ESSAYS ON THE RELATION BETWEEN TELECOMMUTING POLICIES AND EMPLOYEE PERFORMANCE

By

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ABSTRACT

This dissertation investigates the relation between telecommuting policies and employee performance. In the first study, "The Effect of Telecommuting on Information Acquisition: Evidence from the U.S. Patent Office," I examine whether telecommuting, a work arrangement in which employees do not travel to a workplace, affects the acquisition of new information in an environment where thorough search and acquisition of information are essential. I find employees' acquisition of new information increases following telecommuting. Further, I find this effect is greater for employees under greater time pressure and employees experiencing greater distractions at the workplace before telecommuting, and find telecommuting causes adverse consequences for employees least responsive to organizations' incentive systems. Finally, I find the acquisition of new information improves work quality. These results suggest telecommuting benefits employees performing knowledge-intensive tasks by facilitating employees' information acquisition.

In the second study, "Subordinates' Task Performance and Departure Rates when the Supervisor Works from Home," I investigate scenarios in which highly experienced supervisors work from home and relatively inexperienced subordinates work at the office. I examine whether such scenarios affect task performance and subordinates' departure rates. I find causal evidence that task performance is lower when the supervisor works from home, relative to when the supervisor works at the office. I also find the negative performance effect of the supervisor working from home is more pronounced for more complex tasks, which have a greater need for advising. Further, I find subordinates working with home-working supervisors are less likely to remain with the organization. This study highlights the importance of in-person interactions in advising relatively inexperienced employees performing technical analysis in organizations.

CHAPTER 1

INTRODUCTION

Telecommuting (also called telework or working from home) policies have diffused widely across organizations over the past few decades. Specifically, as of 2016, a third of all workers in the U.S. had the option to work from home at least part of the day and 23% of employees worked some or most (10-99%) of their usual hours at home (Matos, Galinsky, and Bond 2016). The current COVID-19 global pandemic has instigated a massive experiment in telecommuting around the world (Guyot and Sawhill 2020). While scholars and practitioners have long debated the potential benefits and costs of implementing telecommuting policies, we still have limited knowledge of *when* and *how* telecommuting impacts employee performance (Gonsalves 2020). One reason for this lack of knowledge is that telecommuting arrangements for each employee are seldom recorded in a form that can be analyzed. In addition, prior literature on telecommuting relies mainly on case studies, interviews, and surveys to evaluate the effect of telecommuting in organizations and thus is often unable to provide causal evidence on the impact that telecommuting has on employee performance.

To surmount these difficulties in empirically testing the impact of telecommuting on employee performance, this dissertation utilizes archival field data that I received pursuant to a Freedom of Information Act (FOIA) request. Specifically, the organization I study in chapters two and three is the United States Patents and Trademark Office (USPTO) in which patent examiners decide whether to grant a patent on inventions. From the time the USPTO started its telecommuting policies in 2006, it has recorded the precise day on which patent examiners started working from home, allowing examination of the impact of telecommuting on patent examiners' performance *across* telecommuting and non-telecommuting examiners and *within* a given examiner.

In the first study, “The Effect of Telecommuting on Information Acquisition: Evidence from the U.S. Patent Office,” I investigate the association between telecommuting and employees’ information acquisition patterns in an environment where thorough search and acquisition of information is essential. This chapter presents two contrasting predictions as to the relation between telecommuting and employees’ information acquisition. On the one hand, I predict that telecommuting hampers information acquisition because of reduced communication with colleagues. On the other hand, I predict that telecommuting enhances information acquisition because telecommuting can shift commuting time into work time and enables quieter and uninterrupted working environments. Consistent with the latter, I find telecommuting improves information acquisition of employees. Furthermore, I find the improvement in information acquisition is more pronounced for tasks for which employees likely exert relatively less time and attentional resources before telecommuting. Contrary to common criticism of telecommuting, I find telecommuting does not hamper employees’ ability to acquire new information from their colleagues, as evidenced by a non-significant effect of telecommuting on the acquisition of new information that is already searched and digested by an employee’s colleagues. Finally, I find the improvement of information acquisition is associated with greater work quality, as measured by fewer complaints from patent applicants about the patent examination process.

In the second study, “Subordinates’ Task Performance and Departure Rates when the Supervisor Works from Home,” I investigate whether office-working subordinates show a lower level of performance when their supervisors work from home, relative to when their supervisors work at the office. This scenario stands in contrast to virtually all the prior literature on telecommuting that focuses on the impact on the performance of telecommuting subordinates working on tasks. In practice, however, many organizations demand employees have several years of work experience on the job for training purposes before they start to work from home, leading to a situation where they need to work at the office but their experienced supervisors work from home. Using the USPTO as an empirical testing ground, I find patent examination quality is lower for examiners whose supervisors work from home, relative to when supervisors work at the office. Further, I find the negative effect of supervisor telecommuting on subordinate performance is more pronounced for examiners reviewing more complex technologies, suggesting the importance of in-person interactions in advising relatively inexperienced employees performing technical analysis in organizations. Finally, I find subordinates working with home-working supervisors are less likely to remain with the organization.

In summary, my dissertation finds countervailing effects of telecommuting policies in the USPTO: telecommuting enhances information acquisition of employees who actually work on tasks, but telecommuting deteriorates performance of office-working subordinates when their supervisors telecommute. My results provide insight on why there is mixed evidence in the prior literature on telecommuting. That is, scholars and practitioners have not previously distinguished the environment where employees who actually work on tasks telecommute, from the environment where supervisors telecommute while their subordinates work at the office. To my knowledge, this dissertation is the first to examine the impact of telecommuting policies on employee performance while distinguishing these two different work environments.

CHAPTER 2

THE EFFECT OF TELECOMMUTING ON INFORMATION ACQUISITION: EVIDENCE FROM THE U.S. PATENT OFFICE

2.1 INTRODUCTION

I examine whether telecommuting affects the acquisition of new information in an environment where thorough search and acquisition of information are essential. Telecommuting is a work arrangement in which employees do not travel to a central workplace. As of 2019, about 24 percent of all workers in the U.S. do some or all of their work at home (U.S. Bureau of Labor Statistics 2019). Furthermore, in 2020, the COVID-19 pandemic forced about 34% of workers to switch to telecommuting in the U.S. (Brynjolfsson et al. 2020). The pervasive use of telecommuting programs has spurred debate about whether they are beneficial to the organizations (Bloom, Liang, Roberts, and Ying 2015; Brüggen, Feichter, and Haesebrouck 2020). Given the lack of systematic evidence on the impact of telecommuting on employee productivity, it is important to understand when telecommuting can be beneficial.

Critics commonly argue telecommuting hampers the process by which individuals acquire information. Critics suggest telecommuters are less able to acquire information relevant to decision-making than non-telecommuters because telecommuting dampens communication between individuals and impedes information transfer among employees (Allen, Golden, and Shockley 2015). For example, when Yahoo discontinued its telecommuting policy in 2013, the Chief Executive Officer (CEO) Marissa Mayer stated, "[t]o become the absolute best place to work, communication and collaboration will be important, so we need to be working side-by-side" (Goudreau 2013). However, this does not explain the widespread use of telecommuting, especially in knowledge-intensive industries, for which thorough search and acquisition of information are essential. Indeed, a recent survey indicates the professional, scientific, and technical service industries have the highest volume of telecommuters, followed by healthcare, finance, and insurance industries (Global Workplace Analytics 2017).

To help address the gap between criticism of telecommuting and its prevalence, I use a knowledge-intensive setting to examine an aspect of how individuals acquire information that is overlooked in previous telecommuting studies. That is, individuals can acquire relevant information themselves, not solely relying on information transfer. Information acquisition is costly as it consumes an individual's limited time and attention (Gabaix, Laibson, Moloche, and Weinberg 2003, 2006; Browne, Pitts, and Wetherbe 2007; Falkinger 2008). In the absence of sufficient time and attention, an employee will likely rely on available information, such as information acquired when completing a past task, rather than engaging in the time- and attention-consuming acquisition of new information.

I predict telecommuting will increase information acquisition by reducing time pressure and increasing attentional resources. Prior literature suggests telecommuting relaxes the time pressure that employees face, due to decreased commute time (Bloom et al. 2015). In addition, telecommuting can allow employees working at home to avoid incessant interruptions from unexpected conversations and background noise that can "inhibit employees' ability to be totally involved in the task at hand" (Fonner and Roloff 2010, 340).[1] Nardi and Whittaker (2002, 98) describe employees "withdrawing from (face-to-face) communication" and suggest "most people need time alone" when they concentrate on difficult work. Therefore, relative to an employee

[1] A 2020 survey of 9,000 employees suggests this sentiment also applies to post-pandemic work environments, noting that "despite pets marching over keyboards and children popping up on laps […], people also felt like their time was better utilized working from home" and that "traditional office environments may hinder people's ability to handle tasks that require deep focus […] as there may be too much ambient noise [and] too many unwanted interruptions by colleagues" (Microsoft 2020, 9).

working in a collocated environment, telecommuting employees can engage in information acquisition more extensively due to relaxed time pressure and increased attentional resources.

However, there are at least two reasons that telecommuting may not lead employees to acquire new information. First, organizations rarely consider the extent to which employees acquire new information when designing their performance measurement systems and instead rely on easily observable input and output measures, such as employees' time spent on the job and the total amount of work done (Hwang, Erkens, and Evans 2009). Thus, telecommuting may not increase information acquisition because doing so does not increase their compensation. Second, telecommuting may lead to an increase in employee shirking. Even if telecommuting provides employees with less time pressure and more attentional resources, this does not guarantee employees use them to acquire new information to complete tasks.

I examine the effects of telecommuting on employees' information acquisition using the work of patent examiners at the United States Patent and Trademark Office (USPTO). Patent examiners review, evaluate, and decide whether to grant patents on inventions. In order to decide whether a patent should be granted, a USPTO examiner is expected to thoroughly search relevant prior publications and inventions ("prior art"), which mainly consist of previous granted patents and denied patent applications that were disclosed to the public, to evaluate whether any prior art entirely or partly covers an invention. Because the USPTO randomly assigns patent applications to examiners (Lemley and Sampat 2012; Farre-Mensa, Hedge, and Ljungqvist 2020), a higher proportion of using prior art that an examiner has used before in evaluating the patentability of inventions indicates less thorough search of prior art (Cockburn, Kortum, and Stern 2002; Langinier and Lluis 2021). The USPTO allows the public to observe which prior art is cited by an examiner as the basis for the decision made on an application through the Public Patent

Application Information Retrieval (Public PAIR) online system. I use this online system to identify whether prior art cited in an official letter to an applicant is used by each examiner for the first time or a subsequent time. I also use a data set that includes personnel information on patent examiners (e.g., the exact date on which each examiner started telecommuting) obtained directly from the USPTO via Freedom of Information Act (FOIA) Requests.

I find the likelihood of acquiring new information increases following telecommuting. The effect is economically significant, with telecommuting being associated with a 1.3 percent increase in the proportion of the acquisition of new information. This translates into an increase in the number of new prior art used by 1,278 per month and 15,336 per year that examiners would not have used if the telecommuting program did not exist.[2]

In cross-sectional analyses, I find the effect of telecommuting on information acquisition is stronger for examiners under greater time pressure. In addition, I find the positive effect of telecommuting on information acquisition is concentrated in examiners who are more likely to experience greater distractions at the workplace before telecommuting. I also find telecommuting leads to *less* information acquisition for employees in my sample who are most prone to shirking (those least likely to respond to the USPTO's incentive systems).

I find consistent results using propensity score matching, mitigating the concern that telecommuting examiners are dissimilar to non-telecommuting examiners (i.e., functional form misspecification) (Shipman, Swanquist, and Whited 2017). My findings are also robust to controlling for the non-random assignment of examiners to telecommuting.

[2] I calculate this effect using the mean of the number of prior art used by an average examiner per month (19.27; see Table 1, Panel A), a 1.3 percent increase in the number of the proportion of new information acquisition, and the total number of examiners telecommuting at the USPTO during my sample period (5,100; see p. 10): 1,278 (= 19.27 × 0.013 × 5,100) more new prior art per month and 15,336 (= 1,278 × 12 months) more new prior art per year.

In additional analyses, I find information acquired from colleagues does not necessarily decrease following telecommuting, possibly owing to various communication technologies that examiners frequently use. Further, I use the number of applicant complaints as a proxy for work quality and find work quality is positively associated with the extent to which an examiner cites new prior art. This suggests the acquisition of new information, which is facilitated by telecommuting, is associated with positive work outcomes. Finally, I find my main results are robust to alternative research-design choices.

My findings contribute to the management control literature by providing evidence of *when* and *how* telecommuting can be beneficial. Prior literature on telecommuting generally argues telecommuting negatively affects information transfer between employees (Taskin and Bridoux 2010). By contrast, my findings suggest telecommuting can be beneficial by enhancing another way of acquiring information. That is, telecommuting benefits organizations by helping their employees acquire relevant information themselves. As such, this benefit provides a partial explanation for the prevalence of telecommuting in environments where employees are required to thoroughly search for and acquire information.

My findings also suggest employees in relatively higher paid, knowledge-intensive jobs can enhance their performance by telecommuting (Choudhury, Foroughi, and Larson 2021). Prior literature on telecommuting focuses mainly on employees in lower paid jobs because output is easily measurable for such jobs. For example, Bloom et al. (2015) find call-center employees paid based on the number of phone calls made increase the number of calls they make following telecommuting. However, they also caution that "the direct implications [of their findings] are limited to these types of jobs" (Bloom et al. 2015, 171). My setting is distinct from prior papers that focus on lower paid, routine jobs with easily measurable performance because, unlike these jobs, the examiner jobs at the USPTO require thorough search and acquisition of information that are essential to perform complex tasks but do not receive compensation for such difficult-to-measure activities. Therefore, my paper provides insight into how telecommuting can improve employee performance in higher paid, knowledge-intensive jobs.

My study also contributes to the literature on telecommuting by documenting that the effect of telecommuting is heterogeneous based on employees' responsiveness to organizations' incentive systems, an individual-level characteristic that is not easily observable to those outside the organization. Bloom et al. (2015) find the effect of telecommuting does not differ based on easily observable individual characteristics, such as marital and family status, gender, education levels, and living arrangements. Brüggen et al. (2020) do not find evidence that telecommuting employees are lazy and unmotivated. By contrast, I find the effect of telecommuting differs based on factors related to incentive systems that prior telecommuting scholars rarely examine.

2.2 RESEARCH SITE

2.2.1 Patent Examination Process at the USPTO

The USPTO is a federal governmental agency charged with granting patents on inventions. There are currently nine technology centers, which consist of operational teams of 10-30 patent examiners responsible for similar technological areas (Art Units).[3] The USPTO employs approximately 9,000 patent examiners whose role is to read the patent application, search relevant prior publications and inventions ("prior art"), read and evaluate prior art, and evaluate the application in a written document that they provide to the applicant.

Patent applicants have a duty of candor to disclose previously granted patents, patent applications that are not granted or abandoned by the applicants, or other publications that are

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[3] For more information on the current technology centers and Art Units in the USPTO, see https://www.uspto.gov/patent/contact-patents/patent-technology-centers-management.

material to the patentability of the invention.[4] However, the patent law cannot require the applicant to disclose what the applicant does not know about (Jaffe and Lerner 2004). In addition, applicants have a "clear disincentive to explore the prior art thoroughly" (Jaffe and Lerner 2004, 139) because an examiner reviewing an application can use the prior art that is disclosed by applicants against them to argue that it is not valid (Key 2018).[5] Aware of applicants' incentives, examiners generally ignore the prior art submitted by the applicant and rely almost exclusively on prior art they find themselves as formal grounds for the decision made – that is, rejection or allowance of the claims of the invention (Cotropia, Lemley, and Sampat 2013). Usually, an examiner performs a prior art search using a keyword search of large patent databases, scientific publications, or web search engines (Google or YouTube).

After conducting their own search of prior art, examiners assess the patentability of the application in light of the criteria delineated in patent law. Even when examiners grant a patent, they can choose to allow only a portion of the claims of the applications in light of the prior art references discovered through the examiner's own search. In all cases, an examiner must set forth the basis for a full or partial rejection for rejected claims ("decision grounds"). For example, an examiner might suggest a single or multiple prior patents or pre-grant patent applications as decision grounds for why the application fails to meet the patentability standards in a written document provided to the applicant. Appendix A provides an example of decision grounds provided by an examiner in rejecting some or all claims of the invention.

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[4] The American Inventor's Protection Act (AIPA) requires every patent application filed on or after November 29, 2000 to be disclosed even if it is not granted by the USPTO.

[5] In addition, applicants are not motivated to search the prior art thoroughly due to fears of a "willful infringement," in which case applicants are liable for three times the damage that they would otherwise have to pay if they are later found to have knowingly infringed a patent, making the applicant not want to make sure that "it finds out about all of the patents related to a technology it is pursuing" (Jaffe and Lerner 2004, 139).

After evaluating the patentability of an invention, an examiner issues a "first office action on the merits (FOAM)," which either allows all claims of an invention and grants a patent or, more generally, provides the applicant with the reasons for why some or all claims of an invention are not allowed to be patented.[6] A FOAM is non-final in nature (a non-final rejection), in that an applicant can respond to a FOAM by 1) amending an abstract, specification, claims, drawing, or arguments of an invention and/or 2) arguing the examiner is incorrect. Upon receiving the response from an applicant, an examiner issues a second office action that either grants the patent or rejects claims of an invention. If rejected, an applicant can choose to reply by filing a Request for Continued Examination (RCE) to re-start the entire application review process, appeal the denied application to a board of appeals, or abandon the application. RCEs allow applicants to express their dissatisfaction with the review process, which mainly arises from disagreement between examiners and applicants on which prior art should be used as decision grounds. An RCE is one of the main reasons the review process of an application at the USPTO gets lengthened (Lemley and Sampat 2012).

2.2.2 Examiners' Work Requirements and Their Implications for Examination Quality

When applications arrive at the USPTO, the supervisory patent examiners within each of the Art Units assign patent applications to examiners in the appropriate Art Unit, based on a first-in-first-out system. On average, a patent examiner spends only 18 hours reviewing one application, including reading an application, searching for prior art and comparing it to an application, writing a decision letter, and often conducting an interview with the applicant or the applicant's attorney (Frakes and Wasserman 2019). An internal survey conducted by the USPTO reveals most examiners have "less time than needed to complete a thorough examination" and

[6] An office action refers to a patent decision that indicates whether a patent application is allowed or rejected.

frequently work uncompensated (and thus unrecorded) overtime to meet their production goals in the past six months (U.S. Government Accountability Office [GAO] 2016, 25). In addition, examination time allotted to examiners decreases upon promotion.

This insufficient time allotted for evaluating patent applications is at odds with patent quality. An internal report by the USPTO indicates "there are trade-offs between timeliness and patent quality" and "the office's focus on timeliness trumps high quality work at the agency" (GAO 2016, 25). While enhancing the quality of the patent review process is important to the USPTO,[7] there is a stronger emphasis on promoting examination throughput because the "biggest challenge is to decrease the backlog of applications awaiting review" (Frakes and Wasserman 2017a, 562).[8] Indeed, the USPTO offers monetary incentives to examiners for timely processing of applications, but not for conducting high-quality reviews.[9] Thus, examiners tend to complete their work quickly and sacrifice work quality (Frakes and Wasserman 2017a).

2.2.3 Challenges in Identifying Relevant Prior Art

Patent examiners face several challenges in finding relevant prior art for each application. First, patent applications are not easy to understand because there is often no standard term to describe technologies. In my conversations with patent examiners, one examiner indicated patent lawyers are notorious for using obscure terms in their applications. Second, several government reports and commentators note the number of patents and publications has grown exponentially,

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[7] For example, in her speech at Stanford Law School in 2014, the former director of the USPTO, Michelle K. Lee, said "improving patent quality has always been at the core of the PTO's mission. But, for too long, due to uncertain budgetary conditions and limited resources, the PTO has had to make do with less. Despite our best intentions, we've had to accept trade-offs between quality and application backlog and pendency."

[8] In the late 2000s, the amount of time a patent application remained with the USPTO until the final decision (patent pendency) hovered around 39-42 months (32-35 months) including (excluding) RCEs. By 2015, patent pendency decreased to 26 months (35 months) including (excluding) RCEs, partly due to the USPTO's various efforts in reducing patent pendency.

[9] Patent examiners are given production bonuses in 5 percent increments from 110% to 135% of their production targets; the bonuses can amount to a significant portion of their annual compensation. In addition, patent examiners need to continuously meet the production target to warrant a promotion to higher-level positions.

making it difficult for examiners to meet their production targets in their allotted time while finding the most relevant prior art in reviewing each application (GAO 2008, 2016). Finally, examiners may not have access to relevant prior art. A GAO survey report indicates "some relevant prior art may require a fee to access, may not be in a text-searchable format, may not be in a database, or may otherwise be difficult to access" (GAO 2016, 16).

2.2.4 Telecommuting Program at the USPTO

The USPTO began a telecommuting program in 2006 called the Patents Hoteling Program (PHP), which basically requires patent examiners to work from home four days a week and work in the office once a week. Patent examiners are eligible for the PHP if they achieve a General Schedule (GS)-12 level, work at the USPTO for at least two years, and receive positive performance ratings.[10] Participating examiners are not eligible for relocation expenses, relinquish their office spaces, and use a hoteling station when they work at the office. Importantly, participation in the PHP does not affect an examiner's production goals and the way patent applications are assigned to examiners.

Prior to the PHP, most patent examiners worked at USPTO headquarters in Alexandria, VA.[11] In 2006, a total of 362 patent examiners elected into the PHP, which gained popularity over time. By the end of 2017, approximately 5,100 of the 8,147 patent examiners participated in the PHP. The PHP also helped the USPTO save costs by decreasing the need for additional office space (U.S. Patent and Trademark Office [USPTO] 2017).

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[10] The General Schedule (GS) system refers to the U.S. government's classification system for organizing and defining federal positions. While the GS system includes 15 defined grade levels (from GS-1, the lowest level, to GS-15, the highest level), the USPTO is organized in a hierarchical system with eight grades: GS-5, GS-7, GS-9, GS-11, GS-12, GS-13, GS-14, and GS-15. USPTO examiners generally start at a GS-7, GS-9, GS-11, or GS-12, depending on their education level and past work experience.

[11] Aside from the USPTO headquarter, there are four other satellite USPTO offices. The locations are Dallas (TX), Denver (CO), Detroit (MI), and San Jose (CA), which opened in 2015, 2014, 2012, and 2015, respectively.

2.3 DATA, MEASURES, RESEARCH DESIGN, AND EMPIRICAL RESULTS

2.3.1 Data

My final data set consists of 2,109 telecommuting examiners and 1,617 non-telecommuting examiners, yielding 161,090 examiner-month observations. I construct my data set using multiple sources. First, I obtain individual application data from the Public Patent Application Information Retrieval (Public PAIR). While prior literature generally focuses on determinants and consequences of patent *grant* activity, only a small subset of empirical research studies the *process* of obtaining a patent grant from the patent office, mainly due to the lack of readily available data. In accordance with the Open Government Initiative that began with the Obama administration, Public PAIR first became available in 2015, and contained all activities of approximately 11.1 million applications between November 29, 2001 through December 31, 2017 when I started my data collection.[12] From Public PAIR, I obtain the data including the name and unique identifier of the examiner, the exact date on which each examiner made decisions on the application, the nature of each decision made by the examiner, the prior art cited in each application by an applicant and/or examiner, and entity status of an applicant. Second, for research purposes, the USPTO provided me with detailed personnel data on patent examiners via FOIA Requests, including the year in which each examiner joined the USPTO, each examiner's GS-level each year, and the exact date, month, and year in which each examiner started telecommuting. I merge these examiner-level observations with the application-level data.

