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Autonomy versus Learning Effects at the United States Patent Office

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While employees might prefer work arrangements that offer greater autonomy, such as work from anywhere (WFA) policies, there are possible negative productivity effects of WFA, due to a lack of learning from co-located peers and increased coordination costs. We study the effects of WFA on productivity at the United States Patent and Trademark Office (USPTO) and exploit two features of the setting that lend themselves to econometric analysis: First, our setting allows us to tease out how the lack of opportunities to learn from co-located peers, affects productivity. Second, we exploit a natural experiment in which the implementation of WFA was driven by negotiations between managers and the union of patent examiners, leading to exogeneity in the timing of individual examiners' transition to WFA. We observe mixed results of WFA across experienced and new hires: for experienced hires, WFA results in a 3.9% increase in output and a 24% reduction in turnover, without affecting the proportion of rework. For new hires, an increase in output due to WFA is followed by an additional increase in rework, indicating a negative learning effect from the lack of colocation with experienced peers. We employ micro-data on cost of living, degree of autonomy, and proxies for examiner effort, to shed light on mechanisms. Back-of-the-envelope welfare estimates indicate that the 3.9% increase in patent grants at the USPTO could potentially create $1.16 billion in value for the U.S. economy.

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INTRODUCTION

Whether companies should offer remote work policies is the subject of intensive debate. Despite high-profile retreats from remote work policies by companies like Yahoo and IBM (Swisher, 2013; Simon, 2017), several organizations such as NASA, Amazon, Apple, Akamai, GitHub, American Express and Glassdoor offer remote work programs to employees.[2] Demand for remote work and other flexible work arrangements is driven in large part by the costs of commuting, child care, and elder care faced by a population increasingly comprised of dual-career families (Council of Economic Advisors, 2014).[3] Nonetheless, recent evidence suggests that companies are increasing controls over remote work policies (IFMA/WE, 2018), reflecting the fact that managers and firms continue to struggle in achieving the right balance for remote work.

One of the reasons for the lack of direction in setting remote-work policies has been a paucity of robust empirical research on the impact of remote work policies on worker productivity. While there exists a rich literature on the productivity effects of non-pecuniary incentives (Sauermann & Cohen, 2010; Kryscynski 2011), with the exception of Bloom, et al., (2015), robust empirical research on the productivity effects of remote work is relatively thin. Additionally, prior research on remote work has not fully explored a core theoretical tension underlying this debate: the inherent conflict between the benefits and costs of giving workers autonomy.

On one hand, we know that workers value autonomy, and that remote work has been related to increased perception of job autonomy (Gajendran & Harrison, 2007). Modern theories of motivation, such as self-determination theory (Ryan & Deci, 2000) and the job characteristics model

[2] Source: https://www.glassdoor.com/blog/companies-that-let-you-work-remotely/

[3] In its State of the American Workplace survey, Gallup noted that it "consistently has found that flexible scheduling and work-from-home opportunities play a major role in an employee's decision to take or leave a job" (2017: 5). Another survey finds "74% of employees saying they would quit their jobs to work for an organization that would allow them to work remotely more often, even if their salary stayed the same" (Softchoice, 2017:3). A contemporaneous benefits survey reports that 40% of surveyed firms indicated that offering more flexible work arrangements was one of their most effective recruiting strategies (Society for Human Resource Management, 2017). In this survey, 62% of firms reported allowing some type of remote work/telecommuting.

(Hackman & Oldham, 1976) are fairly explicit that offering workers autonomy in their jobs is a potentially powerful source of intrinsic motivation, leading to higher employee performance outcomes. Economists agree that non-monetary job characteristics such as autonomy can be an effective form of intrinsic motivation (Sauermann & Cohen, 2010).

Yet, granting autonomy might also decrease productivity, particularly in the context of remote work, through two possible mechanisms: the loss of learning from co-located peers and additional coordination costs. There is a rich prior literature documenting the relationship between geographic proximity and learning (Allen, 1984, Jaffe, Trajtenberg, & Henderson, 1993; Singh and Marx 2013; Choudhury, 2015, 2017; Catalini, 2017). Remote work practices could negatively affect learning as workers are no longer co-located, and this negative effect is likely to be more salient for newly hired workers, who lack task- and firm-specific human capital (Becker, 1964; Gibbons & Waldman, 2004). Additionally, the firm has been viewed as a system to coordinate effort and communicate knowledge across multiple intra-firm actors (Srikanth and Puranam, 2014; Grant, 1996; Thompson, 1967). Altering the spatial distribution of employees changes the means of coordination, limiting the ability of workers to rely on tacit coordination mechanisms (Srikanth & Puranam, 2014), and potentially leading to increased coordination costs via difficulties in knowledge-sharing. (Cramton, 2001; Gibson & Gibbs, 2006). Thus, any management practice – such as remote work – which increases worker autonomy while also increasing learning barriers and coordination costs naturally triggers a fundamental question: Will the productivity gains realized from higher autonomy be offset by higher learning and coordination costs? We believe that this question is at the heart of much of the current debate about remote work policies.

We begin to address this debate with a study that leverages the ideal setting to observe productivity effects from remote work: a context where the completion of tasks requires relatively less coordination among workers and where a natural experiment allows us to control for several endogeneity concerns. Our setting exhibits pooled interdependence, a form of interdependence with potentially few requirements for coordination (Thompson, 1967). In settings where workers have a higher need to coordinate with peers, any observed decline in productivity from remote work could be due to higher learning and/or coordination costs and the econometrician would not be able to easily disentangle the two effects. However, prior research has shown that patent examination is mostly conducted by a single patent examiner working on her own (Lemley and Sampat, 2012; Choudhury et al., 2018). Hence, our context enables us to disentangle these two mechanisms, enabling us to focus on how remote work affects productivity exclusively through the effects of learning from co-located peers. Importantly, we are able to further isolate the effects of learning on productivity by looking across experienced and newly-hired workers, as the latter group has arguably lower levels of firm- and task- specific human capital and thus a stronger need to learn from co-located peers

Our setting also allows us to exploit a natural experiment related to the implementation of a relatively strong case of remote work – a work-from anywhere (WFA) policy. The bureaucratic process governing the implementation of the WFA policy at our setting, the U.S. Patent and Trademark Office (USPTO), allows us to mitigate endogeneity concerns related to worker selection into the WFA policy. We exploit a natural experiment in which the implementation of WFA was driven by negotiations between USPTO managers and the union of patent examiners, leading to a monthly enrollment quota that created exogeneity in the *timing* of individual examiners' transition to WFA. Exploiting this bureaucratic policy-induced variation, we employ within-examiner fixed effects and find that experienced examiners enjoy an increase in work output of 3.9% when on the WFA program, with no significant increase in the amount of rework. Similarly, we find that experienced employee turnover falls substantially–on the order of 24% –when an employee enrolls in WFA. To study the effect of learning on productivity, we separately estimate effects for newly hired workers who migrate to WFA. We find that while new hires also enjoy increases in output, roughly 54% of this increase in output is offset by rework. We interpret this increase in rework as a learning effect: newly-hired workers who are *not* physically co-located with experienced colleagues face greater difficulties in learning tacit knowledge needed to perform their task. We additionally present evidence related to a key mechanism, autonomy; namely that remote work programs offering higher levels of autonomy result in greater increases in output. Finally, we test whether measures related to examiner effort and leniency change when an employee transitions to WFA—we find no evidence of increased leniency or reduced effort, as measured by examiner-added citations. Using the mean value of a patent to a U.S. assignee estimated by Bessen (2008), our back-of-the-envelope calculations also indicate that a 3.9% increase in production of patent grants at the USPTO potentially creates $1.16 billion in value for the U.S. economy.

Our findings contribute to the literature on remote work and nonpecuniary incentives. By unpacking a core theoretical tension on the benefits and costs of granting workers autonomy, our results show WFA can lead to productivity gains, especially for experienced workers in a pooled-interdependence regime. Our results also contribute to the literature on worker colocation and productivity. While the colocation literature has shown evidence that colocation affects collaboration and knowledge spillovers, we shed light on a novel complementary mechanism on how colocation affects productivity: our study design enables us to study the effect of colocation on individual learning and individual worker productivity. We contribute to the management practices literature, by helping to reconcile some conflicting prior findings about the impact of family-friendly work practices on productivity.

REMOTE WORK: A FORM OF NON-PECUNIARY INCENTIVE

In this paper, we examine the effects of one type of a non-pecuniary incentive – a work-from-anywhere (WFA) policy – on employee productivity. In prior literature, non-pecuniary incentives provided by firms to workers – such as challenge and autonomy (Sauermann & Cohen, 2010), information on quality of work (Kolstad, 2013), and tolerance of early failure (Azoulay, Zivin & Manso, 2011; Ederer & Manso, 2013) – have been shown to have effects on worker productivity that is incremental to the effects of pecuniary incentives. Sauermann & Cohen (2010) argue that pecuniary incentives are designed to appeal to employees' extrinsic motivations, while non-pecuniary incentives appeal to employees' intrinsic motivations by enabling them to gain greater satisfaction and challenge from the work itself. Prior research on incentives has argued that employers should design both wages and non-monetary benefits to best attract an ideal employee; however, the hedonic wage analysis literature predicts a "negative trade-off between wages and 'positive' job attributes, attributes like status or flexibility in hours of work" (Lazear & Shaw, 2007: 102-103). Indeed, empirical research demonstrates at least some willingness to exchange wages for non-monetary benefits (Stern, 2004). Mas & Pallais (2017) find that on average, workers are willing to accept 8% lower wages in exchange for a remote work option, suggesting that remote work policies are perceived as a valuable non-pecuniary benefit by employees. However, in some cases (such as the USPTO), the firm does not decrease wages for employees choosing a WFA regime. As stated earlier, this raises an interesting question for scholars of strategic human capital, economists, and practitioners alike: holding wages equal, does implementing a remote work policy yield a net benefit to an organization?

