Resilient Innovation: Corporate Invention and Remote Work

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September 30, 2022

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Abstract

This paper investigates whether the large increase in remote work that began during the COVID-19 pandemic had an impact on 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. Using this variation as an instrument for visits to the office, I find evidence which rules out large effects of remote work on innovative activity during 2020. In response to a 10% increase in visits, the 95% confidence interval rules out increases in patent applications of more than 1.0% and declines less than 0.9%. I find even more precisely estimated null effects on distant collaboration and team size. The results suggest that firms and inventors were able to endogenously adjust to the post-pandemic world in order to maintain their innovative productivity.

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1 Introduction

Innovation is highly concentrated in cities. Indeed, Balland et al. 2020 document that: "the ten most innovative cities in the United States account for 23% of the national population, but 48% of patents." Further, this concentration has been increasing since the 1970s (Chattergoon and Kerr 2022). All this suggests that geographic proximity is important for the production of new knowledge (Glaeser 1999; Ellison et al. 2010). In support of this idea, Moretti 2021 finds that the number of co-located inventors in an inventor's field has a large positive effect on an inventor's productivity.

A vast literature has attempted to illuminate the underlying explanations for these facts. One contributing factor seems to be in-person interactions. The innovation economics literature has shown that plausibly exogenous increases in a variety of local factors that increase socialization, such as: coffee shops (Andrews and Lensing 2020), bars (Andrews 2020), sidewalk density (Roche 2020), and lower sickness (Pennington 2020) all increase collaboration, and innovation. Not only does academic research provide evidence that in-person interaction matters, but firms themselves believe in the benefits of face-to-face communication. In 2015, Microsoft redesigned their offices and relocated 1,200 engineers in order to encourage in-person interactions (Nielsen 2016). This discussion suggests two facts. First, physical interaction with a large pool of researchers can enhance innovation. Second, firms endogenously respond to this perception, optimizing the environment of their workforce.

On the other hand, Bloom, Liang, et al. 2015 and Emanuel and Harrington 2021 find that the productivity of call center employees improved when they began working remotely and Choudhury et al. 2021 find that the productivity of United States Patent and Trademark Office's (USPTO) examiners increased when they transitioned from work-from-home (WFH) to work-from-anywhere. Although these occupations are significantly different from that of an inventor, the results show that it is possible for remote work to generate significant productivity gains. Consistent with this, many technology companies have embraced some form of WFH, citing increased productivity for certain tasks and types of workers (Barrero et al. 2021).

This study contributes to our understanding of remote work, innovation, and firm strategy by examining how the production of innovation responds to an increase in working from home. The swift and unexpected arrival of the COVID-19 pandemic dramatically increased the prevalence of WFH. The increase in demand for WFH displayed significant geographic variation across the United States that is correlated with the political ideology of the locality. Particularly, counties that had large Donald Trump vote shares in the 2016 election displayed significantly lower declines in mobility after the start of the pandemic. My empirical strategy compares offices that are part of the same firm but are located in counties with varying support for Donald Trump. Using cellphone data from SafeGraph, I find that offices with higher Trump support see significantly more individuals coming into the office relative to offices within the same firm that have lower Trump support. A one standard deviation increase in Trump support leads to an 20% increase in visits. In contrast, I find no evidence that this change in visiting activity is associated with changes in innovative output. In response to a 10% increase in visits, the 95% confidence interval rules out increases in patenting of more than 1.3% and declines less than 0.5%. Further, I find even more precisely estimated null effects on the share of inventors collaborating from another office and team size.

The results are consistent with two potential stories. While there is a large effect on visits to the office, it may be the case that firms are able to optimally allocate labor across WFH and in-person work environments. In this scenario, the firm may be able to keep inventors in the office if that is important to their productivity. This would be consistent with the decline in visits to the office for low Trump offices being driven by a decline in non-inventor visits.

Alternatively, the increase in visits for offices located in high Trump counties may represent a true increase in office visits for inventors. Under this scenario, the results suggest that WFH and a decline in face-to-face interaction has little effect on research productivity. While I cannot distinguish between these two alternatives, my results do suggest that corporate innovation has been remarkably resilient to the large increase in WFH demand created by the pandemic. Whether through endogenous placement of inventors, WFH infrastructure, or the lack of need for physical interaction, the large increase in WFH created by the pandemic does not appear to be slowing corporate innovation as some have feared.

2 Data

2.1 Safegraph Data

My first data source comes from the Safegraph Patterns data product. Safegraph uses a panel of ≈20 million cellular devices to provide data on the number of daily visits to ≈4.5 million points of interest (POI) in the United States. Safegraph assigns each POI a six-digit NAICS code along with the 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 19, 2021. I refer to these POIs as offices. In the data there are 8,597 unique offices that belong to 392 companies.

To check the coverage of the Safegraph data, I examined the offices of three high-technology companies: Lam Research, Raytheon Technologies, and Boston Scientific.[1] These companies were chosen because they are highly innovative firms in distinct industries with activity distributed across many locations. The website of Lam Research[2] 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 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 392 companies present in the data, Safegraph provides good

[1] 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.

[2] https://www.lamresearch.com/company/locations/

coverage of their offices.

