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 all firms in my sample along with this variation in local political attitudes as an instrument for visits to the office, I find that increased intensity of work from home does not significantly impact patenting productivity. When limiting to the offices of firms who are highly innovative, operate in rapidly evolving areas of technology, or are large, I find a negative effect of working from home on patenting productivity.

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

JEL: O31, O32, J40

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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 2023), bars (Andrews 2023), 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) and in 2013 Yahoo banned working from home with Zappos CEO, Tony Hsieh, taking to Yahoo's defense and arguing that more face time in the office leads to a more innovative work culture. This discussion suggests that physical interaction with a large pool of researchers can enhance innovation. On the other hand, during the onset of the COVID-19 pandemic many technology companies have embraced some form of WFH, citing increased productivity for certain tasks and types of workers (Barrero et al. 2021).

In light of COVID-19 pandemic which brought about a five-fold increase in WFH prevalence from 2019-2023, the question of how WFH has affected corporate innovation is particularly salient (Barrero et al. 2023). Despite the importance of the issue, we have relatively little direct evidence on the topic due to the difficulty of finding the right setting to causally examine the link between WFH and innovation. Further, we know even less about the conditions which cause WFH to differentially impact innovative productivity. This study fills the gap by using the unexpected arrival of the COVID-19 pandemic, along with pre-existing variation in local political attitudes to generate plausibly exogenous variation in within firm WFH tendencies. After the start of the COVID-19 pandemic, I find that a one standard deviation increase in Trump support leads to approximately a 20% increase in visits which persists through 2021. While I find that, on average, WFH does not impact the innovative productivity of offices in my sample of firms, WFH does negatively impact the patenting output of offices belonging to highly innovative firms. The results suggest that the more important innovation is to a firm, the more important in-person interaction is for generating innovation. Further, large firms face a larger innovation penalty from WFH, consistent with the notion that it is harder to virtually navigate within large firms. Finally, the results indicate that WFH has no effect on team size or tendency to collaborate with geographically distant inventors. This finding supports the view that there are substantial frictions to forming relationships with other inventors.

2 Hypotheses

2.1 WFH and Productivity

The prior literature studying the effects of WFH on productivity is mixed, with studies finding both positive and negative effects. Bloom, Liang, et al. 2015 and Emanuel and Harrington 2023 find that the productivity of call center employees improved when they began working remotely. Since call center workers are engaged in routine and solitary work while inventors are typically engaged in non-routine and collaborative work, the results are less likely to be generalize to this context, but they provide an example of when WFH can improve productivity. There are several studies which examine the effects of WFH on the productivity of knowledge workers which is more relevant to this study. Two studies find negative effects of WFH on knowledge worker productivity in the context of IT workers (Gibbs et al. 2021) and professional Chess players (Künn et al. 2022). Other studies document positive effects of WFH on productivity in the context of United States Patent and

Trademark Office's (USPTO) examiners[1] (Choudhury et al. 2021), workers involved in new product development (Coenen and Kok 2014), academic researchers (Aczel et al. 2021), and white collar workers at various firms (Hill et al. 1998; Angelici and Profeta 2023). In a systematic review of 26 studies on the effect of WFH on productivity, Anakpo et al. 2023 find mostly positive effects of WFH on productivity.

Aczel et al. 2021 find that academic researchers are more productive in solitary tasks at home while collaborative tasks are more productively performed in the office. This is consistent with Criscuolo et al. 2021 which reports that managers and workers most commonly advocate for 2-3 days of WFH in order to balance collaborative and non-collaborative work. Tønnessen et al. 2021 examine how the COVID-19 pandemic impacts the creativity of knowledge workers in Norway. They find that employees who engage in more digital sharing of knowledge have higher creative performance, highlighting the importance of collaboration in creating original work. Consistent with this, Tripathi and Burleson 2012 find that computer programmers who have more face-to-face interactions display increased creativity and higher quality code. These studies suggest that work which requires collaboration will be more productively completed with some amount of in-person interaction. Although many studies find a positive effect of WFH on productivity (Anakpo et al. 2023), the process of invention is highly collaborative and often involves a significant amount of complex knowledge sharing. These are the conditions under which WFH is likely to have a negative effect on productivity. This leads us to my first hypothesis.

Hypothesis 1: *During the COVID-19 pandemic, WFH will negatively affect the patenting productivity of the offices of sufficiently innovative firms but for less innovative firms the effect may be positive or negative.*

Measuring productivity for high-skilled knowledge workers is a significant problem for most studies, including the ones cited above. Indeed, many studies which examine the effect of WFH on the productivity of knowledge workers resort to using qualitative and self-reported measures of productivity (Anakpo et al. 2023) or input based measures of productivity, such as whether the individual was "on task" as measured by monitoring software on their

[1] This study examined the effect of transitioning from WFH to work-from-anywhere

computer (Gibbs et al. 2021). As reflected in Hypothesis 1, my research design addresses this directly by looking at a natural form of output for inventors, patent applications. This allows me to directly observe the innovative output of individual inventors, an improvement on much of the prior literature.

Further, this study explores the heterogeneous effects of WFH on inventor productivity. As Anakpo et al. 2023 note in their meta-study, the effect of WFH on employee productivity can depend on various factors such as whether the work is collaborative, the nature of the industry, and the nature of the occupation. There is a lack of research on this topic as most studies with plausibly exogenous variation in WFH look at one firm or office, leaving them with no variation to examine heterogeneity in effects whereas my study is able to examine the conditions under which WFH matters as I have a large sample. This allows me to separately estimate the effect of WFH on patenting for highly innovative firms and those firms which are less innovative, which is crucial for testing Hypothesis 1.

The current literature has documented that WFH can provide gains in productivity related to solitary and routine tasks, but that WFH can be detrimental to complex collaborative work. Hypothesis 1 reflects these facts as I suppose that any gains in productivity related to doing routine and solitary tasks at home will be overshadowed by the negative effects of WFH on collaborative work for offices that are sufficiently focused on innovation.

The positive connection between face-to-face interaction and creativity suggests that when starting a new innovation project in-person interaction may particularly useful as it could help the team build rapport with colleagues, brainstorm ideas about the project, and pivot quickly as ideas are attempted and either discarded or refined. Indeed, media synchronicity theory suggests that synchronous communication (such as in-person interactions) is better at helping groups converge on ideas (Dennis et al. 2008). Also, email communication hinders the ability to establish rapport with colleagues, which can lead to less productive teamwork and less knowledge sharing (Morris et al. 2002). Finally, a significant body of research has demonstrated the importance of in-person interaction in forming new working relationships (Freeman et al. 2014; Boudreau et al. 2017; Campos et al. 2017; Catalini 2018). Taken together, the evidence suggests that in-person interaction is particularly important in the initial phases of a project as new ideas and relationships are formed, leading to my second hypothesis.

Hypothesis 2: *WFH will have a larger negative effect on patenting productivity for the offices of firms who innovate in rapidly evolving areas of technology.*

Firms who operate in rapidly evolving areas of technology must constantly be experimenting and testing out new ideas. Given the importance of face-to-face interaction for experimentation and testing, WFH should be particularly detrimental to innovative firms who must iterate quickly on ideas in order to operate in their technological area.

Given the importance of firm size for many outcomes (Arora et al. 2022), it is natural to suppose that firm size may alter the effect of WFH on productivity. Despite this, I am not aware of any theoretical or empirical studies examining how firm size may alter the effect of WFH on productivity. In a larger firm, being in the office may be even more necessary as it prevents workers from getting lost among a large group of employees. On the other hand, being in a large firm may result in less face-to-face interaction when in the office, reducing any positive effect from working in the office. Hypothesis 3 reflects this uncertainty in how firm size may change the effect of WFH on innovation.

Hypothesis 3: *WFH may have a larger or smaller effect on patenting productivity for the offices of firms who are large.*

Some firms were more naturally able to move their workforce to WFH during the pandemic relative to other firms due to the nature of the work done by their employees (Dingel and Neiman 2020). For example, working on a manufacturing floor cannot be done from home, whereas software engineering can be done at home. It is natural to suppose that innovators operating in industries which allow them to more easily work from home would not see their productivity fall as much relative to inventors working in industries which are difficult to transition to remote work.

Hypothesis 4: *WFH will have a smaller effect on patenting productivity for the offices of firms who operate in industries where innovation workers can easily transition to WFH.*

2.2 WFH and Collaboration

During the COVID-19 pandemic, much of the world transitioned to remote work, suggesting that new collaborator relationships may have formed between inventors who had more incentive to communicate online with other geographically distant inventors. While the notion that the move to WFH could broaden collaboration networks and increase team size has some merit, the current literature indicates that in-person interaction is particularly important in building initial relationships with co-authors. Freeman et al. 2014 document that for their sample of scientific fields, most collaborators first met at the same institution while Catalini 2018 exploits a natural experiment and finds that colocation increases the likelihood of joint research by 3.5 times. The experimental evidence of Boudreau et al. 2017 highlights the importance of face-to-face interactions and Campos et al. 2017 examines how academic conferences shape collaboration networks. Consistent with the importance of in-person meetings for the formation of new working relationships, Yang et al. 2022 examine the effect of WFH at Microsoft and find that remote work causes collaboration networks to become more "static and siloed." Taken together, the results suggest that new collaborator relationships are unlikely to form remotely which leads to the formation of Hypothesis 5.