THEORETICAL TENSION: THE BENEFITS AND COSTS OF AUTONOMY

In our view, the answer to this question lies in the nuanced interplay between the benefits and the costs of granting employees increased autonomy over their work. The WFA regime that we study is arguably a strong version of employee autonomy, with employees granted the ability to determine their work location anywhere within the continental United States. Yet with increased autonomy comes reduced employee learning opportunities from co-located peers, as well as increased coordination costs. Prior theory has shown that coordination costs are most importantly shaped by the level of task interdependence prevalent in the focal firm, which in our pooled-interdependence setting is quite low. This low-coordination condition enables us to focus on the productivity effects of reduced learning opportunities from co-located peers in a WFA setting.

Autonomy

Theories of motivation have argued that autonomy is a core driver of individual intrinsic motivation (Ryan, Kuhl & Deci, 1997), and that jobs giving employees autonomy are more likely to be motivating (Hackman & Oldham, 1976). Autonomy has also been positively related to employee satisfaction (Fried & Ferris, 1987; Humphrey, Nahrgang & Morgeson, 2007), engagement (Rupp, et al. 2018) and self-esteem (Schwalbe, 1985). A longstanding literature with roots in human relations theory has also argued that worker satisfaction is strongly related to worker performance (Vroom, 1964; Schwab and Cummings, 1970; Petty, McGee and Cavender, 1984), suggesting that increased autonomy should enhance job performance, via intrinsic motivation and greater worker satisfaction.

Coordination Costs and Interdependence

Coordination costs can reduce or even outweigh the benefits of remote work particularly in information-intensive fields (Kotha, George & Srikanth, 2013). Building on Lawrence and Lorsch (1967), Grant (1996) viewed coordination costs as necessary to reduce intraorganizational goal conflicts. Prior research also indicates that coordination costs vary based on the "interdependence regime" prevalent in the focal firm. Thompson (1967) outlines three different types of interdependence, the weakest of which is pooled interdependence, in which each organizational part (e.g. worker) renders a discreet contribution to the whole and each is supported by the whole. Thompson (1967) also builds on March and Simon (1958) to discuss how coordination between organizational actors depends on the interdependence regime. With pooled interdependence, coordination is achieved by standardization, i.e. establishment of routines or rules which constrains action of each worker, rather than the mutual planning and adjustment among workers required in high-interdependence contexts.[4]

Co-location and Learning

Another possible negative effect of increasing autonomy through remote work is a reduced opportunity to learn from co-located workers. There is a rich literature on learning within organizations (Grant 1996; Argote 1999. Edmondson 2002). Edmondson (2002) argues that organization learning is local, interpersonal and variegated. Argote and Miron-Spektor (2011) outline that learning could be related to 'declarative knowledge or know what' or to 'procedural knowledge or know how'. Building on Polanyi (1966), Dasgupta and David (1994) argue that know how is often tacit and define tacit knowledge as the "context which makes focused perception possible, understandable and productive" (Dasgupta and David, 1994: 493)

Past research strongly suggests that colocation results in knowledge spillovers among workers (Allen, 1984, Jaffe, Trajtenberg, & Henderson, 1993; Singh and Marx 2013; Choudhury, 2015, 2017; Catalini, 2017). This literature dates back to Allen (1984) who reported an exponential decline in communication between workers based on the physical distance that separated them. Colocation might help workers explicitly seek knowledge needed to perform their task from peers; this knowledge might be either codified or tacit. In a recent paper, Choudhury (2017) argues that in a distributed organization, face-to-face interactions between workers leads to sharing of tacit knowledge and affects individual-level innovation outcomes. Catalini (2017) finds that colocation increases the likelihood of joint research by 3.5 times, an effect that is mostly driven by higher search

[4] In the second type of interdependence which Thompson (1967) describes as sequential interdependence, worker A must act before worker B can act. The third form of interdependence can be labeled as reciprocal interdependence referring to the situation in which the outputs of each become the inputs for the others. With sequential interdependence, coordination is achieved by planning, i.e. the establishment of schedules for the interdependent workers, by which their actions are governed. For reciprocal interdependence, coordination is achieved by mutual adjustment, i.e. the transmission of new information and feedback between interdependent workers, during the process of action.

costs ex ante. Colocation might also help novice workers' vicarious learning from experienced peers, through transfer mechanisms including demonstration, personal instruction and by provision of expert services such as advice, and consultation (Coleman, Katz and Menzel, 1957; Dasgupta and David, 1994; Greenwood et al., 2017; Myers, 2018; Thornton and Thompson, 2001).

RESEARCH CONTEXT

The ideal setting to observe productivity effects from WFA, particularly to tease out the effects of altering colocation patterns on learning from peers, is an organization where the completion of tasks requires relatively low coordination among workers. This thinking led to our choice of the empirical context: the United States Patent and Trademark Office (USPTO).

The USPTO is a federal government agency with the authority to evaluate patent and trademark applications. The agency employs just under 13,000 people, including slightly more than 8,000 patent examiners. The USPTO is headquartered in Alexandria, Virginia, with satellite offices in Detroit, Michigan; Denver, Colorado; San Jose, California; and Dallas, Texas. Patent examination comprises roughly 90% of USPTO's work; in 2015, the USPTO received 629,647 patent applications and granted 325,979 patents spanning a wide range of industries and technologies (Choudhury, Khanna, Mehta, 2017).

A patent application specifies a set of "claims" that defines the invention that the applicant wishes to protect. Applications are assigned to examiners based on the required area of technical expertise (software, chemicals, mechanical, etc.). Examiners are organized by nine "technology centers," each made up of smaller "art units." Within a given art unit, a Supervisory Patent Examiner (SPE) assigns each new patent application to a specific patent examiner (Lemley & Sampat, 2012). The examiner is then responsible for reviewing the claims and moving the application through the examination process, with minimal supervisory oversight. Examiners must determine whether patent claims in applications meet criteria of "novelty" and "non-obviousness" in order to be patentable. In order to determine the validity of claims in an application, the patent examiner uses several proprietary search tools to review the body of publicly available work (called "prior art," and including existing patents, published patent applications, academic and trade journal articles and other publications). In order to determine "novelty," the examiner must determine that the claims within the application are not already wholly addressed by another single patent or published work. For the criterion of "non-obviousness," the examiner must determine whether there are parts of existing patents that could easily (or "obviously") be combined to result in the invention claimed in the application (Frakes & Wasserman, 2017).

Once the examiner has (to her knowledge) exhausted the existing prior art, she issues a "first office action," which can be an "allowance," accepting all claims as patentable, or, more commonly, a "non-final rejection," which indicates that some or all claims are not patentable, and gives the basis for such rejection. Applicants can respond by either withdrawing, narrowing, clarifying, or providing further evidence to support rejected claims. The examiner then reviews the response, accepts additional claims as applicable, and issues another office action. This process continues until the examiner believes that no further response will change the outcome of an application, at which point she issues a "final action." Upon receiving a final action, the applicant has the choice of abandoning all remaining rejected claims, appealing the action to a board of appeal, or re-starting the application process by paying an additional $1,200 fee to initiate a "request for continued examination" (RCE). The RCE re-starts the entire examination process but is carried out by the same examiner, and takes into account all prior communication. There is no limit on the number of RCEs an applicant may file, and approximately one-third of all applicants file at least one RCE, though few file more than three. Our field interviews indicate that applicants often choose to file an RCE because the examiner and the assignee "do not agree on the interpretation of the text related to claims and which prior art should be considered in examining the claims".

Patent examiners are typically highly educated, holding undergraduate degrees in science and engineering, and some holding advanced degrees in technical fields. New employees are hired at a specific grade level (in line with hiring and employee ranking procedures at all federal agencies) based on their experience and skills. At the USPTO, examiners are hired at the civil servant 'grade levels' GS-5, GS-7, GS-9, GS-11, GS-12, GS-13, GS-14, or GS-15 level, with pay and responsibilities increasing with each grade. During labor negotiations, examiners are represented by the USPTO's union, the Patent Office Professional Association (POPA).

The USPTO measures examiner productivity using the number of actions completed by an examiner within a given period of time in relation to an expected productivity level, which is determined based on examiner grade level (a proxy for experience) and the examiner-specific case mix—examiners in more nuanced or complex fields are granted more time to examine a given application. First office actions are weighted more heavily than subsequent rulings in the count of total actions completed. The expected time to complete an action drops as examiner grade and seniority increase, with the highest-level examiner receiving approximately half the time of the lowest-ranked examiner to do the same work.

Following the USPTO's measures, we take number of actions in a given period as the measure of examiner production. We consider number of RCEs in a given period to serve as a measure of re-work. While we recognize that this is an imperfect measure (an inventor is well within rights to doggedly pursue a patent claim via an unlimited number of RCEs, regardless of the accuracy and quality of the examiner's ruling), our field interviews with USPTO personnel leave us satisfied that on balance, a greater number of RCEs for a given examiner is likely to indicate a greater need for rework.

The process of patent examination is largely an individual exercise, but with some supervisory constraints. At lower grade levels, patent examiners are typically newer and less experienced in their fields, and therefore must obtain approval on their actions from a either their assigned SPE or a senior patent examiner. However, given the independent nature of the task, even for junior examiners, there is relatively little coordination that needs to be managed between the examiner and his or her supervisor.

Our field interviews also revealed the importance of learning from peers for examiners to perform their task. The most important knowledge that examiners had to learn from experienced peers related to *how to construct the prior art search string*. Our field interviews revealed that patent lawyers representing firms filing the patents often engaged in "strategic behavior" in framing the language comprising the patent claims. Patent lawyers engaged in this behavior to "secure the broadest possible claims". This phenomenon has been discussed in prior literature (Choudhury, Starr and Agarwal, 2018); for a theoretical discussion, see Anton and Yao, 2004). Given this strategic behavior, our field interviews revealed that experienced patent examiners often "added keywords to their search that comprised language that went beyond the text of the patent claims being examined". This knowledge was relatively tacit and patent examiners often asked co-located colleagues for their knowledge in framing a search string. Our interviews also revealed that novice examiners engaged in vicarious learning on framing search strings, by observing experienced examiners.

