The Direction of Innovation and Work from Home

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Abstract

This study explores how allowing remote work affects firms' innovation activity. I investigate the effect of the significant shift toward working from home that occurred in response to the pandemic on the direction of innovation. I find that work from home has shifted the path of innovation toward technology that supports non–face-to-face communication. Using a sample of patent-holding firms, I document that firms that adopted work from home applied for more patents of non–face-to-face technologies and exhibited more labor flexibility than firms that did not offer work from home. The results are driven by smaller, younger firms, suggesting that these firms had greater digital resilience and were better able to adjust to the unprecedented shock to the working environment. I discuss how these facts contribute to our understanding of the impact of work from home on the direction of innovation, as well as how we may design policy responses to future shocks.

JEL classification: J24, J61, L25

Keywords: work from home, direction of innovation, non-face-to-face technology, Covid-19

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1 Introduction

“Necessity is the mother of invention,” as the saying goes. We believe that new inventions are motivated by a need. However, Diamond (1997) has argued that invention is actually the mother of necessity because technology can create needs that we had not previously felt. Investigating how the path of innovation changes can illuminate how the two conflicting arguments can both be true. For example, the technologies used to transmit video for virtual meetings (e.g., Zoom) were already available before the Covid-19 pandemic, but became essential in the new era of work from home (WFH). To avoid the transmission of the coronavirus, it was necessary to adopt non–face-to-face (NFTF) methods of interaction. Our need for NFTF technologies, as well as our previous experience with such technologies, has encouraged new inventions that support NFTF communication.

Work from home is not a new concept. Prior to the pandemic, some companies offered WFH, also referred to as remote work or telecommuting. However, the gradual adoption of the practice was drastically altered when the unanticipated shock of the Covid-19 pandemic took place. Lockdowns and social distancing in response to the pandemic triggered a significant and sudden shift toward WFH. Firms have allowed individuals to begin working from home in large numbers, and this trend will likely continue after the pandemic is over (Aksoy et al., 2022; Barrero et al., 2021; Bloom et al., 2022).

Previous empirical studies have found that businesses that are conducive to WFH and those with digital platforms have performed significantly better during the pandemic (Bai et al., 2021; Raj et al., 2021). To be specific, Bai et al. (2021) have shown that firms that used WFH before Covid-19 had higher sales and incomes during the crisis. Raj et al. (2021) found that restaurants that had already adopted Uber Eats or other delivery systems before the Covid-19 crisis experienced substantial increases in orders and sales during the pandemic. However, few studies have provided empirical evidence about innovation activity in response to the shift from in-person work to WFH.

This has prompted me to examine the direction of innovation in response to the rise of working from home. The study specifically investigates how the path of invention has changed as firms have adopted WFH, as measured by their total patent applications and patent applications that enhance NFTF technology. I anticipate that as NFTF methods and WFH have become the new norm as a result of the pandemic, the incentives to advance NFTF technologies have increased. Firms that allow WFH and use NFTF technology are more resilient to unexpected shocks that restrict face-to-face contact.

To investigate this question empirically, I collect patent data from 2015 to 2020 from the Korea Intellectual Property Rights Information Service (KIPRIS), which covers all patent applications in Korea. Using text analysis and patent classification, I identify patent applications that advance non–face-to-face technologies. In addition, I collect employment data from the National Pension Service (NPS) and match it with firms in the patent database. The job search site Saramin provides information on whether a firm offers WFH. This enables me to link the firm's adoption of work from home with their patent records.

The results show that firms that have adopted WFH have been more likely to advance patents for NFTF technologies. While the overall innovation activity of firms that have embraced such forms of digital resilience has not differed from that of other firms, the number and percentage of patents for NFTF technologies advanced by the former surged in response to the crisis. To provide causal results, I employ Covid-19 cases in the region where a firm is located as an instrument for firms' adoption of WFH. Falsification tests support the validity of this instrumental variable. Furthermore, firms with digital resilience did not decrease their workforce during the pandemic. Their high flexibility was the driving force behind this outcome. Firms that utilized WFH were more likely to hire new employees and fire incumbent workers. I also discovered that smaller, newer firms drive these results. These digitally resilient firms were better prepared to adapt to the crisis by shifting the direction of innovation and their working arrangements.

To the best of my knowledge, this research provides the first investigation of a causal relationship between work from home and the direction of firms' innovation. This study was inspired by Bloom et al. (2021), who documented that the Covid-19 pandemic had shifted the direction of patents toward technologies that support WFH. However, they did not provide evidence as to which firms have innovated most during the crisis or how firms have modified the direction of their innovations. This paper contributes to three strands of the literature. First, a large body of research has investigated the adoption of WFH and its impact on firms and individuals. Previous research has found that WFH has had several positive impacts (Bloom et al., 2015; Evans et al., 2004; Martin and MacDonnell, 2012; Golden and Veiga, 2005). WFH has led to increased productivity and efficiency in terms of decreased commuting time, sick leave, and attrition; increased work flexibility; and increased job satisfaction. According to Sauermann and Cohen (2010), WFH can provide good motivation to employees in the form of non-monetary rewards. Given the expansion of the digital economy and IT investments in infrastructure and software, a much higher proportion of jobs are now appropriate for WFH (Oettinger, 2011). Furthermore, Choudhury et al. (2021) have identified an increase in productivity among US patent examiners who are permitted to work from any location. However, little research has investigated the impact of WFH on innovation. This paper contributes to the literature by addressing this gap.

A second strand of the literature has investigated how the direction of innovation changes in response to changes in work settings and input supply. Directed technical theories suggest that the supply of inputs to production can affect the direction of technological process (Acemoglu, 1998, 2002; Hicks, 1932). A shift in the relative supply of inputs might spur innovation by supplementing a comparatively abundant resource (Acemoglu, 1998; Kiley, 1999; Hanlon, 2015). However, there have been relatively few empirical studies of this phenomenon. This study investigates the hypothesis that a change in the supply of inputs, in this case workers who WFH, encourages innovations that improve technologies that support WFH. Acemoglu (1998) has motivated me to examine how a sudden and dramatic shift in the way we work, toward non–face-to-face methods, has changed the direction of new technologies.

Finally, a growing literature has begun to examine the extent and incidence of WFH during the Covid-19 pandemic and the outcomes associated with WFH. The pandemic spurred a large and long-term shift toward remote work and hybrid work (when employees work a combination of days at home and at work). These studies have identified positive and negative effects of WFH on productivity during the pandemic, as lockdowns and government restrictions have made in-person work more difficult. The trend toward WFH is expected to persist (Aksoy et al., 2022; Bai et al., 2021; Barrero et al., 2021; Bloom et al., 2022; Choudhury et al., 2022; Gibbs et al., 2021). This paper builds on this growing literature by investigating the causal effect of WFH on innovation activity and the direction of innovation during the crisis.