Public PAIR also allows researchers to identify which prior art is cited as decision grounds in each office action and, more importantly, whether prior art citations are added by applicants or examiners. I use only the prior art citations that are added as decision grounds by

[12] https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-examination-research-dataset-public-pair (retrieved in June of 2019).

examiners for this study. Then, I identify whether the prior art cited in each office action of an application (decision grounds) has been cited for the first time by each examiner. Because Public PAIR did not provide readily available data on prior art citations by examiners until late 2007, I limit the analysis to the examiner-month observations for those who joined the USPTO after 2007 to capture all prior art cited by each examiner. I also require all examiners to have at least two years of experience at the USPTO by the end of 2017 to be included in my sample, meaning examiners must have joined the USPTO before 2016.

2.3.2 Measures

I start with *# Office Actions*, defined as the total number of office actions that each examiner completes in each month. Next, I define *# Total Cites* as the total number of examiner-added citations that are used as decision grounds by each examiner in each month. *# Total Cites* represents the amount of work implemented by each examiner in a given month. Then, I decompose *# Total Cites* into two subsets, ones that are cited for the first time by each examiner and ones that are cited for the second or subsequent time by each examiner. I use the former subset to create *# New Cites*, defined as the number of examiner-added citations that serve as decision grounds by each examiner in each month that a focal examiner has not used in reviewing prior patent applications. To examine my research question, I use *% New Cites*, defined as the ratio of *# New Cites* to *# Total Cites*, as my main dependent variable.[13]

Table 1 presents descriptive statistics for all variables. Panel A shows approximately 12 percent of all examiner-month observations are subject to the treatment of participation in the telecommuting program. The average total number of examiner-added citations for a given

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[13] In an untabulated test, I also use the number of examiner-added citations that are used for the first time by each examiner per office action (*# New Cites* scaled by *# Office Actions*) as a dependent variable and find consistent results.

examiner in a given month, *# Total Cites*, is 19.272. On average, *# New Cites* is 9.125 citations per month for a given examiner. The average value of *% New Cites* is 49.7 percent, meaning 49.7 percent of examiner-added citations are first used by a given examiner each month. Panel B shows the number of examiners who start telecommuting by year and month. Panel B shows the number of examiners who join the PHP is evenly dispersed within each year while the number of examiners telecommuting generally increases over time. Finally, Panel C shows the number of examiners by tenure (the number of years working at the USPTO) when they started telecommuting. Approximately one third of examiners (728 out of 2,109 telecommuting examiners) started telecommuting by the year when they became eligible to telecommute (two years after joining the USPTO), followed by their third (673 examiners) and fourth (326 examiners) year at the USPTO. I define all variables in Appendix B.

2.3.3 Primary Analyses

2.3.3.1 Research Design

I examine my research question using the following examiner-month level OLS regression with a difference-in-differences (DiD) methodology:

$$\%\ New\ Cites = \beta_0 + \beta_1 Treatment + \beta_n(Fixed\ Effects) + \varepsilon. \tag{1}$$

For treatment examiners, the main independent variable, *Treatment*, is a binary variable equal to one for examiner-month observations after participating in the PHP, and zero otherwise. For examiners who never telecommute, *Treatment* is equal to zero for all examiner-month observations. The dependent variable, *% New Cites*, represents the proportion of examiner-added citations that are used for the first time by each examiner in a given month.

In my DiD estimation that exploits the staggered PHP election dates over time, the first difference is the change in the proportion of new citations used by examiner *i* before and after telecommuting. The implicit control group consists of examiners who do not telecommute in my sample period. The change in the proportion of new citations within this control group is the second difference that I capture in my tests. I estimate the difference in those two differences to test the effect of telecommuting on new information acquisition.

I include individual examiner fixed effects and year-month fixed effects to account for variation in the likelihood of information acquisition by each examiner and over time. I include GS-Level fixed effects to account for concerns that examination time constraints that differ based on the GS levels might affect the examiner's propensity to acquire new information. In addition, I control for tenure fixed effects, with tenure defined as the number of years each examiner has worked, to control for variation in the propensity of information acquisition by experience level. I cluster standard errors at the individual examiner level to correct for autocorrelation within given examiners over time.

2.3.3.2 Results

The regression results reported in Table 2 indicate the acquisition of new information increases following telecommuting. Column (1) presents the estimated results when I include all year-months for both treatment and control examiners. The estimated coefficient on *Treatment* is positive and statistically significant (two-tailed $p < 0.01$), suggesting telecommuting led to a 1.3 percent increase in *% New Cites*. Given that the average examiner uses 19.27 prior art per month, and that about 5,100 examiners have participated in the telecommuting program by 2017, examiners were able to cite an average of 1,278 (= 19.27 × 0.013 × 5,100) more new prior art per month and 15,336 (= 1,278 × 12) more new prior art per year that they would not have used if the telecommuting program did not exist. Given the USPTO's concerns that examiners do not provide a thorough review of patent applications due to an insufficient search of prior art, the result that telecommuting increases the use of new prior art indicates that, following telecommuting, examiners are able to conduct a sufficient search of prior art that prior research argues leads to higher quality examinations (Frakes and Wasserman 2019, 2020).

Figure 1 presents observation points capturing the average number of new citations by each telecommuting examiner across time points divided into spans of one month. Notably, the number of new citations used started out relatively high and decreased over time prior to telecommuting. Prior to telecommuting, the relatively high levels of new information acquisition mainly reflect examiners' relatively short tenure at the USPTO. Over time, the use of citations by each examiner accumulates, decreasing the likelihood of acquiring new information. This causes the downward trend in the acquisition of new information prior to telecommuting. However, the average levels of new information acquisition increased significantly after telecommuting, supporting the notion that employees' acquisition of new information increases following telecommuting.

One notable pattern in Figure 1 is that the number of new citations decreases sharply prior to telecommuting and increases sharply after the telecommuting month. Thus, this pattern around the telecommuting month, and not telecommuting itself, could explain my primary results. To address this concern, I re-estimate Equation (1) after excluding months $t-2$ through months $t+2$, where month t is a telecommuting month for each examiner. As Column (2) of Table 2 shows, the estimated coefficient on *Treatment* is positive and statistically significant (two-tailed $p < 0.01$). Therefore, my primary results are not likely driven by the pattern that the number of new citations increases or decreases sharply around the telecommuting date.

To mitigate the concern that the use of the entire time period might capture confounding events, I re-estimate Equation (1) focusing on six months before and after the telecommuting month and present the results in Column (3) of Table 2. I find the estimated coefficient on *Treatment* remains positive and statistically significant (two-tailed $p < 0.10$).

To remove potential tenure effects, I plot the average number of new citations by telecommuting examiners versus that of matched non-telecommuting examiners who joined the USPTO in the same year-months as their matched telecommuting examiners. For the purpose of Figure 2, I de-mean the number of new citations at the examiner level to eliminate individual fixed effects. Using a one-to-one design, I assign a pseudo-telecommuting month to the matched non-telecommuting examiner. The pseudo-telecommuting month is equal to the telecommuting month of the matched telecommuting examiner. As Figure 2 shows, the average number of new citations follows reasonably parallel, with gradual downward trends for both telecommuting and non-telecommuting examiners prior to the (pseudo-) telecommuting month. However, after the (pseudo-) telecommuting month, I observe that the slopes representing these two groups change substantially. The telecommuting group starts to use more new citations leading to an increase in the average number of new citations, but the non-telecommuting group shows a continued decrease in the average number of new citations, suggesting no evidence of the violation of the parallel trends assumption.

2.3.4 Time Pressure and New Information Acquisition

I also theorize telecommuting increases information acquisition due to relaxed time pressure. If true, then I would expect the effects of telecommuting on information acquisition to be stronger for examiners under greater time pressure.

To examine the role of reduced time pressure, I use work hours per examiner for each Art Unit. The rationale underlying the use of this measure is twofold. First, the USPTO rewards and/or punishes the supervisory patent examiners within each of the Art Units based on the total work completed at the Art Unit-level. My conversations with a patent examiner indicated some supervisory patent examiners pressure their examiners to complete more office actions than others by spending more time working. Second, consistent with peer pressure behaviors among examiners (Frakes and Wasserman 2017b), I expect examiners to work longer if peers in the same Art Unit work longer to complete more office actions.[14] Accordingly, I estimate the following OLS regression to test whether examiners who are in Art Units with long work hours will benefit more from telecommuting:

$$\begin{aligned}\%\,New\ Cites = \beta_0 + \beta_1 Treatment + \beta_2 Treatment * High\ Art\ Unit\ Work\ Hours \\ + \beta_3 High\ Art\ Unit\ Work\ Hours + \beta_n(Fixed\ Effects) + \varepsilon.\end{aligned} \tag{2}$$

I define *High Art Unit Work Hours* as an indicator variable equal to one if an examiner is in an Art Unit with an above-median examining hours per examiner in a given year, and zero otherwise. For each measure, I consider two sets of examining hours: 1) total examining hours and 2) overtime examining hours.[15] The coefficient on β_2 captures the extent to which the proportion of new prior art varies following telecommuting for examiners under greater time pressure. A positive coefficient on β_2 suggest the benefits of telecommuting I find in my earlier analyses is due to an increase in time spent working.

Table 3 presents the results of estimating Equation (2). I find the coefficient on β_2 is positive and statistically significant using total examining hours (Column (1); two-tailed $p < 0.05$) and overtime examining hours (Column (2); two-tailed $p < 0.05$). These results indicates the increase in the acquisition in the new information following telecommuting is more

[14] One consideration here is whether work hours of an Art Unit simply captures examiners' ability or intrinsic motivation, and not whether external forces such as supervisory patent examiners and peers impose a pressure on examiners. However, examiners rarely have an option to choose the Art Unit to which they are assigned; the USPTO assigns examiners to each Art Unit based on its need for personnel. Thus, the effects of examiners' individual characteristics such as their ability, intrinsic motivation and/or responsiveness to monetary incentives on work hours of an Art Unit are effectively held constant across Art Units.
[15] With a few restrictions, examiners are allowed to work overtime if they meet their production goals.

pronounced for examiners under greater time pressure. However, I also find reduced time pressure does not fully explain the positive effects of telecommuting, as the coefficient on *Treatment* (β_1) is positive and statistically significant.

2.3.5 Art Unit Size and Information Acquisition

My theory suggests telecommuting employees can increase their available attentional resources by eliminating the sources of distractions that they face at the workplace. To corroborate that the increase in attentional resources drive my results, I use a measure of the extent to which examiners experienced distractions during the pre-treatment period. Specifically, I expect the number of examiners in an examiner's Art Unit captures variation in the extent to which examiners experienced distractions because interruptions from unexpected conversations and background noise will likely increase with the number of examiners in an examiner's Art Unit. In my conversations with patent examiners, one examiner indicated examiners often experience interruptions when working at the workplace due to interruptions from other examiners in the same Art Unit. In addition, patent examiners in the same Art Units generally work "in close proximity to one another in the Patent Office – e.g., same floor, same section of the hallway, etc." (Frakes and Wasserman 2017b, 3), increasing the possibility of being interrupted while conducting a task in the office versus working at home.

I estimate the following OLS regression to test whether the effect of telecommuting on information acquisition is greater for examiners in larger Art Units:

$$\begin{aligned}\%\,New\ Cites = \beta_0 + \beta_1 Treatment + \beta_2 Treatment * High\ Art\ Unit\ Size \\ + \beta_3 High\ Art\ Unit\ Size + \beta_n(Fixed\ Effects) + \varepsilon. \qquad (3)\end{aligned}$$

High Art Unit Size is an indicator variable equal to one if an examiner is in an Art Unit with an above-median number of examiners, and zero otherwise. All other variables are defined as above. I control for the same set of fixed effects as in Equation (1).

Table 4 presents the results of estimating Equation (3). I find the coefficient on the interaction of *Treatment* and *High Art Unit Size* is positive and statistically significant (two-tailed $p < 0.01$). The coefficient on *Treatment* is not statistically significant (two-tailed $p = 0.39$), indicating the treatment effect is present only among examiners in larger Art Units.[16]

While I use *High Art Unit Size* to capture variation in the extent to which examiners experienced interruptions during the pre-treatment period, it is important to consider the limitations of this analysis. Specifically, this analysis does not speak to the potential interruptions that examiners might face while working at home. While prior literature finds the impact of telecommuting does not differ based on potential sources of interruptions at home, such as marital and children status (Bloom et al. 2015), I am not able to observe such individual characteristics of examiners at the USPTO. Therefore, my analysis lacks empirical evidence of whether potential sources of interruptions at home moderate the relationship between telecommuting and information acquisition in my setting.

2.3.6 Examiners' Responsiveness to Incentive Systems

While a common criticism of telecommuting is that employees might shirk at home, the analyses thus far do not show such evidence, consistent with prior literature finding the overall increase in performance and work hours after telecommuting (Bloom et al. 2015). In recent years, however, critics and policymakers have expressed concerns over the USPTO's telecommuting policy (U.S. Department of Commerce [DOC] 2014). Specifically, there have been adverse incidences in which examiners abuse time and attendance rules, "with a relatively small number of workers responsible for a large share of questionable attendance reports"

[16] *High Art Unit Size* might also capture the potential for information exchange between patent examiners. However, to the extent that this is the case, this will most likely bias against finding support for my expectation that the treatment effect is more pronounced for examiners in larger Art Units.

(Mazmanian 2018). Therefore, while I find an overall improvement in information acquisition following telecommuting, it is possible such benefits would not materialize for a small number of examiners likely to shirk at home. However, the research literature provides little guidance on the factors related to one's likelihood of shirking at home.

To identify factors that might be related to shirking, I use insights gained from my conversations with examiners. One examiner indicated that while examiners do not compete for a position that results in a promotion and can promote to the next GS-level once they complete testing and training programs (Frakes and Wasserman 2017a), some examiners intentionally do not progress to the next GS-level (which increases compensation) because their production goals would increase significantly (see Appendix C for examiners' pay scale details). Specifically, the examiner indicated GS-12 is one such level at which some examiners do not want a promotion to the next GS-level because it leads to a significant increase in production goals.[17] Based on this insight from the field, I expect examiners who remain at GS-12 significantly longer than their peers are those who are less likely to respond to the USPTO's incentive system and instead seek to enjoy a "quiet life" at the expense of higher salaries than other examiners.

On average, examiners in my sample remain at GS-12 for 1.4 years before getting promoted to GS-13 (untabulated). I define *Purposefully Unpromoted* as an indicator variable equal to one for examiners who remain at GS-12 for two years or more. My sample includes 938 *Purposefully Unpromoted* examiners, out of the total 3,726 examiners (25% of total examiners). To address the concern that *Purposefully Unpromoted* examiners do not progress to the next GS-level due to lower performance, I test whether performance levels differ between *Purposefully Unpromoted* examiners and other examiners who have not promoted to GS-13 by the end of my

[17] While a promotion at other levels (GS-7 to GS-9, and GS-11 to GS-12) increases examiners' production goals by 10 percent, a promotion from GS-12 to GS-13 increases their production goals by 15 percent.

sample period. I find *Purposefully Unpromoted* examiners complete an average of 8.94 office actions per month while other examiners complete an average of 8.22 office actions per month, suggesting low performance does not explain why some examiners tend to stay longer at GS-12.[18] Then, I estimate the following OLS regression to test whether the effect of telecommuting on information acquisition is weaker for *Purposefully Unpromoted* examiners:

$$\begin{aligned}\%\ New\ Cites = \beta_0 + \beta_1 Treatment + \beta_2 Treatment * Purposefully\ Unpromoted \\ + \beta_n(Fixed\ Effects) + \varepsilon. \qquad (4)\end{aligned}$$

All variables are defined as above.[19] I control for the same set of fixed effects as in Equation (1).

Table 5 presents the results of estimating Equation (4). Consistent with my primary analyses, the coefficient on *Treatment* is positive and statistically significant (two-tailed $p < 0.01$). I also find the coefficient on the interaction of *Treatment* and *Purposefully Unpromoted* is negative and statistically significant (two-tailed $p < 0.01$). These results suggest the proportion of new information acquisition following telecommuting actually decreases by 0.08 for examiners who remain at GS-12 for two years or more.[20] I posit two non-mutually exclusive explanations for these results: (1) *Purposefully Unpromoted* examiners exploit more time and attentional resources that they obtain from telecommuting to engage in their personal activities and (2) *Purposefully Unpromoted* examiners choose to telecommute to engage in personal activities. My evidence suggests telecommuting may have adverse consequences for employees least likely to respond to organizations' incentive systems.

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[18] The difference in the number of office actions completed per month between two groups is statistically significant (two-tailed $p < 0.01$).

[19] Note that I do not include *Purposefully Unpromoted* separately as it is absorbed in the individual examiner fixed effects.

[20] Note that $\beta_1 + \beta_2 = 0.21 - 0.29 = -0.08$.

2.3.7 Robustness Tests

2.3.7.1 Propensity Score Matching

Prior research finds factors determining whether an employee chooses to telecommute in organizations are mostly time-invariant. For example, Bloom et al. (2015) examine which factors predict voluntary participation in a telecommuting program and find observable characteristics of employees, such as employees' commute time, marital and family status, education levels, firm tenure, wage levels, age, and gender, explain only 3 percent of their voluntary participation in a telecommuting program. They also argue volunteering for telecommuting is "strongly influenced by individual preferences" (Bloom et al. 2015, 180). They further find employees' personal characteristics that are likely to be time invariant, such as the fear of loneliness, mainly explain whether employees decide to telecommute. Therefore, individual fixed effects in my estimations help control for any differences between treatment and control examiners.[21]

Nonetheless, I cannot rule out the possibility that my results suffer from functional form misspecification (i.e., telecommuting examiners are dissimilar to non-telecommuting examiners) (Shipman et al. 2017). Thus, to ensure that examiners who chose to telecommute during my sample period (treatment examiners) are comparable to those who do not (control examiners), I use a propensity score matching (PSM) model based on individual and Art Unit characteristics. I perform a one-to-one match without replacement with a caliper of 0.001. Specifically, I obtain a propensity score for each examiner using a logit model that includes identifiable variables that could explain an examiner's likelihood of telecommuting:

[21] In addition to accounting for examiners' individual characteristics, I am also able to account for the features of the technologies reviewed by each examiner because of the quasi-random assignment of applications to patent examiners (Lemley and Sampat 2012; Farre-Mensa et al. 2020).

$$\begin{aligned}\Pr(Telecommuting) &= \beta_0 + \beta_1 Female + \beta_2 Ethnic\ Minority + \beta_3 \#\ New\ Cites\ Average \\ &+ \beta_4 \%\ New\ Cites\ Average + \beta_5 \#\ Office\ Actions\ Average \\ &+ \beta_6 Art\ Unit\ Size\ Average + \beta_7 Overtime\ Art\ Unit\ Work\ Hours\ Average \\ &+ \beta_8 Total\ Art\ Unit\ Work\ Hours\ Average + \beta_n (Fixed\ Effects) + \varepsilon. \qquad (5)\end{aligned}$$

The explanatory variables are threefold. First, I include individual characteristics, such as *Female* (whether an examiner is female)[22] and *Ethnic Minority* (whether an examiner is ethnic minority).[23] Second, I include measures capturing individual performance, such as *# New Cites Average* (the total number of citations that are used for the first time by each examiner, averaged over all months), *% New Cites Average* (the proportion of examiner-added citations that are used for the first time by each examiner in a given month, averaged over all months), and *# Office Actions Average* (the total number of office actions completed by each examiner, averaged over all months).[24] Third, I include Art Unit characteristics, such as *Art Unit Size Average* (the number of examiners in an examiner's Art Unit, averaged over all months), *Overtime Art Unit Work Hours Average* (the number of overtime examining hours per examiner of an examiner's Art Unit in a given year, averaged over all months), and *Total Art Unit Work Hours Average* (the number of total examining hours per examiner of an examiner's Art Unit in a given year, averaged over all months). Except for *Female* and *Ethnic Minority*, I average all explanatory

[22] I collect information on each examiner's gender through a FOIA request to the USPTO. However, because the data set that the USPTO provided me was incomplete, I also use the online service genderize.io, which provides gender probabilities to first names of examiners in my sample.

[23] Following prior research (Merkley, Michaely, and Pacelli 2020), I identify examiners' ethnicity by mapping examiners' surnames to the geographic regions most likely to represent examiners' country of ancestry. Specifically, I use various sources, including the *Oxford Dictionary of American Family Names*, Ancestry.com, and Forebears.io, and map the country of origin to one of ten cultural clusters: (i) Anglo, (ii) Nordic Europe, (iii) Latin America, (iv) Southern Asia, (v) Confucian Asia, (vi) Middle East, (vii) Eastern Europe, (viii) Sub-Saharan Africa, (ix) Latin Europe, and (x) Germanic Europe. Then, following Flam, Green, Lee, and Sharp (2020), I aggregate these ethnicities into two groups, that is, ethnic minority and nonminority. Ethnic minority examiners are those falling into the following groups: Latin America, Southern Asia, Confucian Asia, Middle East, and Sub-Saharan Africa. I classify other examiners who fall into the remaining ethnic groups (Anglo, Nordic Europe, Eastern Europe, Latin Europe, and Germanic Europe) as nonminority examiners.

[24] I use these three measures as proxies for each examiner's performance because I am not able to observe each examiner's actual performance ratings.

variables in Equation (5) over year-months right before the telecommuting month for treatment examiners and do not include months after telecommuting. This ensures I estimate a propensity score based on pre-treatment levels of individual performance and Art Unit characteristics. I also include technology center fixed effects, office location fixed effects, and hired year fixed effects to address cross-sectional differences across technology-specific characteristics, office locations, and tenure, respectively.[25]

As Panel A of Table 6 shows, six measures significantly predict an examiner's voluntary participation in the PHP. While examiners' gender does not predict their choice to telecommute, ethnic minority examiners are less likely to telecommute. Consistent with the USPTO requiring examiners to have high performance ratings to be eligible for telecommuting, examiners with relatively higher individual performance prior to telecommuting are more likely to telecommute. Finally, examiners in larger Art Units and in Art Units with more overtime examining hours are more likely to telecommute. The combined explanatory power results in an area below the receiver operating characteristic (ROC) curve of 0.76, suggesting good explanatory power (Hosmer and Lemeshow 2000). Panel B of Table 6 presents a covariate balance after the match. The results suggest no significant differences for all explanatory variables, providing validation of my matching procedure.

My final matched sample includes 898 treatment examiners and 898 control examiners. I assign a "post" period to each control examiner, consistent with the period for the corresponding treatment examiner. Utilizing a matched control sample, I perform a DiD test with the following OLS regression with standard errors clustered by examiner:

$$\%\ New\ Cites = \beta_0 + \beta_1 Post + \beta_2 Post * Treated\ Examiner + \beta_n (Fixed\ Effects) + \varepsilon. \quad (6)$$

[25] Office locations refer to whether an examiner works at the Alexandria (VA), Dallas (TX), Denver (CO), Detroit (MI), or San Jose (CA) USPTO offices.

In Equation (6), *Treated Examiner* is an indicator variable equal to one for examiners who choose to telecommute during my sample period, and *Post* is an indicator variable equal to one for examiner-months after the telecommuting event occurred. Since each control examiner is matched to a treatment examiner, *Post* for the control examiner is defined as *Post* for the corresponding treatment examiner. Consistent with my primary analyses, I use all available year-months for both treatment and control examiners. I control for the same set of fixed effects used in Equation (1).[26]

I report the results of estimating Equation (6) with my PSM sample in Panel C of Table 6. I find the coefficient on the interaction of *Post* and *Treated Examiner* is positive and statistically significant (two-tailed $p < 0.01$). Therefore, my findings from estimating a DiD on a propensity score matched control sample provide strong support for my earlier findings that examiners are more likely to acquire new information when telecommuting.

