Is Hybrid Work the Best of Both Worlds? Evidence from a Field Experiment

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Abstract

This paper reports causal evidence on how the extent of hybrid work—the number of days worked from home relative to days worked from the office—affects outcomes relevant for workers and firms. Collaborating with an organization in Bangladesh, we randomized the number of days that individual employees worked from the office for nine weeks. We find that an intermediate number of days in the office resulted in greater self-reported work-life balance and lower isolation from colleagues. Furthermore, hybrid work also led to a greater volume of emails, more unique email recipients, and more unique information conveyed in the emails. Hybrid work was also linked with better performance ratings from managers.

Keywords: Hybrid Work; Remote Work; Work-from-Home; Field Experiment; Productivity; Employee Engagement.

JEL Codes: J23, J24, O10, O33

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1 Introduction

"Hybrid work," where employees spend some of their work days in the physical office and the rest of their work days working remotely, is emerging as a novel form of organizing knowledge work globally (Teevan, 2021; Cutter, 2021). Barerro et al. (2022) estimate that 20 percent of full workdays will be supplied from home after the pandemic ends, compared with just 5 percent before.[1] The emergence of hybrid work has also led to a global debate between workers and employers, with individual workers expressing the need for flexibility and yet prominent employers remaining skeptical. On one hand, Aksoy et al. (2022) find that workers highly value the option to work-from-home (WFH) a few days a week and the average willingness to pay for the WFH option is around 5 percent of pay. On the other hand, prominent business leaders, such as David Solomon at Goldman Sachs and Elon Musk at Tesla, have said publicly they want workers back in the office five days a week and for 40 hours a week, respectively.[2]

Despite these ongoing debates, we lack causal evidence on how hybrid work affects outcomes relevant for workers, such as their self-reported work-life balance, and outcomes relevant for firms, such as work-related communication and worker performance. Pre-pandemic studies, such as Bloom et al. (2015) and Choudhury et al. (2020), document causal productivity gains of workers transitioning from the office to work-from-home, and from work-from-home to work-from-

[1] Brynjolfsson et al. (2021) report that, while 30 percent of respondents reported that they were working fully remotely and 39.1 percent reported that they were working in a hybrid arrangement as of October 2020, as many as 9.5 percent and 20.8 percent reported that they anticipated fully remote or hybrid work, respectively, in the long run. Other relevant papers include Hansen et al. (2022). Recent commentary has hypothesized that hybrid and remote work have the potential to transform cities and the spatial composition of the workforce (Choudhury, 2020; Eisen, 2019; Poleg, 2021), reminiscent of hypotheses at the turn of the 21st century with the introduction of the Internet and increased use of computers (Glaeser, 1998).

[2] https://fortune.com/2022/03/10/goldman-sachs-office-hybrid-remote-work-david-solomon/ and https://www.inc.com/jason-aten/elon-musks-7-word-rule-for-working-remotely-is-better-than-you-think-every-leader-should-copy-it.html.

anywhere, respectively. Other studies, such as Gibbs et al. (2022), Yang et al. (2021), and Emanuel and Harrington (2022) document how a pandemic-era transition to all employees working remotely all the time had adverse effects on productivity outcomes.[3] However, to the best of our knowledge, we lack studies that document causal evidence on how the extent of hybrid work—rather than fully remote work—affects outcomes relevant for individual workers or for the firm.[4]

To address this important and timely question, we report results from a field experiment conducted in the summer of 2020 in collaboration with BRAC, the world's largest non-governmental organization (Khanna and Ramachandran, 2021). We randomized the number of days that 130 workers worked from the physical office over a period of nine weeks. Following the lifting of a national lockdown, a bureaucratic policy mandated by ongoing COVID-19 health and safety concerns restricted the number of employees allowed back in the physical office. Exploiting this policy, daily lotteries determined which workers were directed to work from the office versus working from home. Our sample includes workers in the human resources department, performing administrative tasks at the headquarters of the organization in Dhaka, Bangladesh. While 130 employees took part in the experiment, we have complete data (including email communication data) for 108 HR employees.[5] The randomization protocol ensures that the number of days worked in the office

[3]Bloom et al. (2015) provides the first causal evidence on WFH, finding that performance increased by 13 percent when WFH was introduced in a large Chinese call center. Using a natural experiment, Choudhury et al. (2020) presents causal evidence on how the adoption of a work-from-anywhere (WFA) program in 2012 led to a 4.4 percent increase in output among patent examiners in the United States Patent and Trademark Office who transitioned from WFH to WFA. Yang et al. (2021) provide some evidence consistent with concerns in firm-wide remote work. Using data on 61,182 Microsoft employees from December 2019 to June 2020, they find a decline in the formation of new intrafirm communication ties. Emanuel and Harrington (2022) study remote work at a Fortune 500 retailer and report that during the lockdown, workers who originally chose remote jobs answered 18-21 percent fewer calls than those who originally chose on-site ones, indicating adverse selection into remote work. Gibbs et al. (2022) report that employee productivity fell 8-19 percent during a pandemic-era transition to WFH at an Asian technology company.