The rest of this paper is organized as follows. Section 2 explains the conceptual framework. Section 3 describes the data and presents descriptive statistics. Section 4 outlines my empirical methods, presents the results, and discusses their implications. Section 5 concludes and outlines next steps for future study.

2 Conceptual Framework

The impact of working from home on innovation has not yet been established. Though most research has shown that working from home has a beneficial impact on productivity, some studies have found a negative impact. While WFH may boost productivity, it is unclear whether this is associated with greater innovation.

WFH experiments conducted by Bloom et al. (2015, 2022) have shown that WFH has reduced attrition rates, improved job satisfaction, and increased productivity. Another experiment conducted during the pandemic also supports the positive impact of WFH on productivity (Choudhury et al., 2022). According to survey results (Barrero et al., 2021; Aksoy et al., 2022), WFH has improved employee job satisfaction, and it is likely that WFH will continue when the pandemic is over. However, Gibbs et al. (2021) found a detrimental influence of WFH on productivity during the epidemic. They found that women and employees with children at home were more likely to experience reduced productivity.

WFH has potential negative implications since it forces office workers to use information and communication technologies (ICTs) to fulfill tasks. Ayyagari et al. (2011) discovered that ICTs generate stress among workers, a condition they call technostress. They present evidence that work overload and job insecurity increase because ICTs put additional strain and stress on workers who are unfamiliar with these technologies and must learn new skills. Bailey (2022) has documented the negative consequences of new technology on labor. In particular, new technologies have enabled managers to remotely monitor and regulate employees' performance. For example, digital surveillance technologies like ActivTrak enable businesses to monitor employees' web browsing and email conversations and calculate their email response times and network connectivity. Businesses were already engaging in workplace monitoring and surveillance prior to the outbreak of Covid-19. For example, employers have used swipe cards to monitor employees' entrances and exits. More recently, businesses have begun adopting "bossware" or "tattleware" software systems that monitor employees' online movements and activities as they WFH, inflicting stress on employees. These systems may increase productivity in the short term, but may also increase attrition and impair job satisfaction.

To understand how WFH affects innovation, I explore the relationship between non-monetary rewards and innovation. Sauermann and Cohen (2010) have found that workers' motivation is associated with their innovation. If WFH promotes job happiness and motivation, it will boost innovative activity. WFH also has a substantial impact on workplace environments and workplace groups, both of which affect teams' abilities to generate innovative ideas. Hennessey and Amabile (2010) have documented that a large body of research supports the idea that creative work is accomplished by two or more people working closely together rather than a single person. If WFH reduces interaction among team members and isolates individual workers, it will not spur innovative activity. Alternatively, workers' experiences WFH using NFTF technologies could lead to advancements in technologies that support NFTF communication. For example, workers may come up with fresh ideas to remedy the little inconveniences they experience using NFTF technologies. Previous experience with NFTF technologies and the need for such solutions could promote new inventions that support NFTF communication. This research, therefore, investigates how WFH affects innovation and particularly innovation in the direction of NFTF technologies.

3 Data

3.1 Patent data

I collect patent data from the Korea Intellectual Property Rights Information Service (KIPRIS). All patent applications in Korea from 1983 to the present are publicly available on the service. Specifically, this empirical analysis uses 1,125,214 patent applications between 2015 and 2020. Each patent document includes the 1) application date, 2) patent classification (Cooperative Patent Classification; CPC), 3) applicant (corporate), 4) inventors, and 5) other pieces of information. I create data sets for empirical analysis using the first three variables: application date, patent classification, and applicant.

I first restrict the data to patents applied for by corporate applicants. Patents applied for by individuals are removed from the sample. KIPRIS provides a 10-digit business registration number and corporate name, allowing me to create data on patent applications by firm and by year. A single firm is defined as a corporate applicant with a unique combination of a business registration number and a corporate name in a patent document.

To identify patents that pertain to non–face-to-face technologies, I create a list of NFTF terms based on a review of relevant articles written in English and Korean: "non–face-to-face," "non face-to-face," "non-facing," "contactless," "contact-free," "*untact*"(in Korean), "*bidaemyeon*"(in Korean) and WFH terms.[1] If the patent application title or description contains at least one term from the list above, I regard the patent application

[1] telecommuting, telework, teleworking, working from home, mobile work, remote work, flexible workplace, work from home, mobile working, remote working, work remotely, working remotely, remote workplace, telecommuter, teleworker, home-sourced worker, home-sourced employee, work-at-home, work at home, telecommuting specialist, nomadic worker, nomadic employee, work-from-home, work-from-anywhere, video conference, video conferencing, virtual office, distance work, flexible work, virtual work, virtual office, virtual employee, home office, home-based office, home-based work, work from anywhere, working from anywhere, work-from-anywhere, digital workplace, video chat, video call, teleconference, teleconferencing, working from a remote location, and work from a remote location. See the details in Bloom et al. (2021).

as one that advances NFTF technologies. Sample patent applications (title, application number, and filing date) include “Non face-to-face access control and traffic management system” (1020200085146; July 10, 2020) and “System for Providing Conversational Artificial Intelligence Chatbot Service Optimized by Non–face-to-face Civil Affair Administration” (1020200167802; December 3, 2020).

3.2 Work from home, Covid-19, and Employment

I collect WFH data from an online recruiting platform, Saramin[2], to determine whether a firm offers WFH. This job-search site is the most popular platform for job hunting in Korea, with a market share of 46% in 2021. I scrape data on WFH availability from job postings and company-level data to determine whether a firm offers WFH. Saramin also contains information about the year each firm was founded. I match this data set with the patent data set using firms’ corporate names and business registration numbers after some data cleaning of the corporate names. For example, terms like “Inc.,” “Incorporated,” and “(Inc.)” were removed, as were parentheses and some typos.

The Korean equivalent of the CDC, officially known as the Korea Disease Control and Prevention Agency, reports the number of confirmed Covid-19 cases by region. I match this figure to the geographic location of patent applicants (firms) from the patent data set.

Employment data at the firm level is collected from the National Pension Service (NPS) public data portal.[3] In Korea, it is mandatory for employers with more than two employees to contribute to the cost of the national pension plan for the employees. The National Pension Service data on each firm include the number of employees on the pension plan, the corporate name, and the business registration number. The data is released on a monthly basis on the public data portal. I identified 1,820,667 firms that provided the number of employees on the pension plan between 2015 and 2020. I consider the number of employees currently enrolled in the plan as a proxy for the number of employees in a firm and create

[2] http://saramin.co.kr/
[3] www.data.go.kr

employment data at the firm level. I then use the firm name and business registration number to match this data with the patent data.