To test the validity of my empirical strategy, I expand my event window to capture the dynamics of the telecommuting effect. Specifically, I replace *Post* in the regressions with indicator variables for each of the six months prior to telecommuting ($month_{-1}$ to $month_{-6}$), the month of telecommuting ($month_0$), each of the 12 months after telecommuting ($month_1$ to $month_{12}$), and 13 months or more after telecommuting ($month_{13+}$). Examiner-months more than six months prior to telecommuting serve as benchmark months. I present the results of this analysis in Panel D of Table 6. The coefficients on the interaction of the indicator for each of the six months prior to telecommuting ($month_{-1}$ to $month_{-6}$) and *Treated Examiner* are insignificant. This suggests control examiners are a valid counterfactual for treatment examiners and supports the parallel trends assumption (Roberts and Whited 2013). In addition, the effect of

[26] Note that I do not include *Treated Examiner* separately as it is absorbed in the individual examiner fixed effects.

telecommuting on *% New Cites* starts to materialize one month after telecommuting. Telecommuting continues to have a positive and significant effect on the proportion of new citations beyond the first 12 months, suggesting telecommuting has a long-lasting impact on the information acquisition patterns of examiners.

2.3.7.2 Plausibly Exogenous Assignment of Examiners to Telecommuting

In this subsection, I take steps to alleviate the concern that the assignment of examiners to telecommuting is not random. Specifically, I examine whether telecommuting increases new information acquisition using a sample that consists only of examiners who opted into the PHP shortly after meeting the two-year tenure requirement. The two-year tenure requirement provides benefits similar to those of an exogenous shock. First, the timing of opting into the PHP is exogenous in the sense that it differs only because of differences in the point of time an examiner joins the USPTO. Second, all examiners are homogenous in the sense that they all choose to telecommute. To implement the test, I limit my sample to examiner-months for those who opted into the PHP within one month or two months, respectively, after the two-year tenure requirement and re-estimate Equation (1). Consistent with my primary analyses, the event window for each examiner is all available year-months before and after the telecommuting month. This DiD specification takes as the control group all other examiners with an overlapping event window who did not choose to telecommute at time *t* but have already chosen to telecommute before or will telecommute later on (Bertrand and Mullainathan 2003).

The results presented in Table 7 suggest examiners choosing to telecommute shortly after the two-year requirement also increase the use of new prior art. Column (1) presents the results when I limit my sample to those choosing to telecommute within one month after the two-year requirement. This sample includes 12,785 examiner-month observations that correspond to 253 examiners. The coefficient on *Treatment* is positive and statistically significant (two-tailed $p < 0.01$). Column (2) presents the results when I limit my sample to those choosing to telecommute within two months after the two-year requirement. This sample includes 21,787 examiner-month observations that correspond to 455 examiners. The coefficient on *Treatment* is positive and statistically significant (two-tailed $p < 0.01$). In sum, I find my primary results regarding the effects of telecommuting are robust to controlling for the non-random assignment of examiners to telecommuting.

2.4 ADDITIONAL ANALYSES AND SENSITIVITY ANALYSES

2.4.1 Additional Analyses

2.4.1.1 Does Telecommuting Reduce the Amount of Information Acquired from Colleagues?

The results discussed in Section 3 are consistent with greater information acquisition following telecommuting. However, telecommuting may lead to less information acquisition from colleagues. If so, then I would expect a decrease in the acquisition of information that is new for a focal examiner, but is *not* new for the focal examiner's colleagues. To explore this possibility, I decompose the proportion of new citations by each examiner in a given month into 1) the proportion of new citations that a focal examiner has not previously used *and* colleagues (other examiners) have also not previously cited, and 2) the proportion of new citations that a focal examiner has not previously used *but* colleagues *have* previously cited. I consider two sets of colleagues: 1) all examiners at the USPTO and 2) all examiners in the same Art Unit. Specifically, I decompose *% New Cites* into *% New Cites USPTO* (*% New Cites Art Unit*) and *% Old Cites USPTO* (*% Old Cites Art Unit*), and I define colleagues as all employees at the USPTO (in the same Art Unit). *% New Cites USPTO* (*% New Cites Art Unit*) is the total number of examiner-added citations in a given month that any examiner at the USPTO (in the same Art

Unit), including a focal examiner, has not used in reviewing prior patent applications, divided by the total number of examiner-added citations in a given month. *% Old Cites USPTO* (*% Old Cites Art Unit*) is the total number of examiner-added citations in a given month that a focal examiner has not previously used but other examiners at the USPTO (in the same Art Unit) have previously cited, divided by the total number of examiner-added citations in a given month.

Table 1 presents the descriptive statistics for these measures. Out of 49.7 percent of examiner-added citations that are first used by a given examiner (% *New Cites*) each month, an examiner uses 27.3 percent (45 percent) of examiner-added citations that have not been previously used by anyone at the USPTO (in the same Art Unit). I replace the dependent variable in Equation (1), *% New Cites*, with one of the four dependent measures described earlier, and re-estimate Equation (1).

The results presented in Table 8 suggest telecommuting does not hinder examiners' ability to acquire new information from their colleagues. Columns (2) and (4) of Table 8 present the regression results when the dependent measure is *% Old Cites USPTO* (Column (2)) or *% Old Cites Art Unit* (Column (4)). The coefficient on *Treatment* is not statistically significant in either Column (2) (two-tailed $p = 0.16$) or Column (4) (two-tailed $p = 0.48$).

Notably, analysis of the other two dependent measures suggests that the information that examiners are acquiring is expanding the Art Unit's and USPTO's knowledge boundaries. Specifically, I present the regression results when the dependent measure is *% New Cites USPTO* or *% New Cites Art Unit* (Column (1) and Column (3), respectively). The coefficient on *Treatment* is positive and statistically significant in both Column (1) and Column (3) (both two-tailed $p < 0.01$).

Telecommuting may not reduce examiners' information acquisition from fellow examiners because examiners extensively use various technologies to encourage communication between examiners. Indeed, prior research suggests "telework does not necessarily have a detrimental effect on knowledge transfer" (Beauregard, Basile, Canónico 2019, 515), as long as appropriate *communication zones*, defined as "a potentiality for productive communication between two people" (Nardi and Whittaker 2002, 84), are created through communication technologies (Coenen and Kok 2014). For example, examiners can have instant communication through WebEx cameras installed on a PC, allowing them to conduct informal meetings to talk about work. They also use Skype to have frequent meetings to discuss the work. However, it is possible that contextual factors could lead to less information sharing following telecommuting, such as the degree of teamwork efforts necessary to perform tasks. Therefore, the results should be interpreted within the context of these institutional characteristics.

2.4.1.2 Acquisition of New Information and Work Quality

I extend the analysis and take preliminary steps towards exploring the link between information acquisition and examiners' work quality. To start, I create a measure of work quality using the incidence of Request for Continued Examinations (RCEs). RCEs occur when applicants are dissatisfied with the review process, arising mainly from disagreement between examiners and applicants on which prior art should serve as decision grounds. I use this measure as a proxy for work quality following Frakes and Wasserman (2020) who suggest RCEs prolong the review process, which the USPTO states as its biggest challenge. To examine whether information acquisition is related to work quality, I estimate the following equations:

$$\%\, RCE = \beta_0 + \beta_1 \%\, New\ Cites + \beta_2 \%\, Rejection + \beta_n (Fixed\ Effects) + \varepsilon. \tag{7}$$

$$\% \, RCE = \beta_0 + \beta_1 \# \, New \, Cites + \beta_2 \# \, Total \, Cites + \beta_3 \% \, Rejection + \beta_n (Fixed \, Effects) + \varepsilon. \quad (8)$$

The dependent variable for both equations, *% RCE*, is the ratio of the number of office actions implemented by an examiner in a given month that eventually led to patent applicants' RCEs to the total number of office actions implemented by an examiner in a given month. A higher *% RCE* represents a higher incidence of RCEs. As shown in Table 1, 37.3 percent of final office actions ultimately led to RCEs. I control for *% Rejection*, which is the ratio of the number of office actions for which an examiner rejects in a given month to the total number of office actions implemented by an examiner in a given month, because a higher ratio of rejections on applications will naturally lead to a higher ratio of RCEs from applicants. I include the same fixed effects as with Equation (1). In estimating Equations (7) and (8), I expect negative coefficients on *% New Cites* and *# New Cites*.

Table 9 presents the results of estimating Equations (7) and (8). Column (1) presents the estimation of Equation (7). The coefficient on *% New Cites* is approximately −0.08 (two-tailed $p < 0.01$), which indicates examiners are able to decrease the number of RCEs by 72 per month and 864 per year that they would have to legally respond to if the telecommuting program did not exist.[27] Column (2) presents the estimation of Equation (8). The coefficient on *# New Cites* is −0.004 (two-tailed $p < 0.01$). These findings suggest the increase in information acquisition following telecommuting is positively associated with one dimension of work quality (incidences of RCEs).

[27] I calculate this effect using the mean of *# Office Actions* (11.873; see Panel A of Table 1), the mean of *% RCE* (0.373; see Panel A of Table 1), the total number of examiners telecommuting at the USPTO during my sample period (5,100; see page 10), and the fact that telecommuting increases the number of the use of new prior art by 1.3 percent (see section 3.3.2): 11.873 × 0.373 × (4 percent × −0.08) × 5,100 = 72 less RCEs per month and 864 (= 72 × 12 months) less RCEs per year.

2.4.2 Sensitivity Analyses

As reported in Table 10, the main results are robust to considering alterative research-design choices. First, I re-estimate Equation (1) and use twelve months prior to and twelve months following the telecommuting month (Column (1)) and three months prior to and three months following the telecommuting month (Column (2)). Second, I exclude non-telecommuting examiners from my analyses (Column (3)). I find consistent results across these tests, except for Column (2) in which I use three months prior to and three months following the telecommuting month (two-tailed $p = 0.14$). These results indicate relatively delayed effects of telecommuting on the acquisition of new information.

2.5 CONCLUSION

Using data from the USPTO, I examine whether telecommuting affects employees' information acquisition. I find telecommuting leads to greater information acquisition, and find this effect is greater for employees experiencing greater distractions at the workplace before telecommuting. My findings also suggest the effect of telecommuting is heterogeneous based on the extent to which employees respond to the organization's incentive systems. Additional analyses indicate information acquired from an employee's colleagues does not decrease following telecommuting. Finally, I provide evidence that employees' information acquisition is positively associated with their work quality.

My findings contribute to the telecommuting and management control literatures by identifying an additional benefit of telecommuting that has not been fully explored in prior literature. While previous research examines the effect of telecommuting on productivity and/or job satisfaction, I document the effect of telecommuting on information acquisition. My study complements prior research by suggesting a productivity-enhancing mechanism through which employees' productivity increases following telecommuting.

My study is subject to the following limitations. First, my findings should be viewed in the context of the study, which is based on an institution that is characterized by an independent and isolated work environment. This work environment may reduce the harmful effects on work quality that might arise due to limited information transfer between colleagues when telecommuting. The results may not hold in organizations with a teamwork environment in which face-to-face communication with colleagues is crucial. Second, despite design choices I employ to reduce the likelihood that the association between telecommuting and information acquisition arises due to the nonrandom assignment of examiners, I cannot rule out the possibility that an unobservable and time-varying omitted variable associated with the decision to telecommute influences examiners' information acquisition patterns. In the absence of an experimental design that randomly assigns examiners into a telecommuting group or a control group, it is not possible to make causal inferences. Finally, examiners' production performance is measured at the individual level with a precisely developed system under which every action made by an examiner on patent applications is recorded and examiners earn incentive bonus payments if they exceed their production goals (Frakes and Wasserman 2020). This feature may have favored successful implementation of telecommuting at the USPTO.

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APPENDIX A
Selected Examiner Citation Example

1. Granted patent as a decision ground of a patent application

(1) Cover page of a final rejection regarding the Patent Application No. 14/976,134

UNITED STATES PATENT AND TRADEMARK OFFICE

UNITED STATES DEPARTMENT OF COMMERCE
United States Patent and Trademark Office
Address: COMMISSIONER FOR PATENTS
P.O. Box 1450
Alexandria, Virginia 22313-1450
www.uspto.gov

APPLICATION NO.	FILING DATE	FIRST NAMED INVENTOR	ATTORNEY DOCKET NO.	CONFIRMATION NO.
14/976,134	12/21/2015	Kyle Hart	RHNO-1-1004-1	4749

12299 7590 05/12/2016
Puget Patent PS
2917 Pacific Ave Ste 102
Everett, WA 98201-5312

EXAMINER	
HANCOCK, DENNIS	

ART UNIT	PAPER NUMBER
2852	

NOTIFICATION DATE	DELIVERY MODE
05/12/2016	ELECTRONIC

(2) Lack-of-Novelty (35 USC § 102) decision ground regarding the patent application No. 14/976,134 documented by the examiner on May 12th, 2016

Claim Rejections - 35 USC § 102

4. Claims 1-16 are rejected under 35 U.S.C. 102(a)(1) as being anticipated by Hart (Patent No.: US 8,721,199 B1) and Hart (Patent No.: US 8,858,098 B1) (both references use identical figures and references and so the rejections will be identical for both).

APPENDIX A (Continued)
Selected Examiner Citation Example

2. Pre-Grant Patent Publication as a decision ground of a patent application

(1) Cover page of a non-final rejection regarding the Patent Application No. 12/802,682

UNITED STATES PATENT AND TRADEMARK OFFICE

UNITED STATES DEPARTMENT OF COMMERCE
United States Patent and Trademark Office
Address: COMMISSIONER FOR PATENTS
P.O. Box 1450
Alexandria, Virginia 22313-1450
www.uspto.gov

APPLICATION NO.	FILING DATE	FIRST NAMED INVENTOR	ATTORNEY DOCKET NO.	CONFIRMATION NO.
12/802,682	06/11/2010	Daniel Travis Shay	01-2777A	5233

24114 7590 06/21/2013
LyondellBasell Industries
Legal IP Department
1221 McKinney Street, Suite 700
LyondellBasell Tower
Houston, TX 77010

EXAMINER	
DARJI, PRITESH D	

ART UNIT	PAPER NUMBER
1731	

NOTIFICATION DATE	DELIVERY MODE
06/21/2013	ELECTRONIC

(2) Obviousness (35 USC § 103) decision ground regarding the patent application No. 12/802,682 documented by the examiner on June 21st, 2013

Claim Rejections - 35 USC § 103

Claims 1-5, 8-9 and 10 are rejected under 35 U.S.C. 103(a) as being unpatentable over Harris (US 2002/0025905) in view of Sagae (US 2005/0261125).

Regarding claims 1-2, Harris teaches coating composition comprising 70 wt % titania, 10 wt % tungsta and 20 wt % alumina ([0059] and [0047]).

This appendix provides sample decision grounds of two patent applications on Public PAIR. The highlighted boxes show the information I use in order to construct variables capturing examiner-added citations.

APPENDIX B
Description of Variables

Variable	Description
Main Variables	
Treatment	For treatment examiners (examiners who choose to telecommute during my sample period from 2008 to 2017), *Treatment* is an indicator variable that takes the value of one for examiner-month observations after participating in the PHP, and zero otherwise. For control examiners (examiners who do not telecommute during my sample period from 2008 to 2017), *Treatment* is an indicator variable that takes the value of zero for all examiner-month observations;
# Total Cites	The total number of examiner-added citations in a given month;
# New Cites	The total number of examiner-added citations in a given month that a focal examiner has not used in reviewing prior patent applications;
% New Cites	The proportion of examiner-added citations that are used for the first time by each examiner in a given month (The ratio of *# New Cites* to *# Total Cites*);
# Office Actions	The total number of office actions that each examiner completes in each month;
Art Unit Work Hours	The number of examining hours per examiner defined at the Art Unit-year level;
High Art Unit Work Hours	An indicator variable equal to one if an examiner is in an Art Unit with an above-median examining hours per examiner in a given year, and zero otherwise;
Art Unit Size	The number of examiners in an Art Unit an examiner is in in a given month;
High Art Unit Size	An indicator variable equal to one if an examiner is in Art Units with an above-median number of examiners, and zero otherwise; and
Purposefully Unpromoted	An indicator variable that equals one if an examiner remains at GS-12 for two years or more, and zero otherwise.
Variables used in Propensity Score Matching analyses	
Female	An indicator variable that equals one if an examiner is female, and zero otherwise;
Ethnic Minority	An indicator variable that equals one if an examiner is identified as an ethnic minority, and zero otherwise;
# New Cites Average	*# New Cites* averaged over six examiner-months right before the telecommuting month for examiners telecommuting during my sample period, and *# New Cites* averaged over all examiner-months for examiners not telecommuting in my sample period;
# Total Cites Average	*# Total Cites* averaged over six examiner-months right before the telecommuting month for examiners telecommuting during my sample period, and *# Total Cites* averaged over all examiner-months for examiners not telecommuting in my sample period;
# Office Actions Average	*# Office Actions* averaged over six examiner-months right before the telecommuting month for examiners telecommuting during my sample period, and *# Office Actions* averaged over all examiner-months for examiners not telecommuting in my sample period;
Art Unit Size Average	The number of examiners in an Art Unit an examiner is in, averaged over six examiner-months right before the telecommuting month for examiners telecommuting in my sample period, and averaged over all examiner-months for examiners not telecommuting during my sample period;
# Art Unit Office Worker Average	The number of examiners working at the office in an Art Unit an examiner is

	in, averaged over six examiner-months right before the telecommuting month for examiners telecommuting during my sample period, and averaged over all examiner-months for examiners not telecommuting in my sample period;
Post	An indicator variable that equals one if examiner-month is after the telecommuting month, and zero otherwise; and
Treated Examiner	An indicator variable that equals one if an examiner chooses to telecommute during my sample period, and zero otherwise.
Variables used in Additional Analyses	
% New Cites USPTO	The total number of examiner-added citations in a given month that any examiner at the USPTO, including a focal examiner, has not used in reviewing prior patent applications, divided by the total number of examiner-added citations in a given month;
% Old Cites USPTO	The total number of examiner-added citations in a given month that a focal examiner has not used but other examiners at the USPTO have previously used in reviewing prior patent applications, divided by the total number of examiner-added citations in a given month;
% New Cites Art Unit	The total number of examiner-added citations in a given month that any examiner in the same Art Unit, including a focal examiner, has not used in reviewing prior patent applications, divided by the total number of examiner-added citations in a given month;
% Old Cites Art Unit	The total number of examiner-added citations in a given month that a focal examiner has not used but other examiners in the same Art Unit have previously used in reviewing prior patent applications, divided by the total number of examiner-added citations in a given month;
% RCE	The ratio of the number of office actions implemented by an examiner in a given month that eventually led to patent applicants' request of continued examinations (RCEs) to the total number of office actions implemented by an examiner in a given month; and
% Rejection	The ratio of the number of office actions for which an examiner rejects in a given month to the total number of office actions implemented by an examiner in a given month.

APPENDIX C
Patent Examiner Annual Pay Scale as of 2018*

Grade	Step1**	Step2	Step3	Step4	Step5	Step6	Step7	Step8	Step9	Step10
GS-5	$44,286	$45,762	$47,239	$48,715	$50,192	$51,668	$53,145	$54,621	$56,097	$57,574
GS-7	$54,857	$56,685	$58,513	$60,342	$62,170	$63,998	$65,827	$67,655	$69,483	$71,312
GS-9	$64,031	$66,166	$68,300	$70,435	$72,569	$74,704	$76,838	$78,973	$81,107	$83,242
GS-11	$73,756	$76,215	$78,674	$81,133	$83,592	$86,051	$88,510	$90,969	$93,427	$95,886
GS-12	$84,588	$87,408	$90,227	$93,047	$95,866	$98,686	$101,506	$104,325	$107,145	$109,964
GS-13	$100,585	$103,938	$107,291	$110,644	$113,997	$117,350	$120,703	$124,056	$127,409	$130,762
GS-14	$118,862	$122,824	$126,786	$130,748	$134,710	$138,672	$142,635	$146,597	$150,559	$154,521
GS-15	$139,814	$144,474	$149,134	$153,795	$158,455	$163,115	$164,200	$164,200	$164,200	$164,200

* Salary levels in this pay scale exclude production bonuses that examiners are eligible to receive when they beat their production goals.

**Within each Grade Scale (GS)-level, there are ten steps (step 1 through step 10) that are usually determined by working experience at the USPTO.

Source: https://www.uspto.gov/sites/default/files/documents/Examiner%20brochure%202018%20downloadable.pdf

FIGURE 1
Effects of Telecommuting on the Number of New Citations by Each Examiner

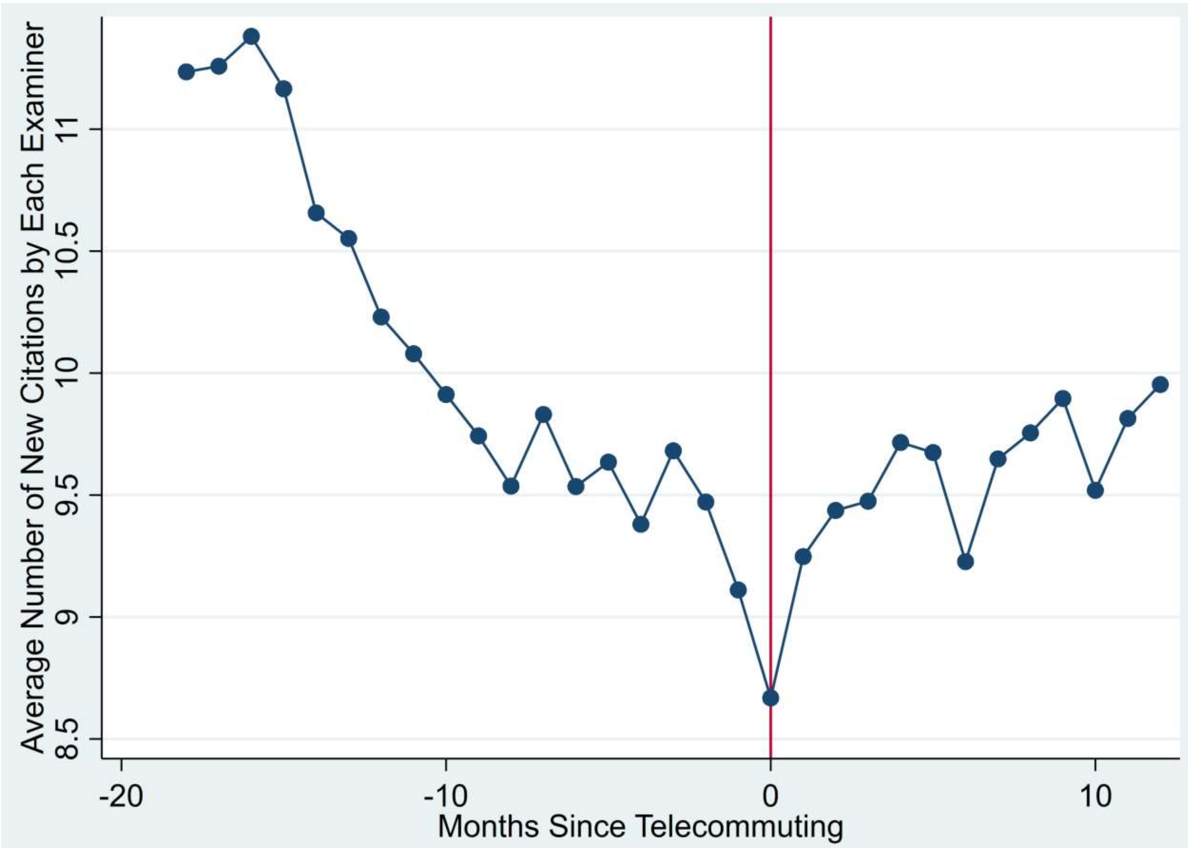

Figure 1 illustrates observation points capturing the average number of new citations by each telecommuting examiner across time points divided into spans of one month. Each observation point in Figure 1 captures 18 months before the telecommuting event and 12 months after.