Remote work programs at USPTO

The USPTO experimented with more than one remote work program: at one end there was a classic WFA program called "Telework Enhancement Act Pilot Program (TEAPP)" which allowed eligible examiners to live and work at any location in the U.S.; on the other hand, the USPTO implemented remote work programs such as the "Patents Hoteling Program (PHP)" that offered examiners less autonomy on location choice. Below we describe institutional details related to all the remote work programs at the USPTO. The bulk of our empirical analysis focuses on the TEAPP program, to which we will refer hereafter as "WFA."

This paper will focus on the two most prominent telework programs at USPTO: WFA (i.e. TEAPP) and PHP. The USPTO introduced the voluntary Patents Hoteling Program (PHP) in January 2006 with an initial cohort of 500 patent examiners. The PHP provides eligible employees with equipment and remote access to systems and allows them to work from home up to four days per week. When they report to the office, they reserve desk space through an online system. Initially, eligibility for the program was limited to those at the GS-14 level and above, but in subsequent years, this was lowered to GS-12. In addition, participants must have worked at the USPTO for at least two years and demonstrated "satisfactory performance". Eventually, the PHP program grew to include two sub-programs – (1) the "PHP within 50 miles" program (i.e., those examiners who lived within the 50 mile radius of the USPTO headquarters in Alexandria and reported to the USPTO headquarters at least once per week) and (2) the "PHP greater than 50 miles" program (i.e. those examiners who lived at least 50 miles from headquarters but still were required to report to the USPTO headquarters at least once a week).

In December 2010, President Barack Obama signed the Telework Enhancement Act, which set standard rules and regulations for remote work at federal government agencies. Thus, in early 2011, the USPTO began planning to pilot a WFA program (i.e., TEAPP), allowing employees "to work anywhere in the contiguous U.S. (greater than 50 miles from the USPTO)" and traveling to headquarters periodically, at their own expense. In other words, WFA awarded eligible patent examiners freedom to choose their geographic location. Importantly for our purposes, the USPTO did not adjust wages for employees opting to participate in either the PHP or WFA programs; this feature helps us to test the net impact on firm productivity of the WFA benefit in the absence of any offsetting reduction in wages.

Employees were eligible to participate in WFA if they: 1) were already enrolled in the "PHP greater than 50-miles" program, 2) had access to the Internet and USPTO systems, 3) agreed to change their "duty station" (i.e. home office) to a location greater than 50 miles from USTPO headquarters, and 4) waived their rights to travel reimbursement for required trips back to headquarters. The USPTO capped the number of trips that teleworking employees would need to make to headquarters at 12 days and/or five trips during a fiscal year. The USPTO also provides WFA workers with online communication tools such as Microsoft Lync, WebEx webinar services, and Cisco Voice over Internet Protocol (VoIP). Remote workers report hours worked on a biweekly timesheet. On January 30, 2012, the USPTO officially launched the WFA program.

HYPOTHESES DEVELOPMENT

We first develop hypotheses on whether a WFA regime results in increased employee productivity for experienced workers. In prior literature, improvements related to remote work appear to relate to both time gained from not having to commute to the office and the higher quality work environment. Bloom et al. (2015) found evidence that telework led to a 13% performance increase; 9% was due to fewer breaks and less sick days and 4% was due to a "quieter and more convenient" work environment. Improved work-life balance is one way that employers can increase intrinsic motivation of employees, particularly employees whose incentives are aligned to maintaining a balance between work and personal life (Akerlof & Kranton, 2005; Sauermann & Cohen, 2010). Much of the improvement in productivity appears related to the increase in available time made possible by the elimination of commuting to and from work; this newly found time appears to be split between additional time spent working, and additional time devoted to family and personal life (Bloom, et al., 2015).

It seems likely that the benefits identified in Bloom et al (2015) would be mirrored in our context. WFA employees at the USPTO have no mandated commute time (assuming a base case of working at home), other than the occasional trip to headquarters in Alexandria. Because of the independent nature of the work, examiners can also enjoy more flexible working hours, unlike the subjects in Bloom, et al (2015), who, as customer service representatives, were tied to specific work schedules, despite their remote work location.[5] So, it is safe to assume that WFA at the USPTO offers employees increased autonomy in both place and time of work, well above that available to employees who were working in the office. Given the literature on autonomy and productivity discussed earlier, within our context, we expect to see that an implementation of WFA results in increased work output, particularly among experienced employees, who have already reached diminishing returns to learning from co-located peers. We hypothesize:

H1a: For experienced workers who work in a pooled-interdependence (low-coordination) setting, transition into a work-from-anywhere regime leads to higher work output.

To study the net productivity effects of implementing WFA, we turn our attention to the effects of implementing WFA on an examiner's level of rework. In a more general setting, while increased autonomy awarded by WFA could positively affect work output, WFA could result in higher rework due to both increased coordination costs and fewer opportunities to learn from co-located peers. However, we argue that in our setting neither of these effects are likely to affect rework, especially for experienced patent examiners.

First, experienced patent examiners are not likely to suffer negative learning effects due to lack of colocation with peers. As prior research (Katila and Ahuja, 2002; Rosenkopf and McGrath, 2011, Argote and Miron-Spektor, 2011) has shown, learning by doing is accrued through the experience of performing a task repeatedly in the past; experienced patent examiners are expected to

[5] In the case of USPTO, employees working in Alexandria may be allowed some flexibility in work hours (under the U.S. government employees' Flex Time policy, https://www.opm.gov/policy-data-oversight/pay-leave/work-schedules/fact-sheets/alternative-flexible-work-schedules/), but this is typically a shifting of hours within a relatively narrow band of weekday time (e.g., 7:30am-4:00pm versus 9:30am-6pm).

have already developed the requisite absorptive capacity (Cohen and Levinthal, 1990) and task-specific human capital, to perform tasks such as prior art search.

Second, as described earlier, patent examiners carry out their tasks (researching, searching for prior art, writing decisions, and communicating with applicants) independently and there are relatively few requirements to coordinate with peers. In this pooled-interdependence setting, patent examiners reach out to peers mainly to seek advice on relevant prior art. WFA examiners at the USPTO have technological tools which allow them to access pooled knowledge of peers. Experienced examiners could continue to leverage their intraorganizational social ties even after migrating to a WFA program and our field interviews yielded examples of experienced WFA examiners calling peers (who might be based in Alexandria or elsewhere) on the video-conferencing calling tool WebEx to ask "do you have a search for me?" (that is, have you searched this topic previously and if so could you share the results?) or "Can you take a look at my drawings and suggest prior art?" WFA workers can share their computer screens on the USPTO's WebEx tool to look at relevant drawings or other documents.

In summary, experienced examiners have already developed firm- and task- specific human capital and have technological means to reach out and seek advice from prior co-located colleagues. Given this, we anticipate that the amount of rework will *not* increase after such employees move to a WFA regime. We hypothesize:

H1b: For experienced workers who work in a pooled-interdependence (low-coordination) setting, transition into a work-from-anywhere regime does not lead to an increase in rework.

To further study beneficial productivity effects due to increased autonomy, we study turnover. As discussed previously, job autonomy plays a significant role in increasing several employee outcomes which ultimately enhance productivity. One of the outcomes through which autonomy could create value for the firm is reduced employee turnover. Humphrey, Nahrgang & Morgeson's (2007) meta-analysis reveals no significant relationship between autonomy and turnover intention yet does find a negative relationship between autonomy and absenteeism, which has been related to *actual* turnover, in addition to turnover intention (Borda & Norman, 1997). The stronger relationship to absenteeism suggests that, consistent with the self-determination theory of motivation (Ryan & Deci, 2000), employees with lower levels of autonomy may be more likely to work with a lack of intrinsic motivation, withdrawing from work (via absenteeism) even if they are not willing or able to actually leave the job. We expect to find that transferring a group of employees from working at the office to a WFA regime (thus increasing their autonomy) would lead to reduced turnover of those employees. This effect is expected to be particularly salient for experienced workers, who as theorized above are less likely to be affected from negative learning effects due to lack of colocation. We hypothesize:

H1c: For experienced workers who work in a pooled-interdependence (low-coordination) setting, transition into a WFA regime will be associated with a subsequently lower turnover rate among those workers.

We next study the effects of WFA on inexperienced, new hires and theorize about two separate effects related to (i) work output, and (ii) learning and rework.

In terms of work output, we anticipate a benefit of WFA in relation to new hires: the broadening of the available pool of talent. Dahl and Sorenson (2010) estimate a strong revealed preference of knowledge workers to live close to family and friends. Relatedly, the literature reports psychic costs of being separated from family and friends (Sjaastad, 1962; Schwartz, 1973; Choudhury and Kwon, 2018), which can be lessened by the work location being closer to one's hometown. Given the utility-maximizing choices of individuals to live close to home, firms might be more able to attract better quality talent if individuals could join the firm but keep working from a location closer to friends and family, as they could under a WFA regime. The ability to recruit from a broader base implies that an organization will have access to a larger pool of high-quality candidates, and as such, is likely to recruit an overall higher quality worker. Accordingly, we expect that WFA allows the USPTO to recruit a higher-quality set of examiners that should exhibit a disproportionate increase in their work output relative to experienced workers who migrate to WFA. We hypothesize:

H2a: Newly hired workers, recruited after the implementation of a work from anywhere policy will have disproportionate gains in work output when they become WFA workers, compared to experienced workers who transition to WFA.