3.3 Summary Statistics

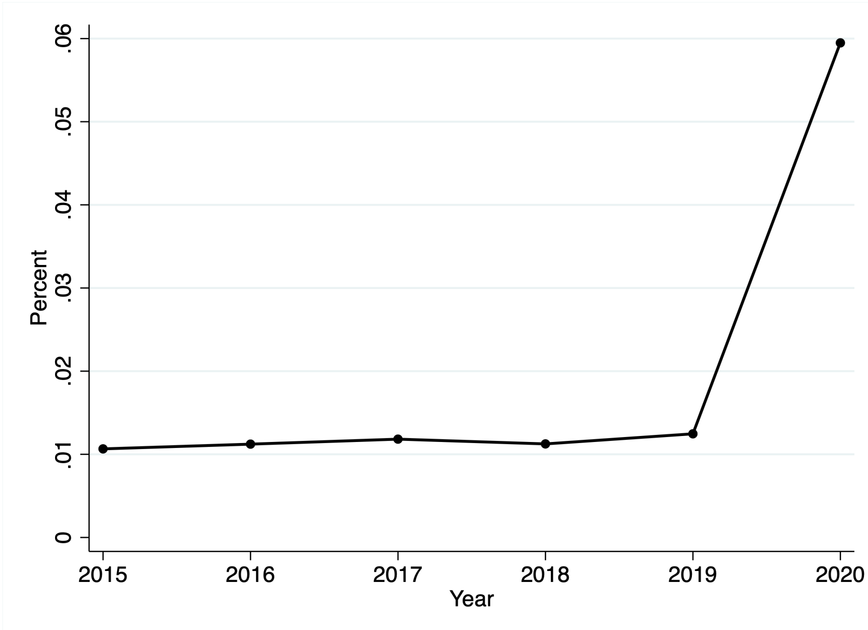
Table 1: SUMMARY STATISTICS AND DATA SOURCES

	Mean	SD	Observations	Source
Work from home (WFH)	0.019	0.138	429,684	Job-search site
COVID-19 cases per thousand in region	1.231	0.601	429,684	Korea CDC
Total patents	1.099	14.592	429,684	Patent Database
Non-face-to-face (NFTF) patents	0.008	0.678	429,684	Patent Database
Work from home (WFH) patents	0.006	0.364	429,684	Patent Database
Employees	47	661	261,988	National Pension Service
Year of establishment	2,011	8	343,980	Job-search site
Number of firms			71,614	

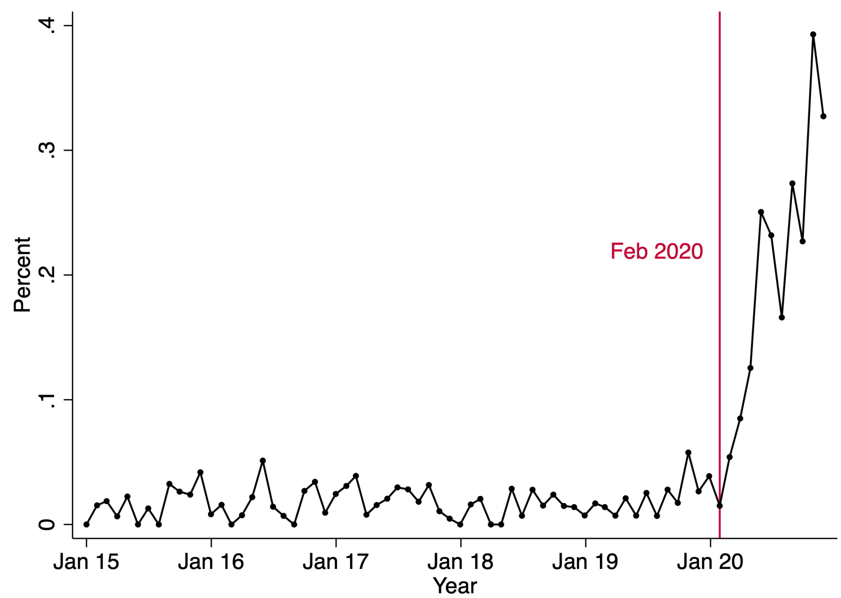
Notes: This table describes summary statistics and data sources. The sample of firms covers years 2015 to 2020. The job-search site is the recruiting platform Saramin. The Korea CDC is an organization under the Ministry of Welfare and Health, officially called the Korea Disease Control and Prevention Agency. The patent database is the Korea Intellectual Property Rights Information Service (KIPRIS). The national pension service provides information on the number of subscribers.

Table 1 reports summary statistics on the data used in the analysis. The sample is made up of firms that filed at least one patent application between 2015 and 2020. The independent variable is the annual average of the percentage of firms that offer WFH. This percentage surged in 2020 when the Covid-19 pandemic took hold, as shown in Figure 1. Figure 1 (b) shows the percentage of patent applications related to NFTF technologies by month. This also increased significantly in 2020.

There is typically a lag between the filing of a patent application and its publication. Considering that I collected the patent data from the KIPRIS database in 2022, it should be noted that the number of patent applications is incomplete because of the delay in publishing patents. To investigate the direction of patent applications using a fraction of the patent filings, I assume that there is no difference between the lags for all published patent applications and the lags for published patent applications related to NFTF technologies. Figure 2



(a) Work from home



(b) Non-face-to-face patents

Figure 1: WORK FROM HOME AND PATENTS THAT SUPPORT NON-FACE-TO-FACE TECHNOLOGIES, 2015-2020

Notes: The figures show the percentage of firms that adopts WFH and the percentage of patent applications that support NFTF technologies filed to Korean Intellectual Property Office from 2015 to 2020.

shows the distributions of these lags. I cannot reject the equivalence of these distributions using the Kolmogorov-Smirnov test (p-value = 0.259). The similarity of the distribution of the lags provides evidence for the assumption.