FIGURE 2
Telecommuting and Non-telecommuting Examiners Matched on Tenure

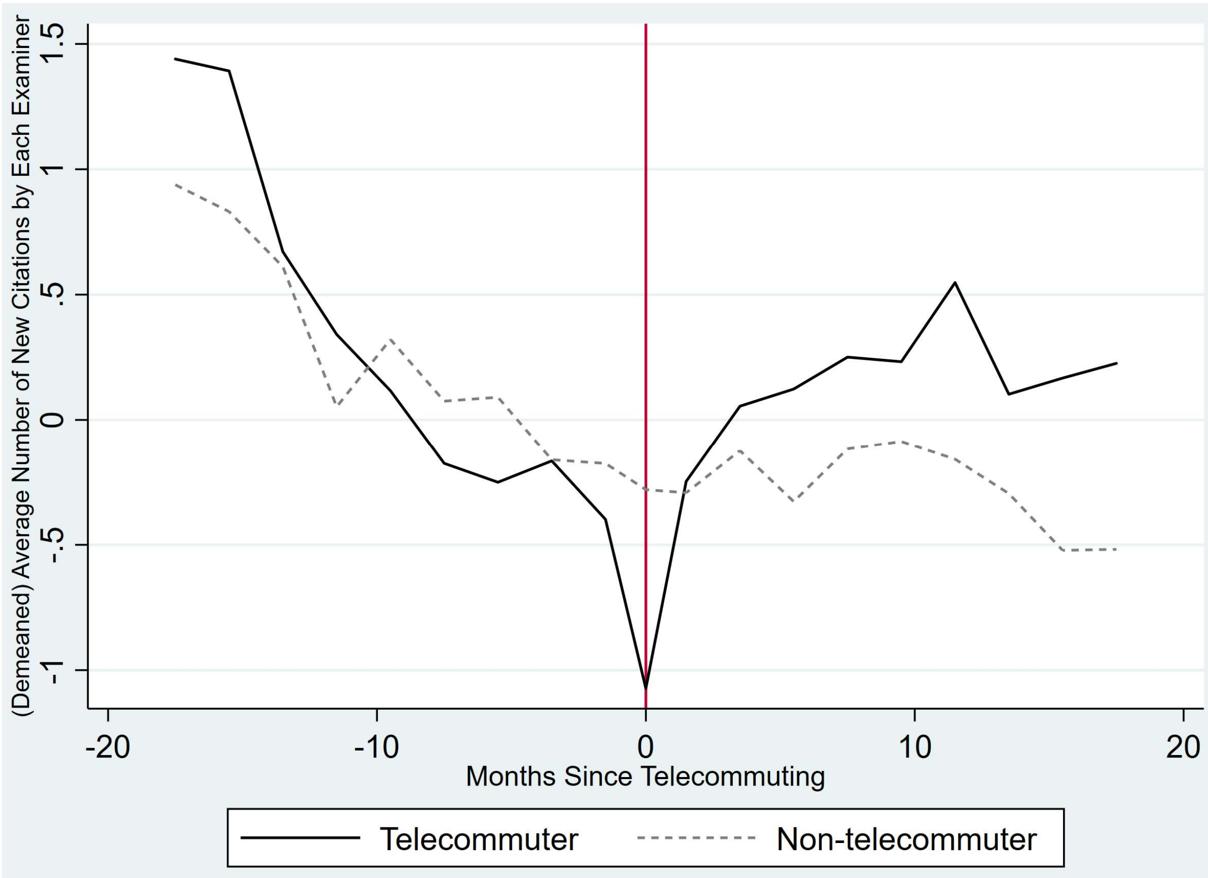

Figure 2 presents the average number of new citations by telecommuting examiners versus that of matched non-telecommuting examiners who joined the USPTO in the same year-months as their matched telecommuting examiners for the 36-month window around the (pseudo-) telecommuting month. Using a one-to-one design, I assign a pseudo-telecommuting month to the matched non-telecommuting examiner. The pseudo-telecommuting date is equal to the telecommuting month of the matched telecommuting examiner. For the purpose of Figure 2 I de-mean the number of new citations at the examiner level to remove individual fixed effects.

TABLE 1
Descriptive Statistics

Panel A. Descriptive Statistics

Measure	N	Mean	Median	Q1	Q3	Std. Dev.
Treatment	161,090	0.340	0.000	0.000	0.000	0.474
# Total Cites	161,090	19.272	16.000	9.000	26.000	14.533
# New Cites	161,090	9.125	8.000	3.000	13.000	7.595
% New Cites	161,090	0.497	0.500	0.300	0.688	0.276
# Office Actions	161,090	11.873	11.000	8.000	15.000	5.116
Art Unit Size (continuous)	142,610	22.162	16.000	14.000	21.000	18.161
Purposefully Unpromoted	161,090	0.269	0.000	0.000	1.000	0.443
Art Unit Work Hours (Total)	3,487	1,558.32	1,516.18	1,400.45	1,638.37	604.25
Art Unit Work Hours (Overtime)	3,487	103.038	92.429	55.583	139.161	71.934
% New Cites USPTO	161,090	0.273	0.224	0.100	0.393	0.233
% Old Cites USPTO	161,090	0.224	0.200	0.091	0.333	0.182
% New Cites Art Unit	161,090	0.450	0.429	0.254	0.625	0.268
% Old Cites Art Unit	161,090	0.047	0.000	0.000	0.067	0.083
% RCE	161,090	0.373	0.333	0.167	0.500	0.274
% Rejection	160,620	0.775	0.800	0.667	0.917	0.183

TABLE 1 (Continued)

Panel B. Number of Examiners by the PHP Start Year and Month

	PHP Start Month												
PHP Start Year	**Jan.**	**Feb.**	**Mar.**	**Apr.**	**May.**	**Jun.**	**Jul.**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**	**Total**
2010	0	3	10	5	1	4	7	14	0	13	6	0	63
2011	14	18	22	11	7	13	15	21	0	19	11	0	151
2012	22	15	12	12	12	15	11	41	12	16	13	13	194
2013	47	29	23	19	26	42	25	13	11	10	11	15	272
2014	18	16	17	13	37	32	41	46	48	52	26	1	347
2015	40	31	44	22	25	33	22	34	27	36	27	24	365
2016	38	24	21	36	32	19	22	46	27	28	25	39	357
2017	26	26	23	32	29	35	42	23	23	27	35	39	360
Telecommuters Total													2,109
Non-Telecommuters Total													1,617
Total Examiners in Full Sample													3,726

Panel C. Number of Examiners by Tenure When They Started the PHP

	Tenure when Examiners Started the PHP								
	2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Total**
Telecommuters Total	728	673	326	182	81	59	32	28	2,109
Non-Telecommuters Total									1,617
Total Examiners in Full Sample									3,726

Panel A reports the summary statistics of the main variables. Panel B shows the number of examiners by when each examiner started telecommuting by year and month. Panel C tabulates the number of examiners by tenure (measured as the number of years working at the USPTO) when they started telecommuting.

TABLE 2
Effects of Telecommuting on New Information Acquisition

	DV = *% New Cites*		
	Full Sample Period	**Full Sample Period excluding 2 months around the telecommuting month**	**Subsample period (month –6 to month +6)**
	(1)	**(2)**	**(3)**
Treatment	**0.013*****	**0.016*****	**0.007***
	(3.89)	**(4.10)**	**(1.92)**
Individual Fixed Effects	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes
GS-Level Fixed Effects	Yes	Yes	Yes
Tenure Fixed Effects	Yes	Yes	Yes
Clustered by	Individual	Individual	Individual
Observations	161,045	159,236	78,690
ADJ R^2	0.317	0.318	0.317

Table 2 tabulates the estimation results of Equation (1) using OLS regression, where all *t*-statistics (in parentheses) are based on standard errors clustered at the examiner level. For Column (1), I include all year-months of telecommuting examiners prior to and following the telecommuting month. For Column (2), I include all year-months of telecommuting examiners prior to and following the telecommuting month, excluding two months around the telecommuting month (i.e., I exclude months *t*-2 through months *t*+2, where month *t* is a telecommuting month for each examiner). For Column (3), I include examiner-month observations from six months before the telecommuting month to six months after the telecommuting month for treatment examiners. For Columns (1) through (3), I use all examiner-month observations between 2008 and 2017 for control examiners. For Columns (1) through (3), the dependent variable is *% New Cites*. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3
Treatment Effect Heterogeneity by Time Pressure

	DV = *% New Cites*	
Work Hours Measure:	**Total Work Hours**	**Overtime Work Hours**
	(1)	**(2)**
Treatment	**0.009****	**0.008****
	(2.17)	**(2.02)**
*Treatment * High Art Unit Work Hours*	**0.009****	**0.010****
	(2.34)	**(2.18)**
High Art Unit Work Hours	-0.003	**-0.011*****
	(-1.19)	**(-3.28)**
Individual Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes
GS-Level Fixed Effects	Yes	Yes
Tenure Fixed Effects	Yes	Yes
Clustered by	Individual	Individual
Observations	159,466	159,466
ADJ R^2	0.318	0.318

Table 3 tabulates the estimation results of Equation (2) using OLS regression, where all *t*-statistics (in parentheses) are based on standard errors clustered at the examiner level. *High Art Unit Work Hours* is an indicator variable equal to one if an examiner is in an Art Unit with an above-median examining hours per examiner in a given year, and zero otherwise. The dependent variable is *% New Cites*. See Appendix B for other variable definitions. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 4
Treatment Effect Heterogeneity by Art Unit Size

	DV = *% New Cites*
	(1)
Treatment	0.003
	(0.75)
*Treatment * High Art Unit Size*	**0.014*** **
	(2.83)
High Art Unit Size	0.001
	(0.37)
Individual Fixed Effects	Yes
Year-Month Fixed Effects	Yes
GS-Level Fixed Effects	Yes
Tenure Fixed Effects	Yes
Clustered by	Individual
Observations	142,570
ADJ R^2	0.315

Table 4 tabulates the estimation results of Equation (3) using OLS regression, where all *t*-statistics (in parentheses) are based on standard errors clustered at the examiner level. *High Art Unit Size* is an indicator variable equal to one if an examiner is in Art Units with an above-median number of examiners, and zero otherwise . The dependent variable is *% New Cites*. See Appendix B for other variable definitions. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 5
Treatment Effect Heterogeneity by Responsiveness to Incentive Systems

	DV = *% New Cites*
	(1)
Treatment	**0.021*****
	(5.44)
*Treatment * Purposefully Unpromoted*	**-0.029*****
	(-4.62)
Individual Fixed Effects	Yes
Year-Month Fixed Effects	Yes
GS-Level Fixed Effects	Yes
Tenure Fixed Effects	Yes
Clustered by	Individual
# of *Purposefully Unpromoted* examiners	938
Observations	161,045
ADJ R^2	0.317

Table 5 tabulates the estimation results of Equation (4) using OLS regression, where all *t*-statistics (in parentheses) are based on standard errors clustered at the examiner level. *Purposefully Unpromoted* is an indicator variable that equals one if an examiner remains at GS-12 for two years and more, and zero otherwise. The dependent variable is *% New Cites*. See Appendix B for other variable definitions. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 6
Propensity Score Matching

Panel A: Logit Regression Used to Find Propensity Score

	Pr(Telecommuting)	
	(1) Coefficient	(2) z-statistics
Individual Characteristics		
Female	0.124	(1.38)
Ethnic Minority	**-0.157***	**(-1.94)**
Individual Performance		
# New Cites Average	**0.098*****	**(8.52)**
% New Cites Average	**4.154*****	**(13.45)**
# Office Actions Average	**0.151*****	**(9.40)**
Art Unit Characteristics		
Art Unit Size Average	**0.006****	**(2.48)**
Overtime Art Unit Work Hours Average	**0.002*****	**(2.81)**
Total Art Unit Work Hours Average	-0.0003	(-1.34)
Technology Center Fixed Effects	Yes	
Office Location Fixed Effects	Yes	
Hired Year Fixed Effects	Yes	
N (Number of Examiners)	3,519	
Number of Telecommuting Examiners	1,920	
Pseudo R^2	0.159	
Area under ROC Curve	0.757	

Panel B: Covariate Balance for a Propensity Score Matched Sample

Variable	Treatment Examiners (n = 898): A Mean	Control Examiners (n = 898): B Mean	Mean Difference (A - B) t-test
Individual Characteristics			
Female	0.235	0.252	-0.82
Ethnic Minority	0.400	0.402	-0.10
Individual Performance			
# New Cites Average	8.729	8.750	-0.11
% New Cites Average	0.521	0.519	0.33
# Office Actions Average	10.659	10.684	-0.17
Art Unit Characteristics			
Art Unit Size Average	23.596	23.088	0.63
Overtime Art Unit Work Hours Average	104.76	104.17	0.22
Total Art Unit Work Hours Average	1,532.3	1,536.2	-0.51

TABLE 6 (Continued)

Panel C: Difference-in-Differences Regressions on a Propensity Score Matched Sample

	DV = *% New Cites*
	(1)
Post	-0.008
	(-1.42)
*Post * Treated Examiner*	**0.029*** **
	(4.47)
Individual Fixed Effects	Yes
Year-Month Fixed Effects	Yes
GS-Level Fixed Effects	Yes
Tenure Fixed Effects	Yes
Clustered by	Individual
Observations	80,689
ADJ R^2	0.308

TABLE 6 (continued)

Panel D: Analysis of the Parallel Trends Assumption and the Persistence of the Effect

	DV: *% New Cites*	
	(1) Coefficient	**(2) t-statistics**
$Month_{-6}$ * *Treated Examiner*	-0.007	(-0.56)
$Month_{-5}$ * *Treated Examiner*	-0.005	(-0.37)
$Month_{-4}$ * *Treated Examiner*	-0.0002	(-0.01)
$Month_{-3}$ * *Treated Examiner*	-0.021	(-1.48)
$Month_{-2}$ * *Treated Examiner*	0.005	(0.37)
$Month_{-1}$ * *Treated Examiner*	0.015	(1.09)
$Month_{0}$ * *Treated Examiner*	0.021	(1.49)
$Month_{1}$ * *Treated Examiner*	**0.030****	**(2.08)**
$Month_{2}$ * *Treated Examiner*	0.021	(1.52)
$Month_{3}$ * *Treated Examiner*	0.020	(1.38)
$Month_{4}$ * *Treated Examiner*	**0.032****	**(2.18)**
$Month_{5}$ * *Treated Examiner*	**0.028***	**(1.93)**
$Month_{6}$ * *Treated Examiner*	**0.051*****	**(3.41)**
$Month_{7}$ * *Treated Examiner*	**0.046*****	**(3.11)**
$Month_{8}$ * *Treated Examiner*	**0.034****	**(2.32)**
$Month_{9}$ * *Treated Examiner*	0.016	(1.13)
$Month_{10}$ * *Treated Examiner*	**0.026***	**(1.73)**
$Month_{11}$ * *Treated Examiner*	**0.040****	**(2.54)**
$Month_{12}$ * *Treated Examiner*	**0.026***	**(1.65)**
$Month_{13+}$ * *Treated Examiner*	**0.028*****	**(3.12)**
Month Indicators	Yes	
Individual Fixed Effects	Yes	
Year-Month Fixed Effects	Yes	
GS-Level Fixed Effects	Yes	
Tenure Fixed Effects	Yes	
Clustered by	Individual	
Observations	80,252	
ADJ R^2	0.307	

Table 6 tabulates the estimation results of my propensity score matched analyses. Panel A presents the estimation results of Equation (5) using logistic regression. *Female* is an indicator variable that equals one if an examiner is female, and zero otherwise. *Ethnic Minority* is an indicator variable that equals one if an examiner is identified as an ethnic minority, and zero otherwise. *# New Cites Average*, *% New Cites Average* , and *# Office Actions Average* are averaged values of *# New Cites*, *% New Cites* , and *# Office Actions*, respectively, over all examiner-months before the telecommuting month for treatment examiners, and over all examiner-months for control examiners. *Art Unit Size Average*, *Overtime Art Unit Work Hours Average*, *Total Art Unit Work Hours Average* are averaged values of the number of total examiners, the number of overtime examining hours per examiner at the Art Unit-year level, and the number of total examining hours per examining at the Art Unit-year level, respectively, over all examiner-months before the telecommuting month for treatment examiners, and over all examiner-months for control examiners. Panel B presents a covariate balance analysis using t-tests to compare differences in means. Panel C presents the estimation results of Equation (6). The dependent variable is *% New Cites*. *Post* is an indicator variable that equals one if examiner-month is after the telecommuting month, and zero otherwise. *Treated Examiner* is an indicator variable that equals one if an examiner chooses to telecommute during my sample period, and zero otherwise. In Panel C, I use all examiner-month observations between 2008 and 2017 for both treatment and control examiners. Panel D shows the effect of telecommuting on new information acquisition using dynamic regressions. Panel D shows the effect of telecommuting on new information acquisition using dynamic regressions. In Panel D, I include all examiner-months for both treatment and control examiners. See Appendix B for other variable definitions. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 7
Plausibly Exogenous Variation in the Timing of Telecommuting

	DV = *% New Cites*	
	Telecommuting within 1 month after 2-year requirement	**Telecommuting within 2 months after 2-year requirement**
	(1)	**(2)**
Treatment	**0.032***** **(2.98)**	**0.030***** **(3.72)**
Individual Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes
GS-Level Fixed Effects	Yes	Yes
Tenure Fixed Effects	Yes	Yes
Clustered by	Individual	Individual
Number of Examiners	253	455
Observations	12,785	21,787
ADJ R^2	0.341	0.341

Table 7 tabulates the estimation results of Equation (1) using OLS regression, where all *t*-statistics (in parentheses) are based on standard errors clustered at the examiner level. In Column (1), I limit my sample to examiner-months for those who opted to telecommute within one month after the two-year tenure requirement. In Columns (2), I limit my sample to examiner-months for those who opted to telecommute within two months after the two-year tenure requirement. *Treatment* is an indicator variable that takes the value of one for examiner-month after transitioning into the telecommuting program and zero for examiner-month before transitioning into the telecommuting program. The dependent variable is *% New Cites*. See Appendix B for other variable definitions. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 8
Differential Effects of Telecommuting on External and Internal Information Acquisition

	Colleagues defined at the USPTO-level		Colleagues defined at the Art Unit-level	
	(1) DV: ***% New Cites USPTO***	**(2) DV:** ***% Old Cites USPTO***	**(3) DV:** ***% New Cites Art Unit***	**(4) DV:** ***% Old Cites Art Unit***
Treatment	**0.010*****	0.003	**0.014*****	-0.001
	(4.08)	(1.40)	**(4.26)**	(-0.71)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
GS-Level Fixed Effects	Yes	Yes	Yes	Yes
Tenure Fixed Effects	Yes	Yes	Yes	Yes
Clustering by:	Individual	Individual	Individual	Individual
Observations	161,045	161,045	161,045	161,045
ADJ R^2	0.428	0.230	0.327	0.204

Table 8 shows whether the effect of telecommuting on information acquisition differs based on whether examiners acquire new information themselves or from their colleagues. I estimate the results using OLS regression, where all *t*-statistics (in parentheses) are based on standard errors clustered at the examiner level. For Columns (1) and (2), the dependent variable is *% New Cites USPTO* and *% Old Cites USPTO*, respectively. *% New Cites USPTO* is the total number of examiner-added citations in a given month that any examiner at the USPTO, including a focal examiner, has not used in reviewing prior patent applications, divided by the total number of examiner-added citations in a given month. *% Old Cites USPTO* is the total number of examiner-added citations in a given month that a focal examiner has not used but other examiners at the USPTO have previously used in reviewing prior patent applications, divided by the total number of examiner-added citations in a given month. For Columns (3) and (4), the dependent variable is *% New Cites Art Unit* and *% Old Cites Art Unit*, respectively. *% New Cites Art Unit* is the total number of examiner-added citations in a given month that any examiner in the same Art Unit, including a focal examiner, has not used in reviewing prior patent applications, divided by the total number of examiner-added citations in a given month. *% Old Cites Art Unit* is the total number of examiner-added citations in a given month that a focal examiner has not used but other examiners in the same Art Unit have previously used in reviewing prior patent applications, divided by the total number of examiner-added citations in a given month. See Appendix B for other variable definitions. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 9
Effects of Information Acquisition on Work Quality as Measured by Customer Complaints

	DV: *% RCE*	
	(1)	**(2)**
% New Cites	**-0.078***** **(-28.39)**	
# New Cites		**-0.004***** **(-24.08)**
# Total Cites		**0.002***** **(27.51)**
% Rejection	**0.720***** **(132.74)**	**0.709***** **(125.98)**
Individual Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes
GS-Level Fixed Effects	Yes	Yes
Tenure Fixed Effects	Yes	Yes
Clustered by:	Individual	Individual
Observations	160,569	160,569
ADJ R^2	0.390	0.389

Table 9 tabulates the estimation results of Equations (7) and (8) using OLS regression, where all *t*-statistics (in parentheses) are based on standard errors clustered at the examiner level. The dependent variable is *% RCE*, which is measured as the ratio of the number of office actions implemented by an examiner in a given month that eventually led to patent applicants' request of continued examinations (RCEs) to the total number of office actions implemented by an examiner in a given month. *% Rejection* is the ratio of the number of office actions for which an examiner rejects in a given month to the total number of office actions implemented by an examiner in a given month. *% New Cites* is the ratio of *# New Cites* to *# Total Cites*. See Appendix B for other variable definitions. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 10
Sensitivity to Research-Design Choices

	DV = *% New Cites*		
	(1) Pre & Post 12 Months Each	**(2) Pre & Post 3 Months Each**	**(3) Telecommuters Only**
Treatment	**0.016*** **	0.002	**0.010*** **
	(4.82)	(0.57)	**(2.74)**
Individual Fixed Effects	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes
GS-Level Fixed Effects	Yes	Yes	Yes
Tenure Fixed Effects	Yes	Yes	Yes
Clustered by:	Individual	Individual	Individual
Observations	95,667	68,953	110,006
ADJ R^2	0.299	0.311	0.327

Table 10 tabulates the estimation results of Equation (1) using different research-design choices, where all *t*-statistics (in parentheses) are based on standard errors clustered at the examiner level. The dependent variable is *% New Cites*. For treatment examiners, *Treatment* is an indicator variable that takes the value of one for examiner-months after transitioning into the telecommuting program and zero for examiner-months before transitioning into the telecommuting program. For control examiners, *Treatment* is an indicator variable that takes the value of zero for all examiner-month observations. For Column (1), treatment examiners are included from 12 months before the telecommuting month to 12 months after the telecommuting month. For Column (2), treatment examiners are included from three months before the telecommuting month to three months after the telecommuting month. For Column (3), I include all year-months of telecommuting examiners prior to and following the telecommuting month for treatment examiners and exclude all examiner-month observations for control examiners. See Appendix B for other variable definitions. ***, **, and * denote two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

CHAPTER 3

SUBORDINATES' TASK PERFORMANCE AND DEPARTURE RATES WHEN THE SUPERVISOR WORKS FROM HOME

3.1 INTRODUCTION

I examine the effect of the supervisor working from home on the subordinate's task performance and departure rates. Working from home (WFH; also called telecommuting or telework) policies have become increasingly popular. As of 2016, a third of all workers in the U.S. had the option to work from home at least part of the day, and 23% of employees worked some or most (10-99%) of their usual hours at home (Matos, Galinsky, and Bond 2016). More recently, the COVID-19 global pandemic has instigated a massive experiment in WFH around the world (Guyot and Sawhill 2020; Dreyfuss 2020). While scholars and practitioners debate the potential benefits and costs of implementing WFH policies, we still have limited knowledge of *when* and *how* WFH impacts employee- and organization-level outcomes (Bloom, Liang, Roberts, and Ying 2015; Gonsalves 2020).

One reason for the lack of knowledge on the effect of WFH on employee performance is the failure to consider *who* is working from home. Prior literature almost exclusively focuses on examining the effect of telecommuting on various work-related outcomes in environments where employees working on tasks are telecommuting (Osterman 1995; Rothbard, Phillips, and Dumas 2005; Gajendran and Harrison 2007; Bloom et al. 2015; Lyttelton, Zang, and Musick 2020; Gonsalves 2020). However, there has been little research examining the effect of telecommuting in environments where supervisors charged with monitoring, advising, and approving work done by their subordinates work from home while those subordinates work at the office.[28]

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[28] An exception is Lill (2020), who uses an experiment and finds greater physical monitoring distance between a supervisor and employee increases performance misreporting.

