When Working From Home Matters

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Abstract

This paper investigates how the large increase in remote work that began during the COVID-19 pandemic impacted corporate innovation. Utilizing within firm variation, I find that after the start of the pandemic, offices located in counties with high support for Donald Trump have higher visit rates to the office. Using this variation in local political attitudes as an instrument for visits to the office, I find that increased visits to the office raise novel patenting productivity for R&D intensive firms. I find that visiting the office increases novel patenting productivity exclusively when inventor teams are geographically distributed or large, suggesting there exists complementarity between in-person interactions and having a large, remote network of collaborators. Visiting the office does not disproportionately generate novel patents with new collaborators.

Keywords: Work From Home, Innovation, Corporate R&D, Productivity, COVID-19 Pandemic

JEL: O31, O32, J40

1 Introduction

In light of the five-fold increase (Barrero et al. 2023) in work-from-home (WFH) prevalence from 2019-2023, brought about by the COVID-19 pandemic, the question of how WFH affects employee productivity is particularly salient. Despite the importance of this issue we have surprisingly little empirical evidence about how WFH impacts the productivity of a particularly important subset of workers, innovation workers. This lack of certainty about how WFH impacts knowledge workers is evidenced by the divergent WFH policies that innovative firms have adopted (*The Official List of Every Company's Back-to-Office Strategy* 2025).

This paper fills this gap in our knowledge by providing an empirical examination of how WFH impacted the productivity of corporate inventors. Indeed, an empirical examination of this question is particularly important as there are valid theoretical arguments on both sides of the question. In favor of a positive causal relationship between WFH and innovative productivity, are the arguments that solitary tasks can be performed more efficiently (Aczel et al. 2021) while collaborative work can take place through video-conferencing software (Bathelt et al. 2004). Further, engaging in remote collaboration allows inventors to access a broader pool of expertise, which is particularly important in the process of creating novel ideas (Clancy 2022; Frey and Presidente 2022; Esposito 2023). On the other hand, there is a literature which argues that WFH damages innovative productivity on the grounds that in-person interactions are crucial for the transmission and circulation of knowledge required for invention (Wouden 2020; Lin et al. 2023; Atkin et al. 2022; Duede et al. 2024; Andrews 2023; Andrews and Lensing 2023; Roche 2020).

To empirically distinguish between these two stories for U.S. corporate innovation, I utilize a dataset documenting the number of cell phones which enter corporate offices and then match inventors and patents to these offices. While prior literature on WFH and innovation often examines one firm (Yang et al. 2022), the offices in my sample come from a wide variety of innovative industries and account for approximately 20% of U.S. patenting activity. Relative to the existing literature, this both increases the external validity of my results and allows me to examine factors which moderate the effect of visiting the office on innovation.

A potential reason there has been a dearth of literature on how WFH impacts innovative productivity is the difficulty in measuring the output of knowledge workers. Indeed, the output of knowledge workers is often intangible and hard to normalize across tasks and projects. My empirical setting addresses these issues by utilizing patents, which provides a standardized and comparable measure of the output generated by inventors.

Another roadblock to identifying the effect of WFH on the productivity of knowledge workers for a broad sample of innovative companies is finding plausibly exogenous variation in WFH across disparate firms. I utilize the unexpected arrival of the COVID-19 pandemic, combined with within-firm variation in the local political attitudes of corporate R&D offices to identify the effect of WFH. Offices belonging to the same firm but located in more politically conservative counties experienced increased levels of visits to the office through 2021, relative to offices belonging to the same firm but located in more politically liberal counties. Specifically, I find that a one standard deviation increase in the 2016 Donald Trump vote share led to a persistent $\approx$20% increase in visits through 2021.

Using this plausibly exogenous within-firm variation in visits to the office, I examine how office visits impact the novel patenting productivity of inventors. I find that for R&D intensive firms, increased visits to the office cause substantial increases in novel patenting productivity. Specifically, I find that a 10% increase in visits to the office leads to a 14% increase in novel patenting productivity off of mean levels.

Another advantage of utilizing patent data is that it allows me to examine characteristics of the team who created the patent as all inventors on the patent are identified and geolocated. This useful feature of patents allows me to examine what team characteristics are associated with the novel patents created by office visits. Guided by theoretical considerations regarding the mechanisms of how in-person interactions affect innovative productivity, I test whether the patents generated by increased office visits are disproportionately created by geographically remote or co-located teams. I find that the teams generating novel patents from office visits are geographically remote, and I also find that they tend to be large teams. These results suggest that there are complementarities between an inventor visiting the office and having a large and geographically dispersed network. This finding aligns with the increasing burden of knowledge placed on inventors (Jones 2009) and the need for inventors to recombine knowledge with a diverse set of expertise to create novel inventions (Clancy 2022). Finally, I examine whether increased visits to the office primarily produces novel patents which are created by teams with a new collaboration or teams where all existing team members have worked together before. I do not find evidence that the effect of visiting the office is stronger for either subset of novel patenting, suggesting that new collaboration is not the mechanism causing an increase in novel patenting. These findings are consistent with the idea that inventors have already exhausted the relationships afforded by their workplace, leaving little chance that in-person interaction would generate a new collaborative relationship.

2 Theory and Literature Review

While this study's main contribution is an empirical examination of WFH and innovative productivity, there is an extensive literature which seeks to understand how the geography of innovation and, more specifically, how in-person interactions affect innovation. A wide variety of studies have documented that innovations tend to disproportionately originate from densely populated areas (Carlino et al. 2007; Mewes 2019; Balland et al. 2020; Grashof et al. 2021; Berkes and Gaetani 2021; De Noni and Belussi 2021; Baum-Snow et al. 2024). While this stylized fact suggests that in-person interactions are important in driving innovation, there has been a three-fold increase in the distance between patent collaborators from 1990-2015, suggesting that in-person collaboration may be declining in importance for innovation (Wouden 2020). As such, the literature has taken an interest in identifying the specific impacts of in-person interaction on innovation.

One benefit of in-person interaction is that it effectively creates knowledge flows for researchers. Duede et al. 2024 survey academic researchers and ask about the influence of each citation a researcher makes on a project. They find that co-location is important for generating influential citations and that this "influence premium" of others' work is greater if the work a focal researcher is citing is more distant from the focal researcher's paper. The results indicate that co-location is important for exploratory search as researchers disproportionately find influential prior work from co-located researchers. Wouden and Youn 2023 also find evidence suggesting that local collaboration allows a researcher to gain expertise in a new field. Specifically, they show that academic researchers are more likely to solo author a publication in a new sub-discipline after they publish a paper with a local coauthor relative to a remote coauthor. Atkin et al. 2022 examine the effect of in-person meetings for corporate inventors and find that an increase in in-person meetings between inventors at different establishments in Silicon Valley increases the patent citations between establishments. This suggests that in-person meetings create knowledge flows between firms. Taken together, these studies provide evidence that in-person interaction is important for the transmission of unfamiliar knowledge and for engaging in exploratory search.

The recombinant view of innovation posits that novel innovation mainly comes from new combinations of previously known components (Fleming 2001). As discussed previously, in-person interactions allow researchers to learn about unfamiliar components (Atkin et al. 2022; Wouden and Youn 2023; Duede et al. 2024), giving researchers a more diverse pool of components to draw on when engaging in the innovative search process. Having access to a large and diverse set of components increases the likelihood that an inventor will be able to generate a novel innovation (Nieto and Santamaría 2007; Mewes 2019; Balland et al. 2020; Berkes and Gaetani 2021; Abbasiharofteh et al. 2023). Therefore, in-person interactions should foster novel innovation. The literature has found significant support for this hypothesis with Wouden 2020 showing that from 1836-1975, US inventive teams are more likely to produce a complex patent if the team is co-located. Lin et al. 2023 find similar results in the contemporary period of 1975-2020, showing that disruptive patents are more likely to come from co-located inventor teams. Similarly, several studies have identified a link between the density of urban areas and the novelty of patenting activity (Balland et al. 2020; Berkes and Gaetani 2021) with Mewes 2019 highlighting that novel patenting is concentrated in geographies with diverse local knowledge stocks. Since population density does not directly capture in-person interactions or collaborations, several studies have worked to explore the mechanisms underlying the relationship between density and novel invention. Andrews 2023 and Andrews and Lensing 2023 respectively show that bars and coffee shops increase patenting activity while Roche 2020 finds an effect of sidewalk density on invention.

These studies highlight how in-person socialization is an important mechanism through which density impacts innovation. As inventors socialize they are likely to share disparate ideas which can be recombined into novel invention, with this socialization more likely to take place in dense urban areas.

But several studies have provided evidence showing that remote collaboration can also be effective in generating novel innovation, especially with the advent of modern communication technologies. Frey and Presidente 2022 find that for a given academic team, remote collaboration increases the likelihood that a team will publish a breakthrough paper during the 2000-2015 time period. Esposito 2023 finds that from 1975-2000, novel patents created in major metropolitan areas with a large breadth of patenting activity are more impactful if they are created by multi-location teams relative to single-location teams. As the knowledge frontier pushes out, the heavier burden of knowledge increases the returns to collaborating with other innovators who have expertise in diverse domains (Jones 2009). Simultaneously, the advent of modern collaboration technologies (e.g. video-conferencing software) lowers the cost of remote collaboration (Bathelt et al. 2004). The need for varied expertise, combined with the lower cost of getting that collaboration from non-local collaborators, makes remote collaboration an increasingly important factor in generating novel innovation. This is particularly true in light of the findings from Duede et al. 2024 and Wouden and Youn 2023 who show that a researcher is more likely to learn about new ideas locally. This suggests that geographically distributed teams may be able to generate more novel ideas as each member of the team can gain new ideas from their local geography and then those ideas can be recombined through virtual collaboration (Clancy 2022).