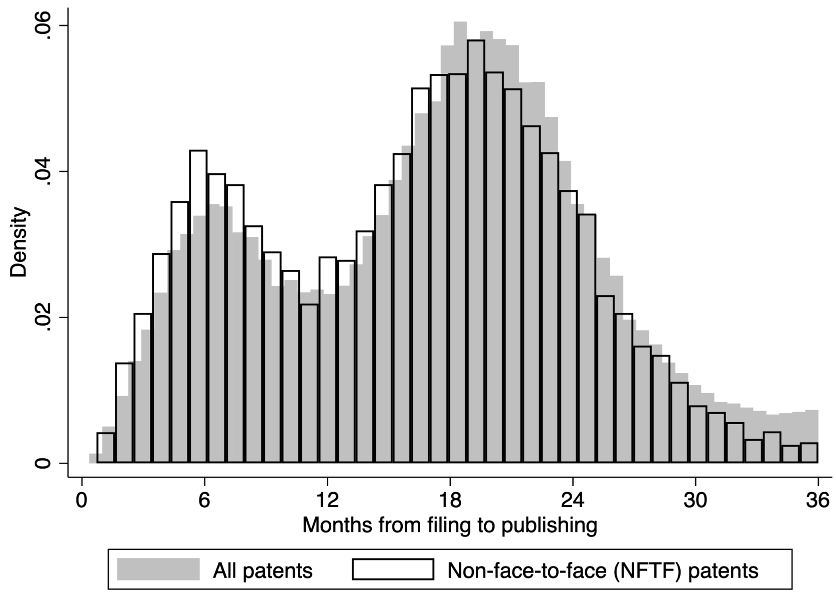


Figure 2: LAGS IN THE FILING TO PUBLICATION OF PATENTS

Notes: The figure plots lags of published patent applications that were filed from 2015 to 2019. For readability, I restrict the data to lags lower than 36 months.

4 Empirical Strategy and Results

4.1 Baseline Estimates

I investigate how work from home affected the direction of innovation in firms when the Covid-19 outbreak and the subsequent economic lockdown hindered traditional face-to-face channels. Specifically, I compare firms that allowed WFH with firms that did not offer WFH. The econometric model takes the following form:

$$Y_{it} = \beta \ (\text{WFH}_i \times \text{Post}_t) + \gamma_i + \tau_t + \epsilon_{it} \tag{1}$$

where Y_{it} is the number of patent applications of firm i in year t: total patents, NFTF patents, or WFH patents. WFH_i is a dummy variable that takes one if firm i offers WFH and Post_t is a dummy variable that switches on in year 2020 when the pandemic occurs. Firm fixed effects γ_i and year fixed effects τ_t are included in the model. Coefficient β measures the effect of WFH on firms' innovation activity.[4]

The identification strategy has both advantages and potential concerns. Firm fixed effects control for all time-invariant firm characteristics and year fixed effects control for any patterns of outcomes that could affect all firms. The identification relies on the assumption that the outcomes of firms that allow WFH and those of other firms that do not offer WFH would not change differently in the absence of work from home. Also, there are assumed to be no other missed factors or uncontrolled events that coincide with WFH and influence firms' innovation.

To address the potential endogeneity of WFH, I use Covid-19 cases in the region where a firm is located as an instrument for the firm's adoption of WFH. This approach exploits the fact that firms were likely to implement WFH in response to an increase in Covid-19 cases and government restrictions, but Covid-19 cases are unlikely to have depended on expectations about a firm's innovation activity.

Table 2 reports the results from this specification. A first-stage regression confirms that Covid-19 cases are a good predictor of the adoption of WFH, with an F-statistic on the excluded instrument of 243.98. The results across OLS estimates and IV estimates suggest that firms with WFH did not increase their overall innovation rate, but they did initiate more patents related to technologies that support non–face-to-face communication or WFH. For example, the IV estimate in column 2 is 0.137, which represents an 0.137 increase in patents that support NFTF technologies when a firm adopts WFH.

To measure the magnitude of the effect given the delay in publishing patents, I also apply alternative types of dependent variables in the form of the log or the percentage of

[4] I also employ the following model: $Y_{it} = \beta \text{ WFH}_{it} + \gamma_i + \tau_t + \epsilon_{it}$ and find consistent results because the majority of firms adopted WFH in response to the pandemic. See Table A.1.

Table 2: THE EFFECT OF WORK FROM HOME ON PATENTS

Dependent variable	Patents (1)	NFTF patents (2)	WFH patents (3)
A. OLS estimates			
Work from home	-0.067	0.038***	0.020***
	(0.296)	(0.009)	(0.006)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	429,684	429,684	429,684
Number of firms	71,614	71,614	71,614
R-squared	0.940	0.316	0.398
B. IV estimates			
Work from home	1.150	0.137***	0.055*
	(1.226)	(0.051)	(0.031)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	429,684	429,684	429,684
Number of firms	71,614	71,614	71,614
Kleibergen–Paap F-statistic	243.98	243.98	243.98

Notes: The sample consists of patent-holding firms from 2015 to 2020. The dependent variable is the number of patent applications per year. NFTF patents are patent applications related to non-face-to-face technology and WFH patents are patent applications related to work from home technology. Work from home is an indicator that takes one if a firm adopts work from home and is instrumented by COVID-19 cases in a region where the firm is located. Standard errors in parentheses are clustered at the firm level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

patents. The estimated coefficients reported in Table 3 exhibit the results consistent with those reported in Table 2. Specifically, the IV estimate in Column 1 shows that firms with WFH increased their NFTF patents by 7.7 percent and the estimate in Column 3 reports an increase of 12 percentage points in NFTF patents as a percentage of total patents.

Table 3: ALTERNATIVE FORMS OF OUTCOMES

Type	Log		Percentage	
Dependent variable	NFTF patents (1)	WFH patents (2)	NFTF patents (3)	WFH patents
A. OLS estimates				
Work from home	0.021***	0.015***	0.015***	0.009***
	(0.003)	(0.003)	(0.003)	(0.002)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	429,684	429,684	429,684	429,684
Number of firms	71,614	71,614	71,614	71,614
R-squared	0.341	0.371	0.199	0.195
B. IV estimates				
Work from home	0.077***	0.048***	0.120***	0.062***
	(0.023)	(0.017)	(0.027)	(0.015)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	429,684	429,684	429,684	429,684
Number of firms	71,614	71,614	71,614	71,614
Kleibergen–Paap F-statistic	243.98	243.98	243.98	243.98

Notes: The dependent variable is NFTF/WFH patent applications per year as a log form in columns 1 and 2, and NFTF/WFH patents as a fraction of total patents in columns 3 and 4. The sample consists of patent-holding firms from 2015 to 2020. Work from home is an indicator that takes one if a firm adopts work from home and is instrumented by COVID-19 cases in a region where the firm is located. Standard errors in parentheses are clustered at the firm level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure A.1 depicts the linear positive relationships among Covid-19 cases, WFH, and NFTF patents, aggregated at the region level. It illustrates the positive first-stage relationship between Covid-19 cases and WFH, the positive OLS relationship between WFH and NFTF patents, and the positive reduced-form relationship between Covid-19 cases and NFTF patents. The regression analysis in Tables 2 and 3 and the diagrammatic illustration in

Figure A.1 clearly show that WFH is highly correlated with Covid-19 cases, and increases patents that support non–face-to-face technologies.