Examining the effects of telecommuting in such work arrangements is important because many organizations require employees to have several years of experience on the job and reach a certain rank within the organization to be eligible for working from home (Beauregard, Basile, and Canónico 2019). For example, when Facebook, Inc. announced its plan to move into remote work on May 21, 2020, the Chief Executive Officer (CEO) Mark Zuckerberg stated that "[w]e're going to focus on experienced employees rather than new college grads, who I think need to be in the office more, for training" (Newton 2020).[29] This announcement suggests Facebook, Inc. will likely be facing situations in which supervisors who work from home oversee office-working subordinates. Therefore, it is crucial for organizations to know whether task performance will differ based on whether relatively inexperienced office-working employees work with home-working supervisors. I address this gap in the literature by analyzing whether and when the supervisor working from home affects task performance.

I predict task performance is lower when the office-working subordinate works with the supervisor who works from home, relative to when they work with the office-working supervisor. Media reports indicate greater physical distance between supervisors and subordinates negatively affects task performance by reducing subordinates' learning opportunities and hindering the development of mentoring relationships (Dhaliwal 2020; Cutter 2020). I also predict this negative effect of the supervisor working from home on task performance will be greater for tasks that require greater supervisor input, such as complex tasks (Daft and Lengel 1984). Finally, prior literature argues subordinates receive less professional development and form weaker identification with the organization in the absence of supervisors

[29] Specifically, Mark Zuckerberg announced that "[i]f you're experienced, if you're at a certain level within the company, if you have good performance ratings, […] and if you get approval, then you'll be able to know now that you'll be a […] remote worker" (Newton 2020).

in the offices (Golden and Fromen 2011). Based on this argument, I predict that, relative to when subordinates work with office-working supervisors, subordinates working with home-working supervisors are less likely to remain with the organization.

I test my predictions using archival data across multiple tasks and individual employees. I use a rich data set containing the work of patent examiners at the United States Patent and Trademark Office (USPTO) for the period 2006 to 2016. The USPTO has provided a WFH program for patent examiners since 2006. To be eligible for working from home, patent examiners must have at least two years of experience on the job. In addition, the USPTO requires supervisors to approve the subordinates' patent decisions (e.g., whether to grant a patent) and oversee the underlying examination process. This feature allows me to analyze whether examination quality of each patent differs based on whether a supervisor works from home.

An advantage of this setting is that I can exploit the quasi-random assignment of patent applications to examiners, regardless of whether an examiner works from home or at the office (Lemley and Sampat 2012; Sampat and Williams 2019; Farre-Mensa, Hegde, and Ljungqvist 2020).[30] This setting allows me to isolate the causal effects of supervisors working from home from those of the underlying invention. In addition, the USPTO requires subordinates to work under different supervisors in each "Art Unit" to learn different patent examination styles.[31] Therefore, the subordinate-fixed-effects strategy allows me to compare across patents that are

[30] Specifically, there are two ways the USPTO assigns patent applications to examiners. First, the USPTO assigns patent applications to examiners based on the last digit of the application serial number. Second, the USPTO gives "the oldest unassigned application to an examiner when that examiner finished examining a prior application" (Lemley and Sampat 2012, 822). In both cases, the USPTO does not assign applications based on any observable innovation-related characteristics. For further details, please see Section 4.1.

[31] An Art Unit is an examining division at the USPTO consisting of patent examiners who specialize in a particular area of technology. While the majority of Art Units include fewer than 20 examiners, some Art Units have more than 60 examiners (Kuhn and Thompson 2019). Art Units are grouped into nine "technology centers" based on the area of technological expertise (e.g., biotechnology, chemical engineering, information security).

overseen and approved by exogenously assigned supervisors who work from home versus at the office but whose examination is completed by the *same* subordinate.

Consistent with my predictions, patents examined by the office-working subordinate are of lower examination quality when the supervisor works from home, relative to when the supervisor works at the office. Also, I find the negative effects of the supervisor working from home on task performance are more pronounced for more complex tasks, providing support for my theory that in-person interactions play a significant role in advising relatively inexperienced employees.[32] Further, I find patents examined by the home-working subordinate show similar examination quality regardless of whether the supervisor works from home versus at the office. Because subordinates must meet the USPTO's requirement that they have at least two years of experience on the job before working from home, this result lends further support for my argument that the difficulty of advising subordinates in distributed work settings, rather than physically monitoring them to ensure that they do not shirk, drives my findings. I also find my findings are robust to including both supervisor- and subordinate-examiner fixed effects, suggesting patents become lower in examination quality when the *same* supervisor shifts from working at the office to working from home while working with the *same* subordinate.

Next, I examine the effects of the supervisor working from home on the likelihood that the subordinate remains with the organization. Using a proportional hazards model, I find greater subordinate turnover when supervisors work from home. Specifically, when a subordinate works with at least one home-working supervisor within two years after the subordinate joins the

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[32] All inventions examined by patent examiners are assigned a particular U.S. Patent Classification (USPC) class-subclass combination that corresponds to one complexity factor that reflects the underlying level of technological complexity (deGrazia, Frumkin, and Pairolero 2018). A higher complexity factor indicates a more complex technology underlying the invention examined. For further details, please see Section 4.2.2.

USPTO, the subordinate is 104 percent more likely to leave the USPTO.[33] When I decompose the two-year window into the first (i.e., years 0-1) and next year of career (i.e., years 1-2) since subordinates' hire date, I find whether an examiner works with a home-working supervisor in earlier years of career (years 0-1) more strongly predicts subordinate departures than in later years of career (years 1-2). These results suggest the supervisor working from home leads to the subordinate's higher departure rates when the subordinate is newly hired relative to when the subordinate has at least one year of experience on the job.

My study contributes to the WFH literature by identifying a new potential cost of WFH. To my knowledge, this study is the first to provide field data evidence demonstrating the negative effects of supervisors working from home. While the use of WFH has become an important trend in business practice, academic research addressing the effectiveness of WFH focuses on examining the effect of WFH on employee performance in environments where employees working on tasks work from home and generally finds positive effects (Bloom et al. 2015; Barrero, Bloom, and Davis 2021; Choudhury, Foroughi, and Larson 2021). By contrast, I provide new insight into the effectiveness of WFH policies by finding the negative effects on task performance when supervisors charged with overseeing work done by their relatively inexperienced subordinates work from home.

My study also has important implications for the physical distance between supervisors and subordinates that is increasing as distributed work settings become more common. The few studies examining physical distance suggest detrimental effects of physical distance between supervisors and subordinates on employee performance, but do not distinguish the environment

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[33] I examine the first two years of subordinates' career at the USPTO because examiners can work from home after two years of experience on the job. For more information about the institutional characteristics of the USPTO, please see Section 3.

where the supervisor working from home oversees the subordinate working at the office from the environment where the supervisor working at the office oversees the subordinate working from home (Antonakis and Atwater 2002; Lill 2020). By finding negative effects on task performance in the former while finding insignificant effects on task performance in the latter, my results contribute to prior research by providing a more nuanced view on the role of physical distance between supervisors and subordinates in affecting productivity.

3.2 HYPOTHESES DEVELOPMENT

With advances in mobile connection technologies and the shift from a manufacturing to a knowledge-intensive economy, organizations have increasingly implemented WFH policies over the last few decades (Allen, Golden, and Shockley 2015). In 2018, about 4 percent of employees in the U.S. worked from home more than half a week. The proportion of employees working from home rose more than ten-fold in 2020 due to the COVID-19 pandemic. Dingel and Neiman (2020) estimate about 37 percent of the workforce is working from home. Using two waves of surveys conducted in 2020, Brynjolfsson et al. (2020) find about half the workforce now work from home. As organizations now take part in an unprecedented experiment in WFH, academics and practitioners alike eager to examine the effects of WFH on organizations.

Previous literature on WFH reports various positive outcomes when employees work from home. For example, when employees are working from home, they show higher organizational commitment and lower intent to leave the organization (Golden 2006). WFH employees also show greater job satisfaction and lower work-family conflict (Allen et al. 2015). In a firm studied by Bloom et al. (2015), call-center employees increase their productivity by 13 percent after they work from home. Baek (2021) finds telecommuting facilitates employees' information acquisition. Using more than 20,000 survey responses, Barrero et al. (2021) find

WFH employees are able to devote more time to their primary job, indoor leisure, and childcare by not commuting. The shift to WFH also provides organizations with other benefits, such as lower office space expenses and an access to a larger pool of job candidates (Levanon 2021).

While prior literature finds WFH is positively related to many individual- and organization-level outcomes, possible negative effects might emerge. Of great concern is whether young, inexperienced employees can receive the same level of guidance, attention, and training from their WFH supervisors. Media reports indicate WFH can have a negative impact on the development of mentoring relationships between supervisors and young employees (Davis 2020; Kelly 2021). Concerned with such drawbacks of WFH, JP Morgan Chase decided that, even during the pandemic, it would bring back at least a portion of its employees to the office. Specifically, the Chief Executive Officer (CEO) Jamie Dimon stated that young workers in their apprenticeship period were “disadvantaged by missed learning opportunities as they were not in the offices” (Dhaliwal 2020). Similarly, the CEO of Stifel Financial Corp. Ronald J. Kruszewski expresses concerns over WFH that inexperienced employees do not acquire skills necessary to perform tasks (Cutter 2020):

“Junior employees learn how to underwrite deals or develop pitch books by sitting beside more experienced colleagues and watching them work. That’s hard to do remotely.”

While the impact of WFH on inexperienced employees’ work outcomes and career prospects seems to be of great concern to organizations, executives, and the media, however, the academic literature on WFH is relatively silent on such dimensions. An exception is Golden and Fromen (2011), who, using an online survey, document that subordinates whose managers are telecommuting produce less favorable work outcomes than those with office-working managers. Golden and Fromen (2011) explain that less desirable work outcomes of subordinates arise because the frequency and richness of interactions between supervisors and subordinates are lower in distributed work settings (Allen and Renn 2003; Burtha and Connaughton 2004; Daft and Lengel 1986). In interacting with WFH supervisors, subordinates need to rely on electronic media that "can constrain the spontaneous flow of information because it contains fewer cues and contextual indicators" (Golden and Fromen 2011, 1454). While subordinates can relatively easily identify salient information and cues from their interactions with collocated supervisors, subordinates with WFH supervisors are more prone to misunderstandings and experience a greater lack of clarity in their interactions due to the decrease in the quality of information transmission (Bass 1990; Napier and Ferris 1993; Antonakis and Atwater 2002; Hinds and Bailey 2003; Hinds and Mortensen 2005).

In contrast to Golden and Fromen (2011), who find work outcomes of subordinates working with WFH supervisors are less favorable, Neufeld, Wan, and Fang (2010) conduct a survey and find physical distance between supervisors and subordinates does not influence performance and communication effectiveness among them. However, Neufeld et al. (2010, 240) suspect that these results arise because their survey respondents have an average of 12 years of tenure at their respective organizations and thus have already absorbed "the details and nuances of an organization's culture and managerial norms over time." Such learning over time may attenuate the negative effect of physical distance on performance. Therefore, whether inexperienced workers may still be disadvantaged due to a loss of learning opportunities when working with WFH supervisors is an empirical question that warrants further investigation. Given the existing evidence is primarily based on cross-sectional research designs (e.g., surveys), my study can also contribute to the WFH literature by drawing causal conclusions. Based on the above discussion, I propose the following hypothesis:

> **H1:** Task performance is lower when office-working subordinates are working with home-working supervisors than when they are working with collocated office-working supervisors.

Next, I develop a hypothesis regarding subordinates' departure rates when they are working with WFH supervisors. Prior literature argues trust and socio-emotional bonding between supervisors and subordinates are less likely to emerge in distributed work settings (Golden and Fromen 2011). This is because the use of electronic media and greater physical distance lead to weaker affective ties and fewer informal interactions between supervisors and subordinates (Antonakis and Atwater 2002; Lautsch, Kossek, and Eaton 2009), leading to subordinates receiving less professional development (Golden and Fromen 2011). As subordinates view supervisors as the embodiment of the organization, subordinates' interactions with their superior are a key driver in subordinates' identification with and commitment to the organization (Levinson 1965; Morris and Sherman 1981; Ogilvie 1986). Therefore, the absence of supervisors in the offices may adversely affect organization commitment and identification of subordinates. In addition, lower task performance of subordinates working with WFH supervisors increases the possibility that such subordinates are forced to leave the organization. Based on the above discussion, I propose the following hypothesis:

> **H2:** Subordinates working with home-working supervisors show higher rates of departures than those working with collocated office-working supervisors.

3.3 RESEARCH SITE

I examine my hypotheses using data from the USPTO. At the USPTO, patent examiners review, evaluate, and decide whether to grant patents on inventions. Patent examiners can be classified into two categories: junior examiners and primary examiners (designed as subordinates and supervisors, respectively, in this study). Primary examiners have signatory authority, which allows examiners to sign their own office actions (e.g., allowances, rejections, etc.) without review by others. Junior examiners do not have signatory authority, and therefore must have their office actions reviewed and approved by primary examiners.[34] Specifically, at grade GS (General Schedule)-13, examiners are eligible to participate in the Partial Signatory Authority Program which grants examiners signatory authority to sign their non-final rejections and other non-final communications to patent applicants.[35] [36] After patent examiners achieve GS-14 and complete an additional phase (the Full Signatory Authority Program), they become a primary examiner with full signatory authority.

Patent examiners are eligible to participate in the Patents Hoteling Program (PHP) that allows them to work from home for four days a week. The PHP began in 2006 and requires examiners to have worked at the USPTO for at least two weeks. Figure 1 presents the percentage of supervisory examiners working from home by year. By the end of my sample period, around 25 percent of supervisory examiners work from home.

For each patent application, a junior examiner is assigned to one primary examiner who works in the same Art Unit. In addition, there is variation in which primary examiner is assigned to each junior examiner within the Art Unit because junior examiners rotate to work under different primary examiners to learn different patent examination styles. Such rotation highlights the role of primary examiners in educating their junior examiners on what they think are best practices in the examination process, or the "systematic apprenticeship process within the USPTO" (Cockburn, Kortum, and Stern 2002, 8). For example, primary examiners deliver subtle and nuanced lessons about how to deal with applicants and their attorneys, and the objective and

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[34] In the rest of the paper, I use the terms "supervisor" and "primary examiner" interchangeably, and also use "subordinate" and "junior examiner" interchangeably.
[35] The General Schedule (GS) system refers to the U.S. government's classification system for organizing and defining federal positions. While the GS system includes 15 defined grade levels (from GS-1, the lowest level, to GS-15, the highest level), an USPTO examiner generally starts at a GS-7 or GS-9 level.
[36] However, *final* office actions by examiners with partial signatory authority must be approved and signed off by primary examiners.

subjective criteria for the granting of patent rights that are likely to vary across technology fields (Cockburn et al. 2002; Raffiee and Teodoridis 2020). Appendix A provides an example of a patent document (Notice of Allowance) reviewed by both junior and primary examiners.

In addition to training junior examiners, primary examiners are responsible for carefully overseeing every patent examination process that their junior examiners work through, thus ensuring the quality of issued patents. In my conversations with patent examiners, one examiner indicated that, in order to meet workload goals, junior examiners need to convince their primary examiners that an application is allowable or not. If primary examiners do not agree with their junior examiners, primary examiners do not sign off on the junior examiners' work, and the work does not qualify for meeting workload goals.

Meeting workload goals is important for examiners because goal attainment is a key metric for their annual performance ratings and performance bonuses (Frakes and Wasserman 2015; Tabakovic and Wollmann 2018). These workload goals are designed to ensure examiners complete their assigned patent examinations in given timeframes that expire at the end of each bi-week period. An internal survey conducted by the USPTO reveals most examiners have "less time than needed to complete a thorough examination" and often work voluntary or uncompensated overtime to meet their goals (U.S. Government Accountability Office [GAO] 2016, 25).[37] Examiners must attain satisfactory ratings to avoid disciplinary actions by the USPTO and to be eligible for a promotion to higher level positions. In addition, when examiners exceed their production goals by 10 percent or more, the USPTO provides an examiner with performance bonuses that can amount to about $20,000 per year.[38]

[37] The same survey also indicates 67 percent of examiners who participated in the survey identified the USPTO's production targets as a primary reason they would consider leaving the USPTO.

[38] In 2018, an average patent examiner is paid approximately $125,000, which includes base salary and bonuses.

3.4 HOME-WORKING SUPERVISORS AND TASK PERFORMANCE

3.4.1 Data

To test the effects of supervisors working from home on their (office-working) subordinates' task performance, I construct my data set using multiple sources. I start with the Public Patent Application Information Retrieval (Public PAIR), which contains detailed information on more than 11 million patent applications filed with the USPTO. Public PAIR contains data on the technology field and the Art Unit to which an application was assigned, and the names of the examiner assigned to each patent application. Public PAIR also assigns a unique identifier to each listed examiner, which allows me to analyze the decisions (e.g., allowances, rejections, etc.) made by examiners on each application. Critical for my study is information identifying the assignment of primary and junior examiners to each patent application. Because Public PAIR only allows researchers to identify who was assigned as a junior examiner, I use another data source to identify primary examiners assigned to each application.

Another primary source of patent data is PatentsView. Supported by the USPTO Office of the Chief Economist, PatentsView is a collaborative effort between the U.S. government agencies such as the USPTO and the U.S. Department of Agriculture (USDA), and universities such as New York University and the University of California, Berkeley. I use PatentsView to collect information identifying the primary examiner for each patent application. Because this data set provides readily available data on primary examiners only on granted patents, I limit my analyses to granted patent observations and eliminate patent applications that are rejected by examiners or abandoned by applicants.

Through a series of Freedom of Information Act (FOIA) requests, I also collect a range of information on examiners, including the day in which they joined and left the USPTO, each examiner's gender and GS-level in each year, and the day in which they started to work from home.[39] I then merge these examiner-specific observations with the application-level data from Public Pair and PatentsView. Because the USPTO's telecommuting program started in 2006, I require granted patents to have their first substantive decision made by an examiner regarding the patentability of the claimed invention (i.e., the first office action on the merits, hereafter FOAM) in or after 2006. In addition, because Public PAIR provides information on patent applications through 2017 when I started my data collection, I also require granted patents to have their FOAM by 2016 because it takes approximately one year, on average, to have a patent granted from the time the application receives its FOAM.

3.4.2 Variables

3.4.2.1 Dependent Variables

I measure junior examiners' task performance using three proxies. The first is *Citation*, defined as the number of examiner-added citations used as decision grounds for each application. In reviewing an application to issue a patent, patent examiners are responsible for finding relevant prior publications and inventions ("prior art") to assess whether an application is not covered by any prior art. Because of the recent exponential growth in the number of patents and publications, examiners spend the majority of their examination time on finding prior art that is relevant to evaluating the patentability of an application (Lemley and Sampat 2012; Cotropia, Lemley, and Sampat 2013; Frakes and Wasserman 2015, 2020; Choudhary et al. 2021). Thus, following prior literature (Frakes and Wasserman 2017), I use *Citation* as a proxy for examination effort of an examiner.

[39] With regard to data on each examiner's gender, the data that the USPTO provided me through a FOIA request was incomplete. To complement this data set, I use the online service genderize.io, which provides gender probabilities to first names of examiners used in my analyses.

The second proxy for task performance is *Days to Issue*, defined as the length of time (in days) between initial application and the date on which an examiner grants a patent. While external forces, such as the speed at which an applicant responds to an examiner's decision, affect the length of time between initial application and patent issuance, prior literature uses *Days to Issue* as an input measure for an examiner's examination quality (Cockburn et al. 2002; Raffiee and Teodoridis 2020). An underlying assumption for *Days to Issue* is that an examiner who puts more effort in reviewing an invention and thus delivers high-quality reviews will take more time in the application process. Frakes and Wasserman (2017) find decreases in examination time are associated with reductions in examination scrutiny, increases in granting tendencies, and decreases in the quality of patents. Similarly, Raffiee and Teodoridis (2020) find more stringent examiners take more time to issue patents of higher quality.

One concern with using *Days to Issue* as a proxy for examination quality is that higher-ability examiners complete an examination of an invention faster than low-ability examiners, yielding a low value of *Days to Issue*. If true, then a lower value of *Days to Issue* would spuriously indicate a higher examination quality. I control for this concern by using junior examiner fixed effects. The fixed-effects strategy allows me to compare patents completed by a given junior examiner but approved by different primary examiners who work from home versus at the office. This ensures lower values of *Days to Issue* indicate the same junior examiner puts less time in the examination of an invention when the primary examiner works from home versus the primary examiner works at the office.[40]

The third proxy for task performance is Kuhn and Thompson's (2019) measure of patent

[40] In addition, my setting can effectively address concerns about the effects of heterogeneity in patent applicants' characteristics, such as the speed at which they respond to examiners' office actions, on *Days to Issue* because the assignment of applications to examiners is random in each technology field and therefore averages out the effect of applicants on *Days to Issue* (Lemley and Sampat 2012; Farre-Mensa, Hegde, and Ljungqvist 2020).

scope, which captures the quality of issued patents. Their measure is based on the idea that patent value increases if the extent of the legal coverage that a patent provides (i.e., patent scope) broadens. When patent scope is overly broad, however, such patents “may lead to an increase in patent infringement suits and hinder innovation by blocking new ideas from entering the marketplace” (GAO 2016, 1). For example, an overly broad patent containing claims on “engines” may impinge on follow-up innovation in all engine-related technology fields while a narrower patent on “airplane engines” can encourage follow-up innovation in the “automobile engine” technology field (Marco, Sarnoff, and DeGrazia 2019). An internal report by the USPTO reveals these overly broad patents approved by examiners are likely “a key factor in many patent infringement lawsuits” because “their unclear boundaries make it easy to unintentionally infringe these patents” (GAO 2016, 1). Based on this practical consideration, Kuhn and Thompson (2019) develop a measure of patent scope by counting the number of words in a patent’s claims (normalized by the Art Unit an examiner is in), with more words corresponding to narrower scope and thus higher patent examination quality. I multiply this measure by negative one so that higher values correspond to broader patent scope (*Patent Scope*).[41]

3.4.2.2 Technological Complexity

To capture technological complexity of a patent, I use the expected number of hours allocated to review one patent application (expectancy). The USPTO determines the expectancy of a patent application based on the belief that a patent examiner in a more complex technology field will need more time to review an application. For example, a GS-12 examiner is expected to review a patent in the “fishing lures” technology field in 16.6 hours and the same-rank examiner is expected to review a patent in the “satellite communication” technology field in 27.7

[41] Similarly, Raffiee and Teodoridis (2020, 6) argue “[m]ore stringent examiners may add more contingencies in patent claim text thus lengthening it and narrowing patent scope.”

hours. I received the data set on the expectancy of each technology field pursuant to a Freedom of Information Act (FOIA) request. The data set indicates approximately 15% of patent-level observations in my sample are assigned the highest expectancy of 31.6 hours for a GS-12 examiner to review. Based on this sample composition, I define *Complex Tech* as an indicator variable that equals one if a patent has the highest possible expectancy (31.6 hours), and zero otherwise.[42] Table 5, Panel A presents examples of technology fields corresponding to expectancy. Table 5, Panel B reports the summary statistics of expectancy in my sample. I define all variables in Appendix B.

3.4.3 Research Design

3.4.3.1 Supervisor Working from Home and Task Performance

My final sample consists of 197,472 patent-level observations for which the FOAMs are completed between 2006 and 2016. In my final sample, there are 4,341 junior examiners and 1,806 primary examiners. On average, each junior examiner rotates to work under 2.427 primary examiners. For my research purposes, I eliminate patents reviewed by only a primary examiner so that my sample consists only of patents that are reviewed by both junior and primary examiners. In addition, I limit my analyses to patents examined by junior examiners who work at the office as of the FOAM date to eliminate the effects of subordinates working from home. Because my proxies for task performance vary in the number of observations and the length of time they have observations for, the final number of observations differs across samples of *Citation*, *Days to Issue*, and *Patent Scope* tests. Table 1 presents my sample selection process.