Finally, we recognize the deleterious effects of the lack of co-location on learning and expect that this effect will be more salient for new employees. Newly hired workers could experience greater challenges in learning in a WFA context, due to lower level of interaction and familiarity among co-workers (Hinds & Bailey, 2003). Remote workers may find ways to gain explicit knowledge through electronic communication with co-workers and supervisors, but are less likely to benefit from the transfer of "tacit knowledge," that is, knowledge that is undocumented (and sometimes unspoken), but is a core means of knowledge transfer among members of an organization (Nonaka, 1994). Not being collocated with experienced workers could especially affect the ability of newly hired workers to engage in vicarious learning, or learning passed on by demonstration (Myers, 2018). Even with the availability of online collaboration tools, these newly hired remote might not even know what questions to ask to their experienced colleagues or to their supervisor. For example, newly hired workers might especially lack knowledge on how to compose the prior art search string, an important component of an examiner's work. Although this lack of learning might not lead to a reduction of output, it might affect the accuracy of an examiner's search, leading to a greater rate of rework, particularly given the strategic behavior of patent lawyers in drafting the language of claims described earlier. We hypothesize:

H2b: Newly hired workers will have disproportionate increases in rework when they become WFA workers.

DATA

This project draws on four main sources of data. We begin with a unique administrative dataset obtained from the USPTO for the years 2007 to 2015 that reports, annually, all patent examiners on the USPTO payroll, their General Schedule (GS) pay level, and a benchmark measure of productivity used for promotion decisions (as a function of the 'United States Patent Classification' or USPC class of their examined patents). We link this data to a separate administrative dataset, again obtained from the USPTO, which identifies which examiners are enrolled in a remote work program, their current home office location, and when they began remote work. From here, we link the combined examiner datasets to publicly available USPTO data on applications and transactions (such as RCEs and examiner-added citations) to quantify examiner-level output, rework, and effort (Table 1). Finally, we use existing county-level data on cost of living to shed light on how increased autonomy in choosing work location affects the cost of living for WFA workers.

[Table 1 about here.]

Examiner Personnel Data

The first dataset used for this study is an annual record of all patent examiners active at the USPTO from 2007 to 2015, with 10,442 unique examiners over these 8 years, inclusive. For the purpose of this study, turnover was defined as an examiner leaving the USPTO before 2015, with 1614 examiners leaving, or approximately 15.5%. This data also provides the GS, or grade level, of every USPTO examiner, data that is otherwise not public. As described earlier, the grade level of an examiner is of particular importance: it serves as a natural hierarchy for promotions, it is mechanically correlated to tenure and experience, and higher-grade examiners have increasing levels of autonomy in their workflow. Controlling for grade level is hence important to account for unobservable task-specific human capital of examiners (Gibbons and Waldman, 2004).

We also utilize a second unique USPTO-provided personnel dataset specifically focused on remote workers. This second dataset includes examiner identifiers, as well as which of the three remote work programs an examiner has enrolled in: WFA, PHP (<50 miles), and PHP (>50 miles). Figure 1 shows the growth in remote working across the three programs from 2007 to 2015, in which WFA appears to gain an increasing share of the teleworking population as examiners substitute away from PHP programs. The examiner-specific start date for each specific telework program is also included, allowing us to track an examiner across programs. This data also identifies the most recent city and state of a teleworking examiner (current as of August 2016), which is important for spatial analyses to be described later. Figure 2 visualizes the location of all teleworkers as of 2016.

[Figures 1 and 2 about here.]

Finally, we were provided with a dataset that included a measure of the expectancy associated with each USPC class, a benchmark measure of effort used for promotion and incentive compensation purposes. The expectancy measures the level of effort that an examiner would be *expected* to expend over a bi-week, as a function of the USPC classes of patents that the examiner is assigned. Naturally, some patent classes have lower expectancies than others—a complex cryptography patent may require more time (and less expected work in a bi-week) than a relatively straightforward mechanical device. Accounting for an examiner's expectancy is far more granular than simply accounting for an examiner's art unit: the expectancy value takes into account the mix of USPC classes for the patents on an examiner's docket and more accurately reflects the productivity benchmarks faced by an examiner at any given moment.

USPTO Patent Data

Data on patents and patent application level transactions were collected from a combination of two publicly available datasets: USPTO's Public PAIR (Patent Application Information Retrieval) dataset and the USPTO PatentsView database. Application data collected includes the name of the examiner assigned to a patent, the examiner's art unit, and the USPC classification of the application. For each patent, we then collect data on all transactions executed by an examiner, focusing on two specific metrics of productivity: total actions (measure of output) and RCEs (measure of rework). Total actions are a measure of aggregate output delivered by an examiner, aligning with the PTO's internal notion of expectancies. The second measure, RCEs, or requests for continued examination, are a measure of *rework*. As explained earlier, RCEs represent re-working a patent application when there is disagreement between the examiner and the applicant on the interpretation of the text related to both the claims and the prior art that should be considered in adjudicating the claims. In alignment with the availability of administrative data from the USPTO, we limit all subsequent patent data to the years 2007 through 2015. Across these 8 years, 2.76 million applications were examined by those all examiners, representing 703 art units, 466 USPC classes, with a total of 7,313,730 actions and 870,689 RCEs. As explained in a later section, to address selection concerns, our baseline estimations only consider examiners who self-selected into the WFA program in 2012-2013, and exploits the natural experiment among those examiners described below.

Spatial Data

City and state data on the most recent location of teleworking patent examiners was obtained through the USPTO administrative dataset on teleworkers. This data was then geocoded and mapped to U.S. counties using data from the U.S. Census Bureau in conjunction with open source GIS tools. Additionally, as a measure of relative cost of living, we utilize a county cost of living index from the Center for Regional Economic Competitiveness. For the purposes of this study, the index is centered at 0 for those examiners residing at the USPTO headquarters in Alexandria, VA, with lower cost of living areas having positive index values to represent positive savings.

IDENTIFICATION STRATEGY

To provide robust econometric estimates related to how the implementation of WFA affected work output, rework, and turnover at the USPTO, we exploit a natural experiment within the USPTO. As outlined earlier, the implementation of WFA was driven by negotiations between the USPTO management and the union of patent examiners. Specifically, these negotiations resulted in a monthly quota for how many eligible examiners could transition to WFA in the first 24 months of implementation of the program. Our field interviews indicated that the monthly quotas were over-subscribed and eligible examiners, in many cases, had to wait for several months to transition into the WFA program. Thus, in order to account for selection into WFA, we exploit the exogeneity in timing for *when* the examiner was able to transition to the WFA program to study how this transition affected production and rework. While it is likely that observable and unobservable factors determine whether or not examiners transition into WFA - we circumvent these concerns by focusing on the sample of examiners who selected to transition into the WFA program over the first 24 months and exploit variation in *when* (i.e. which month) the examiner could transition into WFA given the exogenous monthly quotas determined by the USPTO management and the union. Below we provide details of the implementation of the WFA program that lends itself into a natural experiment.

As a result of the negotiations conducted between the USPTO management and the union of patent examiners called "Patent Office Professional Association," or POPA, the USPTO planned to enroll participants in the WFA program in phases. Additionally, and importantly for the purpose of identification, there was an exogenous quota imposed on how many eligible examiners could be enrolled in the WFA program. The number of slots was decided by a committee comprising management and members of the union. Eligible patent examiners could apply to participate in WFA by submitting an online application and signing an agreement to waive reimbursement for travel expenses to headquarters. If a slot was not available, the employee was placed on a waiting list. Our field interviews indicated that "all slots allocated for the first several months were exhausted", implying that even if an examiner was eligible for WFA, she/he would have to wait an unknown length of time before she could transition to WFA. As such, the timing of when eligible examiners could transition to WFA was relatively exogenous. Our field interviews indicated that prior tenure, experience, or performance were *not* considered in allocating slots to eligible examiners.

To validate our natural experiment and these insights generated by the field interviews, we test whether the variation in WFA transition time was truly exogenous by regressing how long it took an eligible examiner to transition to WFA on observable measures of past performance. As our main results analyze productivity (and include a measure of the expected work as a control), we regress "months to WFA" on measures of total examiner-level output, rework, and expectancy (a measure of expected output), all in the previous year. Results from these analyses are reported later in the paper–we find no evidence of selection on prior performance (or other observables), validating our principle identification strategy.

ESTIMATION AND RESULTS

We focus on utilizing the natural experiment and limit our sample to examiners that enrolled in WFA in either 2012 or 2013. Within this sample, we exploit bureaucratic process-induced variation in enrollment dates to identify the effect of receiving WFA *earlier* than another examiner. As both examiners in this exercise must be eligible and have selected into the program, we avoid the traditional identification issues that arise from self-selection—all examiners in our sample can be thought of as treated, varying only in the amount of time that they have had to wait to be exposed to the treatment, i.e. WFA. Moving forward, we refer to this sample as the "WFA sample".

Evaluating Hypotheses 1a and 1b: Effects of WFA on Experienced Workers

Hypotheses 1a and 1b state that for experienced workers performing pooled-interdependence jobs, transitioning to a WFA regime will lead to both higher work output and no increase in rework, respectively. To evaluate these claims, we utilize the natural experiment described above and employ the following examiner-month level specification:

$$Output_{it} = \alpha_i + \beta_{it} * WFA + \xi_{it} + \gamma_t + \lambda_i + \epsilon_i$$

where *WFA* is a binary indicator that turns on (and stays on) when an examiner enrolls in WFA during the 2012 to 2013 time frame. As described earlier, we use two different measures of individual level output: we measure individual output using total actions and we measure individual rework using the number of RCEs. ξ_{it} is a vector of controls that includes examiner-month specific grade level and examiner-month specific expectancy, while γ_t is a full set of time (year) fixed effects, and λ_i is an optional set of examiner fixed effects. To account for concerns regarding intra-art unit correlation of error terms, standard error estimates are clustered at the art unit level to account for unobserved routines within a given art unit. We do not control for art unit in these (and subsequent) regressions, as our expectancy control is far more granular and more accurately reflects the nature of work performed by an examiner.