Hypothesis 5: *WFH will have no effect on the proportion of inventors who come from outside an office or the size of innovative teams.*

If WFH causes the formation of new geographically distant co-author relationships, then there would be an increase in the proportion of inventors who come from outside the office. In contrast to this, Hypothesis 5 predicts that WFH will not have an effect on the proportion of inventors located at other offices, consistent with the idea that WFH does not foster new working relationships. Another way that WFH could alter collaboration patterns is by changing team size. Similar to before, we have little reason to suppose that WFH would alter the number of people working on a project.

3 Data

3.1 SafeGraph Data

My first data source comes from the SafeGraph Patterns data product.[2] 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 an average of at least 365 visits per year in the pre-pandemic period (2018-2019). Next, I limit down to offices who belong to firms that have more than one office in my data. This is done because in my preferred specification I will be utilizing within firm variation. Finally, I remove all offices who do not file for a patent application during the entire time period. With all these restrictions made, there are 1,775 offices belonging to 158 different firms.

To check the coverage of the SafeGraph data, I examined the offices of three high-technology companies: Lam Research, Raytheon Technologies, and Boston Scientific.[3] These companies were chosen because they are highly innovative firms in distinct industries with activity distributed across many locations. The website of Lam Research[4] 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

[2] https://docs.SafeGraph.com/docs/weekly-patterns

[3] 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.

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

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.

3.2 USPTO Patent Applications

I collect data on patent applications from the USPTO bulk data product which is updated weekly.[5] My analysis includes all patent applications with dates of publication from January 4, 2018 through August 17, 2023. 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 $\times$ inventor observations where the inventor resides in the U.S. I obtain latitude and longitude coordinates for each patent application $\times$ inventor observation by entering the city and state information for the patent application $\times$ inventor observation either by matching to the USPTO PatentViews database, or in the event that I cannot match I use the Bing Maps API.

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.

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

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, Davis, et al. 2021).

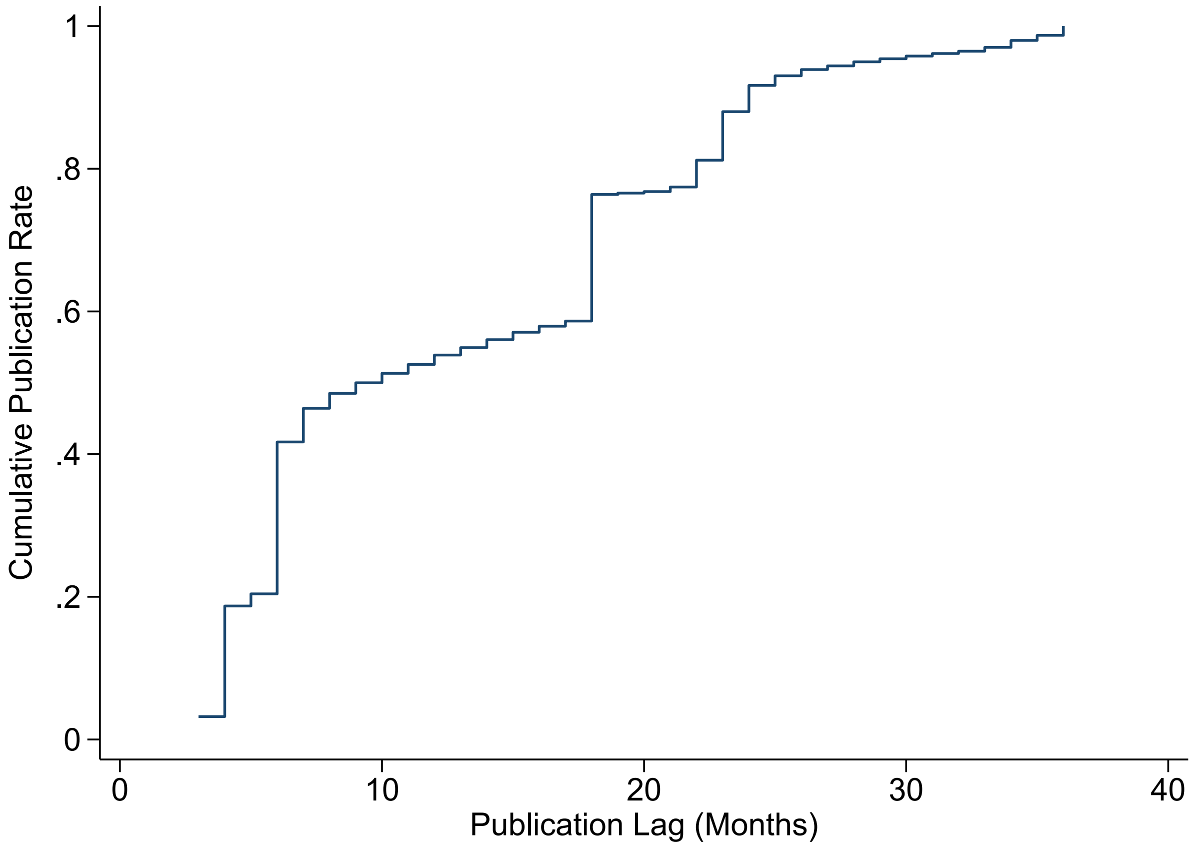
Another consideration is that for all patent applications there is a lag between when the application is filed with the USPTO and when the patent application is published and thus made available to be included in my data. Figure 1 uses all patent applications made in 2015 and displays the share of patent applications that have been published as a function of the lag between the patent's application date and 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 18 months since the observation date and August of 2023 when the most recent patent application data was made available. Given that 76% of applications filed in 2015 were published within 18 months, there has been enough time that most patent applications in my data should be published and thus accounted for.

3.3 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 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 $\times$ 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 $\times$

Figure 1: Publication Lag



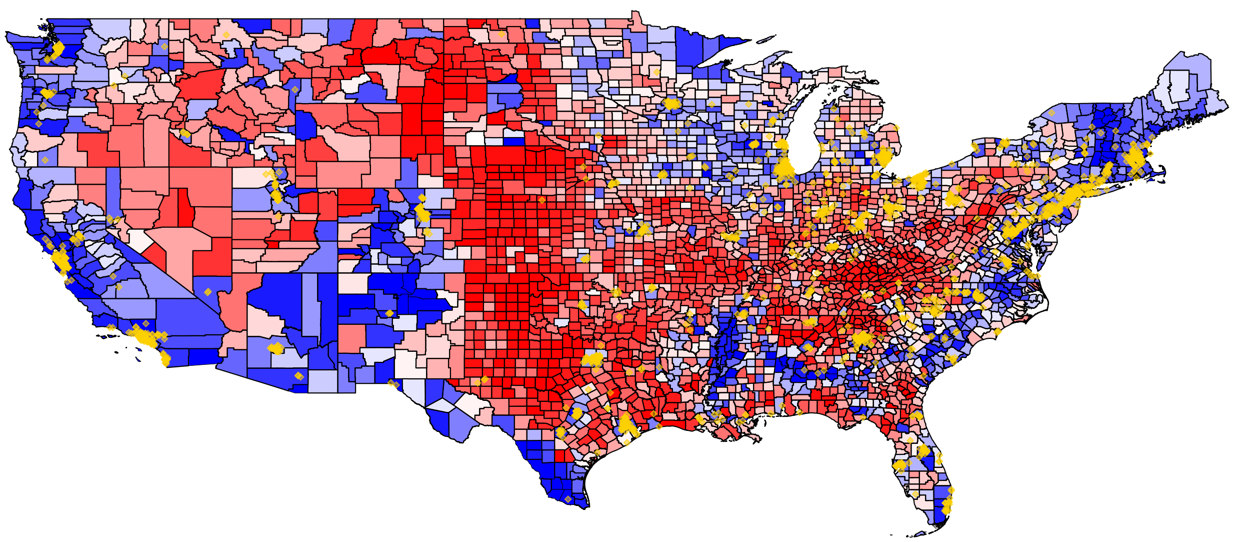
Notes: This figure displays the share of patent applications that have been published X months after the application date, where X is the number on the x-axis. Patent applications in 2015 are used for the analysis and the publication lag is winsorized at 3 years.

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 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 1 displays statistics for the twenty firms who applied for the most patents in the pre-pandemic time period. These twenty firms account for 68% of all the pre-pandemic patenting in my sample. The list includes large and prominent U.S. multinationals. Eight of the top twenty firms are in the "Computer Electronics Mfg" NAICS3 industry.[6] Given the high level of concentration particular industries and the potential for heterogeneity in effects, my analysis will examine how the effect of working from home varies by these different industries. 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 0.18. 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 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.

Figure 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.

[6]NAICS3 codes provide high level categorizations of a firm's economic activity.

Table 1: Top 20 Firms

				Trump Vote Share	
Firm Name	NAICS3 Title	Offices	Patents	Mean	St. Dev.
IBM	Information Services	6	5,429	.35	.13
Qualcomm	Computer/Electronics Mfg	22	4,421	.33	.11
Intel	Computer/Electronics Mfg	39	3,050	.35	.11
Ford Motor	Transportation Equip Mfg	17	2,846	.38	.12
Micron Technology	Computer/Electronics Mfg	11	2,699	.38	.11
Applied Materials	Machinery Mfg	14	1,579	.38	.12
Dell Technologies	Computer/Electronics Mfg	61	1,540	.33	.11
HP	Computer/Electronics Mfg	11	1,444	.33	.13
Boeing	Transportation Equip Mfg	16	1,435	.41	.13
Texas Instruments	Computer/Electronics Mfg	9	1,285	.38	.18
General Electric	Government	43	1,254	.44	.15
Cisco Systems	Computer/Electronics Mfg	50	1,122	.38	.12
Procter & Gamble	Chemical Mfg	3	859	.37	.09
Salesforce	Book Publishing	10	852	.29	.1
Raytheon	Transportation Equip Mfg	7	852	.32	.08
Capital One	Credit Intermediation	4	807	.41	.11
Facebook	Information Services	20	806	.26	.11
Oracle	Information Services	52	780	.34	.11
Halliburton	Mining Support	13	723	.56	.13
Boston Scientific	Computer/Electronics Mfg	6	719	.33	.18

Notes: This table presents statistics on the thirty firms with the most patents applied for pre-pandemic (2018-2019). There are 158 firms in the total sample. is the number of 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.