To explore the relationship between whether a primary examiner works from home and task performance of office-working junior examiners, I estimate the following patent-level

[42] In untabulated analyses, I also partition the sample into quintiles and quartiles and re-define *Complex Tech* as patents falling into the highest ranks. My results are qualitatively similar when using these alternative measures.

ordinary least squares (OLS) regression:

$$\begin{aligned} Performance_{\alpha} &= \alpha + \beta_1 Primary\ WFH_{\alpha} + \beta_2 Primary\ Female_{\alpha} + \beta_3 Primary\ GS_{\alpha} \\ &+ \beta_4 Primary\ Tenure_{\alpha} + \beta_5 Junior\ Female_{\alpha} + \beta_6 Junior\ GS_{\alpha} \\ &+ \beta_7 Junior\ Tenure_{\alpha} + \gamma Fixed\ Effects_{\alpha} + \varepsilon_{\alpha}. \end{aligned} \tag{1}$$

The dependent variable, *Performance*, alternately represents one of three variables, *Citation*, *Days to Issue*, and *Patent Scope*. I include the subscript α to index the individual applications. The explanatory variable of interest is $Primary\ WFH_{\alpha}$, which indicates whether a patent was approved by a primary examiner who worked from home when the FOAM was completed. I expect a negative coefficient on $Primary\ WFH_{\alpha}$ when *Citation* and *Days to Issue* are dependent variables. This indicates patents reviewed by junior examiners who work at the office and primary examiners who work from home have fewer examiner-added citations and take less time in the examination of an invention than patents reviewed by office-working junior examiners and office-working primary examiners. By contrast, I expect a positive coefficient on $Primary\ WFH_{\alpha}$ when *Patent Scope* is a dependent variable. This indicates patents reviewed by junior examiners who work at the office and primary examiners who work from home are of broader patent scope and thus of lower examination quality than patents reviewed by office-working junior examiners and office-working primary examiners.

To account for different examination styles across genders, I include indicator variables equal to one if a primary examiner is female ($Primary\ Female_{\alpha}$) and a junior examiner is female ($Junior\ Female_{\alpha}$), respectively, as control variables. $Primary\ GS_{\alpha}$ and $Junior\ GS_{\alpha}$ represent a set of dummy variables capturing the incidence of the primary and junior examiner, respectively, falling into each of the general schedule (GS) pay grade levels as of the FOAM year. I include these variables to account for examination time constraints and workplace responsibilities that differ based on the GS levels might affect task performance. In addition, I include the number of years each primary (*Primary Tenure*$_\alpha$) and junior examiner (*Junior Tenure*$_\alpha$) has worked for the USPTO as of the FOAM year to control for variation in task performance by experience level.

Table 2 presents the summary statistics for these measures. *Primary WFH* ranges from 0.08 to 0.17, indicating eight to 17 percent of applications were reviewed by a primary examiner who works from home when the FOAM was completed. *Primary Tenure* ranges from 15.96 to 16.26, suggesting an average primary examiner has job tenure of around 16 years at the USPTO. *Junior Tenure* ranges from 2.96 to 3.93, indicating an average junior examiner has job tenure of three to four years at the USPTO.

I also include junior examiner fixed effects, Art Unit fixed effects, and year-month fixed effects to account for variation in task performance by each examiner and Art Unit, and over time, respectively.[43] I include technology class fixed effects based on the United States Patent Classification (USPC) system to account for concerns that technology-specific characteristics might affect my measures of task performance. I cluster standard errors at the junior examiner level to correct for autocorrelation within given examiners across applications.

3.4.3.2 Supervisor Working from Home and Complex Tasks

I predict supervisors working from home leads to worse task performance by inhibiting in-person interactions that play an important role in advising relatively inexperienced employees. To provide support for this argument, I test whether the negative effect of a primary examiner working from home on office-working junior examiners' task performance is more pronounced for junior examiners examining more complex technologies, as the need for advising is greater

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[43] I do not include Art Unit fixed effects when I include junior examiner fixed effects because the effect of Art Unit fixed effects is subsumed by the junior examiner fixed effects. In addition, when I include junior examiner fixed effects, I do not include *Junior Female*$_\alpha$, *Junior GS*$_\alpha$, and *Junior Tenure*$_\alpha$ in the regression because these variables are also subsumed by junior examiner fixed effects. While an examiner's GS-level and tenure can technically vary within the given examiner, *Junior GS*$_\alpha$ and *Junior Tenure*$_\alpha$ rarely change for a given junior examiner over applications in my sample and thus are omitted from the regression.

for these applications. Specifically, I estimate the following OLS model:

$$\begin{aligned} Performance_{\alpha} &= \alpha + \beta_1 Primary\ WFH_{\alpha}\ x\ Complex\ Tech_{\alpha} + \beta_2 Primary\ WFH_{\alpha} \\ &+ \beta_3 Complex\ Tech_{\alpha} + \beta_4 Primary\ Female_{\alpha} + \beta_5 Primary\ GS_{\alpha} \\ &+ \beta_6 Primary\ Tenure_{\alpha} + \beta_7 Junior\ Female_{\alpha} + \beta_8 Junior\ GS_{\alpha} \\ &+ \beta_9 Junior\ Tenure_{\alpha} + \gamma Fixed\ Effects_{\alpha} + \varepsilon_{\alpha}. \end{aligned} \tag{2}$$

All variables in Model (2) are defined above. I expect having a primary examiner work from home is associated with fewer examiner-added citations, shorter review time, and broader patent scope (i.e., lower task performance) for examiners reviewing more complex technologies than for those reviewing less complex technologies. Thus, I predict the coefficient on the interaction term between *Primary WFH* and *Complex Tech* is negative when *Citation* and *Days to Issue* are dependent variables and positive when *Patent Scope* is a dependent variable.

3.4.4 Empirical Results

3.4.4.1 Assignment of Patent Applications to a Home-Working Primary Examiner

I leverage the quasi-random assignment of applications to examiners to draw causal inferences about the effect of the primary examiner working from home on patent examination quality (Farre-Mensa et al. 2020; Dyer, Glaeser, Lang, and Sprecher 2020). Consequently, the characteristics of the innovation are random with respect to whether an examiner works from home or work at the office (Sampat and Williams 2019). Before I proceed, I formally examine this assumption by exploring whether the characteristics of the innovation are systematically associated with whether the patent application is assigned to a home-working primary examiner.

Table 3 presents the estimation results of regressing whether a primary examiner works from home (*Primary WFH*) on three sets of innovation-related characteristics: 1) patent application characteristics, 2) patent inventor characteristics, and 3) patent attorney characteristics. In Column (1), I consider four variables representing patent application characteristics: 1) the natural log of the number of words in patent claims (*# of Words in Patent Claims*), 2) the natural log of the number of patent claims (*# of Patent Claims*), 3) the natural log of the number of figures included with a patent application (*# of Figures*), and 4) the natural log of the number of patent drawings included with a patent application (*# of Drawings*). In Column (2), I use three variables representing patent inventor characteristics: 1) an indicator variable that equals one if an application is submitted by small entities, and zero otherwise (*Small Entity*),[44] 2) the natural log of the number of successful patent applications previously filed by the inventor (*# of Inventor's Prior Patents*), and 3) the natural log of the number of years between the filing year of the inventor's first successful patent application and the application's filing year (*Inventor Experience*). In Column (3), I consider two variables representing patent attorney characteristics: 1) the natural log of the number of successful patent application cases the attorney took before (*# of Attorney's Prior Patents*) and 2) the natural log of the number of years between the filing year of the first successful patent application that the attorney took and the application's filing year (*Attorney Experience*). In Column (4), I use all three sets of the innovation-related characteristics explained above. I find none of the innovation-related variables explain whether the patent application is assigned to a home-working primary examiner, conditional on art unit, technology class, and FOAM year-months. These results confirm the quasi-random assignment of patent applications to examiners.

[44] The USPTO classifies entity status into large versus small based on the applicant or owner of the patent right. The USPTO designates individuals, small business concerns with no more than 500 employees, and non-profit organizations as small entities. Most publicly listed U.S. firms and foreign organizations are designated as large entities.

3.4.4.2 Hypothesis Testing

3.4.4.2.1 Citations

The regression results reported in Table 4 provide support for H1, which predicts task performance is lower when the supervisor works from home versus at the office. As shown in Table 4, Panel A, *Citation* is greater when the primary examiner works at the office (*Citation* = 2.937), relative to when the primary examiner works from home (*Citation* = 2.822). The difference in *Citation* between the two groups is statistically significant (two-tailed $p < 0.01$). Columns (1) and (2) of Table 4, Panel B presents results for testing the association between *Citation* and *Primary WFH*. Column (1) presents estimated results with primary- and junior-examiner-level controls with Art-Unit-level, USPC-level, and Year-Month-level fixed effects. The estimated coefficient on *Primary WFH* is negative and statistically significant (one-tailed $p < 0.01$). Column (2) presents the estimated results with primary-examiner-level controls with junior-examiner-level, USPC-level, and Year-Month-level fixed effects. The estimated coefficient on *Primary WFH* is −0.17 and statistically significant (one-tailed $p < 0.01$), suggesting the *same* junior examiner adds 5.8 percent fewer citations when the primary examiner works from home, relative to when the primary examiner works at the office.[45]

3.4.4.2.2 Days to Patent Issuance

As shown in Table 4, Panel A, *Days to Issue* is greater when the primary examiner works at the office (*Days to Issue* = 1,141), relative to when the primary examiner works from home (*Days to Issue* = 1,054). The difference in *Days to Issue* between the two groups is statistically significant (two-tailed $p < 0.01$). Columns (3) and (4) of Table 4, Panel B presents results for testing the association between *Days to Issue* and *Primary WFH*. Column (3) presents estimated

[45] I calculate this effect using the estimated coefficient on *Primary WFH* (−0.17) and the sample mean of *Citation* (2.92; see Table 2): 5.8 percent (= −0.17 x 2.92) fewer citations.

results with primary- and junior-examiner-level controls with Art-Unit-level, USPC-level, and Year-Month-level fixed effects. The estimated coefficient on *Primary WFH* is negative and statistically significant (one-tailed $p < 0.05$). Column (4) presents the estimated results with primary-examiner-level controls with junior-examiner-level, USPC-level, and Year-Month-level fixed effects. The estimated coefficient on *Primary WFH* is −42.83 and statistically significant (one-tailed $p < 0.01$), suggesting the *same* office-working junior examiner spends 3.8 percent less time examining an invention when the primary examiner works from home, relative to when the primary examiner works at the office.[46]

3.4.4.2.3 Patent Scope

As shown in Table 4, Panel A, *Patent Scope* is greater when the primary examiner works at the office (*Patent Scope* = −0.548), relative to the environment where the primary examiner works from home (*Patent Scope* = −0.173). The difference in *Patent Scope* between the two groups is statistically significant (two-tailed $p < 0.01$). Columns (5) and (6) of Table 4, Panel B presents results for testing the association between *Patent Scope* and *Primary WFH*. Column (5) presents estimated results with primary- and junior-examiner-level controls with Art-Unit-level, USPC-level, and Year-Month-level fixed effects. The estimated coefficient on *Patent Scope* is negative and statistically significant (one-tailed $p < 0.01$). Column (6) presents the estimated results with primary-examiner-level controls with junior-examiner-level, USPC-level, and Year-Month-level fixed effects. The estimated coefficient on *Patent Scope* remains negative and statistically significant (one-tailed $p < 0.01$). This suggests patents reviewed by the *same* office-working junior examiner are of broader patent scope and thus of lower examination quality when the primary examiner works from home versus at the office.

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[46] I calculate this effect using the estimated coefficient on *Primary WFH* (−42.83) and the sample mean of *Days to Issue* (1,131; see Table 2): 3.8 percent (= −42.83 / 1,131) shorter time to issuance.

***3.4.4.3* Moderating Effects of Technological Complexity**

The regression results presented in Table 5, Panel C provide support for my prediction that the negative effect of the supervisor working from home on task performance is more pronounced for more complex tasks. In Columns (1) through (6), I consider the effects of the supervisor working from home on task performance for tasks that vary in technological complexity. The results in Columns (1) through (6) suggest the negative effect of the supervisor working from home on task performance is more pronounced for patents that involve more complex technologies, as indicated by statistically significant coefficients on the interaction of *Primary WFH* and *Complex Tech* (one-tailed $p < 0.05$ for Columns (1), (2), and (6) and $p < 0.01$ for Columns (3), (4), and (5)). These results suggest the effects of the supervisor working from home on task performance are more pronounced for more complex tasks, providing support for my theory that in-person interactions play a significant role in advising relatively inexperienced employees performing technical analysis in organizations.

3.4.5 Physical Distance between Supervisors and Subordinates

The results presented in Section 4.4.2 suggest a negative effect of the supervisor working from home on task performance, and highlights the importance of in-person interactions in advising relatively inexperienced employees in organizations. An alternative explanation for my results is that supervisors find it difficult to monitor subordinates who are physically distanced, regardless of the work arrangement ("lack of monitoring"). For example, subordinates who are physically present at the workplace but physically distant from the supervisor may more easily shirk than if they are in close proximity to the supervisor (Lill 2020). This shirking concern remains, or is even exacerbated, if subordinates working from home are monitored by supervisors who work at the office because subordinates are then away from not only the direct oversight of their supervisors, but also the indirect influence of their peers (Lautsch et al. 2009; Bloom et al. 2015; Groen, van Triest, Coers, and Wtenweerde 2018). Thus, this alternative explanation suggests lack of monitoring is the mechanism underlying my results, and further suggests I will also observe negative effects on task performance when supervisors work at the office and subordinates work from home. However, if advising plays a more important role in explaining the unfavorable effects on task performance, as I hypothesize, then I will not likely observe the negative effects on task performance when supervisors work at the office and subordinates work from home. This is because subordinates who qualify for working from home must meet the organization's requirements that they have several years of experience on the job, suggesting a lower need for advising in performing technical analysis.

To test which of the potential mechanisms drive my results, I compare task performance when both primary and junior examiners work at the office to when primary examiners work at the office and junior examiners work from home. If lack of monitoring drives my findings, then task performance in the latter case is likely to be lower than in the former case. I limit my analyses to patents reviewed by primary examiners who work at the office as of the FOAM date but do not impose such restrictions on junior examiners to allow for variation in where junior examiners work.

Panel A of Table 6 presents the summary statistics of *Junior WFH*, which is equal to one if a junior examiner works from home as of the FOAM date, and zero otherwise. The mean of *Junior WFH* ranges from 0.11 to 0.24, indicating that, when the primary examiner works at the office, 11 to 24 percent of applications were reviewed by the home-working junior examiner.

Panel B of Table 6 reports the results for testing the association between my three proxies for junior examiners' task performance (*Citation*, *Days to Issue*, and *Patent Scope*) and *Junior*

WFH. The estimated coefficient on *Junior WFH* is not statistically significant in all specifications (one-tailed $p > 0.10$), suggesting the negative effects on task performance are nonexistent when the supervisor works at the office while the subordinate works from home. In particular, the coefficients on *Junior WFH* are not statistically significant in specifications including primary examiner fixed effects (Columns (2), (4), and (6)), indicating there is no distinguishable difference between the office-working junior examiner's task performance and the home-working junior examiner's task performance, when both junior examiners are reviewed by the *same* office-working primary examiner. These results suggest my findings are not explained by the mere physical distance between supervisors and subordinates, and lends further support for my argument that the difficulty of advising subordinates in distributed work settings, rather than physically monitoring them to ensure that they do not shirk, drives my findings.[47]

3.4.6 Alternative Identification Strategy

One concern with my primary analyses is that I compare across patents that are approved by different primary examiners who work from home versus at the office, and the primary examiners may vary in their ability to advise their junior examiners. I am unable to observe this source of potential variability. Although I control for various primary-examiner-level controls, correlated omitted individual variables could still drive the negative effects of the supervisor working from home on task performance that I find. For example, primary examiners with lower ability to advise their junior examiners are more likely to choose to work from home because they might want to avoid conflicts with junior examiners. To address this concern, I limit my

[47] In Appendix C, I expand the analysis presented in Section 4.5 and compare task performance when both the supervisor and subordinate work at the office to when both the supervisor and subordinate work from home. I also find the negative effects on task performance are nonexistent when both the supervisor and subordinate work from home, compared to when both the supervisor and subordinate work at the office. This result also lends support for my argument that lack of monitoring does not drive my findings.

sample to patents reviewed by the *same* primary examiner who shifts from working at the office to working from home while working with the *same* junior examiner. Specifically, I regress my three proxies for junior examiners' task performance (*Citation*, *Days to Issue*, and *Patent Scope*) on *Primary WFH*. I also include both primary-examiner and junior-examiner fixed effects in the regression to ensure that I compare across patents approved by the *same* primary examiner when he or she works from home versus at the office and the examinations are completed by the *same* junior examiner.[48]

Table 7, Panel A presents mean difference in proxies for task performance between when the primary examiner works at the office and when the *same* primary examiner works from home. *Citation* and *Days to Issue* are greater when the primary examiner works at the office, relative to when the primary examiner works from home. *Patent Scope* is lower when the primary examiner works at the office than when the primary examiner works from home. The difference in these performance proxies between the two groups is statistically significant (two-tailed $p < 0.01$ for *Citation* and *Days to Issue* and two-tailed $p < 0.05$ for *Patent Scope*), providing initial evidence that task performance is lower when the supervisor works from home than when the *same* supervisor works at the office.

Table 7, Panel B presents results for testing the association between junior examiners' task performance and *Primary WFH*. When the dependent variables are *Citation* and *Days to Issue*, I find task performance is lower when the supervisor works from home, relative to when the supervisor works at the office (one-tailed $p < 0.01$ for Columns (1) and (2)). When the

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[48] I do not include primary-examiner-level (*Primary Female*$_\alpha$, *Primary GS*$_\alpha$, and *Primary Tenure*$_\alpha$) and junior-examiner-level controls (*Junior Female*$_\alpha$, *Junior GS*$_\alpha$, and *Junior Tenure*$_\alpha$) in the regression because these variables are subsumed by primary examiner fixed effects and junior examiner fixed effects, respectively. While an examiner's GS-level and tenure can technically vary within the given examiner, *Primary GS*$_\alpha$ and *Primary Tenure*$_\alpha$ (*Junior GS*$_\alpha$ and *Junior Tenure*$_\alpha$) rarely vary within the given primary (junior) examiner over applications in my sample and are thus omitted from the regression.

dependent variable is *Patent Scope*, however, I do not find patent scope is broader (and of lower examination quality) when the supervisor works from home, relative to when the supervisor works at the office (one-tailed $p > 0.10$ for Column (3)). Overall, I find some evidence that my results are not due to unobservable individual characteristics of primary examiners, such as the ability to advise their junior examiners.

3.5. HOME-WORKING SUPERVISORS AND SUBORDINATES' DEPARTURE RATES

In prior sections, I find subordinates assigned to work with home-working supervisors show lower task performance. In this section, I investigate the long-term career consequences of subordinates who work with home-working supervisors in subordinates' early years of career, measured with subordinates' departure rates. If subordinates perform worse when they are assigned to work with WFH supervisors, these examiners are more likely to be fired or leave sooner than if they are assigned to work with office-working supervisors. In addition, learning opportunities prevent employees from leaving the organization via enhanced organizational commitment (Joo 2010; Proost, van Ruysseveldt, and van Dijke 2012). This argument suggests examiners are more likely to leave due to the loss of learning opportunities if they are assigned to work with home-working supervisors, especially when their need for advising and learning is greater (i.e., in early years of career).

To test whether examiners assigned to work with home-working supervisors in early years of career are more likely to leave the USPTO sooner than those assigned to work with office-working supervisors, I employ the following proportional hazard model (Cox 1972) with robust standard errors and clustering by Art Units:

$$h(t) = h(t_0)\exp(\beta_1 Worked\ with\ WFH\ Supervisor + \beta_2 Female + \beta_3 Ethnic\ Minority$$
$$+ \beta_4 Avg.Task\ Complexity + \beta_5 Avg.\#\ of\ Office\ Actions$$
$$+ \beta_6 Avg.Team\ Size + \beta_7 Avg.Art\ Unit\ Overtime\ Work\ Hours$$
$$+ \beta_8 Avg.Art\ Unit\ Total\ Work\ Hours + \beta_k Fixed\ Effects). \quad (3)$$

The dependent variable, *h(t)*, is the hazard rate, which is the probability that an examiner will leave the USPTO at a point in time, given that the departure has not occurred earlier. The baseline hazard function, $h(t_0)$, is the estimated hazard rate of an event (i.e., an examiner leaving the USPTO) when all covariates are zero. The variable *t* is the number of days between hire date and exit date (*Time to Departure*).[49] My variable of interest is *Worked with WFH Supervisor*, which indicates whether an examiner is assigned to work with at least one home-working primary examiner in the first two years of career at the USPTO. I examine the first two years of career because examiners are allowed to work from home two years after they join the USPTO. Specifically, *Worked with WFH Supervisor* represents one of three variables: *Worked with WFH Supervisor at Years 0-1*, (*0-2*), and [*1-2*]. *Worked with WFH Supervisor at Years 0-1* (*0-2*) is an indicator variable that equals one if an examiner worked with at least one home-working primary examiner within one year (two years) after an examiner joins the USPTO, and zero otherwise. *Worked with WFH Supervisor at Years 1-2* is an indicator variable that equals one if an examiner worked with at least one home-working primary examiner from one year after hire date and until two years after hire date, and zero otherwise.

[49] For examiners who still stay at the USPTO as of the end of 2018 (the last recorded exit date in my data set), *Time to Departure* is the number of days between hire date and the end of 2018. In other words, *Time to Departure* is right-censored for examiners who stay at the USPTO until the end of my sample period. A Cox's proportional hazards model addresses the econometric issues arising from this right-censoring. Prior literature on employee turnover widely uses a proportional hazards model to predict employee departure rates (Sheridian 1992; Lee, Gerhart, Weller, and Trevor 2008; Weller, Holtom, Matiaske, and Mellewigt 2009; Deller and Sandino 2020).

I also control for variables pertaining to individual characteristics of an examiner, task complexity and performance of an examiner, and Art Unit Characteristics that might affect the probability of leaving. First, I control for individual characteristics of an examiner capturing whether he or she is female (*Female*) or ethnic minority (*Ethnic Minority*).[50] Second, I control for task complexity of an examiner (*Avg. Task Complexity*), defined as the expected number of hours allocated to review a patent application that each examiner has reviewed, averaged over all applications that the examiner has reviewed. I also control for task performance of an examiner (*Avg. # of Office Actions*), defined as the total number of office actions completed by each examiner in a month. Third, I control for Art Unit characteristics capturing the number of examiners in an examiner's Art Unit (*Avg. Team Size*), the number of overtime examining hours per examiner of an examiner's Art Unit in a given year (*Avg. Art Unit Overtime Work Hours*), and the number of total examining hours per examiner of an examiner's Art Unit in a given year (*Avg. Art Unit Total Work Hours*).[51] I also include year-month fixed effects and technology center fixed effects.

Table 8, Panel A presents summary statistics for variables used in Model (3). The final sample used in Model (3) is 2,694 examiners who worked an average of 3,414 days during my sample period. About 28 percent (22 percent) of examiners worked with at least one home-working supervisors within the first two years (one year). In addition, 28 percent of examiners are female, and 27 percent are ethnic minority. Examiners completed an average of 12 office actions in a month and worked in an Art Unit consisting of an average of 24 examiners.

[50] To identify whether an examiner is ethnic minority, I follow prior literature (Jung, Kumar, Lim, and Yoo 2019; Merkley, Michaely, and Pacelli 2020; Flam, Green, Lee, and Sharp 2020) and classify examiners of Latin America, Southern America, Confucian Asia, Middle East, and Sub-Saharan Africa descent as ethnic minority and those of Anglo, Nordic Europe, Latin America, Eastern Europe, Latin Europe, and Germanic Europe descent as ethnic nonminority based on an examiner's surname.