Columns 1-4 of Table 2 provide the focal set of results evaluating Hypotheses 1a and 1b, utilizing the natural experiment to infer the effects of WFA on both overall output as well as rework. These columns utilize the sample of existing examiners that transition to WFA in 2012 or 2013, leaving 66,980 examiner-month-level observations across 2007-2015.

[Table 2 here]

Columns 1 and 2 report results relevant to Hypothesis 1a--specifically, column 1 identifies the effect of WFA on the total number of actions completed by each examiner in a given month, with column 2 including a set of examiner fixed effects to identify the effect not just within the sample of examiners transitioning to WFA in 2012 and 2013, but *also* within those examiners. There is a positive, highly significant effect of WFA on overall output, roughly corresponding to a 3.9% increase in the total number of actions on a mean of 10.88 per month, supporting Hypothesis 1a[6].

Columns 3 and 4 present results relevant to Hypothesis 1b, with column 4 including examiner fixed effects (as in Column 2). Consistent with Hypothesis 1b, WFA does not increase the amount of RCEs, or rework, an examiner engages in either specification (with or without examiner fixed effects).

Hypothesis 1c states that experienced examiners will also experience a decrease in turnover, which we test by estimating the following specification:

$$Turnover_i = \alpha_i + \beta_{it} * WFA + \xi_{it} + \gamma_t + \lambda_i + \epsilon_i$$

with controls defined analogous to the previous exercise. Here, $Turnover_i$ is an examiner-specific dummy that identifies examiners who leave the USPTO during the period of our study which ends in 2015. For this exercise, we are unable to utilize the sample of examiners transitioning to WFA in 2012 or 2013, as it would leave us without enough variation in our outcome variable, so we rely on the full sample, utilizing grade-level controls.[7] As turnover is a binary outcome variable, the model is estimated via probit, but results are robust to OLS as well. As we are estimating attrition across all existing examiners, we limit our full sample to those examiners hired before 2012, yielding 554,699 examiner-months across 2007-2015. Column 5 of Table 2 provides results from this estimation exercise, where estimates of selection into WFA points to a reduction in the probability of turnover by 24%, supporting Hypothesis 1c.

Evaluating Hypotheses 2a and 2b: New Hires

Hypotheses 2a and 2b posit that due to the potential broadening of the hiring pool and the inability to learn tacit knowledge due to physical separation from experienced peers, newly hired employees

[6] 0.503/12.9 = 3.9%

[7] Examiner fixed-effects cannot be used here as they would naturally absorb all variation in the outcome variable, defined at the examiner level.

will experience disproportionate increases in both output and rework, respectively, when they transition to a WFA regime. We test this by utilizing our natural experiment and focusing on workers that began working at the USPTO when WFA was available (2012 and onwards). This sample of newly hired examiners would have minimal experience working at the Alexandria headquarters of the USPTO (as low as 6 months on a part time, PHP, basis) before transitioning to WFA. We estimate

$$Output_{it} = \alpha_i + \beta_{1it} * WFA + \beta_{2it} * NEW + B_{3it} * WFA * NEW + \xi_{it} + \gamma_t + \epsilon_i$$

where ξ_{it} is a vector of controls that includes examiner-month specific grade level and examiner-month specific expectancy and γ_t is a full set of time (year) fixed effects. We do not use examiner fixed-effects in this estimation exercise as that would absorb all variation in a key variable, NEW, coded as a binary indicator for those examiners joining the USPTO during the time frame that WFA was available, or 2012 and onwards. Table 3 reports results from a test of Hypothesis 2a, where column 1 shows that newly hired patent examiners experience disproportionate gains in output.

[Table 3 here]

Hypothesis 2b states that due to the lack of tacit knowledge, new hires will disproportionally face rework upon transitioning onto WFA. We run a similar exercise as above, where output here is now rework. Column 2 of Table 3 report results that broadly support this hypothesis—we see that rework increases disproportionately for new hires, and that roughly 54% of the increased overall productivity is spent on rework for this group of employees[8]. Both models are estimated utilizing examiners who transitioned to WFA in 2012 or 2013, now including those that were newly hired, yielding 67,088 examiner-months across 2007-2015. We note that results are robust to utilizing a

[8] 2.042/3.795 = 54% (WFA*NEW coefficient for rework/WFA*NEW coefficient for total output)

broader sample that includes all newly hired examiners, not just limiting to those that transitioned to WFA in 2012 or 2013.

Evidence on Mechanisms

Aside from robust econometric estimation of the effect of WFA on output, rework, and turnover, our setting allows us to tease out some evidence related to mechanisms. More specifically, we can tease out the effect of autonomy and estimate whether WFA offers greater productivity gains than more restrictive remote work regimes that offer less autonomy than WFA. To recap, the USPTO experimented with a series of remote work programs: at one end there was a classic WFA program (i.e. TEAPP) which allowed eligible examiners to live and work at any location in the U.S.; on the other hand, the USPTO implemented remote work programs such as PHP that offered examiners less autonomy on location choice. Given that the bureaucratic assignment to remote work is only valid for WFA, we can no longer rely on the natural experiment in this setting; we estimate the specification below within the full sample of existing examiners across all months (554,699 examiner-months from 2007-2015:

$$Output_{it} = \alpha_i + \beta_{1it} * WFA + \beta_{2it} * PHP_{<50} + B_{3it} * PHP_{>50} + \xi_{it} + \gamma_t + \lambda_i + \epsilon_i$$

where WFA, $PHP_{<50}$, and $PHP_{>50}$ are indicator variables for when an examiner enrolled in either of the three programs, indicators which remain on until the examiner switches programs. As before, ξ_{it} is a vector of controls that includes examiner-month specific grade level and examiner-month specific expectancy, while γ_t is a full set of time (year) fixed effects, and λ_i is a set of examiner fixed effects, which are of particular importance in this exercise as they allow us to track examiners as they switch from program to program. Again, to account for concerns regarding intra-art-unit correlation of error terms, standard error estimates are clustered at the art unit level. Table 4 provides results from this estimation exercise:

[Table 4 about here.]

Columns 1 through 3 report regressions of overall output on dummies for WFA and both PHP programs, with column 3 reporting results from the fully specified model. As these are all models with examiner-fixed effects, we note that the coefficients are semi-additive: WFA captures the effect of remote work above and beyond PHP (>50 miles), as examiners must enroll in the latter before eligibility for the former. Hence in this model, all telework programs increase productivity, with PHP (>50 miles) having the lowest effect, while PHP (<50 miles) has roughly twice the impact. The impact of WFA, when interpreted additively with PHP (>50 miles), is far above and beyond the other remote work programs. It is important to note that we interpret these results in the context of one another rather than as causal estimates; the full sample regressions illuminate the relative differences between the remote work programs rather than the absolute improvements themselves.

We next examine whether WFA examiners relocate to counties that lower their cost of living and in effect increase their real wages. Often used as justification for offering remote work programs and as evidence of remote workers benefiting from autonomy in choosing the work location, cost of living reductions are an important incentive for both employers and employees. While real estate cost reduction for employers is fairly obvious (and described earlier in the context of the USPTO), we now examine whether employees benefit from telework programs by selecting into lower cost-of-living areas. Utilizing previously-described county-level cost of living data, we estimate the effects of telework on an examiner's current home cost-of-living index relative to Alexandria, VA within both the full sample and the sample of examiners transitioning to WFA in 2012-2013. We estimate:

$$Cost\_of\_Living\_Reduction_{it} = \alpha_i + \beta_{1it} * WFA + \beta_{2it} * PHP_{<50} + B_{3it} * PHP_{>50} + \xi_{it} + \gamma_t + \lambda_i + \epsilon_i$$

where $Cost\_of\_living\_reduction_{it}$ is an examiner-specific measure of the reduction in the county cost-of-living index relative to Alexandria, VA, while *WFA*, $PHP_{<50}$, and $PHP_{>50}$ are indicator variables defined as before. This model similarly includes controls for year, grade level, and expectancy, but does not include examiner fixed-effects as those would absorb all time-invariant, examiner-specific variation in cost of living reductions. Columns 1 and 2 of Table 5 report results from regressions utilizing the full sample of examiners, both newly hired and existing[9]. We find evidence of substantial cost reductions associated with PHP (>50 miles) and WFA, on the order of two standard deviations in the distribution of cost reductions across all teleworking examiners. As expected, PHP (<50 miles) does not show evidence of cost reductions, as those examiners must live in and around Alexandria, VA.

[Table 5 here]

Robustness Checks

In order to validate our natural experiment, we look for evidence of selection in the time-to-WFA variation for those employees enrolling in WFA in 2012 or 2013. We estimate a model to determine whether previous performance or expected performance (expectancy) is correlated with how soon an examiner receives WFA. In order to do so, we limit our sample to those examiners active in 2011 who obtained WFA in 2012 or 2013 and estimate variations on the following model:

$$Months_i = \alpha_i + \beta_{1i} * Actions_{2011} + \beta_{2i} * RCE_{2011} + B_{3i} * Expectancy_{2011} + \xi_{it} + \epsilon_i$$

Where $Months_i$ is an examiner specific measure of the number of months (0-23) it took an eligible examiner that enrolled in WFA in 2012 or 2013 to actually get on the program. $Actions_{2011}$ refers to an examiner's aggregate performance in 2011, RCE_{2011} refers to the amount of RCEs an examiner worked on in 2011, and $Expectancy_{2011}$ was the examiner's average expectancy across all patents examined in 2011. ξ_{it} is a set of controls for an examiner's GS at the month level. Table 6 presents results from these regressions.