[4]To the best of our knowledge, the only other contemporaneous field experiment on hybrid work is by Bloom et al. (2022). The authors report that hybrid work reduced attrition rates by 35 percent and improved self-reported work satisfaction scores. Also, hybrid work had no significant impact on performance ratings or promotions.

[5]The sample dropped from 130 to 108, as 108 employees voluntarily consented to their data being shared for the experiment. The data was anonymized prior to being used by the researchers. The relevant IRB and Data Safety

for each worker in our sample is exogenously determined during the nine-week treatment period.

To examine how patterns of hybrid work affect outcomes relevant to workers, such as self-reported work-life balance and isolation, as well as outcomes relevant to firms, such as patterns of work-related communication and information being conveyed in such communication at the individual level, we categorize workers into three groups based on how many days they were assigned to work from the office: high WFH (0-8 days in the office, corresponding to 0-23 percent of work days in the office), intermediate WFH (9-14 days in the office, 23-40 percent) and low WFH (15+ days in the office, greater than 40 percent).[6] Using data on 32,745 emails sent among the 108 HR employees in the pre-treatment (lockdown) and treatment periods, we create several individual-level measures related to patterns of intrafirm communication, including pairwise counts of emails sent by each individual sender, and characteristics of emails (i.e., word length, sentiment, number of unique recipients). Using the text of the emails and the text of 30,323 email attachments and leveraging recent literature on how to code the information uniqueness of text (Aral and Dhillon, 2022), we created measures of individual-level information uniqueness using machine learning and textual analysis methods. We describe these methods—Doc2vec paragraph embeddings, BIRCH clustering, and cosine similarity—in detail in the Appendix.

We report four sets of results. First, we provide experimental evidence that explains results reported in prior surveys such as Aksoy et al. (2022) on why workers highly value intermediate hybrid work options. Here we use prior survey measures from the literature on remote work in organizational theory (Raghuram et al., 2001). This literature has argued that workers with intermediate hybrid might enjoy the "best of both worlds" in relation to two underlying mecha-

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[6]The cutoffs for the three groups are determined to balance the number of workers in each subgroup, but we show later that our results are invariant to slight changes around the cutoff.

nisms: flexibility and isolation. Prior literature has argued that the flexibility to decide how to accomplish a task (Amabile et al., 1996) and the flexibility to schedule one's work week (Elsbach and Hargadon, 2006) positively affect the production of novel work. As Bloom et al. (2014a) document, remote work reduces distractions and commute times and provides greater flexibility to workers. On the flip side, other research has shown that remote work leads to isolation from colleagues (Bartel et al., 2012), and isolation negatively impacts work outcomes (Golden et al., 2008a).[7] Intermediate hybrid work is plausibly the sweet spot, where workers enjoy flexibility and yet are not as isolated compared to peers who are predominantly working from home. We report findings using worker surveys conducted at the end of the experiment that suggest that workers in the intermediate WFH category reported greater satisfaction with working from home, greater work-life balance, and lower isolation compared to workers in the high and low WFH categories.

Second, we study how hybrid work affects outcomes relevant for firms, notably the volume and sparsity of work-related communication (i.e., work-related emails).[8] Using a negative binomial model, we find a statistically significant nonlinear relationship between number of days in the office and patterns of email communication. In particular, we find that intermediate WFH is

[7] Prior organizational research on remote work has argued that physical isolation can have a negative effect on the perceived respect, organizational identification, and overall performance of remote workers. Bartel et al. (2012) argue that physical isolation created by remote work leads to reductions in the level of direct contact with work-related interaction partners as well as detachment from the organization. Mannix et al. (2002) and Hinds and Bailey (2003) argue that distributed teams are more likely to experience conflict because of isolation among team members and the difficulty in managing employees in disparate locations. While information technology can help distributed teams (Wiesenfeld et al., 1999a), a shared identity and organizational identification influence the relationship between work and conflict (Wiesenfeld et al., 1999b; Hinds and Bailey, 2003). This is also consistent with survey evidence on job satisfaction. For example, Golden and Veiga (2005) find that job satisfaction plateaus at higher levels of remote work.

[8] Several studies have used emails as a proxy for work-related communication, as email data gives researchers a way to study communications and social networks in a less biased fashion than analyzing survey responses (Wu et al. (2008)). For instance, Aral et al. (2007) used a combination of accounting data and email metadata to explore information diffusion within an organization. Jacobs and Watts (2021) leveraged a much broader dataset of email metadata spanning 65 companies to study the relationship between organizational network structure and various company characteristics. DeFilippis et al. (2020) examines appointment and email metadata from more than 3 million users in North America, Europe, and the Middle East, documenting increases in meetings per person, attendees per meeting, and the average workday during the COVID-19 lockdown, but a decrease in meeting length.

associated with a 0.814 increase in the number of emails for a given dyad, and low WFH is associated with a 0.537 increase, both relative to the baseline of high WFH. We confirm using a t-test that the two point estimates are statistically different from one another. We also find that intermediate WFH is associated with positive increases in the number of email recipients and the sentiment of email text, measured using natural language processing methods on the content of each email.