[51] For variables *Avg. # of Office Actions* and *Avg. Team Size*, I average the values over all months. For variables *Avg. Art Unit Overtime Work Hours* and *Avg. Art Unit Total Work Hours*, I average the values over all years.

Examiners worked an average of 98 overtime examining hours and 1,560 total examining hours in a year during my sample period.

Table 8, Panel B reports the results of estimating Model (3). In Table 8, I present the estimated hazard coefficients, followed by hazard ratios and z-statistics, on each covariates. Column (1) reports results when I include *Worked with WFH Supervisor at Years 0-2* in a regression model. The statistically significant coefficient on *Worked with WFH Supervisor at Years 0-2* of 0.714 (one-tailed $p < 0.01$) translates to a hazard ratio of 2.041 (=e^(0.714)). This indicates that when an examiner is assigned to work with at least one home-working supervisor within two years after the examiner joins the USPTO, the examiner is 104.1% (=(2.041-1)*100) more likely to leave the USPTO. Columns (2) and (3) report results when I include *Worked with WFH Supervisor at Years 0-1 (1-2)*, respectively. I also find *Worked with WFH Supervisor at Years 0-1 (1-2)* increases the hazard of leaving the USPTO (z-stat. = 4.73 and 3.77, respectively). Column (4) report results when I include both *Worked with WFH Supervisor at Years 0-1* and *Worked with WFH Supervisor at Years 1-2* in the analyses. I find that while the coefficient on *Worked with WFH Supervisor at Years 0-1* is statistically significant (one-tailed $p < 0.01$), the coefficient on *Worked with WFH Supervisor at Years 1-2* is not (one-tailed $p = 0.27$). This suggests whether an examiner is assigned to work with a home-working supervisor in earlier years of career (i.e., years 0-1) more strongly predicts employee turnover than in later years of career (i.e., years 1-2). These results indicate greater turnover rates when a newly hired examiner works with home-working supervisors than when an examiner with at least one year of working experience works with home-working supervisors. Collectively, these findings further support my claim that the difficulty of advising inexperienced subordinates when supervisors are working from home results in higher departure rates.

3.6 CONCLUSION

I study the effects of the supervisor working from home on the performance of subordinates working at the office. I find subordinates whose supervisors work from home add fewer citations used as decision grounds for each application, spend less time examining an invention, and approve patents that are broader in scope and thus of lower examination quality, relative to when the supervisor works at the office. I also find the unfavorable effects of the supervisor working from home are more pronounced for patents that are more technologically complex. Furthermore, I find there is no distinguishable difference between the office-working subordinate's task performance and the home-working subordinate's task performance when both of the subordinates are all reviewed by the *same* office-working supervisor. These results suggest the difficulty of advising subordinates in distributed work settings, rather than physically monitoring them to ensure that they do not shirk, drives my findings. Finally, I find subordinates working with home-working supervisors are less likely to remain with the organization.

These results contribute to a better understanding of current business practices. For example, the academic and practitioner literature often tout the benefits of companies encouraging their employees to work from home, suggesting employers' skepticism that employees would shirk at home is unwarranted (Bloom et al. 2015; Guyot and Sawhill 2020). While this study also complements the results in prior literature in that the difficulty of physically monitoring employees to ensure that they do not shirk does not drive my findings, I highlight an aspect of when and how we may observe detrimental effects of WFH policies that are overlooked in previous studies: the lack of in-person interactions can hinder advising relatively inexperienced employees in organizations.

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APPENDIX A
Selected Example - Patent Examination Document

1. Notice of Allowance Documents - Patent Application No. 13/208,413

Notice of Allowability	**Application No.** 13/208,413	**Applicant(s)** MOQVIST, PÄR	
	Examiner PETER SOLINSKY JR	**Art Unit** 2463	**AIA (First Inventor to File) Status** No

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address--
All claims being allowable, PROSECUTION ON THE MERITS IS (OR REMAINS) CLOSED in this application. If not included herewith (or previously mailed), a Notice of Allowance (PTOL-85) or other appropriate communication will be mailed in due course. **THIS NOTICE OF ALLOWABILITY IS NOT A GRANT OF PATENT RIGHTS.** This application is subject to withdrawal from issue at the initiative of the Office or upon petition by the applicant. See 37 CFR 1.313 and MPEP 1308.

1. ☒ This communication is responsive to *Request for Reconsideration filed 05/08/2014*.
   ☐ A declaration(s)/affidavit(s) under **37 CFR 1.130(b)** was/were filed on______.

2. ☐ An election was made by the applicant in response to a restriction requirement set forth during the interview on _____; the restriction requirement and election have been incorporated into this action.

3. ☒ The allowed claim(s) is/are *1-24*. As a result of the allowed claim(s), you may be eligible to benefit from the **Patent Prosecution Highway** program at a participating intellectual property office for the corresponding application. For more information, please see http://www.uspto.gov/patents/init_events/pph/index.jsp or send an inquiry to PPHfeedback@uspto.gov .

4. ☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).
   Certified copies:
   a) ☐ All b) ☐ Some *c) ☐ None of the:
   1. ☐ Certified copies of the priority documents have been received.
   2. ☐ Certified copies of the priority documents have been received in Application No. _____ .
   3. ☐ Copies of the certified copies of the priority documents have been received in this national stage application from the International Bureau (PCT Rule 17.2(a)).

   * Certified copies not received: _____.

Applicant has THREE MONTHS FROM THE "MAILING DATE" of this communication to file a reply complying with the requirements noted below. Failure to timely comply will result in ABANDONMENT of this application.
THIS THREE-MONTH PERIOD IS NOT EXTENDABLE.

5. ☐ CORRECTED DRAWINGS (as "replacement sheets") must be submitted.
   ☐ including changes required by the attached Examiner's Amendment / Comment or in the Office action of Paper No./Mail Date _____.

   Identifying indicia such as the application number (see 37 CFR 1.84(c)) should be written on the drawings in the front (not the back) of each sheet. Replacement sheet(s) should be labeled as such in the header according to 37 CFR 1.121(d).

6. ☐ DEPOSIT OF and/or INFORMATION about the deposit of BIOLOGICAL MATERIAL must be submitted. Note the attached Examiner's comment regarding REQUIREMENT FOR THE DEPOSIT OF BIOLOGICAL MATERIAL.

Attachment(s)
1. ☒ Notice of References Cited (PTO-892)
2. ☐ Information Disclosure Statements (PTO/SB/08), Paper No./Mail Date _____
3. ☐ Examiner's Comment Regarding Requirement for Deposit of Biological Material
4. ☐ Interview Summary (PTO-413), Paper No./Mail Date _____ .
5. ☐ Examiner's Amendment/Comment
6. ☒ Examiner's Statement of Reasons for Allowance
7. ☐ Other _____.

/PETER SOLINSKY JR/ Examiner, Art Unit 2463	/MARK RINEHART/ Supervisory Patent Examiner, Art Unit 2463

U.S. Patent and Trademark Office
PTOL-37 (Rev. 08-13) **Notice of Allowability** Part of Paper No./Mail Date 20140610

APPENDIX A (Continued)

2. Notice of Allowance Documents - Patent Application No. 13/208,413

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Art Unit: 2463

A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37 CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the mailing date of this final action.

Any inquiry concerning this communication or earlier communications from the examiner should be directed to PETER SOLINSKY JR whose telephone number is (571)270-7216. The examiner can normally be reached on Monday through Thursday 6:30 am to 5:00 pm.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Mark H. Rinehart can be reached on (571) 272-3632. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

This appendix provides an example of a publicly available patent document on Public PAIR reviewed by both junior and primary examiners. The highlighted boxes show junior and primary examiners examining a particular patent application.

APPENDIX B
Description of Variables

Variable	Description	Source
Attorney Experience	The natural log of the number of years between the filing year of the first successful patent application that the attorney took and the application's filing year;	Public Pair
Avg. Art Unit Overtime Work Hours	The number of overtime examining hours per examiner of an examiner's Art Unit in a given year, averaged over all years;	FOIA, Public PAIR
Avg. Art Unit Total Work Hours	The number of total examining hours per examiner of an examiner's Art Unit in a given year, averaged over all years;	FOIA, Public PAIR
Avg. Task Complexity	The expected number of hours allocated to review a patent application that each examiner has reviewed, averaged over all applications that the examiner has reviewed;	FOIA, Public PAIR
Avg. Team Size	The number of examiners in an examiner's Art Unit, averaged over all months;	FOIA, Public PAIR
Avg. # of Office Actions	The total number of office actions completed by each examiner in a month, averaged over all months;	Public PAIR
Citation	The total number of examiner-added citations used in office actions for a given patent application;	Public PAIR
Complex Tech	An indicator variable that equals one if a patent has the highest expectancy, and zero otherwise. Expectancy is the expected number of hours allocated to review one patent application;	FOIA
Days to Issue	The number of days it takes to issue patents for a given patent application;	Public PAIR
Ethnic Minority	An indicator variable that equals one if an examiner is ethnic minority, and zero otherwise;	Oxford Dictionary of American Family names, Ancestry.com, and Forebears.io
Female	An indicator variable that equals one if an examiner is female, and zero otherwise;	FOIA, Patentsview, genderize.io
Inventor Experience	The natural log of the number of years between the filing year of the inventor's first successful patent application and the application's filing year;	Patentsview
Junior Female	An indicator variable that equals one if a junior examiner for a given patent application is female, and zero otherwise;	FOIA, Patentsview, genderize.io
Junior GS	An ordinal variable classifying junior examiners' GS-level ranging from one to eight, where one corresponds to GS-5 and eight corresponds to GS-15;	FOIA, Patentsview
Junior Tenure	The number of years a junior examiner for a given patent application has worked as of first office action date;	FOIA, Patentsview
Junior WFH	An indicator variable that equals one if a junior examiner for a given application works from home as of first office action date, and zero otherwise;	FOIA, Public PAIR, Patentsview

Patent Scope	The number of words added to the first claim for a given patent application by an examiner that is normalized by the Art Unit that the examiner is in and multiplied by negative one. The higher value corresponds to broader patent scope;	Jeffrey Kuhn's website
Primary Female	An indicator variable that equals one if a primary examiner for a given patent application is female, and zero otherwise;	FOIA, Patentsview, genderize.io
Primary GS	An ordinal variable classifying primary examiners' GS-level ranging from one to eight, where one corresponds to GS-5 and eight corresponds to GS-15;	FOIA, Patentsview
Primary Tenure	The number of years a primary examiner for a given patent application has worked as of first office action date;	FOIA, Patentsview
Primary WFH	An indicator variable that equals one if a primary examiner for a given application works from home as of first office action date, and zero otherwise;	FOIA, Public PAIR, Patentsview
Small Entity	An indicator variable that equals one if an application is submitted by small entities, and zero otherwise;	Public Pair
Time to Departure	The number of days between an examiner's hire date and exit date. For examiners who still stay at the USPTO as of the end of 2018 (the last recorded exit date in my data set), *Time to Departure* is the number of days between hire date and the end of 2018;	FOIA
Worked with WFH Supervisor at Years 0-2	An indicator variable that equals one if an examiner worked with at least one home-working primary examiner within two years after an examiner joins the USPTO, and zero otherwise;	FOIA, Public PAIR, Patentsview
Worked with WFH Supervisor at Years 0-1	An indicator variable that equals one if an examiner worked with at least one home-working primary examiner within one year after an examiner joins the USPTO, and zero otherwise;	FOIA, Public PAIR, Patentsview
Worked with WFH Supervisor at Years 1-2	An indicator variable that equals one if an examiner worked with at least one home-working primary examiner from one year after hire date and until two years after hire date, and zero otherwise;	FOIA, Public PAIR, Patentsview
# of Attorney's Prior Patents	The natural log of the number of successful patent application cases the attorney took before;	Public Pair
# of Drawings	The natural log of the number of patent drawings included with a patent application;	Patentsview
# of Figures	The natural log of the number of figures included with a patent application;	Patentsview
# of Inventor's Prior Patents	The natural log of the number of successful patent applications previously filed by the inventor;	Patentsview
# of Patent Claims	The natural log of the number of patent claims; and	Patentsview
# of Words in Patent Claims	The natural log of the number of words in patent claims.	Patentsview

APPENDIX C
Task Performance when both the supervisor and subordinate work from home

In Section 4.5, I compare task performance when both the supervisor and subordinate work at the office to when the supervisor works at the office and subordinate works from home. In Appendix C, I consider a case in which both the supervisor and subordinate work from home. As explained in Section 4.5, if lack of monitoring drives my findings, then task performance when both the supervisor and subordinate work from (their own) home is likely to be lower than when both the supervisor and subordinate work at the office. I limit my analyses to cases either in which both the supervisor and subordinate work at the office or in which both the supervisor and subordinate work from home.

In comparing task performance between these two cases, I estimate the following equation:

$$\begin{aligned} Performance_{\alpha} &= \alpha + \beta_1 Both\ WFH_{\alpha} + \beta_2 Primary\ Female_{\alpha} + \beta_3 Primary\ GS_{\alpha} \\ &+ \beta_4 Primary\ Tenure_{\alpha} + \beta_5 Junior\ Female_{\alpha} + \beta_6 Junior\ GS_{\alpha} + \beta_7 Junior\ Tenure_{\alpha} \\ &+ \gamma Fixed\ Effects_{\alpha} + \varepsilon_{\alpha}. \end{aligned} \tag{E1}$$

The explanatory variable of interest is *Both WFH*$_{\alpha}$, which is an indicator variable that equals one if both the primary and junior examiners work from home, and zero otherwise. All other variables are defined in Section 4.

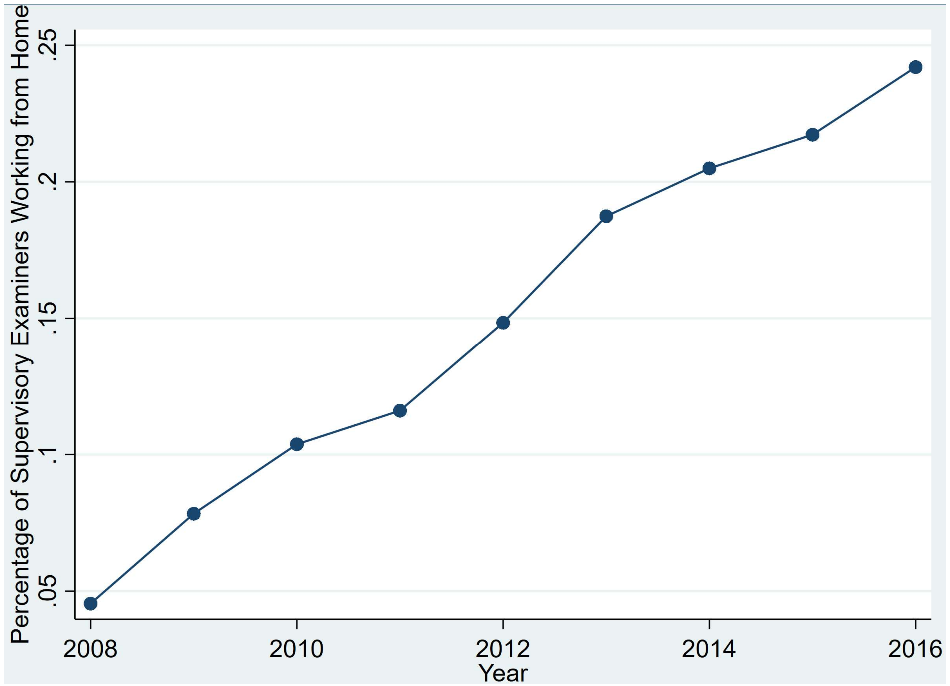
Table A1 presents the regression results of estimating Equations (E1). Columns (1), (2), and (3) present the estimation of Equations (E1) when the dependent variable is *Citation, Days to Issue,* and *Patent Scope,* respectively. The mean of *Both WFH* ranges from 0.02 to 0.07, indicating two to seven percent of applications were reviewed when both the supervisor and subordinate work from home. The estimated coefficient on *Both WFH* is not statistically significant in all specifications (two-tailed p > 0.10), suggesting the negative effects on task performance are nonexistent when both the supervisor and subordinate work from (their own) home, compared to when both the supervisor and subordinate work at the office. These results lend further support for my argument in Section 4.5 that lack of monitoring does not drive my findings.

Table A1

Dependent Variable:	**(1) *Citation***	**(2) *Days to Issue***	**(3) *Patent Scope***
Both WFH	-0.113	6.865	0.106
	(-1.36)	(0.33)	(1.37)
Controls Included	Yes	Yes	Yes
Art Unit FEs	Yes	Yes	Yes
USPC Code FEs	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes
Observations	78,528	182,281	77,000
Sample Mean of *Both WFH*	0.070	0.047	0.015
ADJ R^2	0.150	0.343	0.544

FIGURE 1
The Percentage of Supervisory Examiners Working from Home by Year

Panel A. Number of Examiner-Added Citations Tests



Panel B. Days to Patent Issuance Tests

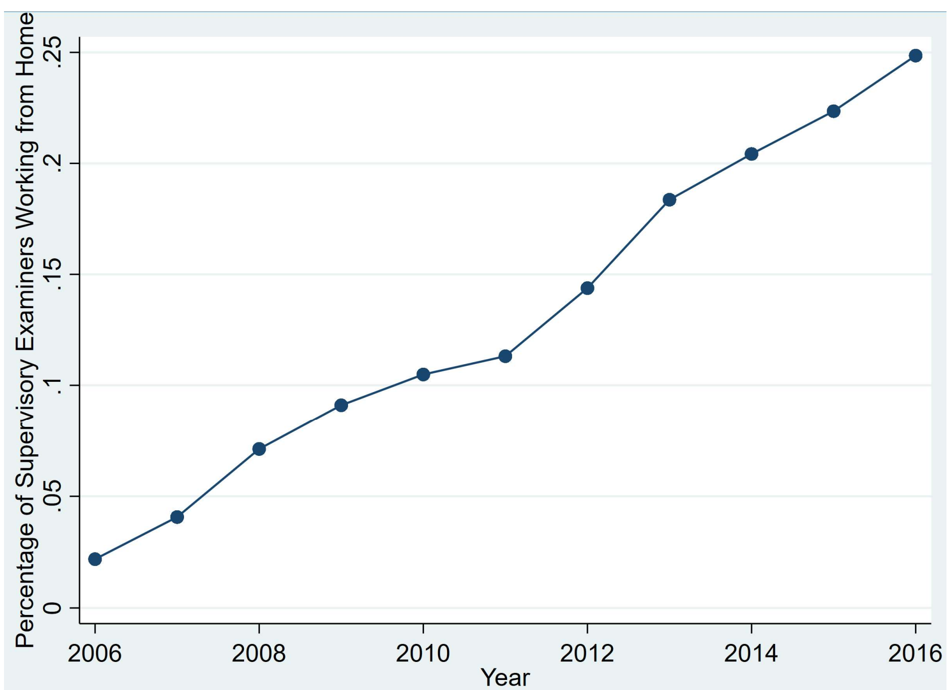


FIGURE 1 (Continued)

Panel C. Patent Scope Tests

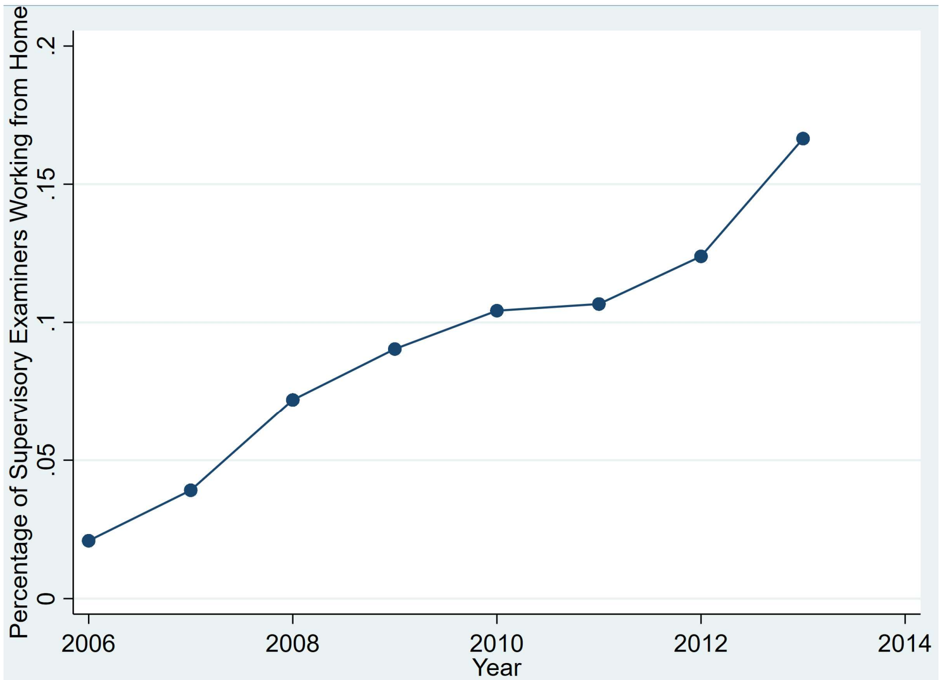


Figure 1 illustrates observation points capturing the percentage of supervisory (primary) examiners working from home across time points divided into spans of one year for the sample used in Number of Examiner-Added Citations Tests (Panel A), Days to Patent Issuance Tests (Panel B), and Patent Scope Tests (Panel C), respectively.

TABLE 1
Sample Selection Procedure

Description	Table	# of Patents
(i) Granted patents that examiners complete first office actions from 2006 to 2016:		2,875,513
Exclude patents examined by primary examiners only:		(1,948,447)
Require non-missing data for variables representing examiner characteristics:		(678,241)
Exclude patents examined by junior examiners who were working from home as of FOAM date:		(51,353)
(ii) Final Sample for tests of days to patent issuance	Panel B of Table 4 (Columns 3 & 4)	197,472
(a) *Require* non-missing data for variables representing patent application, inventor, and attorney characteristics:		(22,055)
(b) *Require* non-missing data for variables capturing citations:		(109,718)
(c) *Require* non-missing data for variables capturing patent scope:		(115,226)
(iii) Final Sample for tests of patent application assignment: (ii) – (a)	Table 3	175,417
(iv) Final Sample for tests of examiner-added citations: (ii) – (b)	Panel B of Table 4 (Columns 1 & 2)	87,758
(v) Final Sample for tests of patent scope: (ii) – (c)	Panel B of Table 4 (Columns 5 & 6)	82,250

Sample selection procedure for tests of patent application assignment (Table 3) and Hypothesis 1 (Table 4).