4.2 Time-Varying Estimates and Pre-Trends

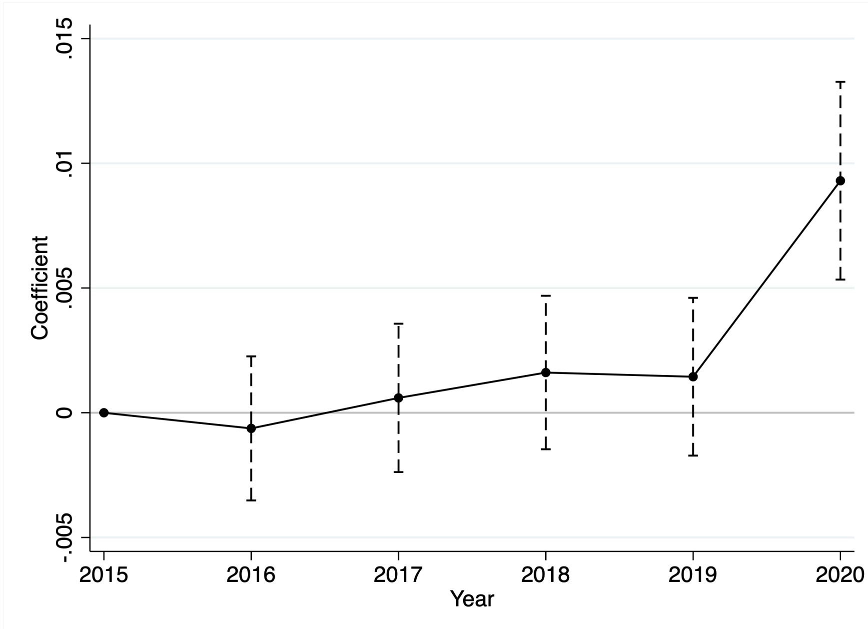
I complement the empirical analysis with a fully flexible time-varying estimation relative to a base year in the following event study specification:

$$Y_{it} = \sum_t \beta_t (\text{WFH}_i \times \text{YearDummy}_t) + \gamma_i + \tau_t + \epsilon_{it} \tag{2}$$

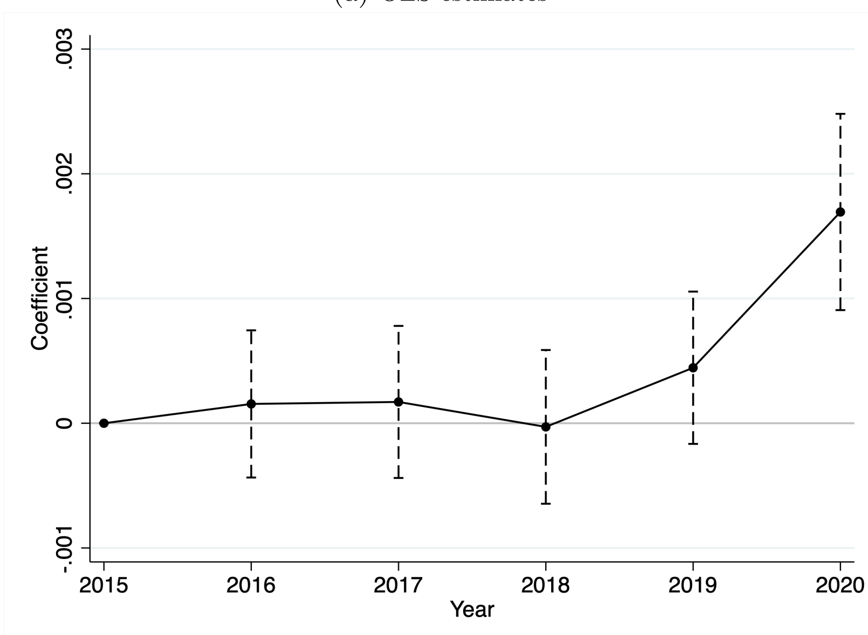
where all variables are defined as in equation 1. The distinction is that WFH_i is interacted with YearDummy_t, a dummy variable that corresponds to a particular year t. The estimates β_t illustrate the differences between firms that offer WFH and those that do not offer WFH in each year relative to a base year of 2015. If, for example, WFH increased NFTF patents in response to Covid-19, then the estimates would remain constant in the years before the pandemic boosted WFH and would increase as WFH surged in response to Covid-19.

I begin by displaying the raw statistics on the number of non–face-to-face patents issued by firms that allow WFH and those that do not in Figure A.2. It clearly depicts an increase in NFTF patents by firms that offered WFH in reaction to the epidemic, while there had been no differential pre-trends between firms that offered WFH and those that did not. The figure provides graphical proof of the WFH effect but does not take into account the possibility of unobservable firm-specific factors and year-specific economic trends that could have influenced the firms' innovation activity. These can be addressed in the regression analysis from equation 3.

Figure 3 plots the OLS and reduced-form estimates of equation 3 with 95% confidence intervals. The reduced-form estimates employ Covid-19 cases in the region where a firm is located as an instrument instead of WFH. The gap between firms remained constant over the pre-treatment years, and increased as the pandemic elevated WFH rates. The findings



(a) OLS estimates



(b) Reduced-form estimates

Figure 3: TIME-VARYING DIFFERENCES IN PATENTS

Notes: The figures show the regression coefficients and 95% confidence intervals relative to the year 2015. The dependent variable is the percentage of non-face-to-face (NFTF) patents per year. Standard errors in parentheses are clustered at the firm level.

support the key identifying assumption that there were no differential pre-trends.

To validate the parallel pre-trend assumption further, I test this assumption by restricting the sample to the years 2015–2019, prior to the pandemic, and estimate the following model:

$$Y_{it} = \sum_t \beta_t(\text{WFH}_i \times \text{Year}_t) + \gamma_i + \tau_t + \epsilon_{it} \tag{3}$$

where Year_t is a linear year trend. The coefficient β_t measures the difference in time trends between firms.