The COVID-19 pandemic created a situation where many inventors were exogenously forced to WFH. This could have several effects on the ability of inventors to produce novel innovation. First, since in-person interactions help inventors to learn about unfamiliar knowledge and explore new ideas, we would expect that WFH would decrease novel innovation. On the other hand, the literature highlights the importance of diversity in team knowledge for creating novel innovations. If WFH causes inventors to substitute away from their former in-person collaborators and towards new and distant collaborators, then WFH may lead to increased production of novel ideas as inventors recombine new ideas from distant collaborators. On the other hand, an exogenous shift to WFH may not change an inventor's collaborators. In support of this idea, several studies have shown that in-person introductions are critical for forming new working relationships, suggesting that WFH may lead to fewer new collaborative relationships (Freeman et al. 2014; Boudreau et al. 2017; Campos et al. 2017; Catalini 2018). If increased WFH either does not affect the collaboration network of an inventor, or if it serves to decrease the number of new connections formed, then the negative effects of WFH are likely to overwhelm any positive effects.

3 Empirical Strategy

With the guidance of prior work, this study seeks to abductively explore how WFH during the COVID-19 pandemic impacted the productivity of corporate offices in producing novel patents. To explore the mechanisms through which WFH may impact innovative productivity, I then examine if WFH changed who inventors collaborate with to create these novel patents.

To explore these questions, I require plausibly exogenous variation in the tendency of an office to engage in WFH activity as endogenous changes in WFH activity are likely correlated with many other confounding factors within a given office. For example, offices with larger declines in visits following the pandemic may be offices that needed to layoff more of their workforce in response to declining demand. Thus, declining visits to the office may not reflect more remote work, but less employment at the office. This is likely to bias the estimate upwards as decreasing office visits may be associated with less patenting due to a smaller workforce, even though remote working intensity has not increased. Further, there is endogenous selection into working from home. Offices that have a low cost to transitioning their workforce to remote work are likely to move more workers to remote work. This would bias the coefficient downward as firms who could successfully navigate remote work would have a negative relationship between visits to the office and novel patent applications.

To address these issues of endogeneity, I adopt a two-stage least squares (2SLS) estimation procedure where I utilize the political climate of an office's geographic location to generate plausibly exogenous variation in the propensity of workers to engage in remote work. The approach uses the fact that those who voted for Donald Trump in 2016 were less cautious about the pandemic and more likely to return to the office. Also, governments in localities with higher Trump support generally had more relaxed approaches to pandemic related restrictions, lowering the burdens of going to the office.

Equation (1) shows the first-stage of my 2SLS strategy where the dependent variable is the inverse hyberbolic sine (IHS) of the number of visits made to office o, belonging to firm f, located in country c, in year t. The IHS transformation approximates a log transformation, but allows for the presence of zeros in the data, which is useful since offices can have zero visits in a given time frame[1]. Trump_c measures the share of the 2016 presidential election vote that went to Donald Trump in the county of the office. I standardize this variable to have mean zero and standard deviation of one for ease of interpretation. $\mathbb{1}\{\text{Post}_t\}$ captures the timing of the COVID-19 pandemic and is an indicator variable that is one in 2020 and 2021[2] and zero otherwise. The coefficient ψ captures the average change in the IHS of visits for offices in counties with one standard deviation higher Trump vote share after the start of the pandemic relative to before.

$$\text{ihs}(\text{Visits}_{ofct}) = \psi(\text{Trump}_c \times \mathbb{1}\{\text{Post}_t\}) + \pi_o + \tau_{ft} + X_{ct} + \upsilon_{ofct} \tag{1}$$

$$\text{Y}_{ofct} = \beta * \widehat{\text{ihs}(\text{Visits}_{ofct})} + \phi_o + \delta_{ft} + X_{ct} + \varepsilon_{ofct} \tag{2}$$

π_o are office fixed effects that remove time-invariant office heterogeneity. τ_{ft} is a set of firm $\times$ year fixed effects. This flexibly controls for common shocks faced by offices of the same firm and forces identification to come from comparing offices in low Trump vote share counties to other offices within the same firm but located in higher Trump vote share counties. For example, the identification strategy compares the Intel office in Maricopa County, AZ (Phoenix) which had a 2016 Trump vote share of 0.48 with the Intel office located in San Francisco County, CA where the Trump vote share was only 0.09. X_{ct} is a vector of controls

[1] No offices have zero visits in a given year, but there are some offices which have zero visits in a given month.

[2] In analyses that are at the office $\times$ month level, the post indicator is one from March 2020-December 2021 and zero otherwise.

that contains the share of individuals reporting poor or fair health in 2016. Data on self reported health is taken from the 2016 Behavioral Risk Factor Surveillance System provided by the County Health Rankings & Roadmap (*National data & documentation* 2025). The share of individuals reporting poor or fair health addresses the issue that workers in counties with poorer health may have suffered more severely from COVID, causing them to have lower productivity in their work. I also control for the monthly unemployment rate in the county. The predicted IHS of visits is then used in the second stage where, β, captures the effect of a percent change in visits on innovative outcome Y. As in the first stage, office and firm $\times$ year fixed effects are included.

My primary innovative outcome is the number of novel patents applied for by an office during a given time frame, scaled by the number of inventors who are located at the office. Scaling the number of novel patent applications by the number of inventors at the office effectively holds innovative labor input constant. This allows me to interpret the regression results as the effect of visiting the office on novel patenting productivity. Further, given that novel patenting is a relatively infrequent occurence, there are many office $\times$ year observations which have no novel patent applications. Scaling novel patenting activity by the number of inventors allow observations with zeros to be retained in the data without the issues that result from using an IHS transformation when there are a significant number of zeros present (Bellemare and Wichman 2020; Aihounton and Henningsen 2021).

To identify the effect of more employees working from home on the novel patenting productivity of offices, several conditions must be met. First, after the start of the pandemic, the Trump vote share of a county must be highly predictive of the change in visits to the office. Later, I will show that there is a strong relationship between the instrument and visits to offices. Second, any changes in the trend of novel patenting activity that occurred after the start of the pandemic for offices in the same firm but in counties with differing Trump vote share must only be attributable to the change in visits to the office. The inclusion of firm $\times$ year fixed effects significantly limits the scope of concerns that the exclusion restriction is violated by removing between firm heterogeneity and effectively making all comparisons within a firm. Finally, in the absence of the pandemic, the novel patenting and visiting activity of offices in high and low Trump counties within the same firm should have evolved similarly. I provide evidence that this is the case by looking for pre-trends in an event study framework.

4 Data

4.1 SafeGraph Data

My first data source comes from the SafeGraph Patterns data product (*Weekly Patterns | SafeGraph Docs* 2025). SafeGraph uses a panel of approximately 20 million cellular devices to provide data on the number of daily visits to approximately 4.5 million points of interest (POI) in the United States. SafeGraph assigns each POI a six-digit North American Industry Classification System (NAICS) code along with a NAICS code description. Using the NAICS codes and their descriptions, I manually looked for descriptions that would indicate the presence of corporate offices or research activity, and I identified NAICS code 551114, "Corporate, Subsidiary, and Regional Managing Offices," as meeting the criteria. Each POI with NAICS code 551114 has information on the company associated with the POI, the latitude and longitude of its location, its address, and the number of visits per day from January 2019-December 2021. I refer to these POIs as offices. In the original data there are 8,597 unique offices that belong to 392 companies. Some offices have very little activity. To remove these offices from my data, I require that an office must have at least 520[3] visits in the pre-pandemic period (2018-2019). In the end, there are 1,675 offices belonging to 203 different firms in the sample.

To check the coverage of the SafeGraph data, I examined the offices of three high-technology companies: Lam Research, Raytheon Technologies, and Boston Scientific.[4] These companies were chosen because they are highly innovative firms in distinct industries with activity distributed across many locations. The website of Lam Research (*Locations* 2025) lists 34 locations under their "United States Offices." The SafeGraph data covers 27 of these offices, with 24 of these offices having non-zero visits in the 2019-2021 time period. One likely

[3]520 visits corresponds to having at least one visit per work day over the two pre-pandemic years.

[4]Lam Research is a high-technology company that designs and manufacturers semiconductor fabrication machinery. Raytheon Technologies operates in aerospace and defense industry. Boston Scientific is a medical device manufacturer.

reason why coverage is not perfect is that several of these offices belong to multi-location campuses, potentially making them difficult to distinguish. On their website, Lam Research has 11 offices located close to one another near their headquarters (HQ) in Fremont, CA. The SafeGraph data covers the HQ location and 7 of the other Fremont, CA offices, but doesn't have perfect coverage of all the Fremont, CA offices. In addition, SafeGraph covers seven of Raytheon's nine U.S. locations and all seven of Boston Scientific's U.S. locations. Overall, this examination suggests that for the companies present in my data, SafeGraph provides good coverage of their offices.

4.2 USPTO Patent Applications

I collect data on patent applications from the USPTO PatentViews database. My analysis includes all patent applications with dates of publication from January 4, 2018 through March 28, 2024. From this data, I am able to identify the date of application and publication, the name(s) of all assignees and inventors, as well as the latitude and longitude of each inventor $\times$ patent application observation. Locations are based on the residence of the inventor and are identified by city, state (if in the United States), and country. I only retain patent application $\times$ inventor observations where the inventor resides in the U.S.

It is important to note several relevant features of these data. First, these data are for patent applications and not granted patents. Patent applications must go through a lengthy review process before the patent application is either approved or rejected. In the economics literature it is standard to only consider patent applications which are ultimately granted since the rejection or abandonment of an application signals that the innovation is of low-quality and may even infringe on prior art. Although I cannot use patent applications that are ultimately granted since it often takes several years to observe the decision whether to grant, I find that 71% of all patent applications published in 2015 had been granted by 2022. Given the high grant rate and the desire to complete the analysis in a timely fashion, I use patent applications without conditioning on a patent's grant decision (Bloom et al. 2021).

Another consideration is that for all patent applications there is a lag between when the application is filed with the USPTO and when the patent application is published and thus made available to be included in my data. Figure A.1 uses all patent applications made in

2015 and displays the share of patent applications that have been published as a function of the lag between the patent's application date and date that the patent application was published. One year after the application date, 54% of the applications have been published. There is a discrete jump at 18 months so that 76% of applications have been published 18 months after application. Two years after application, 92% of applications have been published. My time period of analysis is January 2018-December 2021. All observations have had at least two years since the observation date and March 2024 my patent publication data ends. Given that 92% of applications filed in 2015 were published within two years, there has been enough time that most patent applications in my data should be published and thus accounted for.