2.2 USPTO Patent Applications

I collect data on patent applications from the USPTO bulk data product which is updated weekly.[3] My analysis includes all patent applications which are published from January 3, 2019 through April 14, 2022, which covers filings from December 28, 2018 to April 8, 2022. 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 location of each inventor. 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 × inventor observations where the inventor resides in the US. I obtain latitude and longitude coordinates for each patent application × inventor observation using the Bing Maps API and the provided city and state information.

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. Using all patent applications published in 2015, I find that 71% of applications are ultimately granted. Ideally, I would use patent applications that are ultimately granted, but it often takes several years to observe the decision. Given the high grant rate and the desire to complete the analysis in a timely fashion, I use patent applications without conditioning on a patents grant decision (Bloom, Davis, 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 in the data I use. Figure 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 publication date. 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

[3] https://bulkdata.uspto.gov/

application, 92% of applications have been published. My time period of analysis is January 2019-December 2020. All observations except those in November and December 2020 have had at least 18 months since the observation date and the date of the most recent patent filing data. Given that 76% of applications were published within 18 months, there has been enough time that most patent applications in my data will be published.

[Figure 1 about here.]

2.3 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 I matching all relevant 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 $\times$ 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 $\times$ 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 $\times$ 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 it applies for on a given day.

Since the Safegraph data is not specifically designed to capture innovative offices, I remove offices that do not apply for a single patent in 2019. I also remove offices that have an average of less than one visit per day in 2019 as it is likely that the office is used very little or there is a problem with the Safegraph data. After making these restrictions, I am left with 1,138 offices belonging to 167 different firms. Over the 2019-2020 time period, the patent applications of these offices accounted for 14.6% of all patent applications with assignees. Table 1 displays statistics for the fifteen firms who applied for the most patents in 2019. The list includes large and prominent U.S. multinationals from a variety of high technology industries including: semiconductors, electronic products, vehicle and airplane manufacturing, digital advertising, and others. Each of these firms has multiple innovative offices, creating significant variation in the 2016 Trump vote share within each firm. My identification strategy will leverage this within firm variation in the Trump vote share to generate plausibly exogenous changes in visits to the office.

[Table 1 about here.]

Figure 2 displays the distribution of 2016 Trump vote shares across counties with darker shades of red (blue) indicating higher (lower) Trump vote shares. The 1,138 offices are marked with transparent gold diamonds. Although innovative activity is generally located in metropolitan areas with low Trump vote share, there is still significant variation in Trump vote share across offices.

[Figure 2 about here.]

Table 2 displays summary statistics for all offices in the sample. The average number of visits per day in 2019 was 23. Coinciding with the onset of the COVID-19 pandemic in 2020, this number fell precipitously to 13 visits per day. In 2019 the average office applied for 0.06 patents per day or one patent every 17 days. Despite the large fall in visits, the number of patents applied for held remarkably steady in 2020. The average change in the inverse hyperbolic sine (IHS) of patents being -0.01, indicating that patent applications only fell by approximately 1%.

[Table 2 about here.]

3 Empirical Strategy

My goal is to identify the effect of increasing an office's share of employees working from home on the innovative output of the office. There are several problems with using the number of Safegraph visits to an office to identify this effect. First, is that changes in office visits are likely correlated with many other confounding factors. 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. 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.

To address the issue of endogeneity, 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 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 on going to the office. My preferred specification is a two-stage least squares (2SLS) estimation procedure, outlined in equations (1) and (2). I cluster standard errors at the office level to account for serial correlation in the error term.

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

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

In equation (1), the dependent variable is the IHS of the number of visits made to office o, belonging to firm f, located in country c, in month t. The IHS transformation approximates a log transformation, but allows for the presence of zeros in the data, which is useful since, while rare, offices can have zero visits in a given month. Trump_c measures the share of the 2016 presidential election vote that went to Donald Trump in the the county of the office. I standardize this variable to have mean zero and standard deviation of one for ease of interpretation. $\mathbb{1}\{\text{Post}_t\}$ is an indicator variable that is one in the months of March 2020-December 2020 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. π_o are office fixed effects that remove time-invariant office heterogeneity. τ_{ft} is a set of firm $\times$ month 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 that contains the monthly unemployment rate in the county and the share of individuals reporting poor or fair health in 2016. Data on self reported health is taken from the County Health Rankings & Roadmap.[4] The unemployment rate controls for the labor market conditions in the county, addressing the concern that visits to the office are driven by employment trends and not WFH activity. 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. The predicted IHS of visits is then interacted with a post dummy in the second stage. The coefficient on this interaction, β, captures the effect of a percentage change in visits on innovative outcome Y. As in the first stage, office and firm $\times$ month fixed effects are included.

In order to identify the effect of more employees working from home on the innovative output of offices, several conditions must be met. First, after the start of the pandemic, the Trump vote share of a county must be strongly predictive of 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 patenting activity that occurred after the start of the pandemic for offices in the same firm, but in differing Trump counties must be only attributable to the change in visits to the office. The inclusion of firm $\times$ month fixed effects significantly

[4]Source data comes from the 2016 Behavioral Risk Factor Surveillance System. See https://www.countyhealthrankings.org/explore-health-rankings/rankings-data-documentation/national-data-documentation-2010-2019 for more details

limits the scope of concerns that the exclusion restriction is violated by removing between firm heterogeneity in the distribution of offices across counties. Finally, in the absence of the pandemic, the innovative output 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 Results