3.4 Summary Statistics

Table 2 displays summary statistics across several levels of aggregation in the data. First, are summary statistics on the Trump vote share which is calculated at the office level. The offices of innovative firms are generally located in counties that have low support for Donald Trump with the average support being at 38%. This Trump vote share variable will be used to provide plausibly exogenous variation in the propensity of workers to come into the office based on political attitudes of an office's county.

Next, I provide summary statistics on several variables which I use to examine heterogeneity in the effect of working from home. The first is the size of firms which will be used to test Hypothesis 3. As these variables only varies at the firm level, the 2018 revenue, assets, and number of employees are only considered once for each firm when calculating summary statistics. The firms in my sample are large, with an average 2018 revenue of $28 billion, assets of $76 billion, and 54,970 employees. Even the smallest firm is quite large with $4 billion in 2018 revenue.

Table 2: Summary Statistics

	Mean	St. Dev.	Min	Max	N
Trump Vote Share	0.38	0.15	0.04	0.88	1,775
Revenue in Billions (2018)	27.66	37.54	4.36	232.89	157
Assets in Billions (2018)	75.84	282.85	2.07	3,418.32	157
Employees in Thousands (2018)	54.97	77.19	1.37	647.50	156
Patent Value to Revenue	0.32	0.55	0.00	3.50	96
Rapidly Evolving Technology	0.87	0.82	-0.57	2.42	96
Teleworking Index	0.43	0.23	0.11	0.93	36
Team Size (2018)	3.50	1.82	1.00	16.00	994
Share of Inventors at Office (2018)	0.60	0.27	0.06	1.00	994

Notes: To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office $\times$ year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. "Trump Vote Share" is the share of the 2016 presidential election vote that went to Donald Trump in the county the office is located in. "Teleworking Index" captures the wage weighted share of workers in the firm's 3-digit NAICS industry that do not need to be physically present to perform their jobs and can telework from home (Dingel and Neiman 2020) and is observed once for each office who has non-missing values. "Rapidly Evolving Technology (ReTech)" is observed once for each firm who has non-missing values and is based on the measure from Bowen et al. 2023 and captures whether the firm is operating in a technological area that is rapidly evolving or stable. The ReTech measure is the mean ReTech index value from all of a firm's patents published in 2018 and 2019 as captured in the Kogan et al. 2017 match of patents to publicly traded firms. "Patent Value to Revenue" is observed once for each firm who has non-missing values and takes the market value of all a firm's patents published in 2018-2019, as estimated by Kogan et al. 2017 and divides by the 2018 revenue of the firm in millions.

Hypothesis 1 states that sufficiently innovative firms should see a negative effect of WFH on patenting productivity. To measure whether a firm is innovative, I match granted patents of a firm, which were applied for in 2018, to the Kogan et al. 2017 database which provides the market value of patents through assessing excess stock returns around the issue date of the patent. On average, the value of a firm's 2018 patent portfolio is 32% of their 2018 total revenue.[7]

The next measure captures whether a firm is operating in a relatively stable or rapidly changing area of technology which is used to test Hypothesis 2. The measure is taken from Bowen et al. 2023 and is based on a firm's 2018 patent portfolio of granted patents. For each patent, the "Rapidly Evolving Technology" statistic measures whether the vocabulary in the patent is growing or shrinking rapidly in the entire patent corpus or whether the vocabulary is stable in its usage. Relatively small increases or decreases in the usage of a patent's vocabulary indicate that the technological area of the patent is stable which should lead to a smaller effect of WFH on patenting productivity, according to Hypothesis 2. The average value of this index across firms is 0.87 with significant variation as the standard deviation is 0.82.

Finally, to capture the ability of workers to easily transition to WFH, I use the teleworking index developed by Dingel and Neiman 2020. This measures the wage weighted share of workers in the firm's 3-digit NAICS industry that do not need to be physically present to perform their jobs and can telework from home. When providing summary statistics, I only consider the teleworking index once for each NAICS3 industry as the index varies at the NAICS3 level which is a broad industry/sector categorization. Ideally, I would have a measure of how easy it is for inventors in an industry to work from home as one can imagine that there are industries where a large percentage of the workers could not telework, but inventors would be able to easily telework. Despite the shortcomings of the measure, it provides insight into the propensity for remote work in an industry and can be used to test Hypothesis 4. Hypothesis 5 relates to the effect of WFH on collaboration. For offices who apply for a patent in 2018, the average team size across the office's patents is 3.5. Most inventors on a patent work at the focal office with the average office having 60% of the inventors on the patent residing at the office.

Table 3 displays the correlation matrix of all the variables listed in Table 2. While the measures of firm size (revenue, assets, employment) are positively correlated with one

[7]Firms who don't match to the Kogan et al. 2017 data are not assigned zero for their patent value as there are highly innovative companies who do not match for a variety of reasons. For example, Dell Technologies does not match to the Kogan et al. 2017 database because it was a private company in 2018.

another, the correlations range from 0.196 to 0.857, indicating that each variable captures a unique dimension of firm size. While offices with high patent value to revenue ratios also tend to have high measures on the rapidly evolving technologies measure, the two measures are distinct with a correlation coefficient of 0.4.

Table 3: Correlation Matrix

Variables	Trump	Rev	Assets	Emp	Pval to Rev	ReTech	Tele	Team Size	Frac Inv Off
Trump	1.000								
Rev	-0.081	1.000							
Assets	-0.073	0.352	1.000						
Emp	-0.052	0.857	0.196	1.000					
Pval to Rev	-0.209	0.012	-0.053	-0.003	1.000				
ReTech	-0.278	0.284	0.327	0.241	0.400	1.000			
Tele	-0.214	0.088	0.133	0.097	0.351	0.723	1.000		
Team Size	-0.063	0.063	0.029	0.065	0.069	-0.010	-0.001	1.000	
Frac Inv Off	0.053	-0.146	-0.055	-0.141	-0.024	-0.041	-0.057	-0.637	1.000

Table 4 presents summary statistics on the two main variables of interest in this analysis, visits to the office and number of patent applications, split into the pre and post pandemic time periods and where the observations are at the office × year level. Before the pandemic started, the average number of annual visits to an office was approximately 7,000. The average number of annual visits dropped dramatically in the post-pandemic period by over 3,000 visits per year, a 47% decline. This decline highlights the large effect that the pandemic had on office visiting behavior.

On the other hand, when I examine patent applications there is a small and statistically insignificant decline in patent applications. On average an office applied for approximately 14 patents per year both before and after the COVID-19 pandemic. While there is a small, statistically insignificant decline of half a patent per year, this could be simply a function of the lag between filing for a patent application and the publication of a patent application since patents in the post-pandemic time period have had less time for their patent to be published.

Table 4: Pre and Post Pandemic Comparison of Visits and Patents

	Pre-Pandemic		Post-Pandemic		Difference
	(1)		(2)		(3)
	Mean	St. Dev.	Mean	St. Dev.	Diff
Visits	7,009	13,538	3,738	8,472	-3,271***
Patent Count	14	70	14	89	-.48
Observations	3,550		3,550		7,100

Notes: This table presents summary statistics on visits and patenting, split between the pre-pandemic and post-pandemic time periods, for all office × year observations in the sample. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years.

4 Empirical Strategy

My goal is to identify the effect of increasing an office's share of employees working at the office on the innovative output of the office. While the evidence in Table 4 suggests that the large decline in working from the office had no appreciable effect on patenting output there are several problems with jumping to that conclusion based on the current evidence. First, simply comparing pre and post means in patenting confounds all the other common shocks that occurred at the start of the pandemic, including the stimulus packages, supply chain disruptions, and general uncertainty about the future. An empirical strategy that isolates variation in WFH from other common shocks is necessary. Second, changes in office visits 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 patent applications.

To address these issues 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 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. My preferred specification is a two-stage least squares (2SLS) estimation procedure, outlined in Equation (1) and Equation (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 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 or patents in a given year. 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 and zero otherwise.[8] 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 $\times$ 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 that contains the share of individuals reporting poor or fair health in 2016. Data on self reported health is taken from the County Health Rankings & Roadmap.[9] 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 used in the second

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

[9] 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

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.

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 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 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 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.