4.3 Novel Patents

Given that the prior literature identifies in-person work as effecting novel innovative activity most, I create a measure of novelty for each patent application. My measure of novelty is inspired by the recombinant view of innovation, which views innovations as the product of new combinations of components (Fleming 2001; Strumsky and Lobo 2015). I operationalize this view of novel innovation by identifying whether each combination of International Patent Classification (IPC) groups belonging to a patent has ever[5] been used before (Verhoeven et al. 2016; Pezzoni et al. 2022). I then follow Verhoeven et al. 2016 and identify a patent as novel if the patent contains a combination of IPC groups which have never been used before. In addition, any patent that introduces a new IPC group is considered novel, regardless of if the patent has one or multiple IPC groups.

4.4 Assigning Patents to SafeGraph Offices

In order to match patent applications with SafeGraph offices, I use the list of 392 SafeGraph firm names and manually look for all patent assignee names that correspond with the SafeGraph firm names. I research the existence of subsidiaries when relevant to ensure that

[5]Given that USPTO patent application data dates back to the implementation of the American Inventors Protection Act in November 2000, I am assessing whether the IPC group combination has ever been used in a patent application that was made after 2000.

I match all relevant patent assignees to the SafeGraph firms. Manual matching is desirable for several reasons. First, there are instances where the SafeGraph firm names are abbreviated. For example, "Advanced Micro Devices" is abbreviated to "AMD." Without manual inspection, these matches would be missed. Further, sometimes the company name denotes a parent company with many subsidiaries. For example, the SafeGraph firm name, "Altria Group," includes the cigarette manufacturer, "Philip Morris."

For every patent in my sample, I check to see if the assignee matches with a SafeGraph firm. For every patent × inventor observation that matches with a SafeGraph firm, I then find the office within the firm that is closest to the inventor's residence. I consider a patent × inventor observation to match to an office if the distance between the inventor and the office is less than 50 miles. This distance is used as an upper bound on the ability of an inventor to sustainably commute to the office. Each inventor × patent application observation is assigned $\frac{1}{N}$ patents where N is the number of inventors on the patent (including those who do not match to a SafeGraph office). Each SafeGraph office is then assigned the total number of patents its inventors applies for on a given day.

During my period of analysis (2018-2021), the patent applications of the offices in my sample accounted for 17.6% of all USPTO patent applications with assignees, indicating that the offices in my sample are responsible for a sizeable share of innovative activity in the U.S. Table A.1 displays statistics for the twenty firms who applied for the greatest number of novel patents in the pre-pandemic time period. Each of these firms has multiple innovative offices, creating significant variation in the 2016 Trump vote share within each firm. Among the top twenty patenting firms, the standard deviation in the Trump vote share across offices ranges between 0.08 and 0.24. My identification strategy will leverage this within firm variation in the Trump vote share to generate plausibly exogenous changes in visits to the office. Figure A.2 displays the distribution of 2016 Trump vote shares across counties with darker shades of red (blue) indicating higher (lower) Trump vote shares and transparent gold diamonds indicating the presence of an office. Although innovative activity is generally located in coastal metropolitan areas with low Trump vote share, there is still significant variation in Trump vote share across offices.

4.5 Inventor Productivity

To measure the productivity of offices in generating novel patents, I normalize novel patenting activity of the office by the number of inventors located at each office. To do this, I use data on all USPTO patent applications from 2015-2021, along with the accompanying USPTO PatentViews inventor disambiguation. Similar to the method described in Section 4.4, I locate each inventor × patent application observation at all[6] offices belonging to the assignee on the patent which are within 50 miles of the inventor's residential address. I assume that an inventor stays at their assigned office unless I observe an inventor switch to another office in the SafeGraph data or if the inventor applies for a patent with an assignee that is not captured in the SafeGraph data. As shown by Ge et al. 2016, using patent data to measure inventor mobility can result in recording moves when the inventor was part of contract R&D, a collaboration, a merger or acquisition, or a company name change. To limit these misclassifications, I follow Melero et al. 2020 and do not consider a genuine move to have occurred when an inventor moves back to their prior office within one year of the potential move. I also do not consider moves that are the result of patent applications made within 31 days of a prior patent. This is because patents applied for so quickly after a prior patent are likely related to the same project and may reflect a collaborative component of one project that has been split into multiple patents across multiple firms. Once an inventor has been identified as moving to a new office, I date the move to the midpoint of the application date between the two patents. Using the location of inventors from 2015-2021, I then construct a count of the number of inventors present at each office in my sample.

4.6 Summary Statistics

Table 1 displays summary statistics on the data where observations are at the office × year level. The average office × year observation has approximately 640 inventors, with the distribution being skewed towards larger counts of inventors as the median number of inventors is 72. On average, offices produce an annual number of about four patents per 100 inventors with roughly 5% of those patents being novel. While the offices in the sample are

[6] In the infrequent case where an inventor is located within 50 miles of multiple offices belonging to the assignee firm, I assign the inventor to all the offices in the 50 mile radius.

generally located in counties with low support for Donald Trump in the 2016 election, the standard deviation indicates that there is variation in the support for Trump. R&D spending in 2018 is captured at the firm level and indicates that the offices in the sample generally belong to innovative firms, with the average[7] firm spending 7% of their annual revenue on R&D. Despite this high average spending, nearly 20% of firm $\times$ office observations belong to a firm who is recorded as having spent nothing on R&D in 2018.

Table 1: Summary Statistics

	Mean	Median	St. Dev.	Min	Max	N
Inventors	640.97	72	2,042.38	1	35,586	6,700
$\frac{\text{Patents}}{\text{Inventors}} \times 100$	3.96	2.38	5.54	0	33.33	6,700
$\frac{\text{Novel Patents}}{\text{Inventors}} \times 100$	0.17	0	0.59	0	4.17	6,700
Trump Vote Share	0.38	0.38	0.16	0.04	0.88	6,700
R&D to Sales (2018)	0.07	0.04	0.08	0	0.33	6,700
Visits	5,427.46	2,655	10,567.36	3	278,028	6,700

Notes: This table presents summary statistics on the office $\times$ year observations in my sample.

5 Results

5.1 First Stage

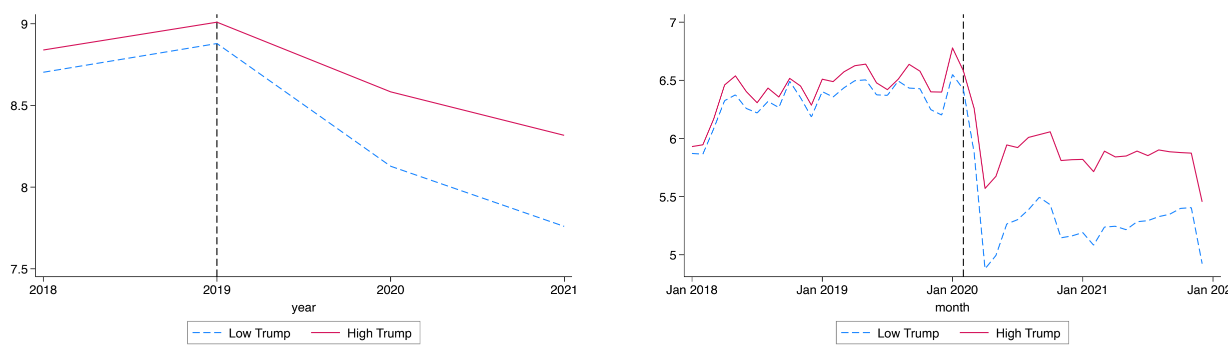
As a first examination of whether the political attitudes of a county impact the number of individuals going to the office, I start by simply dividing counties into those that have above median vote share for Donald Trump in the 2016 election (high Trump) and those that have below median vote share for Donald Trump (low Trump).[8] Panel (a) of Figure 1 plots the natural log of the mean number of visits in each year across the offices, split into the high and low Trump vote share groups. From 2018-2019 the gap between high and low Trump offices

[7]Since R&D spending is captured at the firm level, the R&D spending metrics are weighted average spending amounts with the weights corresponding to the number of offices the firm has in the data

[8]The median is determined from the distribution of vote shares across the offices in my sample.

held steady as visits to the office increased for both groups. Then from 2019-2020 visits to the office feel significantly for both high and low Trump offices, but visits fell more for offices in low Trump counties where they fell about 70 log points relative to the 50 log point reduction for high Trump offices. Panel (b) of Figure 1 more starkly shows the abrupt timing of the COVID-19 pandemic by plotting the series at a monthly frequency. Immediately after the start of the COVID-19 pandemic in February 2020, offices in both high and low Trump counties experienced a substantial decline in the number of visits to the office but offices in high Trump counties experienced smaller declines. Both panels of Figure 1 also reveal that the decline in office visits that happened at the start of the pandemic is quite persistent from April 2020-December 2021, even after the pandemic restrictions ended.

Figure 1: Office Visits Over Time by Trump Vote Share

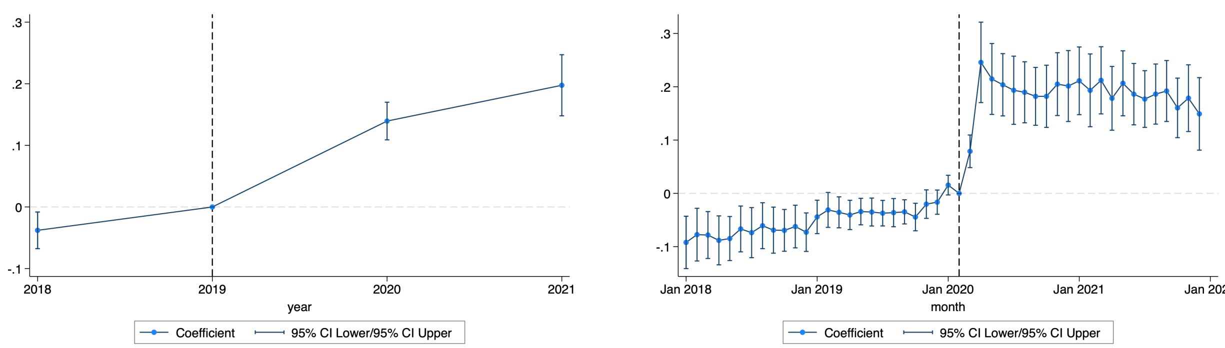


(a) Annual (b) Monthly

Notes: This figure presents the natural log of the average number of visits per month across offices, split by whether the office is above (high Trump) or below (low Trump) the median Trump vote share across counties where the offices are located. Panel (a) presents the series at an annual level while Panel (b) presents the series at a monthly level.