4.1 First Stage

Table 3 reports the results of regressions of the form outlined in equation (1). In column (1) with month and office fixed effects, a one standard deviation increase in an office's 2016 Trump vote share results in approximately a 33% increase in visits. The F-statistic of 134 indicates the instrument is highly predictive. In column (2), I control for the unemployment rate and 2016 self-reported health in each county. While higher unemployment rates are associated with less visits to the office as expected, poorer health is actually associated with more visits to the office. While the point estimate on Trump Vote $\text{Share}_c \times \mathbb{1}\{\text{Post}_t\}$ declines, the point estimate remains large and highly significant with an F-statistic of 94. In column (3) firm $\times$ month fixed effects are included, limiting comparisons to be within firm. Despite this tight specification, the coefficient remains large, highly significant, and the F-statistic still comfortably rules out the possibility of weak instruments. The coefficient indicates that a one standard deviation increase in an office's 2016 Trump vote share results in approximately a 18% increase in visits after the start of the pandemic. Column (4) employs an even tighter specification, relying on within-state and within-firm variation in Trump vote shares to identify the effect. Despite this restrictive specification, the F-statistic still exceeds the conventional threshold of ten and the point estimate remains unchanged relative to my preferred specification in column (3).

[Table 3 about here.]

To explore dynamics in the effect, I run event study specifications where I augment equation (1) by replacing the post indicator with month dummies, omitting the month of

February, 2020. Figure 3 displays the coefficients and 95% confidence intervals from the estimation. In 2019, the coefficients are negative and flat, indicating that the gap in visiting activity between offices in counties with high and low Trump vote shares is smaller in 2019 relative to February 2020. While the coefficients are significant, this is not concerning as there is no trend in the coefficients. In January of 2020 there is a discrete jump which is likely an artifact of annual changes in the SafeGraph data. Consistent with this interpretation, the gap in visiting activity between high and low Trump vote share counties are very similar in January and February of 2020. In March 2020, the coefficient increases and is positive and statistically significant. There is another large increase in April of 2020. In May-December 2020 the coefficients remain generally stable, indicating that offices in Trump counties had persistently higher visits through the rest of 2020. The results indicate that the positive effect of Trump support on visits to the office is not driven by confounding pre-trends.

[Figure 3 about here.]

4.2 Innovation and WFH

To examine the raw correlation between the number of visits to an office and the innovative output of the office, I estimate equation (2) but instead of using predicted visits from the first stage equation, I use the endogenous measure of the IHS of visits. Table 4 displays the results. In column (1) with office and month fixed effects, there is a small and positive coefficient on visits but the estimate is not statistically distinguishable from zero. Adding controls in column (2) leaves the results unchanged. In column (3) when I include firm $\times$ month fixed effects so that all comparisons are being made between offices in the same firm, the point estimate increases and becomes statistically significant. Despite this increase, the estimate is still small in magnitude. A 10% increase in visits is associated with a 0.16% increase in patent applications. When I include state $\times$ month fixed effects so that comparisons are restricted to offices belonging to the same firm and located in the same state, the estimate remains similar. Although the results presented in Table 4 do not account for the endogeneity of visits to the office, they indicate that increased visits to the office are not associated with a meaningful change in patenting activity.

[Table 4 about here.]

As discussed earlier, estimation via OLS is likely to result in biased estimates of the effect of working from home on innovation. To remove this bias, I estimate the 2SLS framework in equations (1) and (2) with the IHS of patent applications as the dependent variable. There is no clear prediction for the sign and magnitude of β. If firms are able to endogenously respond to workers shifting to WFH, they may be able mitigate any negative effects of working from home on innovative output. This endogenous response could involve ensuring that key inventors and support personnel continue working at the office if that is helpful to their productivity. Firms could also set up WFH infrastructure and scheduling that maintains inventor productivity and collaboration even in the presence of geographic distance. If the COVID pandemic provided an opportunity for firms to experiment with remote work, firms that had more of their workforce stay at home may see their innovative output go up. All of these factors would lower β so that increased visits to the office either did little to impact innovative output or even lowered it. On the other hand, if firms are not able to adjust swiftly to WFH and being in the office is important for creating innovation, then β will be positive. This is consistent with a scenario where firms are not able to strategically allocate innovation workers to the location where their marginal product is highest due to WFH during the pandemic.

Table 5 displays the results. In columns (1) and (2) where comparisons are being made between offices at different firms, I find similar point estimates as the OLS specifications but less precisely estimated. In column (3), with firm $\times$ month fixed effects included, the point estimate increases, just as in the OLS specification, but the elasticity remains small. In response to a 10% increase in visits, the 95% confidence interval rules out increases in patenting more than 1.0% and declines less than 0.9%. Table 2 shows that relative to 2019, the average office saw their visits declines by 63 IHS points in 2020. The estimates presented here rule out declines in patenting of more than 5.9% or increases of more than 6.2% due to this dramatic decline in visits. The results indicate that even in response to a large shock such as the COVID-19 pandemic, changes in WFH practices are likely to have small impacts on innovative output.

[Table 5 about here.]

To explore the dynamics of this null result, I estimate event study equations with the IHS of patenting as the dependent variable. Figure 4 displays the point estimates and 95% confidence intervals. Although offices located in Trump counties exhibited a small downward trend at the end of 2019, there is no clear trend before that time and the trend corrects itself in February 2020. From February 2020 through the end of the year, the gap in innovative activity between offices located in the same firm but in counties with differing levels of support for Trump remains remarkably steady. The event study indicates that increased in-person activity at an office does not result in greater innovative output.