Table 4: PRETREATMENT TRENDS

Dependent variable	Patents (1)	NFTF patents (2)	WFH patents (3)
A. Work from home			
Work from home × year	0.107 (0.109)	0.018 (0.018)	0.007 (0.009)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	358,070	358,070	358,070
Number of firms	71,614	71,614	71,614
R-squared	0.949	0.290	0.379
B. COVID-19 cases			
COVID-19 cases × year	0.013 (0.012)	0.002 (0.002)	0.001 (0.001)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	358,070	358,070	358,070
Number of firms	71,614	71,614	71,614
R-squared	0.949	0.290	0.379

Notes: The sample is restricted to patent-holding firms from 2015 to 2019. The dependent variable is the number of patent applications per year. Work from home is an indicator that takes one if a firm adopts work from home and COVID-19 cases take the number of COVID-19 cases per thousand in a region where a firm is located. Standard errors in parentheses are clustered at the firm level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4 reports the results; the coefficients have small magnitudes and none are statistically significant. This confirms that there are no pre-existing differential trends, further supporting the parallel pre-trend assumption.

4.3 Addressing Additional Concerns

I have verified the absence of differential pre-trends in the previous section, but one might be concerned about the likelihood of other possible unknown or unobservable variations related to firms' adoption of WFH. To address this issue, I implement placebo tests. The exclusion restriction for the IV strategy would not be satisfied if the Covid-19 pandemic had a direct impact on firms' innovation activities. The idea is to examine the effect of the instrumental variable of Covid-19 on the patents of firms that did not adopt WFH. In this case, the instrumental variable should not affect these firms' patents, because the firms did not adopt WFH.

The reduced-form estimation results are shown in Table 5. The results of the falsification show that the effect of the instrument on the patents of the firms that did not adopt WFH is close to zero. In Panel A, the coefficients across different types of patents are not statistically significant. However, in Panel B, the reduced-form estimates based on a sample of all firms support the positive link between the instrument and NFTF patents, consistent with the main findings. The results thus support the validity of the instrumental variable.

Another concern is that the results might reflect the effect of firm characteristics other than their adoption of WFH because firms that offer WFH differ from those that do not offer WFH across several dimensions, even though I have controlled for firm-specific fixed effects. I first consider another firm characteristic, whether a firm has a staff lounge or cafeteria, as a placebo treatment. This reflects working environments that facilitate in-person work rather than work from home. The results are presented in Panel A of Table 6. I find no evidence that the placebo treatment had any effect on firms' innovation activities during the period when the working environment was likely to have transitioned toward working from home. In the second placebo test, I consider three placebo outcomes: patents excluding NFTF

Table 5: FALSIFICATION TEST, REDUCED-FORM ESTIMATES

Dependent variable	Patents (1)	NFTF patents (2)	WFH patents (3)
A. Falsification test			
COVID-19 cases	-0.003	0.001	0.000
	(0.013)	(0.001)	(0.000)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	404,124	404,124	404,124
Number of firms	67,354	67,354	67,354
R-squared	0.824	0.203	0.206
B. Reduced-form estimates			
COVID-19 cases	0.029	0.003***	0.001*
	(0.030)	(0.001)	(0.001)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	429,684	429,684	429,684
Number of firms	71,614	71,614	71,614
R-squared	0.940	0.316	0.398

Notes: The table report reduced-form estimates using COVID-19 cases that take the number of COVID-19 cases per thousand in a region where a firm is located. The sample consists of patent-holding firms that have not adopted work from home in panel A, but the sample includes all patent-holding firms from 2015 to 2020 in panel B. The dependent variable is the number of patent applications per year. NFTF patents are patent applications related to non-face-to-face technology and WFH patents are patent applications related to work from home technology. Standard errors in parentheses are clustered at the firm level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6: PLACEBO TESTS

	(1)	(2)	(3)
A. Placebo treatment			
Dependent variable	*Patents*	*NFTF patents*	*WFH patents*
Placebo treatment	0.040*	0.010	0.005
	(0.023)	(0.010)	(0.005)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	429,684	429,684	429,684
Number of firms	71,614	71,614	71,614
R-squared	0.940	0.316	0.398
B. Placebo outcomes			
Dependent variable	*Patent excl. NFTF*	*Patents in CPC D*	*Patents in CPC E*
Work from home	0.009	-0.000	0.000
	(0.055)	(0.002)	(0.004)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	429,684	429,684	429,684
Number of firms	71,614	71,614	71,614
R-squared	0.959	0.923	0.726

Notes: The placebo treatment in panel A indicates whether a firm has a staff lounge and cafeteria. Panel B uses the placebo outcomes of patents not related to non-face-to-face technology, patents assigned to patent classification (Cooperative Patent Classification; CPC) D (textiles), and patents in CPC E (fixed constructions). Standard errors in parentheses are clustered at the firm level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

patents, patents in CPC category D, and patents in CPC category E. Patent classifications (Cooperative Patent Classification; CPC) contain a category letter (A through H, or Y),[5] and few NFTF patents are assigned to CPC D or CPC E. None of these placebo outcomes were affected by WFH, as shown in Panel B of Table 6. Therefore, the findings from the placebo tests support the role of WFH in encouraging non–face-to-face innovation.

4.4 Heterogeneous Effects by Size and Age

In the previous section, I demonstrated that firms that offered WFH increased their patents of technologies that support non–face-to-face interaction and WFH. I investigate the mechanisms by which WFH influenced firm innovation by examining the heterogeneous impacts by firm size, age, and innovation rate. Previous research has found that small firms are more innovative than large firms and more efficient in their innovation activities. In the same context, new firms engage in riskier innovation activities, resulting in greater performance gains if successful, and entrant firms have the highest likelihood of innovation, whereas older organizations produce less innovation (Acs and Audretsch, 1988; Coad et al., 2016; Cohen, 2010; Freeman, 2013; Huergo and Jaumandreu, 2004; Tether, 1998).

Table A.2 shows that small firms are driving the results. Small firms that offered WFH increased their number and percentage of patents for NFTF technologies, whereas large firms that offered WFH did not. Small firms that offered WFH, in particular, had 0.171 more NFTF patents and 0.129 more WFH patents. Young firms also play a similar role in explaining the effect of WFH on firms' innovation direction. New firms with WFH increased their NFTF patents, but older firms with WFH did not. The coefficients in Table A.3 show that young firms with WFH had 0.196 more NFTF patents and 0.091 more WFH patents. The findings are consistent with earlier research findings. Small and youthful firms are more innovative and more inclined to branch out into new areas of innovation. Digital resilience made them more prepared to react to the crisis, which transformed the working environment,

[5] A: Human Necessities, B: Operations and Transport, C: Chemistry and Metallurgy, D: Textiles, E: Fixed Constructions, F: Mechanical Engineering, G: Physics, H: Electricity, Y: Emerging Cross-Sectional Technologies

increasing working from home.