To formally explore dynamics in the effect, I run event study specifications where I augment Equation (1) by replacing the post indicator with year dummies, omitting the year of 2019. Panel (a) of Figure 2 displays the coefficients and 95% confidence intervals from the estimation. In 2018, the coefficient is small and negative and then jumps to be large and positive in 2020 indicating a sharp positive increase in the visits gap between high and low Trump offices. Panel (b) of Figure 2 more clearly illustrates that the effect aligns with the timing of the pandemic as it shows the results from running an event study specification where the post indicator in Equation (1) is replaced by month dummies with February 2020 serving as the omitted category. Before the start of the COVID-19 pandemic, the coefficients are close to zero, indicating that there is no trend in the gap in visiting activity between offices in counties with high and low Trump vote shares before March 2020. The results indicate that the positive effect of Trump support on visits to the office is not driven by confounding pre-trends. In March 2020, there is a sharp and statistically significant increase in the coefficient. The event study coefficient increases again in April 2020 before plateauing at a stable level from July 2020-December 2021. The stability of the coefficients through December 2021 indicates that offices in Trump counties had persistently higher visits through the entire time period. Specifically, a one standard deviation increase in Trump vote share is associated with a 15-20% increase in visits to the office in the April 2020-December 2021 time period.

Figure 2: First Stage (Event Study)



(a) Annual (b) Monthly

Notes: The dependent variable is the inverse hyperbolic sine of visits. Panel (a) of this figure present results from estimating versions of Equation (1) where the post dummy is replaced by year dummies with the 2019 dummy being the omitted category. Office and firm × year fixed effects are included. Panel (b) of this figure present results from estimating versions of Equation (1) where the post dummy is replaced by month dummies with the February 2020 dummy being the omitted category. Standard errors are clustered at the county level with 95% confidence intervals shown.

5.2 Novel Patenting Productivity

I start by examining the endogenous relationship between increased working from the office and novel patenting productivity by estimating a version of Equation (2) where the IHS of visits is not predicted by Equation (1), but is instead left as its endogenous value.

The results are presented in column (1) of Table 2, which shows a statistically insignificant relationship between visiting activity at the office and novel patenting productivity. Given the issues discussed earlier with interpreting the results in column (1) as a casual relationship, I move on to estimating my 2SLS strategy. Column (2) displays the first stage relationship between the 2016 Trump vote share and the IHS of visits to the office. The results show a strong positive relationship between the political attitudes of a county and within-firm variation in office visiting activity. A one standard deviation increase in the Trump vote share leads to approximately 20% more visits to the office, consistent with the findings of Figure 2. Further, the F-statistic is ≈ 88, ruling out weak instruments. Column (3) shows the second stage results which corroborate the findings of the OLS estimation in column (1) with a positive, yet statistically indistinguishable from zero, point estimate. In column (4), controls are included, lowering the coefficient.

Figure 3 displays the point estimates from an event study specification where the post dummy in Equation (1) is replaced with year dummies, where 2019 is the omitted year, and the dependent variable is novel patents per hundred inventors. Figure 3 shows no evidence of a pre-trending relationship between Trump vote share and novel patenting productivity before the start of the pandemic. After the pandemic starts, the coefficients begin a positive trend but the 95% confidence intervals overlap with zero. Although the positive coefficients in Table 2 and Figure 3 are suggestive of a positive effect average effect of visiting the office on novel patenting productivity, the results are ultimately inconclusive due to the lack of precision in the estimates.

While there is no discernible average effect of working from the office on novel patenting productivity, these results may hide that fact that the relationship between visiting the office and novel patenting productivity may be more sensitive for R&D intensive firms who rely on innovation. For firms where R&D is not an important priority, there may be little relationship between visiting the office and novel patenting productivity as the innovations conducted at these firms may be relatively infrequent and routine. This could attenuate estimates in the entire sample to zero. While the sample is restricted to offices that have a positive number of inventors at the office in each year between 2018-2021, there is significant variation in firms' R&D intensity with approximately 20% of firms having zero R&D spending in 2018, while

Table 2: Novel Patenting Productivity and Office Visiting Activity

	OLS		2SLS	
	$\frac{\text{Novel Patents}}{\text{Inventors}} \times 100$	ihs(Visits)	$\frac{\text{Novel Patents}}{\text{Inventors}} \times 100$	
	(1)	(2)	(3)	(4)
ihs(Visits)	0.022		0.072	0.049
	(0.014)		(0.074)	(0.083)
Trump Vote Share × Post		0.187***		
		(0.020)		
Health × Post				-0.050
				(0.598)
Unemp Rate				-0.008
				(0.010)
$\overline{\text{Y}}$	0.17		0.17	0.17
F-statistic		87.90	87.90	66.79
# Clusters	415	415	415	415
Observations	6,488	6,488	6,488	6,488

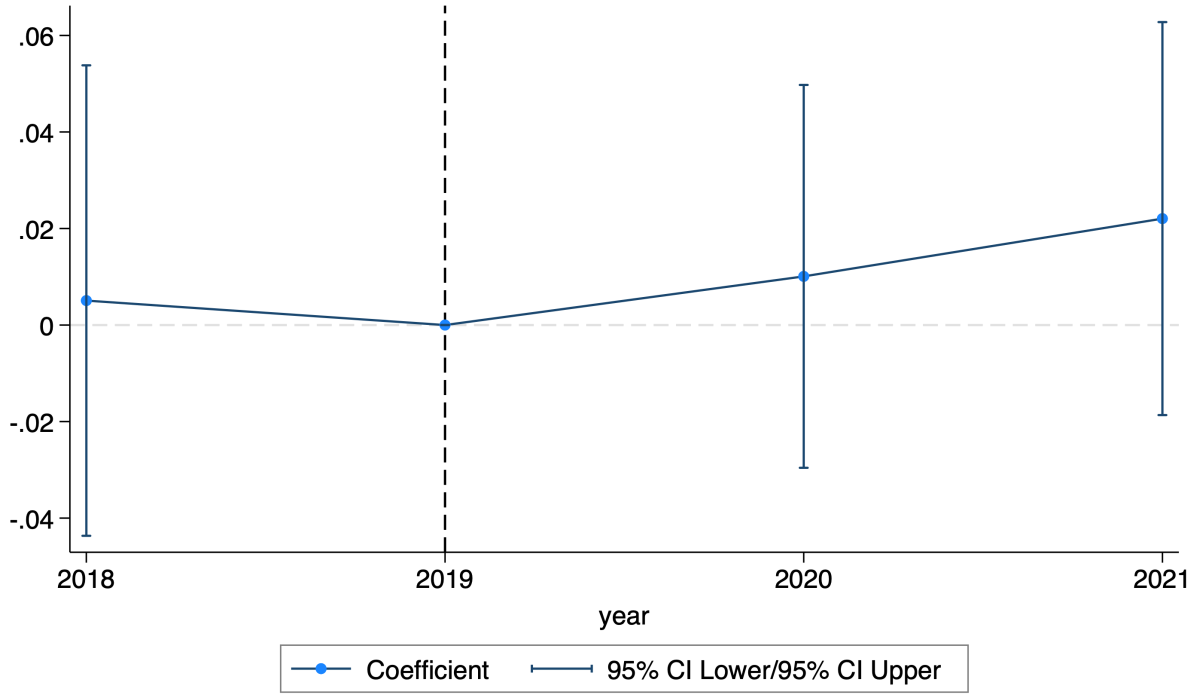
Notes: Column (1) presents results from estimating Equation (2) via OLS. Column (2) presents results from estimating Equation (1) via OLS. Columns (3) and (4) presents results from estimating Equation (2) via 2SLS. Across all columns, the sample includes all office × year observations in the sample. In columns (1), (3), and (4), the dependent variable is the number of novel patents applied for during the year, scaled by hundred inventors at the office. Standard errors are clustered at the county level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

the firm with the highest R&D intensity spent 33% of their 2018 revenue on R&D.

To examine whether R&D intensive firms display a stronger relationship between office visiting activity and novel patenting productivity, I split the sample at the median level of the 2018 R&D to sales ratio[9] and estimate Equation (2) separately for each sample. Column (1) of Table 3 shows a negative and imprecisely estimated effect of visiting activity on novel patenting productivity for firms with low levels of R&D intensity. In contrast, firms with above median levels of R&D intensity see a positive and statistically significant impact of

[9] Since R&D spending and revenue is only available at the firm level, the sample is effectively split into the office × year observations of firms who have below median R&D spending levels and the office × year observations of all other firms

Figure 3: Novel Patenting Productivity



Notes: The dependent variable is the number of novel patent applications per 100 inventors applied for by an office. This figure present results from estimating versions of Equation (1) where the post dummy is replaced by year dummies with the 2019 dummy being the omitted category.

office visiting activity and novel patenting productivity. To contextualize the magnitude of the effect, a 10% increase in visits to the office leads to a 14%[10] increase in novel patenting productivity off of mean levels. Columns (3) and (4) include controls, showing similar results.

Given that visiting the office has a positive effect on novel patenting productivity for R&D intensive firms, for the remainder of the paper I limit the sample to the above median R&D intensity group. To investigate the dynamics of the effect found in Table 3, I estimate the same event study specification used to create Figure 3 but only on the subset of observations where R&D intensity of the firm is above the median level. Figure 4 shows coefficients and 95% confidence intervals, which reveals parallel trends in novel patenting productivity between high and low Trump offices within the same firm before the pandemic started. After the pandemic started, the trends diverged with higher Trump offices having increased levels

[10]The relative effect is calculated as $\frac{0.0171}{0.12}$, where 0.12 is the mean level of novel patents per one hundred inventors in the sample with above median R&D spending.