[Figure 4 about here.]

While the quantity of innovative activity produced by an office was not affected by changes to the number of employees working from home, inventors may have changed how they collaborate. Reductions in visits to the office may result in more virtual meetings, lowering the cost to collaborating with inventors who are not located at the office. This may lead to increases in team size. On the other hand, collaboration requires overlap in knowledge and working relationships are often generated by previous in-person connections (Freeman et al. 2014; Boudreau et al. 2017; Catalini 2018; Campos et al. 2018). To the extent that there are large frictions to finding and integrating new team members, more remote work may not change the composition of teams.

To examine these ideas, I use the same 2SLS framework as before, but I use the average share of inventors on a patent who are located at the office. For any given month, values close to one indicate that the patents applied for by the office are mainly generated by teams where all the inventors work at the office of observation. Table 6 displays the results. The preferred specification in column (3) indicates that in response to a 10% increase in visits, the 95% confidence interval rules out increases in the share of inventors at the office of more than 1.1 percentage points and declines less than 0.5 percentage points. Off of a mean level of 52 percentage points, this amounts to ruling out increases greater than 2.1% or declines more than 1%. Panel (a) of Figure A1 shows that the results are not driven by pre-existing trends. These results suggest that when offices move towards more remote work, this does not change the amount that inventors collaborate with geographically distant inventors. This is consistent with the previous work that highlights the importance of in-person networking in establishing remote working relationships (Freeman et al. 2014; Boudreau et al. 2017; Catalini 2018; Campos et al. 2018).

[Table 6 about here.]

To explore any effects that remote working has on team size, I use the average number of inventors on an office's patents applied for in a given month as the dependent variable. In column (3) of Table 7, I find a precisely estimated null effect. In response to a 10% increase in visits, the 95% confidence interval rules out increases (declines) in the average number of inventors on a patent of 0.07 (0.08) inventors, or 1.5% (1.8%) off the mean level of 4.5 inventors per patent. The results suggest that team size is not responsive to more working from home by offices. Panel (b) of Figure A1 shows that the results are not driven by pre-existing trends. Offices in the same firm but located in counties with higher Trump vote shares were on similar trends going into March 2020, and these parallel trends continued after the start of the pandemic.

[Table 7 about here.]

5 Conclusion

Using within firm variation in office visits that is instrumented by the Trump vote share in the office's county, I examine whether changes in WFH affect the innovative activity of a firm. In the year following these large and persistent changes in WFH, I find no evidence which supports that WFH had an impact on the innovative activity of firms. Increasing the number of workers who come into the office has no effect on the number of patent applications the office makes, collaboration with distant inventors, or team size.

This study has several limitations. First, I can only observe changes in visiting activity at the office level, leaving me unable to directly observe whether inventors changed their WFH behavior. Firms may have been able to keep inventors working at the office if that was important for their productivity. Indeed, if the productivity of inventors is disproportionately affected by being in the office, then a standard neoclassical model would predict them to be less likely to WFH since any declines in productivity from WFH would be passed through to their wages. This suggests that firms and inventors endogenously respond by ensuring that inventors work from the office. On the other hand, the identified change in office visiting activity may be representative of the office visiting activity of inventors. In this case, the results suggest that WFH has little impact on inventor productivity. Future work should look to distinguish between these competing stories.

Further, I am only able to accurately measure patent applications from 2019-2020. If patent applications filed in 2020 represent the results of R&D projects which were carried out before the pandemic, then the null response could simply reflect this lag between work done on a project and patent application. While this could certainly be the case, the economics literature is replete with examples where patent application activity responds to an economic shock in the year following the arrival of the shock. In order to have a more complete view of how WFH affected innovative activity, more time needs to pass in order to be able to accurately measure patent applications. I plan to follow up in future work and examine any longer term impacts the WFH shock may have had on innovative activity.

Despite the shortcomings, this study provides an important first glimpse into the effects of WFH on corporate innovative activity. I can conclude that in response to more WFH at offices, offices are able to maintain their patent application activity in the subsequent year and see no changes in propensity for distant collaborations or team size. The results suggest that firms and/or inventors are able to endogenously adjust to this increased demand for WFH. Future work should seek to explore how this adjustment takes place and the mechanisms responsible for creating the effect that I document.