5 Results

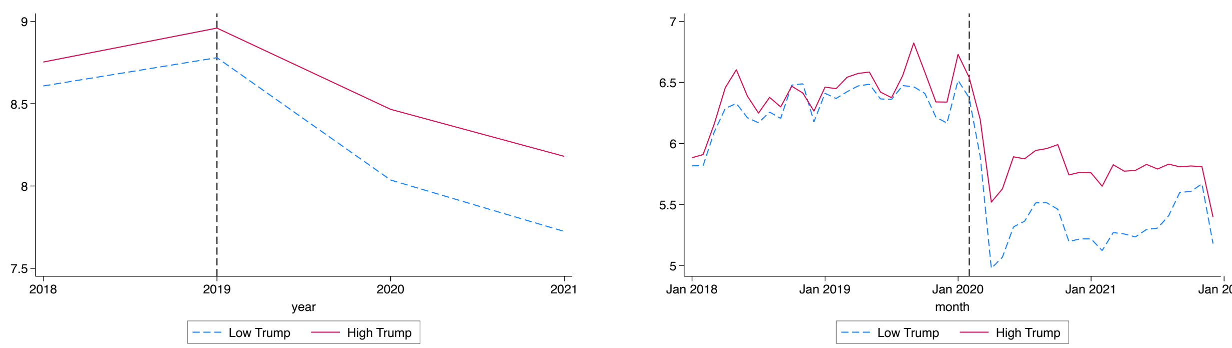
5.1 First Stage

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).[10] Panel (a) of Figure 3 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 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

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

reduction for high Trump offices. Panel (b) of Figure 3 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 3 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 3: 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 more formally test whether the variation in political attitudes drives differences in office visits, I estimate regressions of the form outlined in Equation (1). Table 5 reports the results and 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 27% increase in visits. The F-statistic of 236 indicates the instrument is highly predictive. In column (2), I control for the self-reported health of the county in 2016. While poorer health is surprisingly associated with more visits to the office, the point estimate on Trump Vote Share$_c$ $\times$ $\mathbb{1}\{\text{Post}_t\}$ remains practically unchanged. In column (3) NAICS3 $\times$ year fixed effects are included, limiting comparisons to be within broad industry. 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 an 19% increase in visits in the post-pandemic period. Column (4) employs an even tighter specification, relying on within-firm variation to identify the effect. The coefficient remains similar to the estimate in column (3) and the F-statistic is still high at 96. My preferred specification in column (4) indicates that a one standard deviation increase in an office's 2016 Trump vote share results in approximately an 18% increase in visits in the post-pandemic period.

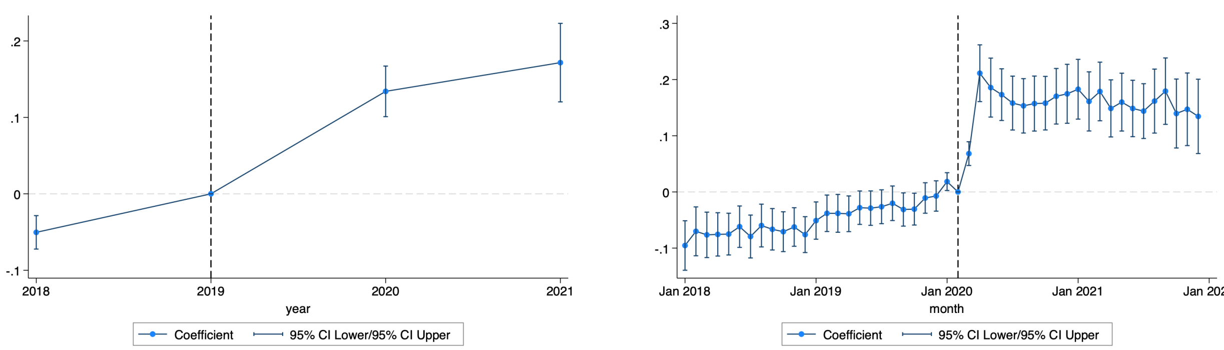
Table 5: First Stage

	ihs(Visits)			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Trump Vote Share × Post	0.269***	0.256***	0.193***	0.178***
	(0.017)	(0.017)	(0.018)	(0.018)
Poor Health × Post		3.255***	2.078***	1.543***
		(0.556)	(0.517)	(0.547)
F-Stat	236.42	218.05	120.34	96.25
Year FE	✓	✓		
NAICS3 × Year FE			✓	
Firm × Year FE				✓
Observations	7,100	7,100	7,100	7,100

Notes: This table presents results from estimating Equation (1) via OLS. To be in the sample, an office must have an average of at least 30 visits per month in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. "Trump Vote Share" is the share of the 2016 presidential election vote that went to Donald Trump in the county the office is located in, standardized to have mean zero and standard deviation of one. "Poor Health" is the share of individuals reporting poor or fair health in 2016 in the county the office is located in, as reported by the County Health Rankings and Roadmap. Standard errors are clustered at the office level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

To 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 4 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 4 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 increase in the coefficient, and it becomes statistically significant. 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 March 2020-December 2021 time period.

Figure 4: 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 office level with 95% confidence intervals shown.

5.2 Innovation and Work-From-Home

5.2.1 Patenting Productivity

Before using the Trump vote share as an instrument for working from home behavior, I start by examining the endogenous relationship between visits to the office and patenting activity. 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 as my independent variable of interest. Table 6 displays the results. In column (1) with office and month fixed effects, the point estimate is close to zero and adding the "Poor Health" control in column (2) does little to change that result. In column (3) when comparisons are made within NAICS3 industry, the coefficient increases but is not statistically different from zero. In my preferred specification in column (4) where firm $\times$ year heterogeneity is absorbed by fixed effects, the coefficient increases and becomes marginally significant. This specification indicates that a 10% increase in visits to an office is associated with a 0.3% increase in patenting with the 95% confidence interval ruling out elasticities of patenting with respect to office visits that are greater than 0.07. Although the results presented in Table 6 do not account for the endogeneity of visits to the office, they indicate that increased visits to the office are associated with modest increases in patenting activity.

As discussed earlier, estimation via OLS is likely to result in biased estimates of the effect of working from home on innovation. To address the bias, I use variation in office visits induced by local political attitudes. To visually inspect how patenting activity changed between offices located in politically conservative and liberal counties after the start of the pandemic, I split offices into two groups based on whether they are located in counties with above or below the median Trump vote share across the offices in the sample. For each group, I calculate the average number of patent applications in a given month across the offices in the group and then take the natural log of this number. Panel (a) of Figure 5 shows that in the months after the start of the COVID-19 pandemic, the number of patent applications held steady at offices with low and high and Trump vote shares. The right panel makes this more clear by de-meaning both series, showing that the offices in high and low Trump vote share areas exhibit similar trends of patenting both before and after the pandemic.

Table 6: Patent Applications and Working From Home (OLS)

	ihs(Patents)			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS
ihs(Visits)	-0.003	-0.006	0.017	0.031*
	[-0.035,0.029]	[-0.039,0.026]	[-0.020,0.054]	[-0.003,0.066]
Poor Health × Post		0.632	1.061**	1.215***
		[-0.178,1.442]	[0.246,1.876]	[0.390,2.039]
Year FE	✓	✓		
NAICS3 × Year FE			✓	
Firm × Year FE				✓
Observations	7,100	7,100	7,100	7,100

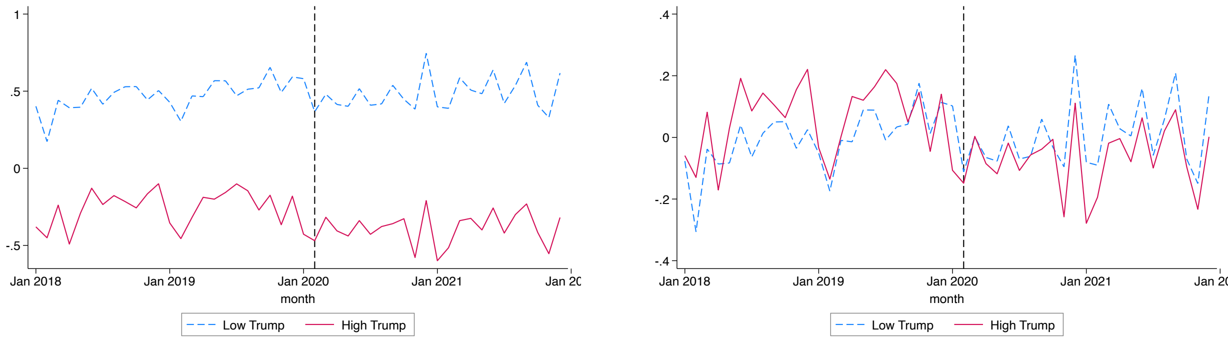
Notes: This table presents results from estimating Equation (2) via OLS where instead of using predicted values of ihs(Visits) from Equation (1) I instead use the endogenous value of ihs(Visits). To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. "Poor Health" is the share of individuals reporting poor or fair health in 2016 in the county the office is located in, as reported by the County Health Rankings and Roadmap. Standard errors are clustered at the office level with 95% confidence intervals shown in brackets. *(p<0.1), **(p<0.05), ***(p<0.01).

While Figure 5 suggests that working from home had little effect on patenting activity in the aggregate, I now turn to formally estimating the 2SLS framework outlined in Equation (1) and Equation (2) with the IHS of patent applications as the dependent variable. Hypothesis 1 states that WFH should have a negative effect on patenting productivity for sufficiently innovative firms. If the firms in my sample are not focused enough on innovation then we may not see any effect of WFH on patenting productivity in this aggregate specification.

Table 7 displays the results. In columns (1)-(3) the point estimates are close to zero but imprecisely estimated. As with the OLS estimation presented in Table 6, when firm × year fixed effects are included the coefficient increases. But unlike the OLS specification, the estimate is imprecisely estimated and the 95% confidence interval does not rule out zero effect.