Table 3: Novel Patenting Productivity by R&D Intensity

	$\frac{\text{Novel Patents}}{\text{Inventors}} \times 100$			
	R&D to Sales			
	(1)	(2)	(3)	(4)
	$<$	$\geq$	$<$	$\geq$
ihs(Visits)	-0.051	0.171**	-0.015	0.135*
	(0.146)	(0.077)	(0.160)	(0.075)
Health $\times$ Post			0.759	-1.073*
			(0.949)	(0.622)
Unemp Rate			0.010	-0.019*
			(0.023)	(0.011)
$\beta_{<} = \beta_{\geq}$ (p)	.19		.38	
$\overline{\text{Y}}$	0.24	0.12	0.24	0.12
F-statistic	48.41	44.93	39.37	36.77
# Clusters	332	213	332	213
Observations	3,172	3,316	3,172	3,316

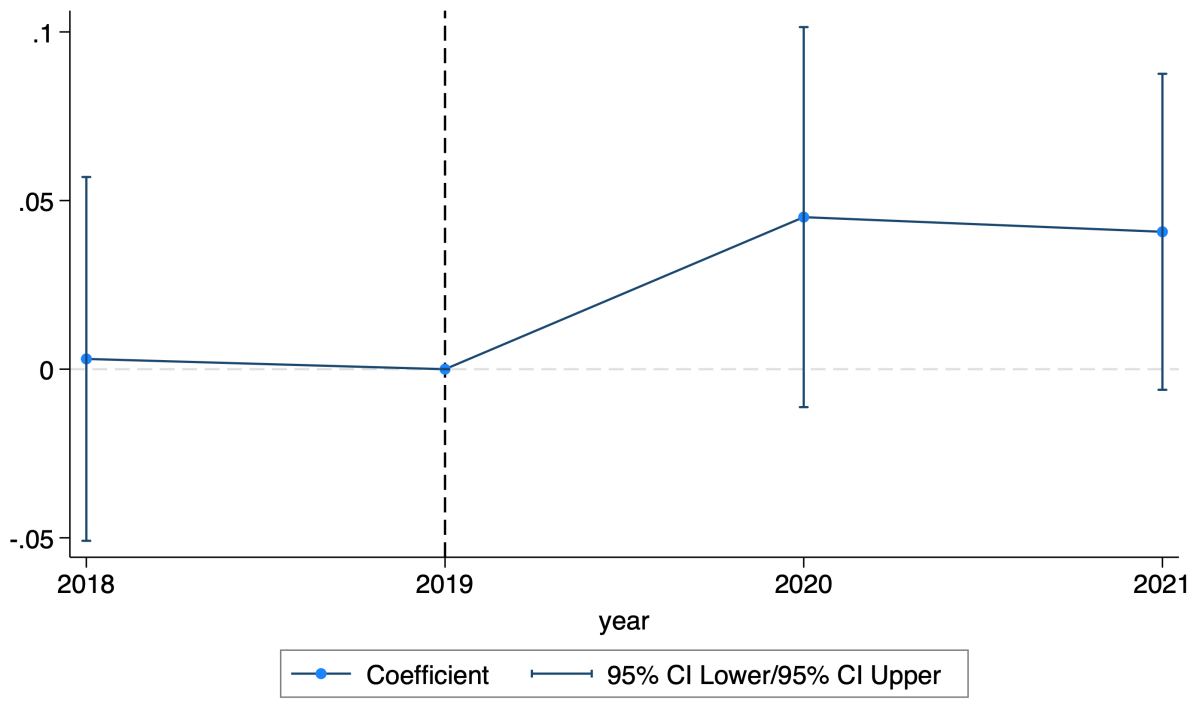
Notes: This table presents results from estimating Equation (1) and Equation (2) via 2SLS. In columns (1) and (3), the sample includes all office $\times$ year observations where the firm's R&D to sales ratio in 2018 is below the median level. In columns (2) and (4), the sample includes all office $\times$ year observations where the firm's R&D to sales ratio in 2018 is above the median level. In all columns, the dependent variable is the number of novel patents applied for during the year, scaled by hundred inventors at the office. Standard errors are clustered at the county level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

of novel patenting productivity through 2021. These results indicate that, for R&D intensive firms, visiting the office increases novel patenting productivity.

5.3 Mechanisms

Given that visiting the office increased novel patenting productivity for R&D intensive firms, it is worthwhile to look for evidence about the mechanisms driving this result. Prior literature highlights that WFH may differentially impact the productivity of an inventor's in-person and remote collaborations. In-person interaction allows researchers to better learn

Figure 4: High R&D Intensity



Notes: The dependent variable is the number of novel patent applications per 100 inventors applied for by an office. This figure present results from estimating versions of Equation (1) where the post dummy is replaced by year dummies with the 2019 dummy being the omitted category.

about unfamiliar ideas, while having access to remote collaboration allows an inventor to recombine their locally gained knowledge in unique ways (Clancy 2022; Duede et al. 2024; Wouden and Youn 2023; Atkin et al. 2022). To better understand how the productivity of in-person and remote collaboration respond to WFH, I split all novel patents in the sample into novel patents with above the median share of inventors who are co-located at the focal office[11] and patents with below the median share. Novel patents with above the median share of inventors located at the focal office can be thought of as primarily in-person collaborations which take place at the office being examined while those with below the median share can be thought of as primarily remote collaborations from the perspective of the inventors at the focal office. I separately aggregate these patents to the office $\times$ year level and scale by

[11] For example, if a patent has a team of three inventors, one who is located at the focal office that the statistic is being calculated for and the other two located at other offices, then this patent would have $33.\overline{3}\%$ of its inventors located at the focal office. As the median share of inventors co-located is 55%, then this patent would be classified as having below the median share of inventors who are co-located at the office.

hundred inventors located at the office. By estimating the effect of visiting the office using these two variables, I will be able to examine whether visiting the office primarily increases the direct productivity of in-person or remote collaboration. As discussed before, I limit my estimation to only include R&D intensive firms.

Columns (1) and (2) of Table 4 present the results with column (1) showing that the positive effect of visiting the office serves to increase the amount of novel patents where the collaboration is primarily remote. In contrast, column (2) shows no effect of visiting the office on the amount of novel patenting done via primarily in-person collaboration. These results suggest that visiting the office does not directly increase the ability of an inventor to create novel inventions with their co-located inventors, but rather visiting the office increases the ability of an inventor to create novel patents with teams primarily composed of remote collaborators. This result fits with the view that while in-person interactions help expose inventors to new ideas, it is often necessary for an inventor to recombine these new ideas with the expertise and greater breadth of knowledge that is available remotely in order to create a truly novel invention.

Relatedly, team size may play a role in moderating the effect of visiting the office on novel patenting productivity. Indeed, the size of a team and the share of the team co-located at an office are negatively correlated[12] in my data. Further, if knowledge that is available through in-person interaction at the office must be recombined with an inventor's remote collaborators, then we should see relatively large team sizes on the new patents which are created because of visits to the office. To test whether this is the case, I identify novel patents which have above and below the median team size. Column (1) of Table 5 shows the results when the dependent variable is the novel patents with below median team size, scaled by hundreds of inventors at the office. The coefficient is small and statistically insignificant. In contrast, column (2) shows a large, positive, and statistically significant coefficient of interest when the dependent variable is the novel patents with above median team size, scaled by hundreds of inventors at the office. The results indicate that visiting the office increases novel patenting productivity where the team size is relatively large. Combining this with

[12] A regression of team size on the share of inventors located at the office yields a coefficient of -4.02 with a t-statistic of -16.31 when standard errors are clustered at the office level.

Table 4: The Effect of Remote Collaboration

	$\frac{\text{Novel Patents}}{\text{Inventors}} \times 100$			
	Share of Inventors at the Office			
	(1)	(2)	(3)	(4)
	$<$	$\geq$	$<$	$\geq$
ihs(Visits)	0.128**	0.006	0.112**	-0.015
	(0.050)	(0.029)	(0.053)	(0.029)
Health × Post			-0.689	-0.076
			(0.464)	(0.200)
Unemp Rate			-0.009	-0.010**
			(0.007)	(0.005)
$\beta_{<} = \beta_{\geq}$ (p)	.02**		.03**	
$\overline{\text{Y}}$	0.07	0.04	0.07	0.04
F-statistic	44.93	44.93	36.77	36.77
# Clusters	213	213	213	213
Observations	3,316	3,316	3,316	3,316

Notes: This table presents results from estimating Equation (1) and Equation (2) via 2SLS. The sample includes all office × year observations where the firm's R&D to sales ratio in 2018 is above the median level. In column (1) the dependent variable is the number of novel patents applied for during the year where the share of inventors on the patent located at the focal office is below the median level, scaled by hundred inventors at the office. In column (2) the dependent variable is the number of novel patents applied for during the year where the share of inventors on the patent located at the focal office is above the median level, scaled by hundred inventors at the office. Standard errors are clustered at the county level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

the results in Table 4, we see that visiting the office generates novel patents which are created by distributed and large teams. These results suggest that novel patenting is created when ideas learned through in-person interaction in the office are recombined with many remote collaborators, highlighting how a large remote network of collaborators is complementary to in-person interactions in the office.

While Table 5 shows that the positive effect of visiting the office is loaded on geographi-

Table 5: The Effect of Team Size

	$\frac{\text{Novel Patents}}{\text{Inventors}} \times 100$			
	Team Size			
	(1)	(2)	(3)	(4)
	$<$	$\geq$	$<$	$\geq$
ihs(Visits)	0.034	0.119**	0.021	0.097**
	(0.033)	(0.049)	(0.038)	(0.049)
Health × Post			-0.061	-0.737*
			(0.294)	(0.387)
Unemp Rate			-0.006	-0.012*
			(0.005)	(0.007)
$\beta_{<} = \beta_{\geq}$ (p)	.12		.18	
$\overline{\text{Y}}$	0.05	0.06	0.05	0.06
F-statistic	44.93	44.93	36.77	36.77
# Clusters	213	213	213	213
Observations	3,316	3,316	3,316	3,316

Notes: This table presents results from estimating Equation (1) and Equation (2) via 2SLS. The sample includes all office × year observations where the firm's R&D to sales ratio in 2018 is above the median level. In column (1) the dependent variable is the number of novel patents applied for during the year where the number of inventors on the patent is below the median level team size, scaled by hundred inventors at the office. In column (2) the dependent variable is the number of novel patents applied for during the year where the number of inventors on the patent is above the median level team size, scaled by hundred inventors at the office. Standard errors are clustered at the county level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

cally distributed and large teams, it may be that in-person interactions at the office help an inventor to gain new collaborators which could lead to novel inventions through the recombination of knowledge. Consistent with this, the literature has documented the importance of in-person interaction in establishing collaborator networks.