[Table 6 here]

[9] This sample has 600,941 examiner-month-level observations across 10,228 examiners. 207 observations were dropped as they corresponded to examiners without cost-of-living data.

We find no evidence of previous performance being correlated with the amount of time it took an examiner to transition to WFA, validating our identification strategy.

A potential concern is that examiners, upon transitioning to WFA, may potentially scale back or distort effort relative to their work prior to being a WFA worker. For instance, while examiners may increase overall output, it is *ex ante* unclear whether leniency and/or effort change. In the following exercise, we check for evidence of either of these distortions in our sample of examiners transitioning to WFA in 2012-2013 by estimating effects on application rejections, as well as examiner-added citations, which we use as a proxy for effort. We estimate the following model as before,

$$Output_{it} = \alpha_i + \beta_{it} * WFA + \xi_{it} + \gamma_t + \lambda_i + \epsilon_i$$

Where *Output* is defined as the count of first office actions, the count of rejections, and the count of examiner-added citations (at the examiner-month level), utilizing the same controls as before (examiner, year, grade-level, expectancy). Table 7 below reports results from this exercise.

[Table 7 here]

Considering columns 1 and 2, we find that the increase in first office actions is matched by a proportional increase in rejections. We interpret this as evidence that examiners are no more or less lenient upon transitioning to WFA. Column 3 reports results for examiner-added citations—we are unable to distinguish from the null here; there appears to be no reduction in examiner-added citations for those examiners transitioning to WFA.

Welfare Estimates

Using our estimates of 3.9% increase in examiner-level production (for experienced examiners) with no increase in the amount of rework (or RCEs), we can make a back-of-the-envelope calculation of the net profit increase at the USPTO under two assumptions. First, we assume that the 3.9% increase in total actions reasonably corresponds to a 3.9% improvement in patents examined, which we argue is plausible. Using the 3.9% increase in patent examination output, we can estimate that USPTO profit increases two ways, one simple and one more nuanced. One, we assume the number of examiners remains fixed and that pendency (i.e. number of outstanding patent examinations) is not a concern to the USPTO, and simply estimate a 3.9% increase on $3 billion in fees collected (USPTO Budget Report, 2017) with no increase in costs for patent examinations, for a total increase of US $138 million. A second, more realistic estimate would also consider the PTO's continuing concerns with pendency, which have caused the PTO to increase hiring substantially over the past few years (GAO report, 2008). The productivity improvements from WFA could reduce the need for new hires in addition to improving output (and hence, fees collected), so above and beyond the $38 million increase in fee revenue, we estimate a 3.9% reduction in FTE and the subsequent fixed hiring and variable wage costs. As the PTO hired 780 additional examiners each year, with an average salary of roughly $80,000 and hiring costs of roughly $20,000 (Choudhury, Khanna and Mehta, 2017), we estimate a one-time reduction of $0.7 million and a continuing annual cost savings of $2.9 million.

In addition, we provide evidence of the effectiveness of WFA for the USPTO based on survey and qualitative evidence. In 2013, due in part to the agency's remote work options, the USPTO was ranked highest on the "Best Places to Work in the Federal Government" survey.[10] Environmental benefits also accrue from the program; in 2015, the agency estimated that its remote workers avoided driving 84 million miles, thereby reducing emissions by over 44,000 tons. Finally, in 2015, the USPTO estimated that it saved $38.2 million in real estate avoidance costs due to remote workers freeing up office space at headquarters.[11]

[10] Source: https://www.uspto.gov/about-us/news-updates/us-patent-and-trademark-office-ranks-1-best-places-work-federal-government
[11] Source: https://www.uspto.gov/sites/default/files/documents/TeleworkAnnualReport2015-508.pdf

Finally, one particular feature specific to our setting is that the USPTO also helps set the rate of US innovation, standing as one last bottleneck in the traditional innovation process. A 3.9% increase in patent grants could lead to innovation spillovers that amount to a total of $1.16 billion. We arrive at this estimate through back of envelope calculations. Choudhury, Khanna and Mehta (2017) indicate that the average number of patent grants between 2009 and 2012 was 211,973 patents per year; this figure, taken into consideration with our estimated 3.9% increase in production, would lead to roughly 9751 more patents being granted every year. Prior literature also indicates that the mean value for patents granted to U.S. patentees was $78,168 in 1992 dollars (Bessen, 2008). The author also estimates the median value of a patent to a U.S. assignee to be $7175 in 1992 dollars. We convert the mean and median values of a patent to a U.S. assignee to 2018 dollars and estimate that a 3.9% increase in production of patents at the USPTO creates $107 million value for the U.S. economy (considering the median value of a patent in 2018 dollars) and $1.16 billion value for the U.S. economy (considering the mean value of a patent in 2018 dollars).

DISCUSSION

We study the relationship between WFA and worker productivity in a highly-skilled work context. Our choice of setting presents us with two important empirical opportunities. First, the presence of a natural experiment originating from a bureaucratic policy allows us to mitigate the impact of endogeneity of selection into a WFA regime. Second, our pooled-interdependence work setting allows us to tease out the effect of colocation (or lack thereof) on individual learning. We find nuanced effects of WFA on experienced workers and new hires: while both sets of workers experience an increase in work output, only new hires experience an increase in rework. We attribute this finding to a negative learning effect for new hires. We provide evidence on mechanisms, including cost of living, degree of autonomy, and examiner effort. A back-of-the-envelope calculation of the impact of the productivity increase under WFA suggests that the increase in patents granted due to higher examiner productivity could result in $1.16 billion of added value to the U.S. economy in the best-case scenario.

This paper makes contributions to research in the areas of non-pecuniary incentives, colocation and learning, remote work, and management practices. First, our findings suggest that under conditions of pooled interdependence such as those found at the USPTO, non-pecuniary incentives can be value-creating for both the firm and the worker; this insight adds to the literature on non-pecuniary incentives (Sauermann & Cohen, 2010; Kryscynski, 2011; Gambardella, Panico and Valentini, 2015; Katz, 2004; Stern, 2004). Our study suggests that the firm can create value through the addition of a non-pecuniary incentive such as WFA, without decreasing wages in the process, contradicting the underlying assumption of hedonic models of compensation. In fact, Lazear and Shaw (2007) questioned the assumption made in hedonic models that productivity enhancements from benefits do not outweigh the costs to the firm. We demonstrate that holding wages constant, the USPTO experienced a net increase in output per experienced employee, post implementation of WFA, providing evidence supporting the assertion made by Lazear and Shaw (2007) that wages and benefits need not be negatively correlated. Further, work by Kryscynski (2011) on firm-specific incentives suggests that companies can use non-pecuniary incentives such as WFA as a source of competitive advantage in recruitment and retention, by implementing the benefit in a way that creates greater value, as perceived by employees, than other firms. We interpret this to say that nonpecuniary incentives can and should be firm-specific. For instance, a firm could choose to provide a WFA option to experienced employees if the tasks performed by knowledge workers in the firm exhibit properties of pooled interdependence; on the other hand, WFA may not create value for other firms that exhibit stronger (i.e. reciprocal or sequential) interdependence regimes, and future research could examine this proposition.

Second, our results contribute to the literature on colocation and learning (Allen, 1977, Jaffe, Trajtenberg, & Henderson, 1993; Singh and Marx 2013; Choudhury, 2015, 2017; Catalini, 2017). As Catalini (2017) asserts, the effect of colocation on inventive outcomes using observational data is likely to return biased results due to selection effects. The prevalence of the natural experiment in our setting allows us to circumvent this concern and identify a negative effect of learning on rework for new hires. Catalini (2017) identifies beneficial effects of colocation on search and execution costs among potential collaborators. We complement these findings by shedding light on an additional effect of colocation, showing that colocation can also affect *individual* worker productivity, through the imposition of increased learning (of tacit knowledge) costs. We are aided by the nature of our context, in which collaboration is not salient, thus allowing us to tease out the learning effect. Our findings are consistent with past research showing that learning relates to access and exposure to the experience of others (Allen, 1977; Darr, Argote & Epple, 1995), and to one's own ability to gain hands-on experience (Katila and Ahuja, 2002; Rosenkopf and McGrath, 2011; Argote and Miron-Spektor, 2011; Myers, 2018).[12] We also contribute to the literature on learning at the organizational level, by providing a baseline result in a setting of low interdependence. Given that newly-hired examiners experience greater rework under WFA than they did in-office, future research should explore whether geographically distributed workers in a higher-interdependence context also struggle to gain the group-level learning from experience that leads to greater organizational performance (Reagans, Argote & Brooks, 2005). Our finding that new hires experience negative learning effects (as evidenced by increased rework) is also consistent with research on performance differences between external hires and internal promotions, suggesting that new hires brought

[12] Learning-from-others and learning-by-doing is enhanced by colocation (Darr, Argote, & Epple, 1995; Argote & Epple, 1990), suggesting that in our context, co-located examiners have more readily available opportunities to learn both the formal process established by the organization as well as the informal "shortcuts" developed by other examiners (Brown & Duguid, 1991).

directly into the WFA regime have fewer opportunities to gain the firm- and task-specific skills possessed by experienced workers (Bidwell, 2011).

Third, we contribute to the literature on management practices, specifically the literature on family friendly work practices such as remote work (Bloom et al., 2015). While our findings support the positive relationship between the autonomy granted by remote work and worker output presented by Bloom et al. (2015), we make several fundamental contributions to this literature. While studying a setting where the task (i.e. patent examination) is more knowledge intensive compared to the task performed by call center employees studied by Bloom et al. (2015), our study sheds light on novel mechanisms (e.g. learning from co-located peers, cost of living), novel measures of productivity (e.g. rework), and speaks to the theoretical tension around benefits and costs of granting autonomy to workers. While our results build on those of Gajendran, Harrison & Delaney-Klinger (2015), in that we find that at least under conditions of pooled interdependence, more autonomy leads to greater work output, we also find a nuanced nonlinear relationship between the intensity of autonomy and worker output. More specifically, we find in that a 'middling' amount of autonomy (i.e., PHP>50) is worse than very little autonomy (i.e. PHP<50) or a very strong case of autonomy (i.e. WFA), evinced by the relative comparison of work output reported in Table 4. This finding has practical implications for managers, in that it suggests that if a company hopes to see the motivational benefits of increased autonomy through the provision of a WFA regime, it needs to 'cut the umbilical cord,' giving employees true autonomy, rather than a piecemeal granting of autonomy.