Figure 6 displays the results from reduced form event study specifications, similar to

Figure 5: Patent Applications Over Time by Trump Vote Share



(a) ln(Patent Count) (b) ln(Patent Count) - $\overline{\text{ln(Patent Count)}}$

Notes: The left panel of this figure presents the natural log of the average number of patents applied for 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. The right panel augments the left panel by subtracting off the mean of each of the respective time series from the left panel.

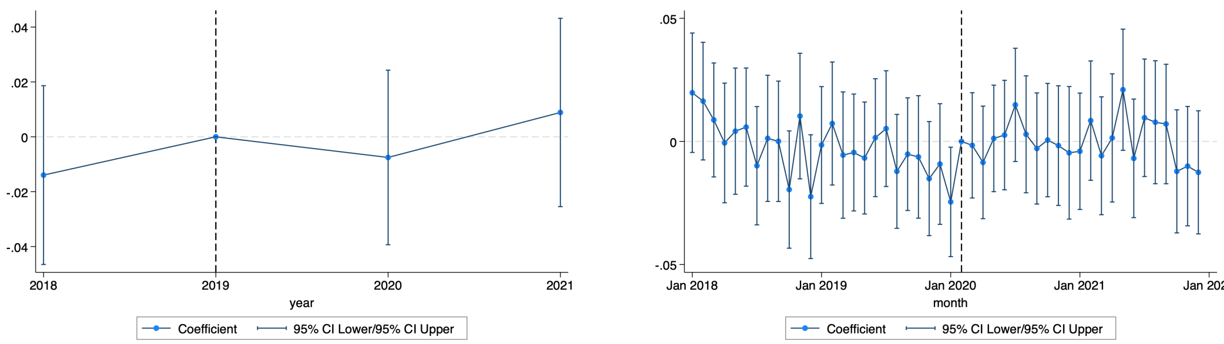
Table 7: Patent Applications and Working From Home (2SLS)

	ihs(Patents)			
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
ihs(Visits)	-0.014	-0.024	-0.009	0.057
	[-0.109,0.082]	[-0.126,0.078]	[-0.154,0.137]	[-0.104,0.219]
Poor Health × Post		0.707	1.126**	1.172**
		[-0.241,1.655]	[0.201,2.050]	[0.278,2.065]
F-statistic	236.45	218.08	120.36	96.27
Year FE	✓	✓		
NAICS3 × Year FE			✓	
Firm × Year FE				✓
Observations	7,100	7,100	7,100	7,100

Notes: This table presents results from estimating Equation (1) and Equation (2) via 2SLS. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years.. "Poor Health" is the share of individuals reporting poor or fair health in 2016 in the county the office is located in, as reported by the County Health Rankings and Roadmap. Standard errors are clustered at the office level with 95% confidence intervals shown in brackets. *(p<0.1), **(p<0.05), ***(p<0.01).

Figure 4 but with the IHS of patent applications as the dependent variable. Both the annual specification in Panel (a) and the monthly specification in Panel (b) reveal no overall impact of WFH on patenting activity as the coefficients remain close to zero both before and after the pandemic starts. The event studies also show no signs of pre-trends in patenting, offices located in high Trump counties were on similar trends in patenting activity before the pandemic started relative to offices located in low Trump counties.

Figure 6: Patent Applications and Working From Home (Event Study)



(a) Annual

(b) Monthly

Notes: The dependent variable is the inverse hyperbolic sine of patent applications. 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 office level with 95% confidence intervals shown.

Hypothesis 1 states that WFH should have a negative effect on patenting productivity for the offices of sufficiently innovative firms. To measure the importance of innovation for a firm we use the value of a firm's 2018 patent portfolio, scaled by a firm's revenue or assets. For firms where the value of innovation makes up a large share of their assets or annual revenue this measure will be high, but for less innovative firms this measure will be low. To test whether the effect of coming to the office is different for innovative or less innovative firms, I split the offices of firms into two groups, those offices that belong to firms with above the median value of the patent value measure and those offices that belong to firms with weakly less than the median value of the patent value measure. I then estimate Equation (1) and Equation (2) via 2SLS separately for each group and test whether the coefficients equal one another.

Table 8 displays the results when the patent value to revenue ratio is used to measure heterogeneity between firms. In column (1) only firms with weakly below the median value of the patent to revenue ratio are included in the estimation and only office and year fixed effects are included. While the F-statistic is quite high, the point estimate is close to zero and statistically insignificant. In contrast, column (2) shows that for firms above the median patent value to revenue ratio, the point estimate is large and statistically significant. For these innovative firms, a 10% increase in visits to the office leads to approximately a 2% increase in patenting. The coefficients in columns (1) and (2) are statistically distinguishable from one another with the p-value testing the equality of the coefficients being 0.05. When NAICS3 $\times$ year fixed effects are included in columns (3) and (4), the general pattern remains the same although some precision is lost. The pattern stays similar when comparisons are made within firm in columns (5) and (6) with column (6) indicating that for innovative firms the elasticity of patenting with respect to office visits is 0.2. Table A.1 shows that the results are robust to scaling a firm's 2018 patent portfolio value by the value of their assets.

To explore the dynamics of these results, I estimate reduced form annual event study specifications separately for firms above and below the patent value to revenue ratio. Figure 7 clearly shows that the results in Table 8 are not driven by confounding pre-trends. After the start of the pandemic, if an office is located in a high Trump county and belongs to an innovative firm, it files for more patent applications relative to offices in the same firm located in low Trump counties. The size of the effect increases in 2021, consistent with there being a lag between shocks and their impact on patent applications. Figure A.1 shows that the event study results are robust to scaling patent value by the value of a firm's assets. Overall, the results from my 2SLS estimation in Table 8 and the event study in Figure 7 provide support for Hypothesis 1; offices belonging to sufficiently innovative firms increase their patenting output when more work is done from the office.

Hypothesis 2 states that WFH should have a larger negative effect for firms operating in rapidly evolving areas of technology as face-to-face interaction has been shown to be particularly important in starting projects, forming relationships, and coming to consensus which are particularly important for firms who are constantly iterating and testing new ideas (Morris et al. 2002; Dennis et al. 2008; Freeman et al. 2014; Boudreau et al. 2017; Campos

Table 8: Patent Applications and the Importance of Innovation (2SLS)

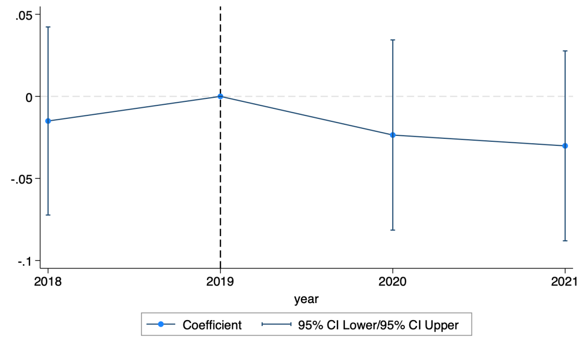
	Outcome: ihs(Patents)					
	Heterogeneity: Patent Value to Revenue Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
	≤	>	≤	>	≤	>
ihs(Visits)	-0.038	0.252**	-0.124	0.211**	-0.171	0.238**
	(0.106)	(0.101)	(0.191)	(0.103)	(0.223)	(0.100)
F-statistic	69.08	53.39	29.39	54.78	20.57	57.52
Test for equal coef (p-value)	.05*		.12		.09*	
Year FE	✓	✓				
NAICS3 × Year FE			✓	✓		
Firm × Year FE					✓	✓
Observations	2,572	2,576	2,572	2,576	2,572	2,576

Notes: This table presents results from estimating Equation (2) and Equation (1) via 2SLS with full interactions between the "Heterogeneity" variable and the endogenous variable and instrument. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. Standard errors are clustered at the office level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

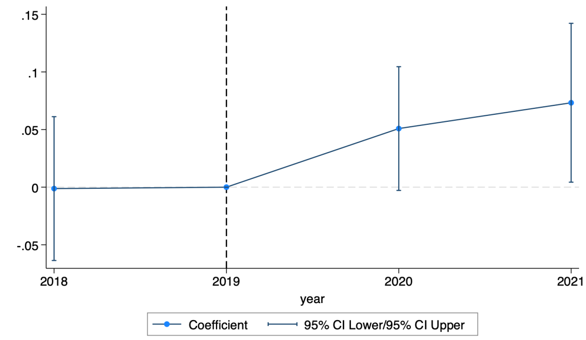
et al. 2017; Catalini 2018). To measure whether a firm is operating in a rapidly evolving area of technology (ReTech) I use the ReTech measure from Bowen et al. 2023 which captures whether the vocabulary of a firm's patents is growing or shrinking rapidly in the entire patent corpus or whether the vocabulary is stable in its usage. I use the average ReTech value across the firm's portfolio of patents in 2018 to measure ReTech.