To test whether visiting the office generates new collaborative relationships which are aimed at novel innovation, I identify novel patents in my data where at least one inventor dyad involves a new collaboration. To measure this, I rely on the USPTO PatentViews disambiguated inventor data, stretching back to 1976. For each inventor who appears in my sample, I identify all inventors who appear on a patent with the focal inventor. These inventors are identified as collaborators of the focal inventor. Starting in 2018, I then examine each patent and the inventor dyads on the patent. If a novel patent has at least one inventor pair which has not worked together previously, I identify that patent as being the result of a new collaboration. As before, I examine whether visiting the office has a larger effect in creating novel patents which have new collaborations. If so, this would indicate in-person interactions help to create new connections. This could be the case if in-person interactions either help an inventor meet other inventors at their office or if in-person interactions help to introduce an inventor to the networks of other co-located inventors. On the other hand, visiting the office may have little impact on the formation of new collaborations if inventors have already met everyone working at their office, leaving little room for new relationships to form.

Table 6 presents the results, showing that visiting the office has roughly the same effect in creating novel patents with new collaborations as creating novel patents without new collaborations. This suggests that visiting the office did not expand the network of inventors, as they were no more likely to patent novel inventions with new collaborators relative to engaging in novel patenting with previously established collaboration. This fits with the view that in-person interaction does little to generate new collaborative relationships as the relationships at the office are generally established.

6 Conclusion

Despite the importance of understanding how WFH impacts the productivity of innovation workers, there has been relatively little systematic evidence on the topic. This study fills this gap in our understanding by examining how visits to the office impact the novel patenting productivity of corporate inventors belonging to highly innovative firms who comprise a sizeable portion of patenting activity in the U.S. In my exploration of this topic, I make several contributions.

First, I highlight the strong relationship between local political attitudes and WFH behav-

Table 6: New Collaborations

	$\frac{\text{Novel Patents}}{\text{Inventors}} \times 100$			
	New Collaboration			
	(1)	(2)	(3)	(4)
	0	1	0	1
ihs(Visits)	0.071**	0.063	0.055*	0.047
	(0.031)	(0.040)	(0.029)	(0.045)
Health × Post			-0.315	-0.472
			(0.232)	(0.396)
Unemp Rate			-0.008**	-0.009
			(0.004)	(0.007)
$\beta_0 = \beta_1$ (p)	.86		.87	
$\overline{\text{Y}}$	0.04	0.06	0.04	0.06
F-statistic	44.93	44.93	36.77	36.77
# Clusters	213	213	213	213
Observations	3,316	3,316	3,316	3,316

Notes: This table presents results from estimating Equation (1) and Equation (2) via 2SLS. The sample includes all office × year observations where the firm's R&D to sales ratio in 2018 is above the median level. In column (1) the dependent variable is the number of novel patents applied for during the year where no inventor dyads on the patent are new collaborations, scaled by hundred inventors at the office. In column (2) the dependent variable is the number of novel patents applied for during the year where at least one inventor dyad on the patent is a new collaboration, scaled by hundred inventors at the office. Standard errors are clustered at the county level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

ior in the 2020 - 2021 time frame. I document that offices located in politically conservative counties experienced much smaller drops in visits to the office relative to offices located in politically liberal counties. This variation could prove useful for scholars in addressing other pressing questions related to the effects of WFH.

My next contribution is to show that, for R&D intensive firms, increased visits to the office has a sizeable impact on the novel patenting productivity of corporate inventors. This finding suggests that managers at highly innovative firms should be careful, when crafting

WFH policies, to ensure that their innovation workers spend considerable time in the office to keep their productivity high. Next, I contribute to our understanding of the mechanisms behind the observed effect by exploring the characteristics of the teams who create novel patents in response to visiting the office. These findings reveal that visiting the office generates novel patents which are created by large, geographically remote teams that are no more likely to have a new collaborative relationship on the team. These results indicate that visiting the office drives productivity when inventors have access to large, remote networks of collaborators. While the current literature focuses on how in-person interaction affects working relationships with other in-person collaborators (Duede et al. 2024; Wouden and Youn 2023), the findings in this study show that realizing the benefits of in-person interaction is dependent on the nature of an inventor's remote network. Specifically, the findings suggest that inventors need a large and geographically dispersed network of collaborators to recombine the knowledge they gain from in-person interactions. This finding highlights the importance of creating conditions which allow inventors to have large networks of collaborators.

A limitation of this study is that I am capturing the short-run effect of visiting the office on novel patenting productivity from 2020-2021. Long-run effects of increased in-person interaction may take more time to materialize. For example, my work suggests that in the short-run, visiting the office doesn't disproportionately impact the amount of novel patenting done with new collaborators. But the longer that WFH policies are implemented, the more likely it is that individuals working from home are missing out on potential collaborative relationships with newcomers to the company. Further, the effects of WFH may be very different for an established inventor, relative to someone who is newly joining the company and is looking to build their collaborative network. Following up to look at these long-run effects would be a welcome contribution to this paper's findings.

References

Abbasiharofteh, Milad, Dieter F. Kogler, and Balázs Lengyel (Dec. 2023). "Atypical combinations of technologies in regional co-inventor networks". In: *Research Policy* 52.10, p. 104886. ISSN: 0048-7333. DOI: 10.1016/j.respol.2023.104886. URL: https://www.sciencedirect.com/science/article/pii/S0048733323001701 (visited on 07/03/2024).

Aczel, Balazs et al. (Mar. 2021). "Researchers working from home: Benefits and challenges". en. In: *PLOS ONE* 16.3. Publisher: Public Library of Science, e0249127. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0249127. URL: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0249127 (visited on 08/25/2023).

Aihounton, Ghislain B D and Arne Henningsen (May 2021). "Units of measurement and the inverse hyperbolic sine transformation". In: *The Econometrics Journal* 24.2, pp. 334–351. ISSN: 1368-4221. DOI: 10.1093/ectj/utaa032. URL: https://doi.org/10.1093/ectj/utaa032 (visited on 11/13/2023).

Andrews, Michael (June 2023). *Bar Talk: Informal Social Networks, Alcohol Prohibition, and Invention*. en. SSRN Scholarly Paper. Rochester, NY. DOI: 10.2139/ssrn.3489466. URL: https://papers.ssrn.com/abstract=3489466 (visited on 08/25/2023).

Andrews, Michael and Chelsea Lensing (2023). *Cup_of_Joe_2020_10.pdf*. URL: https://drive.google.com/file/d/1uZSB6k1ksXEuBDBCAeHu9bBpa-6mGr3X/view?usp=sharing&usp=embed_facebook (visited on 08/25/2023).

Atkin, David, M. Keith Chen, and Anton Popov (June 2022). *The Returns to Face-to-Face Interactions: Knowledge Spillovers in Silicon Valley*. Working Paper. DOI: 10.3386/w30147. URL: https://www.nber.org/papers/w30147 (visited on 07/03/2024).

Balland, Pierre-Alexandre et al. (Mar. 2020). "Complex economic activities concentrate in large cities". en. In: *Nature Human Behaviour* 4.3. Number: 3 Publisher: Nature Publishing Group, pp. 248–254. ISSN: 2397-3374. DOI: 10.1038/s41562-019-0803-3. URL: https://www.nature.com/articles/s41562-019-0803-3 (visited on 08/25/2023).

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis (July 2023). "The Evolution of Working from Home". en. In.

Bathelt, Harald, Anders Malmberg, and Peter Maskell (Feb. 2004). "Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation". en. In: *Progress in Human Geography* 28.1. Publisher: SAGE Publications Ltd, pp. 31–56. ISSN: 0309-1325. DOI: 10.1191/0309132504ph469oa. URL: https://doi.org/10.1191/0309132504ph469oa (visited on 07/05/2024).

Baum-Snow, Nathaniel, Nicolas Gendron-Carrier, and Ronni Pavan (Apr. 2024). "Local Productivity Spillovers". en. In: *American Economic Review* 114.4, pp. 1030–1069. ISSN: 0002-8282. DOI: 10.1257/aer.20211589. URL: https://pubs.aeaweb.org/doi/10.1257/aer.20211589 (visited on 07/03/2024).

Bellemare, Marc F. and Casey J. Wichman (2020). "Elasticities and the Inverse Hyperbolic Sine Transformation". en. In: *Oxford Bulletin of Economics and Statistics* 82.1. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/obes.12325, pp. 50–61. ISSN: 1468-0084. DOI: 10.1111/obes.12325. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/obes.12325 (visited on 11/13/2023).

Berkes, Enrico and Ruben Gaetani (May 2021). "The Geography of Unconventional Innovation". In: *The Economic Journal* 131.636, pp. 1466–1514. ISSN: 0013-0133. DOI: 10.1093/ej/ueaa111. URL: https://doi.org/10.1093/ej/ueaa111 (visited on 07/01/2024).

Bloom, Nicholas, Steven J. Davis, and Yulia Zhestkova (May 2021). "COVID-19 Shifted Patent Applications toward Technologies That Support Working from Home". en. In: *AEA Papers and Proceedings* 111, pp. 263–266. ISSN: 2574-0768. DOI: 10.1257/pandp.20211057. URL: https://www.aeaweb.org/articles?id=10.1257/pandp.20211057 (visited on 08/25/2023).