4.5 Effect on Workforce

The pandemic had a significant impact on employment. Unemployment insurance (UI) claims skyrocketed, while job vacancy ads plummeted (Forsythe et al., 2020). Individuals in precarious employment experienced the brunt of the labor market shocks (Crossley et al., 2021). State and municipal government employees, as well as private-sector employees, also faced dramatic layoffs (Green and Loualiche, 2021). Individuals in occupations that could shift to working from home were less likely to be laid off, while those in occupations that could not shift to working from home were more likely to be seriously impacted. The employment data at the firm level allows me to examine the impact of WFH policies on firms' workforces, particularly the workforces of patent-holding firms.

Table 7 reports the IV estimates in terms of employment. I find no differences in employment across firms regardless of whether or not a firm adopted WFH. The total number of employees was not altered in any way. However, the number of new employees and layoffs increased in firms that allowed WFH. Columns 2 and 3 show that firms that allowed WFH hired 5.2 percent more new employees and fired 3.8 percent more incumbent employees. This trade-off led to the lack of effect on the workforce of firms with WFH. Small-sized firms drove this finding of labor flexibility. Small firms with WFH significantly increased their new employees and layoffs in Panel B, whereas large firms with WFH neither increased nor decreased employees in Panel C. The findings here are consistent with an increase in innovation activity among small firms. To adapt to the crisis, small firms with digital resilience invested in human capital and innovation that advanced NFTF technologies. Overall, the results suggest that small, innovative start-ups with digital resilience found opportunities during a time of crisis.

Table 7: THE EFFECT OF WORK FROM HOME ON EMPLOYEES

Dependent variable	Employees	New employees	Laid-off employees
	(1)	(2)	(3)
A. All firms			
Work from home	0.013	0.052***	0.038***
	(0.011)	(0.016)	(0.011)
Observations	182,124	182,124	182,124
Number of firms	30,354	30,354	30,354
B. Small firms (≤ 84 employees)			
Work from home	0.033**	0.097***	0.055***
	(0.016)	(0.021)	(0.017)
Observations	91,122	91,122	91,122
Number of firms	15,187	15,187	15,187
C. Large firms (> 84 employees)			
Work from home	-0.009	-0.017	0.017
	(0.015)	(0.028)	(0.015)
Observations	91,002	91,002	91,002
Number of firms	15,167	15,167	15,167
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Notes: The table reports the IV estimates using the sample of patent-holding firms from 2015 to 2020 matched with data from the National Pension System. The sample is partitioned into small firms and large firms using a median of the number of employees (84). The dependent variable is the number of employees per year. New members of the National Pension Scheme (NPS) are used as a proxy for new employees, and members who leave the NPS are used as a proxy for laid-off employees. Work from home is an indicator that takes one if a firm adopts work from home and is instrumented by COVID-19 cases in a region where the firm is located. Standard errors in parentheses are clustered at the firm level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

5 Conclusion

This paper investigates the mechanisms through which work from home is associated with firm innovation. I find four main results. First, WFH had little effect on firms' overall innovation activities. Second, firms with WFH significantly increased their patents of technologies that support non–face-to-face interaction and WFH. Third, firms that offered WFH hired new employees and fired incumbent employees, resulting in a stable workforce. Fourth, small and new firms drove these effects of WFH.

Firms that adopted work from home hastened to patent NFTF technologies in reaction to the pandemic-induced shift to working from home. The need for non–face-to-face technologies and firms' previous experience with them sparked a fresh wave of inventions in that area. The results suggest that both the necessity of an invention and experience with an invention play a crucial role in generating new ideas.

Further research is needed, particularly when the patent applications that have been filed in recent years are fully published. It will be interesting to track the flow of NFTF patents. The results suggest that firms with digital resilience found opportunities during a time of crisis and have been better able to adjust to changes in the working environment; start-up firms seem particularly resilient. Building firms' digital resilience could generate large economic benefits coming out of the crisis and prepare the economy to weather future shocks.

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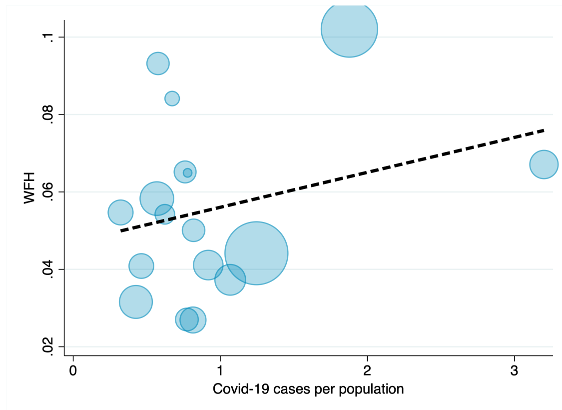
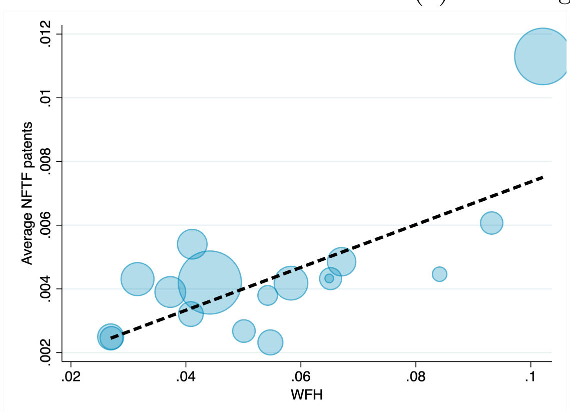
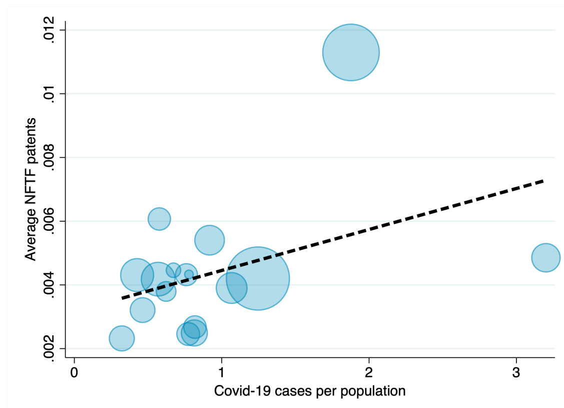