Table 9 displays the results, estimating Equation (1) and Equation (2) via 2SLS separately for the offices of firms above and below the median ReTech measure. In columns (1) and (2) with office × year fixed effects, the effect of visits to the office is negative and statistically insignificant for the offices of firms at or below the median value of ReTech but positive and significant for the offices of firms above the median level of ReTech. For firms operating in rapidly evolving areas of technology, the estimate in column (2) indicates that a 10% increase in visits to the office leads to a 2% increase in patent applications. In columns (1) and (2), the point estimates are statistically distinguishable from one another with the p-

Figure 7: Patent Value to Revenue (Event Study)



(a) At or Below Median



(b) Above Median

Notes: Both panels 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 and the dependent variable is the inverse hyperbolic sine of patent applications. Office and firm × year fixed effects are included. Panel (a) only includes offices belonging to fimrs who are at or below the median level of the "Patent Value to Revenue Ratio" whereas Panel (b) only includes firms above the median value of the "Patent Value to Revenue Ratio." Standard errors are clustered at the office level with 95% confidence intervals shown.

value testing the equality of the coefficients being 0.04. When comparisons are made within NAICS3 industry in columns (3) and (4) and then within firm in columns (5) and (6) the estimates remain stable and continue to be precisely estimated. Figure A.2 estimates event studies and shows that the results are not driven by confounding pre-trends. While the elasticities reported in Table 9 are similar to what was found in Table 8 it is important to note that the two measures are distinct, sharing a correlation coefficient of 0.4 as reported in Table 3. While the patent value to revenue measure captures the importance of innovation to the firm, ReTech captures information about the nature of the innovation, whether it is in a rapidly evolving area of technology.

To unpack the heterogeneity that is driving my results, I took the twenty NAICS3 industries with the most pre-pandemic patenting and separately estimated Equation (1) and Equation (2) for each of these twenty industries.[11] Figure 8 displays the point estimate and 95% confidence intervals for each of the industries. Consider a few of the industries with positive point estimates, which indicates a positive causal relationship between working at the office and patent applications. "Nonstore Retailers" is an industry with one firm in my sample, "Amazon.com" while "Credit Intermediation" is composed of six banking or payment

[11]The firms in my sample belong to 37 distinct NAICS3 industries.

Table 9: Patent Applications and Rapidly Evolving Technology (2SLS)

	Outcome: ihs(Patents)					
	Heterogeneity: Rapidly Evolving Tech					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\leq$	$>$	$\leq$	$>$	$\leq$	$>$
ihs(Visits)	-0.092	0.214**	-0.126	0.201	-0.102	0.262**
	(0.106)	(0.107)	(0.138)	(0.127)	(0.170)	(0.116)
F-statistic	70.08	43.28	48.85	35.82	31.41	42.08
Test for equal coef (p-value)	.04**		.08*		.08*	
Year FE	✓	✓				
NAICS3 × Year FE			✓	✓		
Firm × Year FE					✓	✓
Observations	2,768	2,380	2,768	2,380	2,768	2,380

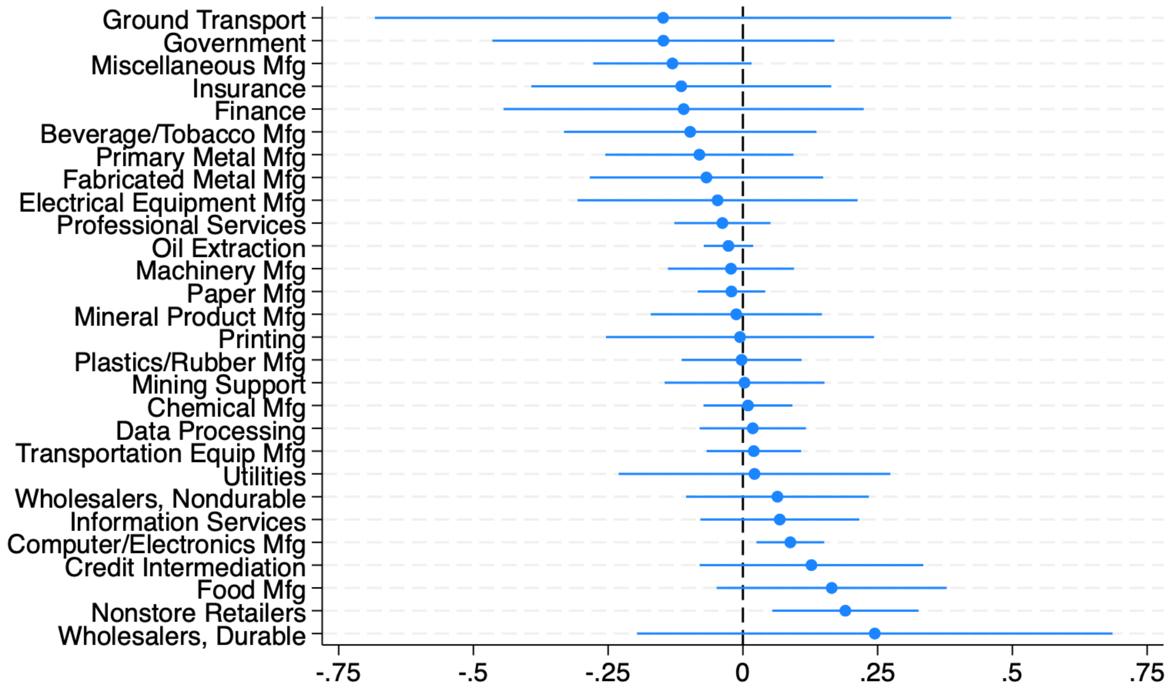
Notes: This table presents results from estimating Equation (2) and Equation (1) via 2SLS with full interactions between the "Heterogeneity" variable and the endogenous variable and instrument. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. Standard errors are clustered at the office level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

processing firms.[12] "Computer/Electronics Mfg" is the largest NAICS3 industry in my data with 24 innovative firms such as NVIDIA, Qualcomm, Intel, and Dell Technologies. Other than the "Nonstore Retailers" industry (which is "Amazon.com") this is the only other industry to have a statistically significant and positive coefficient. "Information Services" has a positive coefficient and comprises four companies: Booking Holdings, Facebook, IBM, and Oracle. In summary, many of the industries with positive coefficients primarily patent in the areas of computing, software, technology, and semiconductor design. Consistent with the results in Table 8, innovation is known to be particularly important in these sectors of the economy. This aligns with Hypothesis 1 which expects that working from the office and face-to-face interactions are most important for innovative firms. In addition, the technology in these sectors is rapidly evolving making the positive point estimates consistent with

[12]These are: Bank of New York Mellon, Capital One Financial, Fannie Mae, Mastercard, Synchrony Financial, and Visa.

Hypothesis 2.

Figure 8: Patenting and WFH for Top 20 NAICS3 Industries



Notes: This figure displays the point estimates and 95% confidence intervals from estimating Equation (1) and Equation (2) via 2SLS separately for the twenty NAICS3 industries with the most pre-pandemic patent applications.

When examining the industries with negative or near zero coefficients, which indicate that the industry is either more productive or no less productive at patenting when WFH increases, there are many manufacturing industries or industries where traditional technological innovation does not play a crucial role. For example, "Insurance" is composed of primarily health insurance companies such as Anthem, Cigna, and UnitedHealth while "Finance" comprises BlackRock, Intercontinental Exchange, and State Street. These industries are surrounded on either side by a variety of manufacturing industries which tend to operate in more stable and established technological domains. The results again confirm that working from the office has a positive impact in the industries where technological innovation is most important and where the technologies are rapidly evolving. The results also suggest that WFH is actually more detrimental to the patenting productivity of inventors who operate in sectors that are traditionally thought of as being able to easily transition to WFH, such as the software, technology, and computing sectors. On the contrary, WFH appears to have no effect on the patenting productivity of the manufacturing industries which are traditionally viewed as being difficult to transition to WFH because of the need to be on-site.

With this background, I turn to a more formal test of Hypothesis 4 which states that WFH should have a smaller effect on the patenting productivity of offices who operate in industries where innovation workers can easily transition to WFH. To measure the ability of a firm to transition to WFH, I use a firm's NAICS3 classification to measure the wage weighted share of workers who can work from home according to Dingel and Neiman 2020. Firms operating in the "information economy" tend to have high values while manufacturing firms have low values of this index. For example, the "Computer/Electronics Mfg" industry has a share of wage weighted teleworking at 74% whereas the corresponding value for "Primary Metal Mfg" is 23%. As before, I split the sample based on the median value of the Dingel and Neiman 2020 measure and report the results in Table 10. The results of an event study specification in Figure A.3 again indicate that the results are not being driven by confounding pre-trends.

The results in Table 10 do not support Hypothesis 4. Regardless of the fixed effects used, the offices belonging to industries where a high share of their workforce can transition to remote work see a positive and statistically significant effect of working from the office on patenting productivity whereas the effect is negative for offices where WFH is difficult. In light of Figure 8, these results are not unexpected and suggest that an industry's ability to WFH is not the most important factor in determining whether WFH will harm innovative productivity. What is more important is assessing the importance of innovation to the firm and whether the firm is operating in a swiftly changing technological environment. If constant innovation is crucial to a firm's success, then the results suggest that whether WFH is feasible or not, face-to-face interaction at the office will increase patenting productivity.