Our study has several limitations. Similar to Bloom et al. (2015), our study is focused on a single organization, and in this sense, follows the tradition of insider econometrics (Bartel, Ichniowski and Shaw, 2004). Additionally, it is plausible that in other settings where workers have greater dependence on coworkers and supervisors to accomplish their tasks, increased coordination costs might offset the gains from higher productivity. Future work should validate our findings in other settings that exhibit other forms of interdependence.

It is important to note that our research contributes to a very active public managerial debate on the effectiveness of WFA. In February 2013, then-CEO Marissa Mayer famously rescinded the remote work program at Yahoo! with the following words drafted in a company memo: "Some of the best decisions and insights come from hallway and cafeteria discussions, meeting new people, and impromptu team meetings. Speed and quality are often sacrificed when we work from home. We need to be one Yahoo!, and that starts with physically being together."[13] Yet, along with these highly visible retreats from WFA regimes, other employers continue (typically with less fanfare) to increase WFA opportunities, and to more generally support the concept of remote work. Akamai's "Akamai Anywhere" WFA policy is one such example.[14] In promoting the agency's WFA policy, NASA's Chief Technology Office noted that "The potential exists for the size of an employee's office to expand from a 12' by 12' room to virtually everywhere".[15]

A series of work studies around WFA could help resolve this debate. It is plausible that the gains from WFA are restricted to firms and settings where workers have approached diminishing returns in learning from peers and/or are relatively less dependent on co-workers and supervisors to accomplish their tasks. Hence, it would be interesting to replicate our study in a setting of designers, software developers, and other contexts with varying degrees of worker interdependence. Future research could also study the duration of physical colocation that leads to new hires "coming up to speed" in terms of learning tacit knowledge needed to perform the task, and not experiencing increases in rework after moving to a WFA program. Similarly, it could be beneficial to pursue

[13] Source: http://allthingsd.com/20130222/physically-together-heres-the-internal-yahoo-no-work-from-home-memo-which-extends-beyond-remote-workers/
[14] https://www.benefitnews.com/news/benefits-professional-of-the-year-creates-a-balance-for-akamai-employees
[15] Source: https://www.nasa.gov/content/work-from-anywhere-how-to-land-that-bigger-office

further study of the conditions (if any) under which workers could benefit from learning from other remote workers and knowledge spillovers among WFA workers. For example, it has been suggested that "innovation spaces," such as coworking spaces and incubators are becoming a source of considerable knowledge transfer that promotes innovation and collaboration.[16] This argument suggests that there could be an optimal policy of WFA that allows employees to work from anywhere while interacting to some degree with professional peers in a *physical* collaborative setting close to home. In doing so, the worker may experience increased benefits to productivity from knowledge spillovers in her home geography; this, however, is an empirical question requiring further exploration.

Thinking beyond the immediate debate around WFA and firm productivity, we believe that future research on WFA could also help inform managerial decision-making in newer forms of organizing knowledge workers. A number of firms primarily in the software and technology fields – such as Mozilla and Art & Logic – are structured as virtual organizations, in which WFA is the dominant form of work.[17] At the same time, the rise of online platforms such as upwork.com – which match potential workers and employers for short-term contract-based jobs – has resulted in a significant increase in alternative work arrangements (Katz & Krueger, 2016), often informally referred to as the "gig economy."[18] With these technologies further enabling WFA, it seems likely that researchers and firms will continue to explore the conditions under which WFA can contribute positively to both worker utility and firm productivity. Our study takes a step in this direction, by suggesting that firms who allow WFA should 'cut the umbilical cord' with remote workers, to fully leverage WFA's productivity-enhancing effects. As we see with the PHP>50 regime, workers who are allowed to work from anywhere and yet are still tethered relatively tightly to the firm, essentially

[16] Source: https://www.brookings.edu/wp-content/uploads/2017/04/cs_20170404_innovation_spaces_pdf.pdf
[17] Source: https://www.flexjobs.com/blog/post/25-virtual-companies-that-thrive-on-remote-work/
[18] Source: https://assets.aspeninstitute.org/content/uploads/2017/02/Regional-and-Industry-Gig-Trends-2017.pdf

experience the least increase (among the remote work programs) in work output. Our results suggest that firms pursuing a WFA policy should give employees the maximum feasible level of autonomy, as USPTO did (to its benefit) with the WFA program.

As technology continues to enable richer communication and collaboration among virtual co-workers, and as major business centers continue to become more populous and congested, there is a strong need to develop our understanding of how policies such as WFA affect productivity. While we present robust econometric evidence that WFA regimes can have positive effects on net worker output, especially for experienced hires in a pooled interdependence setting, our study also outlines the importance of colocation for learning for new hires. In this way, our study is a step in the direction of resolving the ongoing debate about WFA policies, and understanding whether and under what conditions firms should implement work from anywhere policies for their workers.

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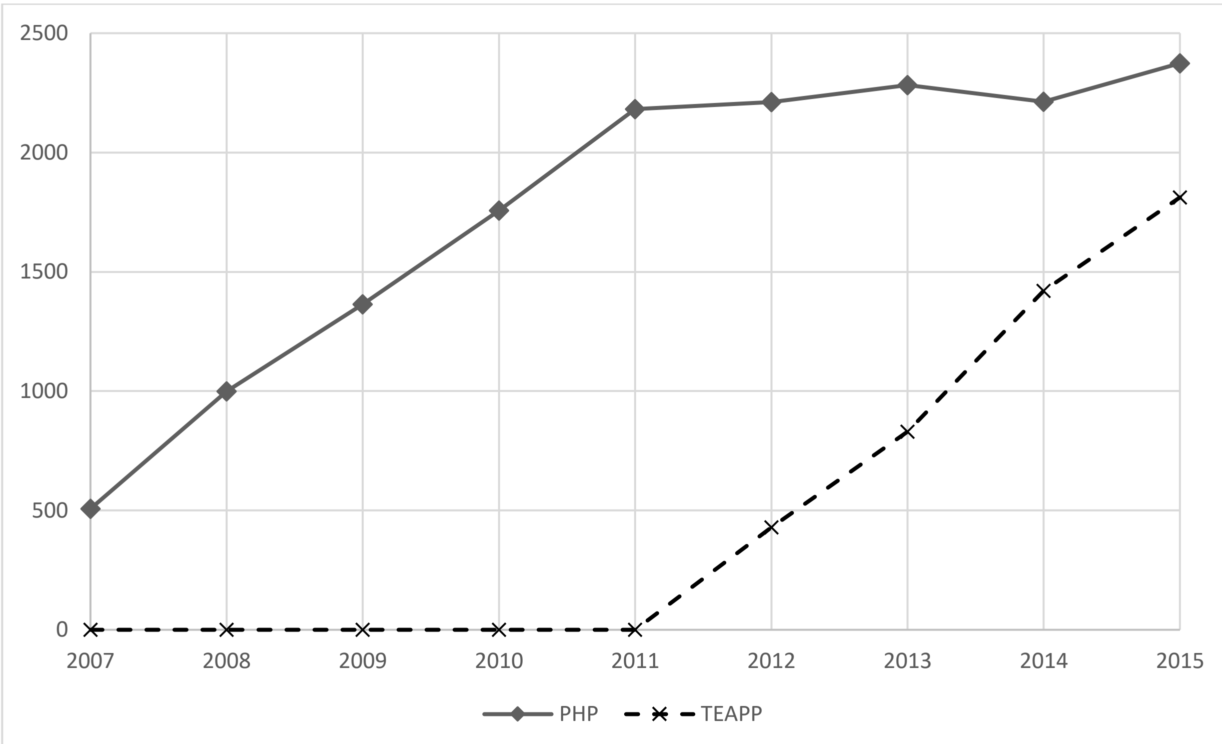
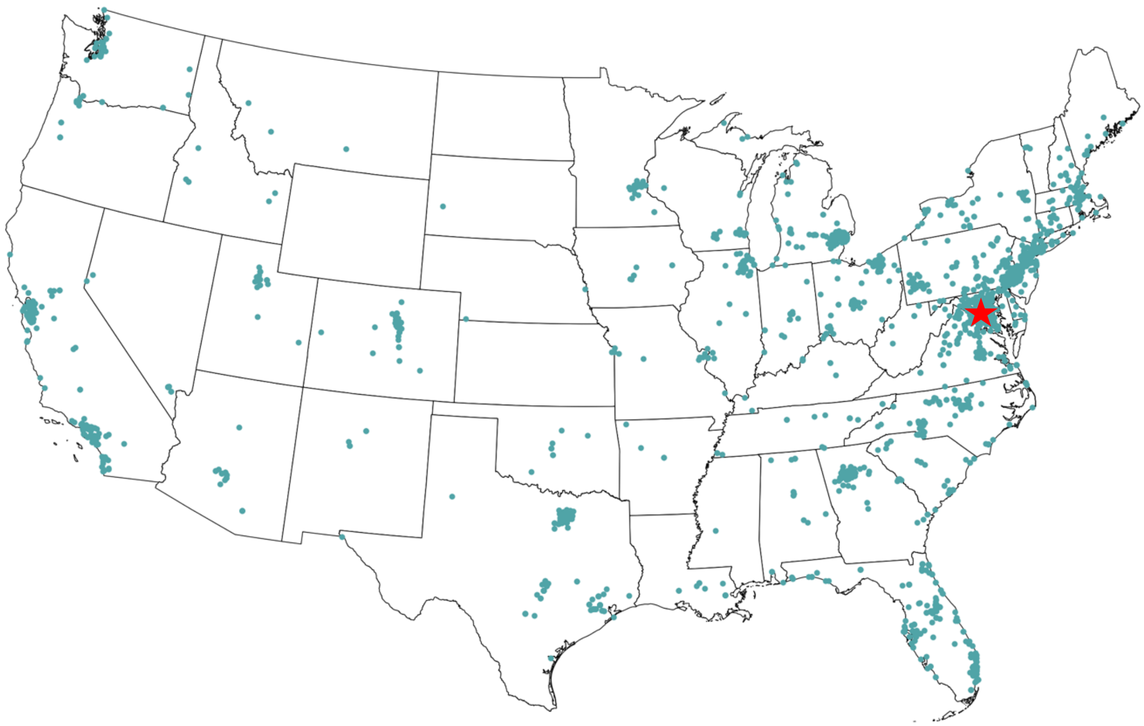
FIGURE 1: Growth in Number of Remote Workers at the USPTO



This figure illustrates the annual number of examiners enrolled in two remote work programs at the USPTO: WFA (TEAPP) and PHP.