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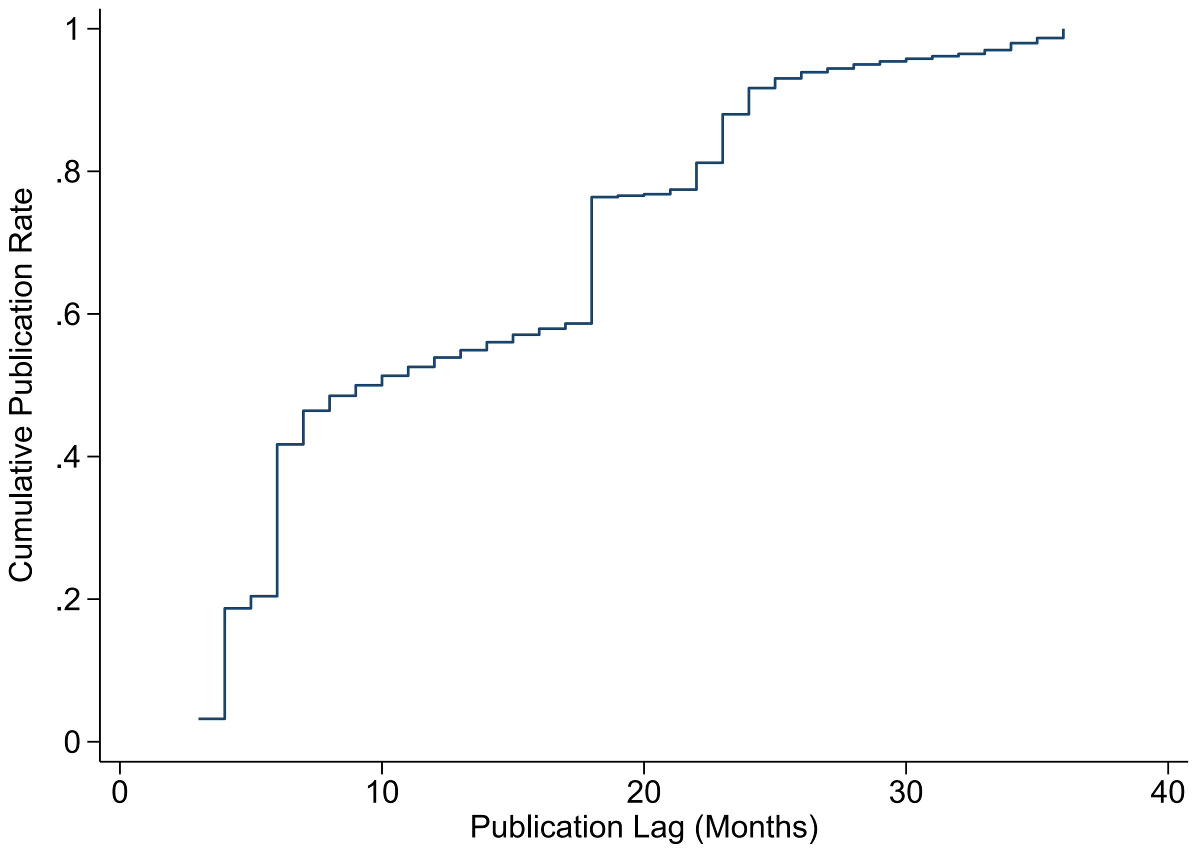
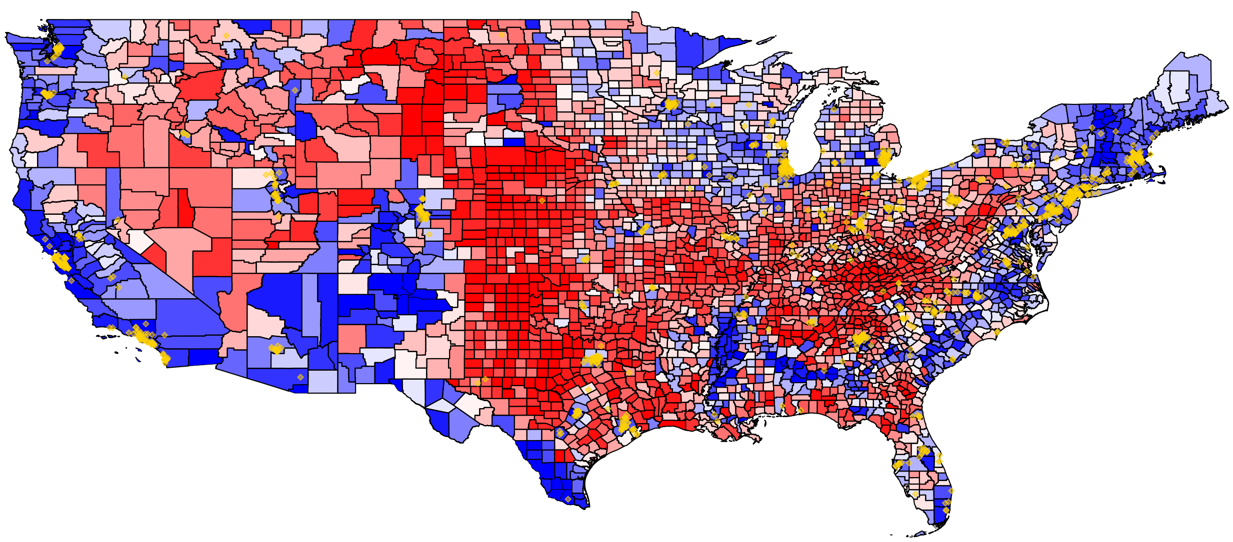
Figure 1: Publication Lag