While Hypothesis 3 does not take a clear stand on whether firm size will change how WFH impacts patenting productivity, we know that firm size directly influences many firm outcomes, including innovation (Arora et al. 2022). My primary measure of firm size will be the total number of employees at the firm, but I present results from using assets and total revenue in Table A.2 and Table A.3. Table 11 displays the results from estimating Equation (1) and Equation (2) via 2SLS separately for the offices of firms with above and

Table 10: Patent Applications and Ease of Teleworking (2SLS)

	Outcome: ihs(Patents)					
	Heterogeneity: Teleworking Index					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\leq$	$>$	$\leq$	$>$	$\leq$	$>$
ihs(Visits)	-0.047	0.182**	-0.162	0.180*	-0.146	0.262**
	(0.083)	(0.086)	(0.127)	(0.095)	(0.151)	(0.105)
F-statistic	91.62	72.04	53.16	62.23	37.98	51.62
Test for equal coef (p-value)	.06*		.03**		.03**	
Year FE	✓	✓				
NAICS3 × Year FE			✓	✓		
Firm × Year FE					✓	✓
Observations	3,592	3,300	3,592	3,300	3,592	3,300

Notes: This table presents results from estimating Equation (2) and Equation (1) via 2SLS with full interactions between the "Heterogeneity" variable and the endogenous variable and instrument. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. Standard errors are clustered at the office level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

weakly below median total employment. Regardless of the fixed effects used, the estimate is positive for the offices of large firms and negative for those of small firms. In addition, the coefficients are statistically distinguishable from each other in all cases. The results indicate that working at the office is significantly more beneficial to patenting productivity when firms are large. This is consistent with the idea that large firms can be difficult to navigate as the number of potential collaborators and stakeholders on a project can be vast. Going in person to the office can help narrow down the scope of interaction, leading to increased team cohesion. In contrast, small firms do not face this problem as acutely. Table A.2 and Table A.3 corroborate that the results are similar when using revenue or assets to measure firm size. In addition, Table 3 confirms that the measures of firm size (employment, assets, and revenue) have minimal correlations with the other measures of interest such as the patent value to revenue ratio, ReTech, and the teleworking index.

Table 11: Patent Applications and Firm Size (2SLS)

	Outcome: ihs(Patents)					
	Heterogeneity: Total Employment					
	(1) $\leq$	(2) $>$	(3) $\leq$	(4) $>$	(5) $\leq$	(6) $>$
ihs(Visits)	-0.089	0.111	-0.176*	0.176	-0.130	0.264**
	(0.058)	(0.090)	(0.106)	(0.109)	(0.106)	(0.128)
F-statistic	163.19	72.99	61.53	59.09	52.35	44.87
Test for equal coef (p-value)	.06*		.02**		.02**	
Year FE	✓	✓				
NAICS3 × Year FE			✓	✓		
Firm × Year FE					✓	✓
Observations	3,556	3,500	3,556	3,500	3,556	3,500

Notes: This table presents results from estimating Equation (2) and Equation (1) via 2SLS with full interactions between the "Heterogeneity" variable and the endogenous variable and instrument. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. Standard errors are clustered at the office level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

5.2.2 Collaboration

Next I turn to the issue of how working from home impacted collaboration. Hypothesis 5 states that WFH should not have an effect on collaboration as measured by the share of inventors who are located at the focal office or team size. The reasoning behind this explanation is that collaborator relationships are subject to a significant amount of friction and are difficult to form without face-to-face interaction (Freeman et al. 2014; Boudreau et al. 2017; Campos et al. 2017; Catalini 2018).

To examine these ideas, I use the same 2SLS framework as before, but the dependent variable is the average share of inventors on an office's patents, averaged across all the office's patents, who are located at the focal office.[13] In a given year, values close to one indicate

[13]For example, if an office had two patents in 2019 where one patent had two of four inventors (50%)located at the office and the other patent had two of six inventors ($33.\overline{3}$%) located at the office, then the office's 2019 share of inventors at the office would be $\frac{.5+.\overline{3}}{2} = 0.41\overline{6}$

that the patents applied for by the office are mainly generated by an individual or teams where all the inventors work at the office of observation whereas smaller values indicate that collaborators are spread across many different offices.

Table 12: Patent Applications and Firm Size (2SLS)

	Share of Inventors at Office			
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
ihs(Visits)	0.011	0.015	0.028	0.023
	[-0.038,0.059]	[-0.039,0.068]	[-0.045,0.102]	[-0.063,0.109]
Poor Health × Post		-0.191	-0.231	-0.180
		[-0.669,0.287]	[-0.715,0.253]	[-0.723,0.363]
$\overline{\text{Y}}$	0.57	0.57	0.57	0.57
F-statistic	93.88	80.95	49.59	40.96
Year FE	✓	✓		
NAICS3 × Year FE			✓	
Firm × Year FE				✓
Observations	3,538	3,538	3,538	3,538

Notes: This table presents results from estimating Equation (1) and Equation (2) via 2SLS. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years.. "Poor Health" is the share of individuals reporting poor or fair health in 2016 in the county the office is located in, as reported by the County Health Rankings and Roadmap. 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 12 displays the results of estimating Equation (1) and Equation (2) via 2SLS but with the share of inventors at the office as the dependent variable. Across all the specifications the point estimates are positive but statistically insignificant. While the lack of precision in the estimates does not allow for conclusive evidence on the topic, the results suggest that WFH did not cause inventors to tilt the composition of their collaborators either towards or away from those who work at an inventor's office. This is consistent with the prior literature which documents substantial frictions in the formation of collaborator relationships (Freeman et al. 2014; Boudreau et al. 2017; Campos et al. 2017; Catalini 2018).

To explore any effects that remote working has on team size, I use the natural log of the average number of inventors on an office's patents applied for in a given year as the dependent variable. Table 13 presents the results. Across all the specifications, the point estimates are negative but not statistically significant suggesting that if anything more visits to the office result in smaller team sizes, but given the imprecision of the estimates there is no conclusive evidence supporting this view. While the results in Table 12 and Table 13 are imprecisely estimated, the lack of a clear finding provides suggestive evidence in favor of Hypothesis 5.

Table 13: Team Size and Working From Home

	ln(Average Number of Inventors)			
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
ihs(Visits)	-0.027	-0.036	-0.055	-0.049
	[-0.134,0.080]	[-0.155,0.084]	[-0.218,0.107]	[-0.240,0.142]
Poor Health × Post		0.418	0.543	0.215
		[-0.697,1.533]	[-0.567,1.653]	[-0.999,1.429]
F-statistic	93.88	80.95	49.59	40.96
Year FE	✓	✓		
NAICS3 × Year FE			✓	
Firm × Year FE				✓
Observations	3,538	3,538	3,538	3,538

Notes: This table presents results from estimating Equation (1) and Equation (2) via 2SLS. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years.. "Poor Health" is the share of individuals reporting poor or fair health in 2016 in the county the office is located in, as reported by the County Health Rankings and Roadmap. Standard errors are clustered at the office level with 95% confidence intervals shown in brackets. *(p<0.1), **(p<0.05), ***(p<0.01).

6 Conclusion

This study contributes to our understanding of how WFH impacts the productivity of workers and the effects of the COVID-19 pandemic on the innovation ecosystem. The first contribution of the paper is highlighting the strong relationship between local political attitudes and WFH behavior. 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 in addressing other questions related to the effects of WFH.

The next contribution is documenting that, on average, the increase in WFH caused by the COVID-19 pandemic does not appear to have had a sizeable impact on innovative output, as measured by the number of patent applications made from 2020-2021. This finding cuts against widespread concerns that WFH will harm innovation on the whole and also calls into question the idea that WFH could lead to large productivity gains for knowledge workers.

This study next delves deeper into the question of understanding when WFH impacts innovative productivity. I find that offices belonging to sufficiently innovative firms or firms operating in rapidly evolving areas of technology see a positive effect of working from the office on their patenting productivity. This is consistent with the idea that both the amount and pace of innovation at a firm determines the importance of face-to-face interaction in driving innovation. When examining the effect by broad industry (NAICS3), I find that industries associated with the "knowledge economy"[14] see positive effects of working from the office on patenting productivity while manufacturing industries are more likely to have no effect of working from the office on patenting productivity. These findings support the view that WFH is particularly detrimental to the patenting productivity of highly innovative firms where the pace of technological change is fast.

As measured by the teleworking index in Dingel and Neiman 2020, firms operating in the "knowledge economy" tend to be able to more easily transition their workers to WFH relative to most manufacturing firms. Counterintuitively, I find that firms who are more easily able to move their workforce to WFH actually see the larger negative effects of WFH

[14] These industries include Nonstore Retailers (an industry which only has one firm: Amazon.com), Credit Intermediation, Computer/Electronics Mfg, and Information Services

on patenting productivity. The result highlights that the ability of a firm to move their workforce to remote work does not imply that it comes without costs. On the contrary, innovative firms operating in rapidly evolving areas of technology have the most to gain, in terms of innovative productivity, from keeping their workforce at the office even if those same firms could easily transition their workers to WFH. Overall, the findings indicate that the intensity and speed of technological innovation are the most important characteristics in determining whether WFH will a negative effect on innovative productivity.

Despite firm size being relatively uncorrelated with my measures of the importance of innovation and the pace of technological change, I find that the positive effects of working from the office are concentrated in large firms, consistent with the idea that large firms are more difficult to virtually navigate and working from the office helps to limit the potential scope for interaction at a large firm. Further, I find that WFH has no measurable effect on collaboration activity as measured by team size or the share of inventors on a patent who are not located at the focal office. The results add to our knowledge about the formation of research teams and indicate that WFH is unlikely to significantly alter collaboration networks in the short-run. The results in this study help paint a more comprehensive picture of the conditions needed for WFH to impact the knowledge production function, something that we have had limited information about, up until this point.

This study has several limitations. First, I examine the quantity of patent applications made by an office, but I am not able to measure how WFH affected the value of those applications. As more time passes, it will be possible to observe whether these patent applications are ultimately granted, the number of citations they receive, and other measures of the patent's value. Second, the study is only able to examine the effect of WFH on patent applications from 2020-2021. To the extent that there is a lag between WFH and its effect on patenting productivity, some of the long-run effects may be hidden. While there certainly could be long-run effects that have not been measured, the economics literature is replete with examples where the effects of a shock to patenting are observed in the year after the shock (Berkes and Nencka 2021). Further, enough time has passed that most patent applications which were filed between 2020-2021 have been published and are in my data. Following up to look at the long-run effects of this WFH shock would be a welcome contribution to this paper's findings.