(a) First-stage relationship



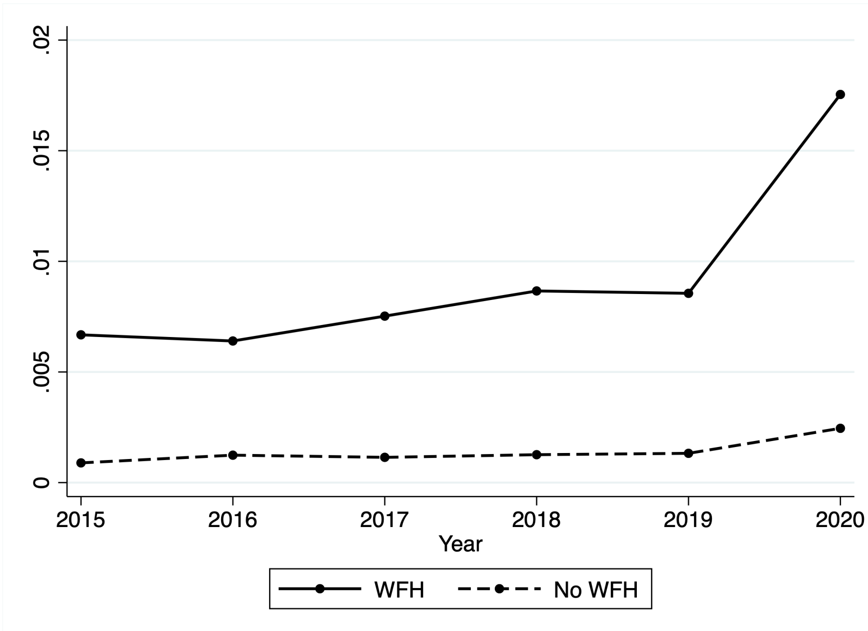
(b) OLS relationship



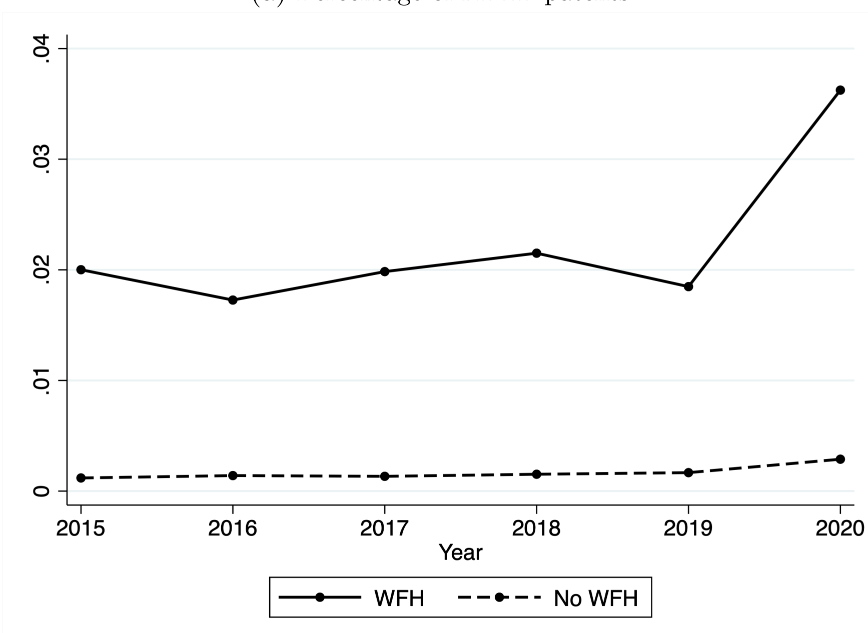
(c) Reduced-form relationship

Figure A.1: RELATIONSHIPS BETWEEN WORK FROM HOME, COVID-19 CASES, AND NFTF PATENTS

Notes: The figure shows the linear relationship bewteen variables at the region level. WFH presents the percentage of firms that adopt WFH. Each bubble represents a region's population size.



(a) Percentage of NFTF patents



(b) Log of NFTF patents

Figure A.2: PATENTS BY STATUS

Notes: The figures plot the annual average of non-face-to-face (NFTF) patents by firms that adopts work from home (WFH) and other firms without WFH.

Table A.1: THE EFFECT OF WORK FROM HOME ON PATENTS

Dependent variable	Patents (1)	NFTF patents (2)	WFH patents (3)
A. OLS estimates			
Work from home	0.313	0.017**	0.008
	(0.277)	(0.007)	(0.005)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	429,684	429,684	429,684
Number of firms	71,614	71,614	71,614
R-squared	0.940	0.316	0.398
B. IV estimates			
Work from home	1.431	0.171***	0.069*
	(1.525)	(0.064)	(0.039)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	429,684	429,684	429,684
Number of firms	71,614	71,614	71,614
Kleibergen–Paap F-statistic	231.33	231.33	231.33

Notes: The table uses work from home which is a time-varying indicator that equals one if a firm adopts work from home from a job search site. If job postings and firm information are missing in that year, then a value of work from home in the previous year is used. Standard errors in parentheses are clustered at the firm level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.2: THE EFFECT OF WORK FROM HOME BY FIRM SIZE

Dependent variable	Patents (1)	NFTF patents (2)	WFH patents (3)
A. Small firms			
Work from home	-0.414 (1.589)	0.171* (0.097)	0.129** (0.063)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	91,002	91,002	91,002
Number of firms	15,167	15,167	15,167
B. Large firms			
Work from home	2.364 (3.209)	0.086 (0.082)	0.022 (0.051)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	91,122	91,122	91,122
Number of firms	15,187	15,187	15,187

Notes: The table reports the IV estimates using the sample of patent-holding firms from 2015 to 2020. The sample is partitioned into two types of firms: small firms with less than or equal to 84 employees and large firms with more than 84 employees. Work from home is an indicator that takes one if a firm adopts work from home and is instrumented by COVID-19 cases in a region where the firm is located. Standard errors in parentheses are clustered at the firm level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.3: THE EFFECT OF WORK FROM HOME BY FIRM AGE

Dependent variable	Patents (1)	NFTF patents (2)	WFH patents (3)
A. Young firms			
Work from home	1.782 (1.282)	0.196** (0.086)	0.091** (0.046)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	161,040	161,040	161,040
Number of firms	26,840	26,840	26,840
B. Old firms			
Work from home	1.289 (2.286)	0.102 (0.069)	0.056 (0.043)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	182,940	182,940	182,940
Number of firms	30,490	30,490	30,490

Notes: The table reports the IV estimates using the sample of patent-holding firms from 2015 to 2020. The sample is partitioned into two types of firms: young firms established in year 2014 or later and old firms established before year 2014. Work from home is an indicator that takes one if a firm adopts work from home and is instrumented by COVID-19 cases in a region where the firm is located. Standard errors in parentheses are clustered at the firm level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.