TABLE 2
Sample

Panel A. Summary Statistics

Measure	N	Mean	Median	Q1	Q3	Std. Dev.
Number of Examiner-Added Citations Tests						
Citations	87,758	2.918	2.000	1.000	4.000	2.310
Primary WFH	87,758	0.169	0.000	0.000	0.000	0.375
Primary Female	87,758	0.142	0.000	0.000	0.000	0.349
Primary Tenure	87,758	16.171	14.000	10.000	22.000	8.037
Primary GS	87,758	14.576	15.000	14.000	15.000	0.546
Junior Female	87,758	0.278	0.000	0.000	1.000	0.448
Junior Tenure	87,758	3.932	3.000	1.000	5.000	4.190
Junior GS	87,758	10.891	11.000	9.000	12.000	1.878
Days to Patent Issuance Tests						
Days to Issue	197,472	1,131	1,063	750	1,434	542.3
Primary WFH	197,472	0.123	0.000	0.000	0.000	0.329
Primary Female	197,472	0.133	0.000	0.000	0.000	0.340
Primary Tenure	197,472	15.960	14.000	10.000	21.000	7.722
Primary GS	197,472	14.621	15.000	14.000	15.000	0.534
Junior Female	197,472	0.281	0.000	0.000	1.000	0.450
Junior Tenure	197,472	3.549	2.000	1.000	5.000	3.991
Junior GS	197,472	10.735	11.000	9.000	12.000	1.968
Patent Scope Tests						
Patent Scope	82,250	-0.518	-0.591	-0.939	-0.133	0.748
Primary WFH	82,250	0.079	0.000	0.000	0.000	0.270
Primary Female	82,250	0.102	0.000	0.000	0.000	0.303
Primary Tenure	82,250	16.259	15.000	10.000	22.000	7.466
Primary GS	82,250	14.682	15.000	14.000	15.000	0.508
Junior Female	82,250	0.259	0.000	0.000	1.000	0.438
Junior Tenure	82,250	2.956	2.000	1.000	4.000	3.295
Junior GS	82,250	10.412	11.000	9.000	12.000	2.054

TABLE 2 (Continued)

Panel B. Sample Composition by Year (by First Office Action Year)

YEAR	*Citation*		*Days to Issue*		*Patent Scope*	
	N	**Mean**	**N**	**Mean**	**N**	**Mean**
2006			18,161	1,152	11,527	-0.333
2007			18,789	1,267	11,854	-0.486
2008	374	2.668	21,063	1,324	13,893	-0.532
2009	3,191	2.755	20,527	1,317	13,611	-0.568
2010	7,353	2.785	17,285	1,232	10,313	-0.587
2011	14,008	2.984	19,968	1,242	10,923	-0.577
2012	14,818	3.120	20,259	1,082	8,087	-0.544
2013	15,870	3.045	20,656	954	2,042	-0.547
2014	13,121	2.903	15,865	928		
2015	12,234	2.795	15,199	894		
2016	6,789	2.529	9,700	780		
Total	87,758	2.918	197,472	1,131	82,250	-0.518

Panel C. Sample Composition by Technology

	Citation		*Days to Issue*		*Patent Scope*	
	N	**Mean**	**N**	**Mean**	**N**	**Mean**
Biotechnology and Organic Fields	5,223	1.708	16,517	1,093		
Chemical and Materials Engineering	10,285	2.848	22,613	1,200	10,897	-0.539
Computer Architecture Software and Information Security	5,572	2.883	14,768	1,295	6,842	-0.489
Computer Networks, Multiplex, Cable, and Cryptography/Security	9,155	3.615	17,195	1,361	5,806	-0.523
Communications	7,348	3.271	19,834	1,282	10,501	-0.530
Semiconductors, Electrical and Optical Systems, and Components	20,661	2.758	46,125	892	22,107	-0.520
Transportation, Electronic Commerce, and National Security	12,266	2.720	25,735	1,019	11,934	-0.457
Mechanical Engineering, Manufacturing, and Products	17,248	3.149	34,685	1,233	14,163	-0.553
Total	87,758	2.918	197,472	1,131	82,250	-0.518

Panel A reports the summary statistics on the variables used in my analyses. Panels B and C present the sample composition by First Office Action year and technology, respectively.

TABLE 3
Determinants of Patent Application Assignment

	DV = *Primary WFH*			
	(1)	**(2)**	**(3)**	**(4)**
Patent Application Characteristics				
# of Words in Patent Claims	0.001			0.001
	(0.38)			(0.38)
# of Patent Claims	$-4.493E^{-4}$			$-4.392E^{-4}$
	(-0.18)			(-0.18)
# of Figures	-0.002			-0.002
	(-0.87)			(-0.89)
# of Drawings	0.002			0.002
	(0.86)			(0.90)
Patent Inventor Characteristics				
Small Entity		$-1.718E^{-4}$		$2.680E^{-4}$
		(-0.07)		(0.10)
# of Inventor's Prior Patents		$-1.580E^{-5}$		$-1.960E^{-5}$
		(-0.02)		(-0.02)
Inventor Experience		$-2.069E^{-4}$		$-2.587E^{-4}$
		(-0.22)		(-0.27)
Patent Attorney Characteristics				
# of Attorney's Prior Patents			$8.090E^{-5}$	$1.053E^{-4}$
			(0.12)	(0.15)
Attorney Experience			0.003	0.003
			(0.92)	(0.94)
Art Unit FEs	Yes	Yes	Yes	Yes
USPC Code FEs	Yes	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes	Yes
Observations	175,395	175,395	175,395	175,395
ADJ R^2	0.336	0.336	0.336	0.336

Table 3 presents the estimation results of regressing whether a primary examiner works from home (*Primary WFH*) on innovation-related characteristics. All *t*-statistics (in parentheses) are based on standard errors clustered at the Art Unit level. *# of Words in Patent Claims* is the natural log of the number of words in patent claims. *# of Patent Claims* is the natural log of the number of patent claims. *# of Figures* is the natural log of the number of figures included with a patent application. *# of Drawings* is the natural log of the number of patent drawings included with a patent application. *Small Entity* is an indicator variable that equals one if an application is submitted by small entities, and zero otherwise. *# of Inventor's Prior Patents* is the natural log of the number of successful patent applications previously filed by the inventor. *Inventor Experience* is the natural log of the number of years between the filing year of the inventor's first successful patent application and the application's filing year. *# of Attorney's Prior Patents* is the natural log of the number of successful patent application cases the attorney took before. *Attorney Experience* is the natural log of the number of years between the filing year of the first successful patent application that the attorney took and the application's filing year.

TABLE 4
Effects on the Number of Examiner-Added Citations, Days to Patent Issuance, and Patent Scope

Panel A. Mean Difference

Measure	Primary Examiner Works at the Office		Primary Examiner Works from Home		Mean Difference
	N	Mean	N	Mean	
Citation	72,939	2.937	14,819	2.822	-0.116***
Days to Issue	173,116	1,141.31	24,356	1,054.24	-87.07***
Patent Scope	75,734	-0.548	6,516	-0.173	0.374***

TABLE 4 (Continued)

Panel B. Regression Results

Dependent Variable:	*Citation*		*Days to Issue*		*Patent Scope*	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Primary WFH	-0.127***	-0.167***	-26.519**	-42.828***	0.234***	0.286***
	(-2.41)	(-3.76)	(-2.12)	(-2.90)	(3.88)	(4.66)
Primary Female	-0.021	0.002	1.224	35.342	0.004	-0.017
	(-0.33)	(0.04)	(0.09)	(1.53)	(0.06)	(-0.23)
Primary Tenure	-0.011***	-0.008***	-3.329***	-3.310***	0.038***	0.031***
	(-4.07)	(-2.82)	(-5.02)	(-3.34)	(13.21)	(9.39)
Primary GS	-0.186***	-0.224***	-103.02***	-114.35***	-0.422***	-0.420***
	(-4.97)	(-6.61)	(-13.33)	(-12.72)	(-12.57)	(11.76)
Junior Female	0.016		19.332**		0.016	
	(0.31)		(2.05)		(0.68)	
Junior Tenure	-0.061***		1.972		0.004	
	(-7.48)		(1.44)		(1.43)	
Junior GS	-0.187***		-72.815***		0.011	
	(-9.91)		(-21.42)		(1.55)	
Art Unit FEs	Yes	No	Yes	No	Yes	No
Junior Examiner FEs	No	Yes	No	Yes	No	Yes
USPC Code FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87,726	87,392	197,450	197,103	82,205	81,913
ADJ R^2	0.151	0.247	0.338	0.424	0.514	0.675

Panel A presents the mean differences in *Citation*, *Days to Issue*, and *Patent Scope* between the environment where the primary examiner works from home and the environment where the primary examiner works at the office. Panel B reports the estimation results of Model (1) using OLS regression, where all *t*-statistics (in parentheses) are based on standard errors clustered at the junior examiner level. For Columns (1) and (2), the dependent variable is *Citation*, defined as the total number of examiner-added citations used in office actions for a given patent application. For Columns (3) and (4), the dependent variable is *Days to Issue*, defined as the number of days it takes to issue patents for a given patent application. For Columns (5) and (6), the dependent variable is *Patent Scope*, defined as the number of words added to the first claim for a given patent application by an examiner that is normalized by the Art Unit that the examiner is in and multiplied by negative one. Columns (1), (3), and (5) report results with primary- and junior-examiner-level controls with Art-Unit-level, USPC-level, and Year-Month-level fixed effects. Columns (2), (4), and (6) report results with primary-examiner-level controls with junior-examiner-level, USPC-level, and Year-Month-level fixed effects. ***, **, and * denote one-tailed (two-tailed) statistical significance at the 1%, 5%, and 10% levels, respectively, when a directional (non-directional) prediction is indicated.

TABLE 5
Cross-Sectional Tests

Panel A. Technology Fields by Technological Complexity

	Expectancy (hours)	Technology Fields (Examples)
Simple Technologies	14.3	Purses, Wallets, and Protective Covers; Trunks and Hand-Carried Luggage; Flexible Bags
	15.8	Cutlery; Woodturning; Coopering; Work Holders
↑	16.9	Tent, Canopy, Umbrella, or Cane; Flexible or Portable Closure, Partition, or Panel
	17.5	Boring or Penetrating the Earth; Railway Wheels and Axles; Mining or In Situ Disintegration of Hard Material
	18.2	Internal-Combustion Engines; Surgery Tools
	19.7	Sugar, Starch, and Carbohydrates; Metal Treatment
	20.5	Radiant Energy; Wave Transmission Lines and Networks
	21.9	Concentrating Evaporators; Mineral Oils; Distillation; Gas Separation
	22.4	Batteries (Thermoelectric and PhotoElectric); Chemistry (Electrical and Wave Energy)
	23.6	Recorders; Incremental Printing of Symbolic Information; Television (Sound Signal, Noise Inversion)
	24.4	Semiconductor Cleaning; Chemical Bleaching, Oxidation, or Reduction
	25.9	Drug, Bio-Affecting, and Body Treating Compositions; Molecular Biology and Microbiology
	26.3	Kinesitherapy; Television (Motion Picture Film Scanner, Mechanical Optical Scanning, Motion Detection)
	27.5	Data Processing (Vehicles, Navigation, and Relative Location)
	28.2	Multiplex Communications (Data Assembly or Formatting, Internet Protocol, Emulated Lan)
↓	28.9	Image Analysis (Vehicle or Traffic Control, Motion or Velocity Measuring, Radiography, Blood Cells, Neural Networks)
Complex Technologies	31.6	Data Processing (Database and File Management, Data Structures, Digital Audio Data Processing System); Computer Graphics Processing; Operator Interface Processing; Selective Visual Display Systems

Panel B. Summary Statistics

Measure	N	Mean	Median	Min.	Q1	Q3	Max.	Std. Dev.
Expectancy (Hours)	182,966	23.603	22.400	14.300	20.300	27.500	31.600	4.623

TABLE 5 (Continued)

Panel C. Regression Results

Dependent Variable:	*Citation*		*Days to Issue*		*Patent Scope*	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
*Primary WFH * Complex Tech*	-0.181**	-0.181**	-103.30***	-74.391***	0.400***	0.324**
	(-1.68)	(-1.78)	(-4.28)	(-2.78)	(2.57)	(2.03)
Primary WFH	-0.123**	-0.128***	-6.518	-25.240*	0.174***	0.251***
	(-2.07)	(-2.49)	(-0.46)	(-1.46)	(2.76)	(3.93)
Complex Tech	0.121	0.196	45.497	3.352	-0.072	-0.075
	(0.63)	(1.07)	(1.15)	(0.08)	(-0.85)	(-1.11)
Controls Included	Yes	Yes	Yes	Yes	Yes	Yes
Art Unit FEs	Yes	No	Yes	No	Yes	No
Junior Examiner FEs	No	Yes	No	Yes	No	Yes
USPC Code FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,581	80,245	182,942	182,600	75,866	75,569
ADJ R^2	0.155	0.252	0.349	0.432	0.512	0.672

Panel A presents examples of technology fields corresponding to expectancy, which is the number of expected hours allocated to review a patent application determined based on technological complexity of each patent. Panel B reports the summary statistics of expectancy (denoted in hours) in my sample. Panel C reports the estimation results of Model (2) using OLS regression, where all *t*-statistics (in parentheses) are based on standard errors clustered at the junior examiner level. The dependent variables are *Citation*, *Days to Issue*, and *Patent Scope* for Columns (1) & (2), (3) & (4), and (5) & (6), respectively. For Columns (1), (3), and (5), controls and fixed effects are identical to those in Column (1) of Table 4. For Columns (2), (4), and (6), controls and fixed effects are identical to those in Column (2) of Table 4. *Complex Tech* is an indicator variable that equals one if a patent has the highest expectancy of 31.6 hours, and zero otherwise. ***, **, and * denote one-tailed (two-tailed) statistical significance at the 1%, 5%, and 10% levels, respectively, when a directional (non-directional) prediction is indicated.

TABLE 6
Effects of Junior Examiners Working from Home when Primary Examiners Work at the Office

Panel A. Summary Statistics of Junior Examiners Working from Home

Measure	N	Mean	Median	Q1	Q3	Std. Dev.
Number of Examiner-Added Citations Tests						
Junior WFH	94,211	0.238	0.000	0.000	0.000	0.426
Days to Patent Issuance Tests						
Junior WFH	206,942	0.177	0.000	0.000	0.000	0.382
Patent Scope Tests						
Junior WFH	84,168	0.111	0.000	0.000	0.000	0.314

Panel B. Regression Results

Dependent Variable:	***Citation***		***Days to Issue***		***Patent Scope***	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Junior WFH	-0.025	-0.032	-6.529	-2.839	-0.008	-0.005
	(-0.53)	(-0.68)	(-0.64)	(-0.28)	(-0.32)	(-0.37)
Controls Included	Yes	Yes	Yes	Yes	Yes	Yes
Art Unit FEs	Yes	No	Yes	No	Yes	No
Primary Examiner FEs	No	Yes	No	Yes	No	Yes
USPC Code FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,171	94,110	206,918	206,815	84,117	84,004
ADJ R^2	0.143	0.150	0.335	0.352	0.572	0.831

Panel A reports the summary statistics of *Junior WFH*, defined as an indicator variable that equals one if a junior examiner for a given application works from home as of first office action date, and zero otherwise. Panel B reports the estimation results of regressing proxies of junior examiners' task performance on *Junior WFH*, controls, and various fixed effects. For Columns (1), (3), and (5), controls and fixed effects are identical to those in Column (1) of Table 4. For Columns (2), (4), and (6), controls and fixed effects are identical to those in Column (2) of Table 4. The dependent variables are *Citation*, *Days to Issue*, and *Patent Scope* for Columns (1) & (2), (3) & (4), and (5) & (6), respectively. All *t*-statistics (in parentheses) are based on standard errors clustered at the junior examiner level.

TABLE 7
Alternative Identification Strategy

Panel A. Mean Difference

Measure	Primary Examiner Works at the Office		Primary Examiner Works from Home		Mean Difference
	N	Mean	N	Mean	
Citation	1,709	3.256	2,936	2.485	-0.771***
Days to Issue	4,352	1,282.85	5,993	1,017.94	-263.91***
Patent Scope	1,676	-0.209	1,827	-0.137	0.072**

Panel B. Regression Results

Dependent Variable:	**(1) *Citation***	**(2) *Days to Issue***	**(3) *Patent Scope***
Primary WFH	-0.385***	-175.35***	-0.023
	(-2.60)	(-4.58)	(-0.84)
Primary Examiner FEs	Yes	Yes	Yes
Junior Examiner FEs	Yes	Yes	Yes
USPC Code FEs	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes
Observations	4,579	10,301	3,464
ADJ R^2	0.261	0.407	0.954

Panel A presents the mean difference in *Citation*, *Days to Issue*, and *Patent Scope* between the environment where the primary examiner works from home and the environment where the primary examiner works at the office while the junior examiner works at the office. Panel B reports the estimation results of regressing proxies of junior examiners' task performance on *Primary WFH* and supervisory-examiner-level, junior-examiner-level, USPC-level, and Year-Month-level fixed effects, in an environment where the supervisor shifts from working at the office to working from home while the subordinate works at the office. The dependent variables are *Citation*, *Days to Issue*, and *Patent Scope* for Columns (1), (2), and (3), respectively. All *t*-statistics (in parentheses) are based on standard errors clustered at the junior examiner level. ***, **, and * denote one-tailed (two-tailed) statistical significance at the 1%, 5%, and 10% levels, respectively, when a directional (non-directional) prediction is indicated.

TABLE 8
Effects of Primary Examiners Working from Home on Junior Examiners' Time to Departure

Panel A. Summary Statistics

Measure	N	Mean	Median	Q1	Q3	Std. Dev.
Time to Departure (in days)	2,694	3,413.93	3,619	2,331	4,487	1,362.76
Worked with WFH Supervisor at Years 0-2	2,694	0.278	0.000	0.000	1.000	0.448
Worked with WFH Supervisor at Years 0-1	2,694	0.216	0.000	0.000	0.000	0.412
Worked with WFH Supervisor at Years 1-2	2,694	0.242	0.000	0.000	0.000	0.428
Female	2,694	0.275	0.000	0.000	1.000	0.447
Ethnic Minority	2,694	0.271	0.000	0.000	1.000	0.444
Avg. Task Complexity	2,694	24.452	23.272	20.578	28.323	4.783
Avg. # of Office Actions	2,694	12.167	11.830	9.455	14.630	4.117
Avg. Team Size	2,694	23.828	17.100	14.938	23.909	18.745
Avg. Art Unit Overtime Work Hours	2,694	97.941	88.656	57.424	127.830	56.914
Avg. Art Unit Total Work Hours	2,694	1,560.05	1,527.46	1,421.29	1,636.73	420.91

TABLE 8 (Continued)

Panel B. Cox's Proportional Hazard Model Estimation Results

	Analysis Time = *Time to Departure*; Failure Event = *Leave the USPTO*			
	(1)	(2)	(3)	(4)
Worked with WFH Supervisor at Years 0-2	0.714***			
Hazard Ratio	2.041			
(Z-Statistics)	(4.32)			
Worked with WFH Supervisor at Years 0-1		0.814***		0.733***
Hazard Ratio		2.257		2.082
(Z-Statistics)		(4.73)		(3.42)
Worked with WFH Supervisor at Years 1-2			0.603***	0.117
Hazard Ratio			1.827	1.124
(Z-Statistics)			(3.77)	(0.60)
Female	-0.029	0.038	-0.043	0.026
Hazard Ratio	0.971	1.039	0.958	1.027
(Z-Statistics)	(-0.16)	(0.22)	(-0.23)	(0.15)
Ethnic Minority	-0.127	-0.141	-0.155	-0.140
Hazard Ratio	0.881	0.869	0.856	0.869
(Z-Statistics)	(-0.62)	(-0.69)	(-0.75)	(-0.68)
Avg. Task Complexity	-0.084***	-0.083***	-0.087***	-0.083***
Hazard Ratio	0.919	0.921	0.917	0.920
(Z-Statistics)	(-3.28)	(-3.24)	(-3.36)	(-3.27)
Avg. # of Office Actions	-0.246***	-0.249***	-0.247***	-0.248***
Hazard Ratio	0.782	0.779	0.781	0.780
(Z-Statistics)	(-11.10)	(-11.73)	(-11.34)	(-11.50)
Avg. Team Size	0.000	-0.001	0.001	-0.001
Hazard Ratio	1.000	0.999	1.001	0.999
(Z-Statistics)	(0.08)	(-0.07)	(0.31)	(-0.02)
Avg. Art Unit Overtime Work Hours	0.001	0.001	0.001	0.001
Hazard Ratio	1.001	1.001	1.001	1.001
(Z-Statistics)	(0.38)	(0.77)	(0.43)	(0.71)
Avg. Art Unit Total Work Hours	0.000	0.000	0.000	0.000
Hazard Ratio	1.000	1.000	1.000	1.000
(Z-Statistics)	(1.18)	(0.82)	(1.12)	(0.87)
Technology Center FEs	Yes	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes	Yes
Observations	2,694	2,694	2,694	2,694

Panel A presents summary statistics for variables used in a Cox's proportional hazards model. *Time to Departure* is the number of days between the examiner's hire date and exit date (censored at the final sample period exit date [in December 2018] for examiners who still stayed with the USPTO at that time). *Worked with WFH Supervisor at Years 0-1* (*0-2*) is an indicator variable that equals one if an examiner worked with at least one home-working primary examiner within one year (two years) after an examiner joins the USPTO, and zero otherwise. *Worked with WFH Supervisor at Years 1-2* is an indicator variable that equals one if an examiner worked with at least one home-working primary examiner from one year after hire date and until two years after hire date, and zero otherwise. *Female* is an indicator variable that equals one if the examiner is female, and zero otherwise. *Ethnic Minority* is an indicator variable that equals one if the examiner is ethnic minority, and zero otherwise. *Avg. Task Complexity* is the expected number of hours allocated to review a patent application that each examiner has reviewed, averaged over all applications that the examiner has reviewed. *Avg. # of Office Actions* is the total number of office actions completed by each examiner in a month, averaged over all months. *Avg. Team Size* is the number of examiners in an examiner's Art Unit, averaged over all months. *Avg. Art Unit Overtime Work Hours* is the number of overtime examining hours per examiner of an examiner's Art Unit in a given year, averaged over all months. *Avg. Art Unit Total Work Hours* is the number of total examining hours per examiner of an examiner's Art Unit in a given year, averaged over all months. Panel B reports coefficients and hazard ratios of a Cox's proportional hazards model testing the prediction that examiners who worked with home-working primary examiners in the early years of tenure are more likely to leave the USPTO. Z-statistics in parentheses are based on robust standard errors clustered by Art Unit. A positive coefficient of a Cox's proportional hazards model indicates a positive impact on the hazard rate and, thus, a shorter time to examiner departure. A negative coefficient indicates a longer time to examiner departure.

CHAPTER 4

CONCLUSION

In this dissertation, I examine the relation between telecommuting policies and employee performance. To address my research questions, I use the work of patent examiners at the USPTO whose job is to review, evaluate, and decide whether to grant patents on inventions. In the first study, "The Effect of Telecommuting on Information Acquisition: Evidence from the U.S. Patent Office," I examine whether telecommuting affects the acquisition of new information in an environment where thorough search and acquisition of information are essential. I find employees' acquisition of new information increases following telecommuting. Further, I find this effect is greater for employees under greater time pressure and employees experiencing greater distractions at the workplace before telecommuting, and find telecommuting causes adverse consequences for employees least responsive to organizations' incentive systems. Finally, I find the acquisition of new information improves work quality. These results suggest telecommuting benefits employees performing knowledge-intensive tasks by facilitating employees' information acquisition.

In the second study, "Subordinates' Task Performance and Departure Rates when the Supervisor Works from Home," I examine scenarios in which highly experienced supervisors work from home and relatively inexperienced subordinates work at the office. Specifically, I examine whether such scenarios affect task performance and subordinates' departure rates. I find causal evidence that task performance is lower when the supervisor works from home, relative to when the supervisor works at the office. I also find the negative performance effect of the supervisor working from home is more pronounced for more complex tasks, which have a greater need for advising. Further, my findings suggest subordinates working with home-working supervisors are less likely to remain with the organization. My results highlight the importance of in-person interactions in advising relatively inexperienced employees performing technical analysis in organizations.

This dissertation contributes to the literature by finding countervailing effects of telecommuting policies. The first study contributes to the telecommuting and management control literatures by identifying a productivity-enhancing mechanism through which employees' productivity increases following telecommuting. By contrast, the second study provides new insight into the effectiveness of working-from-home policies by finding negative effects on task performance when supervisors charged with overseeing work done by their relatively inexperienced subordinates work from home. Collectively, this dissertation finds moderating factors and scenarios in which telecommuting policies positively or negatively influence various dimensions of employee performance.

This dissertation is subject to the limitation that it uses observations from a single organization, and it is an open question whether I can generalize results from a single research site. Specifically, at the USPTO, examiners' production performance is measured at the individual level with a precisely developed system under which every action made by an examiner on patent applications is recorded and examiners earn incentive bonus payments if they exceed their production goals. Therefore, it is unclear whether my results generalize to settings in which measuring individual performance is difficult. Future research could attempt to expand on my results.