Overall, this study provides a first look into how the large and enduring increase in WFH, created by the COVID-19 pandemic, has impacted corporate innovation. I further provide insight into the conditions needed for WFH to impact patenting productivity by examining heterogeneity in effects. I find that in aggregate WFH has not impacted patenting productivity as some have feared, but for more innovative firms WFH matters as it lowers the patenting productivity of their offices. Future studies which could examine other mechanisms that explain the effect of WFH on innovation would be valuable.

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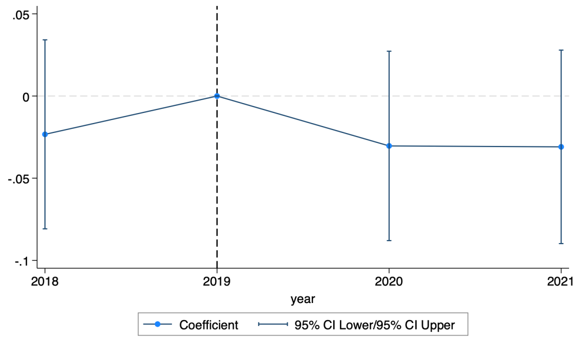
7 Appendix

Table A.1: Patent Applications and Working From Home (2SLS)

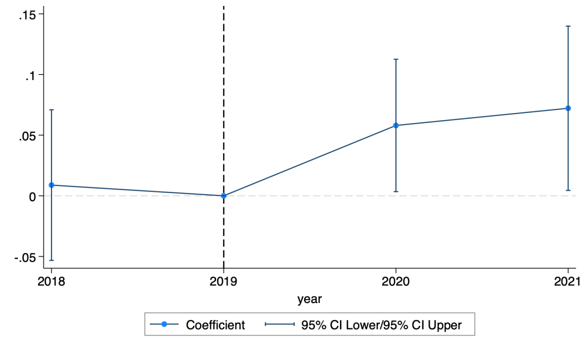
	Outcome: ihs(Patents)					
	Heterogeneity: Patent Value to Asset Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\leq$	$>$	$\leq$	$>$	$\leq$	$>$
ihs(Visits)	-0.044	0.208**	-0.119	0.228**	-0.170	0.224**
	(0.105)	(0.091)	(0.178)	(0.103)	(0.238)	(0.097)
F-statistic	69.82	62.97	32.34	55.72	17.87	61.70
Test for equal coef (p-value)	.07*		.09*		.12	
Year FE	✓	✓				
NAICS3 × Year FE			✓	✓		
Firm × Year FE					✓	✓
Observations	2,512	2,636	2,512	2,636	2,512	2,636

Notes: This table presents results from estimating Equation (2) and Equation (1) via 2SLS with full interactions between the "Heterogeneity" variable and the endogenous variable and instrument. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. Standard errors are clustered at the office level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Figure A.1: Patent Value to Asset (Event Study)



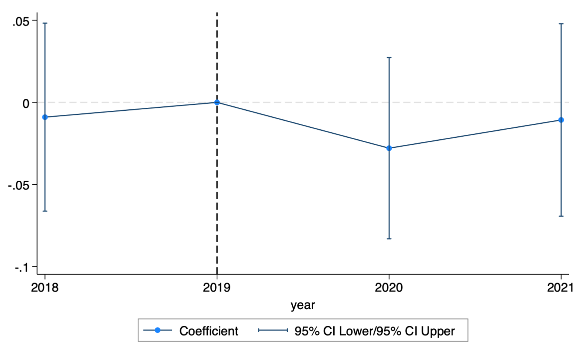
(a) At or Below Median



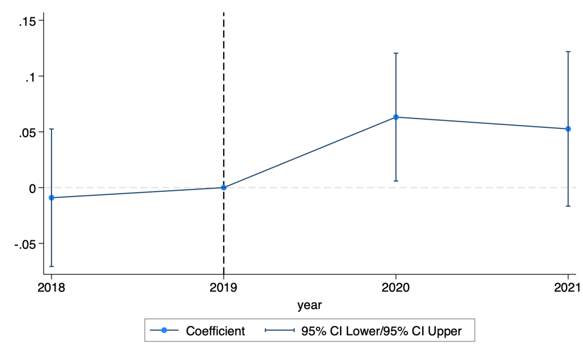
(b) Above Median

Notes: Both panels 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 and the dependent variable is the inverse hyperbolic sine of patent applications. Office and firm × year fixed effects are included. Panel (a) only includes offices belonging to fimrs who are at or below the median level of the "Patent Value to Asset Ratio" whereas Panel (b) only includes firms above the median value of the "Patent Value to Asset Ratio." Standard errors are clustered at the office level with 95% confidence intervals shown.

Figure A.2: Rapidly Evolving Technology (Event Study)



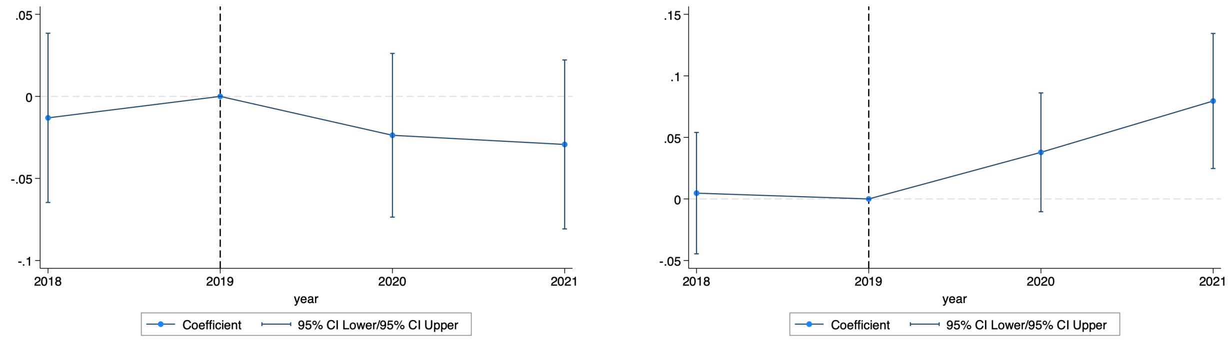
(a) At or Below Median



(b) Above Median

Notes: Both panels 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 and the dependent variable is the inverse hyperbolic sine of patent applications. Office and firm × year fixed effects are included. Panel (a) only includes offices belonging to fimrs who are at or below the median level of the "ReTech" whereas Panel (b) only includes firms above the median value of the "ReTech." Standard errors are clustered at the office level with 95% confidence intervals shown.

Figure A.3: Dingel and Neiman 2020 Teleworking Index (Event Study)



(a) At or Below Median

(b) Above Median

Notes: Both panels 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 and the dependent variable is the inverse hyperbolic sine of patent applications. Office and firm × year fixed effects are included. Panel (a) only includes offices belonging to fimrs who are at or below the median level of the "Teleworking Index" whereas Panel (b) only includes firms above the median value of the "Teleworking Index." Standard errors are clustered at the office level with 95% confidence intervals shown.

Table A.2: Patent Applications and Working From Home (2SLS)

	Outcome: ihs(Patents)					
	Heterogeneity: Total Revenue					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\leq$	$>$	$\leq$	$>$	$\leq$	$>$
ihs(Visits)	-0.086	0.058	-0.122	0.154	-0.065	0.225
	(0.058)	(0.088)	(0.092)	(0.124)	(0.096)	(0.140)
F-statistic	162.35	72.12	74.44	43.06	65.93	35.82
Test for equal coef (p-value)	.17		.07*		.09*	
Year FE	✓	✓				
NAICS3 × Year FE			✓	✓		
Firm × Year FE					✓	✓
Observations	3,520	3,568	3,520	3,568	3,520	3,568

Notes: This table presents results from estimating Equation (2) and Equation (1) via 2SLS with full interactions between the "Heterogeneity" variable and the endogenous variable and instrument. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. Standard errors are clustered at the office level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.3: Patent Applications and Working From Home (2SLS)

	Outcome: ihs(Patents)					
	Heterogeneity: Total Assets					
	(1)	(2)	(3)	(4)	(5)	(6)
	$\leq$	$>$	$\leq$	$>$	$\leq$	$>$
ihs(Visits)	-0.128**	0.129	-0.120	0.197	-0.053	0.201
	(0.062)	(0.096)	(0.090)	(0.122)	(0.103)	(0.132)
F-statistic	154.57	54.55	80.08	42.19	61.84	38.54
Test for equal coef (p-value)	.03**		.04**		.13	
Year FE	✓	✓				
NAICS3 × Year FE			✓	✓		
Firm × Year FE					✓	✓
Observations	3,628	3,460	3,628	3,460	3,628	3,460

Notes: This table presents results from estimating Equation (2) and Equation (1) via 2SLS with full interactions between the "Heterogeneity" variable and the endogenous variable and instrument. To be in the sample, an office must have an average of at least 365 visits per year in the pre-pandemic period and have filed for a non-zero number of patents at some point in the entire time period. The observations are at the office × year level with 2018 and 2019 being the pre-pandemic years and with 2020 and 2021 being the post-pandemic years. Standard errors are clustered at the office level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).