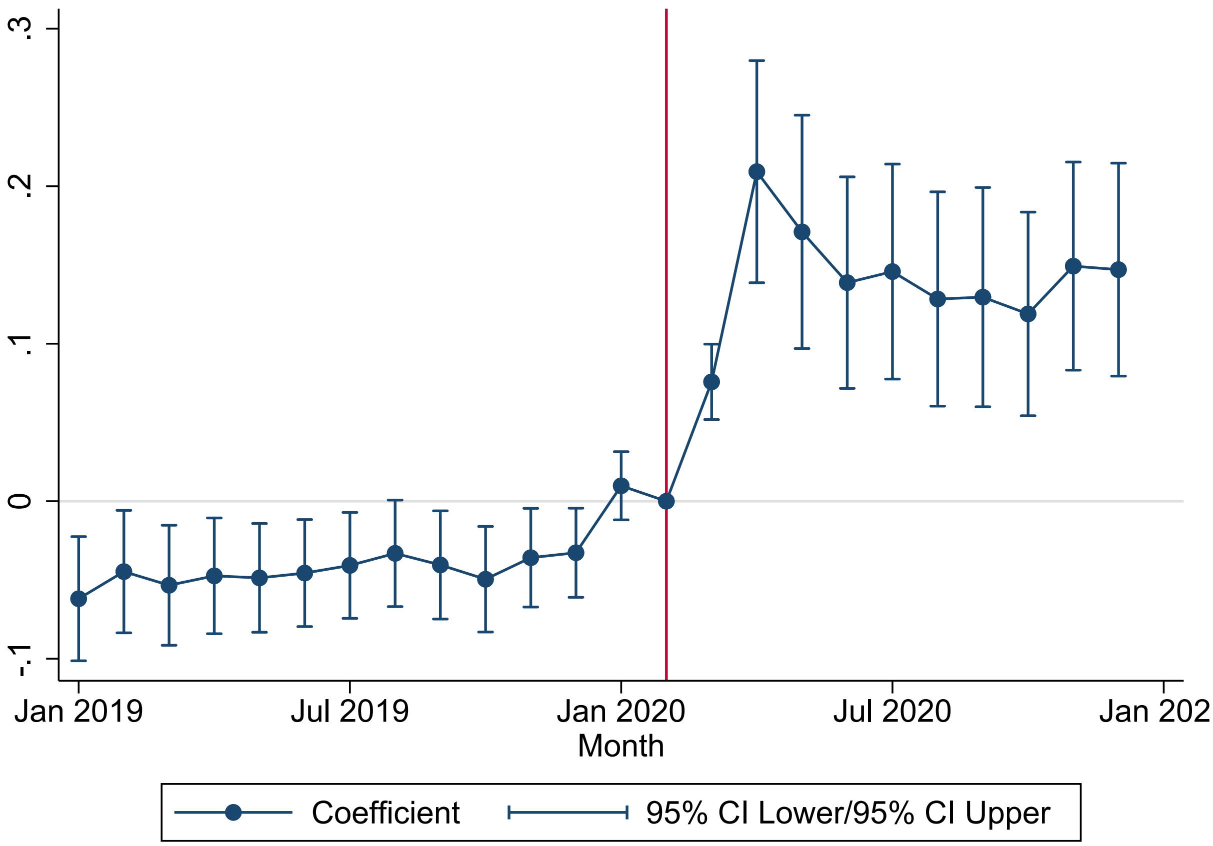
Notes: This figure displays the share of patent applications that have been published X months after the application date, where X is the number on the x-axis. Patent applications in 2015 are used for the analysis and the publication lag is winsorized at 3 years.

Figure 2: Office Map



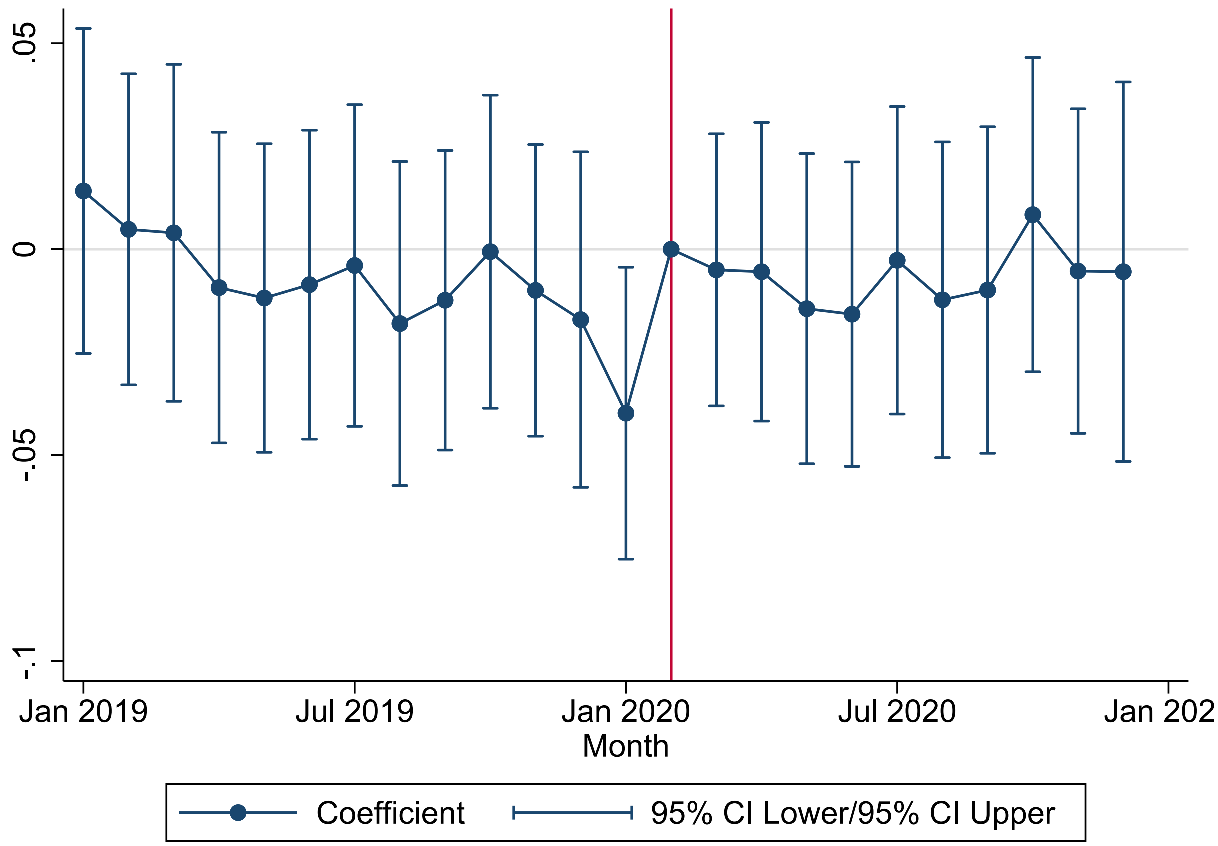
Notes: This figure displays the 1,138 offices as transparent gold diamonds and shades counties based on their 2016 Trump vote share. The darker red (blue) colors indicate higher (lower) Trump vote shares.