Boudreau, Kevin J. et al. (Oct. 2017). "A Field Experiment on Search Costs and the Formation of Scientific Collaborations". In: *The Review of Economics and Statistics* 99.4, pp. 565–576. ISSN: 0034-6535. DOI: 10.1162/REST_a_00676. URL: https://doi.org/10.1162/REST_a_00676 (visited on 08/25/2023).

Campos, Raquel, Fernanda L. L. de Leon, and Ben Mcquillin (Apr. 2017). *Lost in the Storm: The Academic Collaborations that Went Missing in Hurricane Isaac*. en. SSRN Scholarly

Paper. Rochester, NY. DOI: 10.2139/ssrn.2954495. URL: https://papers.ssrn.com/abstract=2954495 (visited on 08/25/2023).

Carlino, Gerald A., Satyajit Chatterjee, and Robert M. Hunt (May 2007). “Urban density and the rate of invention”. In: *Journal of Urban Economics* 61.3, pp. 389–419. ISSN: 0094-1190. DOI: 10.1016/j.jue.2006.08.003. URL: https://www.sciencedirect.com/science/article/pii/S0094119006000817 (visited on 07/03/2024).

Catalini, Christian (Sept. 2018). “Microgeography and the Direction of Inventive Activity”. In: *Management Science* 64.9. Publisher: INFORMS, pp. 4348–4364. ISSN: 0025-1909. DOI: 10.1287/mnsc.2017.2798. URL: https://pubsonline.informs.org/doi/10.1287/mnsc.2017.2798 (visited on 08/25/2023).

Clancy, Matt (Oct. 2022). “Remote Breakthroughs”. en. In: *New Things Under the Sun*. URL: https://www.newthingsunderthesun.com/pub/a8w2cu6h/release/8 (visited on 07/05/2024).

De Noni, Ivan and Fiorenza Belussi (Mar. 2021). “Breakthrough Invention Performance of Multispecialized Clustered Regions in Europe”. In: *Economic Geography* 97.2. Publisher: Routledge _eprint: https://doi.org/10.1080/00130095.2021.1894924, pp. 164–186. ISSN: 0013-0095. DOI: 10.1080/00130095.2021.1894924. URL: https://doi.org/10.1080/00130095.2021.1894924 (visited on 07/03/2024).

Duede, Eamon et al. (Mar. 2024). “Being together in place as a catalyst for scientific advance”. In: *Research Policy* 53.2, p. 104911. ISSN: 0048-7333. DOI: 10.1016/j.respol.2023.104911. URL: https://www.sciencedirect.com/science/article/pii/S0048733323001956 (visited on 07/03/2024).

Esposito, Christopher R. (Sept. 2023). “The geography of breakthrough invention in the United States over the 20th century”. In: *Research Policy* 52.7, p. 104810. ISSN: 0048-7333. DOI: 10.1016/j.respol.2023.104810. URL: https://www.sciencedirect.com/science/article/pii/S004873332300094X (visited on 07/03/2024).

Fleming, Lee (Jan. 2001). “Recombinant Uncertainty in Technological Search”. In: *Management Science* 47.1. Publisher: INFORMS, pp. 117–132. ISSN: 0025-1909. DOI: 10.1287/mnsc.47.1.117.10671. URL: https://pubsonline.informs.org/doi/10.1287/mnsc.47.1.117.10671 (visited on 05/14/2024).

Freeman, Richard B, Ina Ganguli, and Raviv Murciano-Goroff (2014). "Why and Wherefore of Increased Scientific Collaboration". en. In.

Frey, Carl Benedikt and Giorgio Presidente (Apr. 2022). "1Oxford Martin School, University of Oxford". en.

Ge, Chunmian, Ke-Wei Huang, and Ivan P. L. Png (2016). "Engineer/scientist careers: Patents, online profiles, and misclassification bias". en. In: *Strategic Management Journal* 37.1. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/smj.2460, pp. 232–253. ISSN: 1097-0266. DOI: 10.1002/smj.2460. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/smj.2460 (visited on 06/21/2024).

Grashof, Nils, Kolja Hesse, and Dirk Fornahl (2021). "Radical or not? The role of clusters in the emergence of radical innovations". In: *Rethinking Clusters*. Num Pages: 20. Routledge. ISBN: 978-1-00-313022-2.

Jones, Benjamin F. (Jan. 2009). "The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder?" In: *The Review of Economic Studies* 76.1, pp. 283–317. ISSN: 0034-6527. DOI: 10.1111/j.1467-937X.2008.00531.x. URL: https://doi.org/10.1111/j.1467-937X.2008.00531.x (visited on 09/19/2023).

Lin, Yiling, Carl Benedikt Frey, and Lingfei Wu (Nov. 2023). "Remote collaboration fuses fewer breakthrough ideas". en. In: *Nature* 623.7989. Publisher: Nature Publishing Group, pp. 987–991. ISSN: 1476-4687. DOI: 10.1038/s41586-023-06767-1. URL: https://www.nature.com/articles/s41586-023-06767-1 (visited on 07/04/2024).

Locations (2025). en-US. URL: https://www.lamresearch.com/company/locations/ (visited on 01/28/2025).

Melero, Eduardo, Neus Palomeras, and David Wehrheim (Dec. 2020). "The Effect of Patent Protection on Inventor Mobility". In: *Management Science* 66.12. Publisher: INFORMS, pp. 5485–5504. ISSN: 0025-1909. DOI: 10.1287/mnsc.2019.3500. URL: https://pubsonline.informs.org/doi/abs/10.1287/mnsc.2019.3500 (visited on 06/21/2024).

Mewes, Lars (Aug. 2019). "Scaling of Atypical Knowledge Combinations in American Metropolitan Areas from 1836 to 2010". en. In: *Economic Geography* 95.4, pp. 341–361. ISSN: 0013-0095, 1944-8287. DOI: 10.1080/00130095.2019.1567261. URL: https://www.tandfonline.com/doi/full/10.1080/00130095.2019.1567261 (visited on 07/03/2024).

National data & documentation (2025). *National data & documentation: 2010-2022 | County Health Rankings & Roadmaps*. en. URL: https://www.countyhealthrankings.org/health-data/methodology-and-sources/data-documentation/national-data-documentation-2010-2022 (visited on 01/28/2025).

Nieto, María Jesús and Lluis Santamaría (June 2007). "The importance of diverse collaborative networks for the novelty of product innovation". In: *Technovation* 27.6, pp. 367–377. ISSN: 0166-4972. DOI: 10.1016/j.technovation.2006.10.001. URL: https://www.sciencedirect.com/science/article/pii/S0166497206001064 (visited on 07/03/2024).

Pezzoni, Michele, Reinhilde Veugelers, and Fabiana Visentin (Apr. 2022). "How fast is this novel technology going to be a hit? Antecedents predicting follow-on inventions". In: *Research Policy* 51.3, p. 104454. ISSN: 0048-7333. DOI: 10.1016/j.respol.2021.104454. URL: https://www.sciencedirect.com/science/article/pii/S0048733321002468 (visited on 05/07/2024).

Roche, Maria P. (Dec. 2020). "Taking Innovation to the Streets: Microgeography, Physical Structure, and Innovation". In: *The Review of Economics and Statistics* 102.5, pp. 912–928. ISSN: 0034-6535. DOI: 10.1162/rest_a_00866. URL: https://doi.org/10.1162/rest_a_00866 (visited on 08/25/2023).

Strumsky, Deborah and José Lobo (Oct. 2015). "Identifying the sources of technological novelty in the process of invention". In: *Research Policy* 44.8, pp. 1445–1461. ISSN: 0048-7333. DOI: 10.1016/j.respol.2015.05.008. URL: https://www.sciencedirect.com/science/article/pii/S0048733315000840 (visited on 05/09/2024).

The Official List of Every Company's Back-to-Office Strategy (Jan. 2025). en. URL: https://hubblehq.com/blog/famous-companies-workplace-strategies (visited on 01/28/2025).

Verhoeven, Dennis, Jurriën Bakker, and Reinhilde Veugelers (Apr. 2016). "Measuring technological novelty with patent-based indicators". In: *Research Policy* 45.3, pp. 707–723. ISSN: 0048-7333. DOI: 10.1016/j.respol.2015.11.010. URL: https://www.sciencedirect.com/science/article/pii/S0048733315001857 (visited on 07/01/2024).

Weekly Patterns | SafeGraph Docs (2025). en. URL: https://docs.safegraph.com/docs/weekly-patterns (visited on 01/28/2025).

Wouden, Frank van der (June 2020). "A history of collaboration in US invention: changing patterns of co-invention, complexity and geography". In: *Industrial and Corporate Change* 29.3, pp. 599–619. ISSN: 0960-6491. DOI: 10.1093/icc/dtz058. URL: https://doi.org/10.1093/icc/dtz058 (visited on 07/03/2024).

Wouden, Frank van der and Hyejin Youn (Mar. 2023). "The impact of geographical distance on learning through collaboration". In: *Research Policy* 52.2, p. 104698. ISSN: 0048-7333. DOI: 10.1016/j.respol.2022.104698. URL: https://www.sciencedirect.com/science/article/pii/S0048733322002190 (visited on 07/03/2024).

Yang, Longqi et al. (Jan. 2022). "The effects of remote work on collaboration among information workers". en. In: *Nature Human Behaviour* 6.1. Number: 1 Publisher: Nature Publishing Group, pp. 43–54. ISSN: 2397-3374. DOI: 10.1038/s41562-021-01196-4. URL: https://www.nature.com/articles/s41562-021-01196-4 (visited on 08/25/2023).

