	(0.131)	(0.131)	(0.133)	(0.133)	(0.132)	(0.134)
Mi immigrant	-2.895***	-2.962***	-2.797***	-2.869***	-2.800***	-2.872***		
	(0.159)	(0.164)	(0.156)	(0.161)	(0.156)	(0.161)		
Effect as %mean	-2.25	-2.22	-1.56	-1.57	-1.03	-1.01	-1.15	-.64
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^2	0.032	0.060	0.048	0.076	0.048	0.076	0.501	0.501
Outcome mean	22.13	22.12	22.13	22.12	22.13	22.12	22.12	22.12
N clusters (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
Technology Class×Post FE	N	N	Y	Y	Y	Y	Y	Y

Note: The table reports the result of a robustness test for Table 2 by additionally controlling for indicators for immigrant inventor, missing immigrant inventor, and their interactions with *Post*. All regression samples, specifications, and variable definitions mirror those in Table 2. Standard errors in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.

Table A16: 2016 Election DID analysis: Immigrant vs Native-Born Inventors
Patent Citations

VARIABLES	(1) # Citations	(2) # Citations	(3) Scaled #	(4) Scaled #	(5) Normalized #	(6) Normalized #
Panel A: All races						
Immigrant×Post	0.302***	0.284***	0.010	-0.005	0.011	0.009
	(0.106)	(0.104)	(0.076)	(0.075)	(0.012)	(0.011)
Immigrant	-0.209*	-0.203*	-0.066	-0.062	-0.010	-0.009
	(0.109)	(0.110)	(0.043)	(0.043)	(0.010)	(0.010)
Observations	208,874	208,874	208,835	208,835	208,835	208,835
Panel B: White						
Immigrant×Post	0.359***	0.318**	0.086	0.047	0.015	0.013
	(0.135)	(0.132)	(0.120)	(0.118)	(0.018)	(0.017)
Immigrant	-0.225*	-0.218*	-0.046	-0.036	-0.009	-0.009
	(0.132)	(0.132)	(0.050)	(0.050)	(0.012)	(0.012)
Observations	160,179	160,179	160,147	160,147	160,147	160,147
Panel C: Non-white						
Immigrant×Post	0.299*	0.238	-0.038	-0.051	0.013	0.011
	(0.154)	(0.157)	(0.096)	(0.099)	(0.015)	(0.015)
Immigrant	-0.141	-0.118	-0.091	-0.087	-0.011	-0.010
	(0.152)	(0.153)	(0.073)	(0.073)	(0.014)	(0.014)
Observations	48,695	48,695	48,688	48,688	48,688	48,688
Panel D: Asian						
Immigrant×Post	0.311*	0.312*	0.062	0.078	0.023	0.023
	(0.188)	(0.180)	(0.117)	(0.110)	(0.019)	(0.018)
Immigrant	-0.367**	-0.351**	-0.151*	-0.153*	-0.025	-0.025
	(0.165)	(0.171)	(0.079)	(0.078)	(0.016)	(0.016)
Observations	28,619	28,619	28,613	28,613	28,613	28,613
Demographics	Y	Y	Y	Y	Y	Y
Zip×Race FE	Y	Y	Y	Y	Y	Y
Technology Class×Race×Post FE	Y	Y	Y	Y	Y	Y
State×Race×Post FE	N	Y	N	Y	N	Y

Note: The table reports estimates from difference in differences (DID) analyses comparing the number of patent citations to immigrant vs and non-immigrant inventors' patents around the 2008 and 2016 presidential elections. The outcomes in columns (1)-(2), columns (3)-(4), and columns (5)-(6) are, respectively, (i) an inventor's average number of citations across the patents they submitted in each year (# Citations), (ii) the average number divided by the technology class and grant year mean (Scaled), and (iii) the average number after subtracting the mean and dividing by the standard deviation of the technology class and grant year (Normalized). *Immigrant* is an indicator for immigrant patenters. *Post* is one for the first through third years after a presidential election. 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 in parentheses are clustered by zip code. *** 1%, ** 5%, * 10% significance level.