Figure 3: First Stage (Event Study)



Notes: This figure present results from estimating versions of equation (1) where the post dummy is replaced by month dummies with the Feburary 2020 dummy being the omitted category. Standard errors are clustered at the office level.

Figure 4: Patent Applications and Working From Home (Event Study)



Notes: This figure present results from estimating versions of equations (1) and (2) via 2SLS where the post dummy is replaced by month dummies with the Feburary 2020 dummy being the omitted category. Standard errors are clustered at the office level.

Table 1: Top 15 Firms

			Trump Vote Share	
Firm Name	Offices	Patent Apps (2019)	Mean	St. Dev.
International Business Machines	7	3,084	.33	.14
Qualcomm	22	2,149	.33	.11
Micron Technology	11	1,434	.38	.12
Intel	36	1,348	.35	.12
Applied Materials	14	861	.38	.12
Ford Motor	16	859	.37	.11
Boeing	15	722	.4	.13
Cisco Systems	37	661	.36	.11
Texas Instruments	9	645	.38	.19
Hewlett Packard Enterprise	11	529	.33	.14
Facebook	16	463	.24	.09
Corning	24	439	.41	.16
Procter & Gamble	4	430	.34	.09
Capital One Financial	4	427	.41	.13
Halliburton	8	388	.51	.19

Notes: This table presents statistics on the fifteen firms with the most patents applied for in the year 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.

Table 2: Summary Statistics

	Mean	St. Dev.	Min	Max	N
Visits per Day (2019)	23.22	38.45	1.01	761.72	1,138
Visits per Day (2020)	12.55	23.78	0.16	521.25	1,138
Δ ihs(Visits)	-0.63	0.57	-3.67	2.57	1,138
Patents Applied for per Day (2019)	0.06	0.24	0.00	4.47	1,138
Patents Applied for per Day (2020)	0.05	0.22	0.00	5.71	1,138
Δ ihs(Patents)	-0.01	0.05	-0.68	0.25	1,138
Trump Vote Share	0.37	0.15	0.04	0.82	1,138

Notes: This table presents summary statistics on all offices that have average number of visits in 2019 greater than one and apply for at least one patent in 2019. Changes are between aggregates in 2019 and 2020.

Table 3: First Stage

	ihs(Visits)			
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Trump Vote Share$_c$ $\times$ $\mathbb{1}\{\text{Post}_t\}$	0.333***	0.283***	0.179***	0.178***
	(0.029)	(0.029)	(0.030)	(0.036)
Unemp Rate$_{ct}$		-0.028***	-0.020**	-0.015
		(0.008)	(0.008)	(0.012)
Poor Health$_c$ $\times$ $\mathbb{1}\{\text{Post}_t\}$		5.895***	3.656***	5.476***
		(0.857)	(0.845)	(0.994)
F-Stat	134.15	93.60	35.62	23.91
Month FE	✓	✓		
Firm $\times$ Month FE			✓	✓
State $\times$ Month FE				✓
Observations	26,040	26,040	26,040	26,040

Notes: Standard errors are clustered at the office level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 4: Patent Applications and Working From Home

	ihs(Patents)			
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
ihs(Visits)	0.010	0.009	0.015**	0.012*
	[-0.003,0.022]	[-0.004,0.022]	[0.001,0.028]	[-0.002,0.025]
Unemp Rate$_{ct}$		-0.011***	-0.006**	-0.003
		[-0.017,-0.006]	[-0.010,-0.001]	[-0.010,0.004]
Poor Health$_c$ $\times$ $\mathbb{1}\{\text{Post}_t\}$		-0.327	0.214	0.329
		[-0.808,0.155]	[-0.222,0.650]	[-0.183,0.841]
Month FE	✓	✓		
Firm $\times$ Month FE			✓	✓
State $\times$ Month FE				✓
Observations	26,040	26,040	26,040	26,040