A Appendix

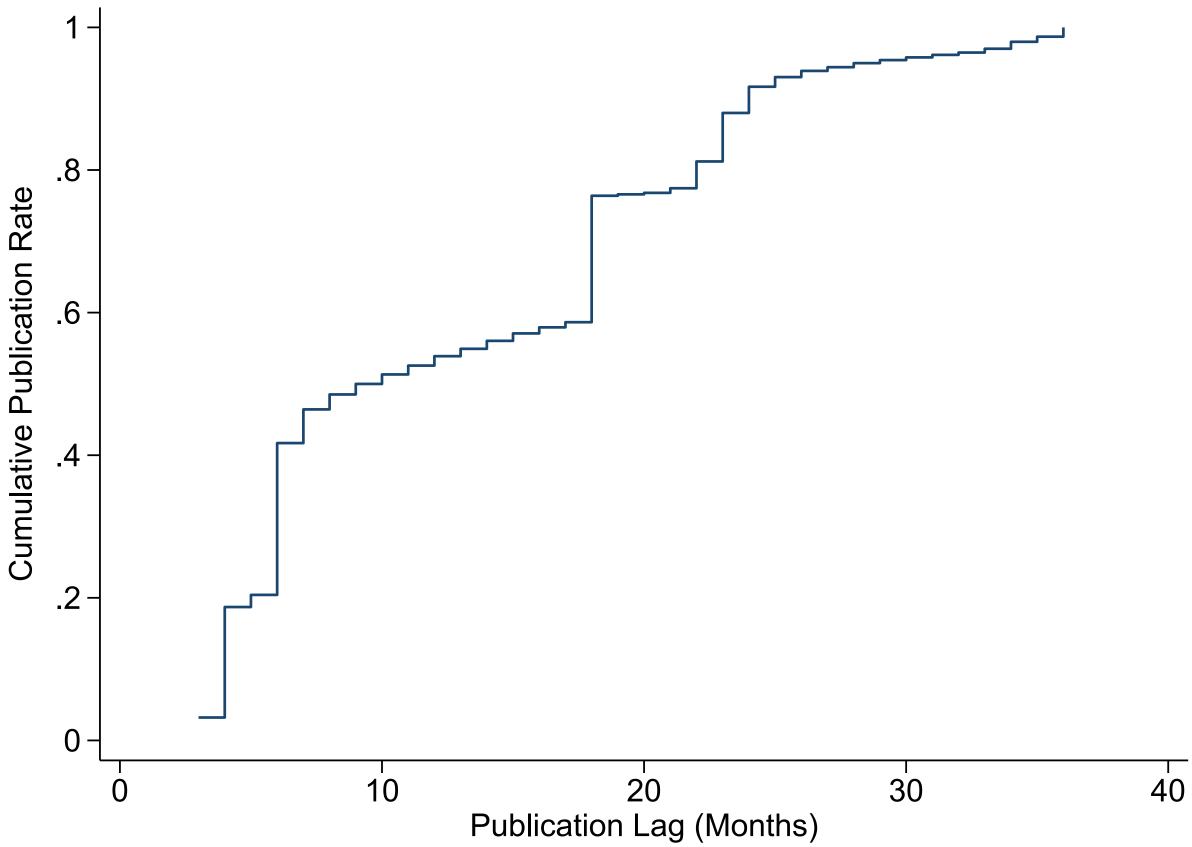
A.1 Additional Results

Table A.1: Summary Statistics on Top 20 Firms

				Trump Vote Share	
Firm Name	NAICS3 Title	Offices	Novel Patents	Mean	St. Dev.
Ford Motor	Transportation Equip Mfg	17	718	.38	.12
IBM	Information Services	8	323	.35	.14
Boeing	Transportation Equip Mfg	16	318	.41	.13
Raytheon	Transportation Equip Mfg	7	226	.32	.08
General Electric	Conglomerate	43	190	.44	.15
Corning	Computer/Electronics Mfg	26	149	.42	.16
Intel	Computer/Electronics Mfg	39	147	.35	.11
Procter & Gamble	Chemical Mfg	4	143	.34	.08
Deere	Machinery Mfg	8	114	.46	.08
Halliburton	Mining Support	13	109	.52	.16
Applied Materials	Machinery Mfg	12	104	.37	.13
Qualcomm	Computer/Electronics Mfg	22	87	.32	.11
Textron	Transportation Equip Mfg	6	85	.43	.11
Dow	Chemical Mfg	8	81	.53	.12
PPG Industries	Chemical Mfg	22	77	.42	.12
HP	Computer/Electronics Mfg	11	75	.33	.13
Eastman Chemical	Chemical Mfg	9	57	.49	.24
BD	Miscellaneous Mfg	21	53	.43	.16
Altria Group	Beverage/Tobacco Mfg	3	51	.29	.11
Stryker	Miscellaneous Mfg	14	50	.38	.12

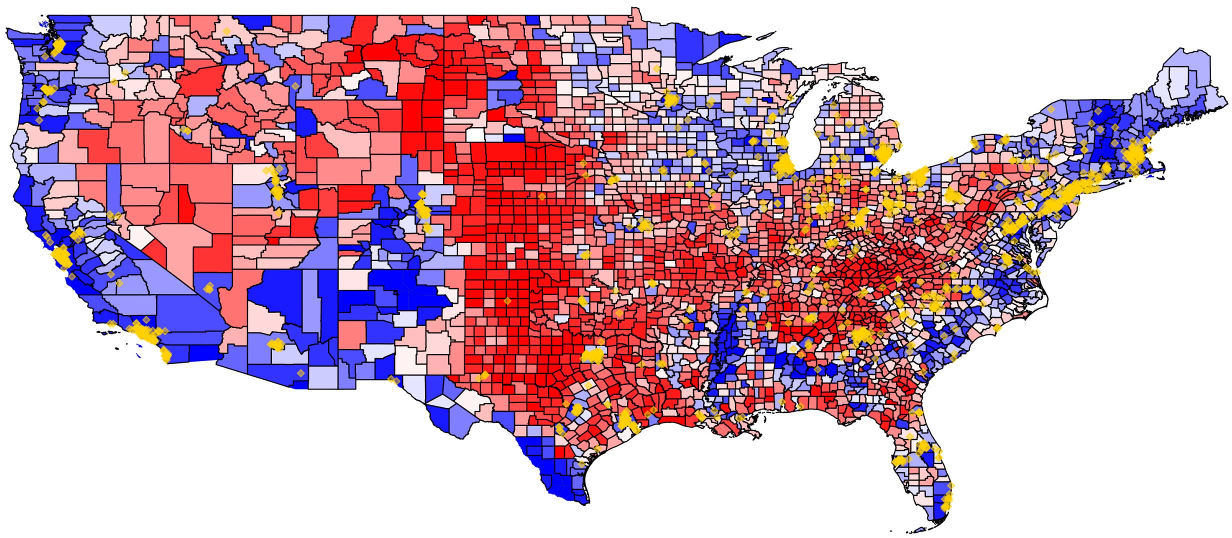
Notes: This table presents statistics on the twenty firms with the most patents applied for pre-pandemic (2018-2019). There are 203 firms in the total sample. "Novel Patents" is the number of novel patents the firm applied for between 2018-2019. Trump (mean/st. dev.) is the mean/standard deviation of the 2016 presidential election vote share that went to Donald Trump across the counties where the firm's offices are located.

Figure A.1: Publication Lag



Notes: This figure displays the share of patent applications that have been published X months after the application date, where X is the number on the x-axis. Patent applications in 2015 are used for the analysis and the publication lag is winsorized at 3 years.

Figure A.2: Office Map



Notes: This figure displays all offices in the sample as transparent gold diamonds and shades counties based on their 2016 Trump vote share. The darker red (blue) colors indicate higher (lower) Trump vote shares.

Table A.2: Visits and Novel Patenting Before & After the Pandemic

	Pre-Pandemic		Post-Pandemic		Difference
	(1)		(2)		(3)
	Mean	St. Dev.	Mean	St. Dev.	Diff
Visits	7,069	12,465	3,786	7,912	-3,282***
$\frac{\text{Novel Patents}}{\text{Inventors}} \times 100$	.22	.66	.13	.51	-.093***
Observations	3,350		3,350		6,700

Notes: This table presents summary statistics on visits and novel patenting productivity, split between the pre-pandemic and post-pandemic time periods, for all office × year observations in the sample. The pre-pandemic years are 2018-2019 and the post-pandemic years are 2020-2021.

Table A.3: Patenting Productivity and Office Visiting Activity

	OLS		2SLS	
	$\frac{\text{Patents}}{\text{Inventors}} \times 100$	ihs(Visits)	$\frac{\text{Patents}}{\text{Inventors}} \times 100$	
	(1)	(2)	(3)	(4)
ihs(Visits)	0.246*		0.769	0.919
	(0.145)		(0.622)	(0.717)
Trump Vote Share × Post		0.187***		
		(0.020)		
Health × Post				5.964
				(4.582)
Unemp Rate				0.063
				(0.093)
$\overline{\text{Y}}$	4.01		4.01	4.01
F-statistic		87.90	87.90	66.79
# Clusters	415	415	415	415
Observations	6,488	6,488	6,488	6,488

Notes: Column (1) presents results from estimating Equation (2) via OLS. Column (2) presents results from estimating Equation (1) via OLS. Columns (3) and (4) presents results from estimating Equation (2) via 2SLS. Across all columns, the sample includes all office × year observations in the sample. In columns (1), (3), and (4), the dependent variable is the number of patents applied for during the year, scaled by hundred inventors at the office. Standard errors are clustered at the county level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.4: Patenting Productivity by R&D Intensity

	$\frac{\text{Patents}}{\text{Inventors}} \times 100$			
	R&D to Sales			
	(1)	(2)	(3)	(4)
	$<$	$\geq$	$<$	$\geq$
ihs(Visits)	0.319	1.129	0.631	1.176
	(1.257)	(0.835)	(1.393)	(0.936)
Health × Post			3.764	7.733
			(5.963)	(8.165)
Unemp Rate			0.086	0.041
			(0.125)	(0.138)
$\beta_{<} = \beta_{\geq}$ (p)	.63		.76	
$\overline{\text{Y}}$	3.09	4.88	3.09	4.88
F-statistic	48.41	44.93	39.37	36.77
# Clusters	332	213	332	213
Observations	3,172	3,316	3,172	3,316

Notes: This table presents results from estimating Equation (1) and Equation (2) via 2SLS. In columns (1) and (3), the sample includes all office × year observations where the firm's R&D to sales ratio in 2018 is below the median level. In columns (2) and (4), the sample includes all office × year observations where the firm's R&D to sales ratio in 2018 is above the median level. In all columns, the dependent variable is the number of patents applied for during the year, scaled by hundred inventors at the office. Standard errors are clustered at the county level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).