FIGURE 2: WFA Examiner Locations



This figure illustrates the spatial distribution of WFA examiners at the USPTO as of August 2016. Each dot corresponds to a single unique examiner. Alexandria, VA (USPTO headquarters) is denoted by a red star.

TABLE 1

Summary Statistics

	Mean ± SD		
Variable	(1)	(2)	(3)
Turnover	0.002 ± 0.042	0.002 ± 0.042	0.065 ± 0.247
Output	12.913 ± 7.259	12.908 ± 7.258	11.321 ± 7.176
Rework	1.634 ± 1.733	1.633 ± 1.732	1.336 ± 1.579
Expectancy	23.335 ± 4.898	23.338 ± 4.900	23.202 ± 5.148
PHP (<50)	N/A	N/A	0.207 ± 0.405
PHP (>50)	0.282 ± 0.450	0.283 ± 0.450	0.073 ± 0.259
WFA	0.471 ± 0.499	0.470 ± 0.499	0.077 ± 0.266
Observations	67,088	66,980	554,699
Sample	WFA sample	WFA sample, experienced examiners	Full sample, experienced examiners

Observations are at the examiner-month level. The 'WFA sample' in column (1) refers to examiners that transition to WFA in 2012 or 2013. The 'WFA sample' in column (2) starts with the sample from column (1) and excludes those examiners hired when the WFA program was available (2012 and after). The full sample in column (3) uses all examiners in our dataset, regardless of their remote work status, excluding those that were hired after the availability of WFA in 2012.

TABLE 2

Hypotheses 1a, 1b and 1c: Experienced Workers

Variables	(1) Output	(2) Output	(3) Rework	(4) Rework	(4) Turnover
WFA	0.450*	0.503***	-0.063	-0.010	-0.235***
	(0.204)	(0.131)	(0.051)	(0.036)	(0.034)
Controls:					
Expectancy	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Grade	Yes	Yes	Yes	Yes	Yes
Examiner	No	Yes	No	Yes	Yes
Observations	66,980	66,980	66,980	66,980	554,699
Adjusted R-squared	0.362	0.560	0.146	0.290	0.280

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Standard errors appear in parenthesis and are clustered at the art unit level. Observations are at the examiner-month level and utilize the 'WFA sample' of experienced examiners for columns (1) through (4)—a subset of the main dataset that limits to experienced examiners (i.e. examiners hired prior to 2012) that transition to WFA in 2012 or 2013. WFA is an indicator variable that turns on for examiner-months that have transitioned into the WFA (i.e. TEAPP) program. Controls are indicated in the table below, and may include year fixed effects, grade level (GS) fixed effects, expectancy (a measure of expected effort/output on an examiner-month level), and examiner fixed effects. Column (5) presents results utilizing the full sample of examiners in order to estimate the effect on turnover. All columns utilize data from 2007-2015.

TABLE 3

Hypotheses 2a and 2b: Newly Hired Workers

Variables	(1) Output	(2) Rework
WFA	0.443*	-0.0641
	(0.204)	(0.0510)
NEW	-0.500	-1.435***
	(1.763)	(0.297)
WFA x NEW	3.795*	2.042***
	(1.772)	(0.401)
Controls:		
Expectancy	Yes	Yes
Year	Yes	Yes
Grade Level	Yes	Yes
Adjusted R^2	0.362	0.146
Observations	67,088	67,088

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Standard errors are clustered at the art unit level. Column (1) reports results from a regression of total examiner actions on a dummy for being on WFA, a dummy for being a new hire (NEW), and an interaction term. Column (2) reports results from a regression of total examiner-level RCEs on the same model as column 1. Both columns utilize the 'WFA sample' of examiners transitioning to WFA in 2012 or 2013. Controls for expectancy, year, and grade level are used, while examiner fixed effects are omitted as they would absorb all examiner-level variation in the NEW variable. All columns utilize data from 2007-2015. Results are robust to utilizing a sample that includes all new hires, not just those transitioning to WFA in 2012 to 2013.

TABLE 4

Autonomy and Output: Comparison of PHP and WFA

Variables	(1) Output	(2) Output	(3) Output
PHP (<50 Miles)	1.687***	1.113***	1.111***
	(0.107)	(0.0970)	(0.0969)
PHP (>50 Miles)	1.345***	0.558***	0.558***
	(0.101)	(0.0941)	(0.0940)
WFA	2.019***	1.176**	1.175***
	(0.113)	(0.105)	(0.105)
Controls:			
Expectancy	No	No	Yes
Year	Yes	Yes	Yes
Grade Level	No	Yes	Yes
Examiner	Yes	Yes	Yes
Observations	554,699	554,699	554,699
Adjusted R-squared	0.559	0.571	0.571

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Standard errors appear in parenthesis and are clustered at the art unit level. Observations are at the examiner-month level and utilize the full sample of experienced examiners (i.e. excluding new hires). WFA is an indicator variable that turns on for examiner-months that have transitioned into the TEAPP WFA program. PHP <50 and >50, respectively, are indicator variables that identify examiner-months that have transitioned into the two PHP programs. Controls are indicated in the table below, and may include year fixed effects, grade level (GS) fixed effects, expectancy (a measure of expected effort/output on an examiner-month level), and examiner fixed effects. All columns utilize data from 2007-2015.

TABLE 5
Cost of Living Reduction

Variables	(1) Cost of Living Reduction	(2) Cost of Living Reduction
PHP (<50 Miles)	0.000364	
	(0.0422)	
PHP (>50 Miles)	18.58***	
	(0.596)	
WFA	18.54***	3.100***
	(0.531)	(0.449)
Controls:		
Expectancy	Yes	Yes
Year Fixed Effects	Yes	Yes
Grade Level Fixed Effects	Yes	Yes
Examiner Fixed Effects	Yes	Yes
Adjusted R^2	0.829	0.760
Observations	600,941	66,830

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Standard errors are clustered at the art unit level. Column (1) reports results from a regression of Cost of Living Reductions, indexed to 0 for Alexandria, VA on dummies for being in either PHP program, and being in WFA. Column (1) utilizes the full sample of examiners. In order to align with our main results, column (2) reports results from the 'WFA sample' of examiners who transition to WFA in 2012 to 2013. Both columns include controls for expectancy, year, and grade level, as well as examiner fixed effects. All columns utilize data from 2007-2015.

TABLE 6

Robustness: Validating Natural Experiment

Variables	(1) Months to WFA	(2) Months to WFA	(3) Months to WFA
Output in 2011	-0.00784		-0.00540
	(0.00574)		(0.00683)
Rework in 2011	-0.0327		-0.0394
	(0.0240)		(0.0262)
Expectancy in 2011		0.0693	0.0435
		(0.0568)	(0.0679)
Grade Fixed Effects	Yes	Yes	Yes
Observations	1,575	1,575	1,575
Adjusted R^2	0.165	0.161	0.165

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Standard errors appear in parenthesis and are clustered at the art unit level. All columns reflect regressions with the 'WFA sample' of examiners that received WFA in 2012 or 2013 and that were active in 2011. Observations are at the examiner-month level, where column (1) estimates a model testing whether prior year output and rework are associated with time to WFA, column (2) estimates a model testing whether prior year expected effort is associated with time to TEAPP, and column (3) presents a fully saturated model. Grade-level fixed effects are used for this analysis.

TABLE 7
Robustness: Examiner Effort and Leniency

	(1)	(2)	(3)
Variables	FOAs	Rejections	Examiner-Added Citations
WFA	0.125*	0.177*	-0.253
	(0.0651)	(0.0895)	(0.286)
Controls:			
Expectancy	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Grade Fixed Effects	Yes	Yes	Yes
Examiner Fixed Effects	Yes	Yes	Yes
Observations	56,777	56,777	56,777
Adjusted R^2	0.322	0.391	0.465

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Standard errors appear in parenthesis and are clustered at the art unit level. Observations are at the examiner-month level, where column (1) utilizes first office actions (FOAs) as an outcome variable, column (2) utilizes rejections as an outcome variable, and column (3) utilizes examiner-added citations as an outcome variable. All regressions reflect analyses on the 'WFA sample', limited to those with data on Examiner-Added citations. WFA is an indicator variable that turns on for examiner-months that have transitioned into the TEAPP WFA program. Controls are indicated in the table below, and include year fixed effects, grade level (GS) fixed effects, examine fixed effects, and expectancy (a measure of expected effort/output on an examiner-month level. The 'WFA sample', restricted to observations that have data on Examiner-Added Citations, is used for all models.