Notes: Office fixed effects are included in all specifications and standard errors are clustered at the office level with 95% confidence intervals shown in brackets. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 5: Patent Applications and Working From Home

	ihs(Patents)			
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
ihs(Visits)	0.009	-0.020	-0.003	0.001
	[-0.043,0.062]	[-0.083,0.043]	[-0.098,0.093]	[-0.114,0.116]
Unemp Rate$_{ct}$		-0.013***	-0.006**	-0.003
		[-0.019,-0.007]	[-0.012,-0.001]	[-0.012,0.005]
Poor Health$_c$ × $\mathbb{1}\{\text{Post}_t\}$		-0.112	0.286	0.385
		[-0.693,0.469]	[-0.237,0.808]	[-0.376,1.147]
F-Stat	134.15	93.60	35.62	23.91
Month FE	✓	✓		
Firm × Month FE			✓	✓
State × Month FE				✓
Observations	26,040	26,040	26,040	26,040

Notes: Office fixed effects are included in all specifications and standard errors are clustered at the office level with 95% confidence intervals shown in brackets. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 6: Geographic Distance and Collaboration

	Share of Inventors at Office			
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
ihs(Visits)	-0.017	-0.023	-0.033	-0.060
	[-0.050,0.016]	[-0.068,0.022]	[-0.111,0.046]	[-0.174,0.055]
Unemp Rate$_{ct}$		-0.003	-0.004	0.003
		[-0.008,0.001]	[-0.011,0.003]	[-0.007,0.012]
Poor Health$_c$ $\times$ $\mathbb{1}\{\text{Post}_t\}$		-0.016	-0.281	-0.198
		[-0.577,0.545]	[-0.869,0.308]	[-0.937,0.541]
$\overline{Y}$	0.52	0.52	0.52	0.52
F-Stat	54.23	36.51	13.89	6.24
Month FE	✓	✓		
Firm $\times$ Month FE			✓	✓
State $\times$ Month FE				✓
Observations	9,269	9,269	9,269	9,269

Notes: Office fixed effects are included in all specifications and standard errors are clustered at the office level with 95% confidence intervals shown in brackets. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 7: Team Size

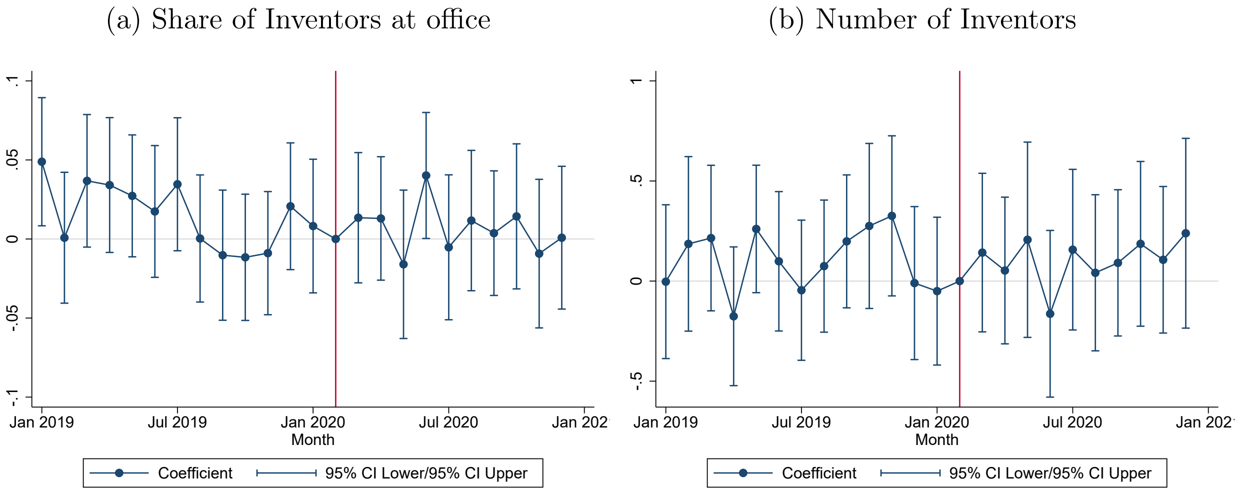
	Number of Inventors			
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
ihs(Visits)	0.209	0.278	0.062	0.074
	[-0.115,0.534]	[-0.159,0.714]	[-0.680,0.803]	[-1.042,1.190]
Unemp Rate$_{ct}$		0.029	0.016	-0.035
		[-0.023,0.080]	[-0.048,0.080]	[-0.121,0.051]
Poor Health$_c$ $\times$ $\mathbb{1}\{\text{Post}_t\}$		-0.604	0.952	1.079
		[-6.190,4.981]	[-4.717,6.620]	[-5.722,7.880]
$\overline{Y}$	4.49	4.49	4.49	4.49
F-Stat	54.23	36.51	13.89	6.24
Month FE	✓	✓		
Firm $\times$ Month FE			✓	✓
State $\times$ Month FE				✓
Observations	9,269	9,269	9,269	9,269

Notes: Office fixed effects are included in all specifications and standard errors are clustered at the office level with 95% confidence intervals shown in brackets. *(p<0.1), **(p<0.05), ***(p<0.01).

A Appendix

[Figure A1 about here.]

Figure A1: Collaboration and WFH (Event Studies)



Notes: This figure present results from estimating versions of equation (1) and (2) via 2SLS where the post dummy is replaced by month dummies with the Feburary 2020 dummy being the omitted category. Standard errors are clustered at the office level.