Third, we study how the extent of hybrid work affects information uniqueness conveyed in email text. Using cutting-edge machine learning and NLP methods (explained later), we find that individuals in the intermediate WFH category demonstrate higher information uniqueness compared to workers in low and high WFH categories, and this difference is statistically significant. Information uniqueness in email and email attachment text increased by 1.073 standard deviations more for intermediate WFH workers than for high WFH employees. This suggests that we are not simply detecting an increase in the quantity of email communication, but also the quality, as measured using information uniqueness and sentiment.

Finally, we document that managers subjectively rate the work output of workers in the intermediate WFH category as being of higher quality than workers in the high WFH and low WFH groups, though the point estimates here are imprecise. Our measure of employee performance ratings builds on a literature in personnel economics that has used subjective performance ratings to study worker turnover and productivity.[9]

Our paper contributes to at least three topical conversations in personnel and labor economics

[9] Prior literature in economics documents that subjective performance ratings might be correlated to productivity outcomes. For example, Hoffman and Tadelis (2020) document that survey-measured people management skills have a strong negative relation to employee turnover. Similarly, Cai and Wang (2022) conduct a randomized experiment with an automobile manufacturer, finding that letting workers evaluate their managers leads to worker turnover reductions and team productivity improvements.

(Bloom et al., 2014c). First, we build upon the experimental results on the effects of fully remote work (Bloom et al., 2015; Choudhury et al., 2020) by studying the causal effects of hybrid work. Such results are important because companies face a spectrum of possibilities for their workforce, choosing between fully in-person and fully remote. Motivated by the adverse effects of fully remote work on work-related communication (Yang et al., 2021), hybrid work might offer a sweet spot with positive effects for both workers and firms. Second, we build upon empirical results on the determinants of employee engagement. For example, Hoffman and Tadelis (2020) find that managers with greater people management skills reduce worker turnover and increase team productivity. Similarly, Frederiksen et al. (2020) draw on subjective ratings data, finding that supervisor heterogeneity explains substantial variation in employee careers. We find that hybrid work practices lead to an increase in work-life balance and job satisfaction, in addition to more communication among colleagues. Taken together, this suggests that human resource practices and managers may be complements in fostering employee engagement. We also build on the tradition of Hoffman and Tadelis (2020) in using a combination of survey-based measures and measures coded from the data in studying outcomes relevant for workers and firms.[10] Third, our results contribute toward the literature on communication and coordination within organizations (Alonso et al., 2008; Bloom et al., 2014a; Friebel and Raith, 2004), the relative importance and relation between face-to-face and electronic communication (Storper and Venables, 2004; Battiston et al., 2021) and the future of cities (Gaspar and Glaeser, 1998; Glaeser, 1998).[11]

[10]The use of performance rating data goes back many years, including: Milgrom (1988), Baker et al. (1994a), Baker et al. (1994b), Flabbi and Ichino (2001), MacLeod (2003), Gibbs and Hendricks (2004), Frederiksen and Takats (2011), and Frederiksen (2013).

[11]Alonso et al. (2008) show that that a higher need for coordination improves horizontal communication but worsens vertical communication within organizations. Bloom et al. (2014b) study the impact of information and communication technology on worker and plant manager autonomy and span of control. Friebel and Raith (2004) argue that the design of an intra-firm communication structure must take into account the firm's human resource practices. Battiston et al. (2021) build a model in which workers choose the amount of communication by trading

In summary, our results contribute to the global debate on hybrid work between employees who value flexibility and employers who want their employees to return to the office full-time. The causal evidence reported in this paper suggests that intermediate patterns of hybrid work may be beneficial for both employees and employers.

2 Data and Measurement

2.1 Experimental Design

We conducted our field experiment in collaboration with BRAC, the world's largest nongovernmental organization, headquartered in Bangladesh. Founded more than four decades ago, the firm has more than 35,000 staff as of September 2020 and more than $1 billion in total income. In 2019, 81 percent of BRAC's revenues came from earned income, and women comprise 42 percent of BRAC's total workforce (Khanna and Ramachandran, 2021). While BRAC is headquartered in Dhaka, it has operations in multiple countries, including Myanmar, Liberia, Sierra Leone, Uganda, and Rwanda. Employees in the BRAC headquarters—the focus of our study—work in a modern office in Dhaka.[12] Prior to the pandemic, these employees had worked all five days in the office.

To study the causal effect of how the extent of hybrid work—low WFH, intermediate WFH, and high WFH—affects outcomes relevant for individual workers and the firm, we randomized the number of days that employees came into the office during a transitional return-to-office period.

off this benefit against the time cost incurred by the sender, and use it to derive a set of empirical predictions. The authors then exploit a natural experiment in an organization where problems arrive and must be sequentially dealt with by two workers. For exogenous reasons, the first worker can sometimes communicate face-to-face with their colleague. The authors then report that the second worker works faster (at the cost of the first worker having less time to deal with incoming problems) when face-to-face communication is possible. Glaeser (1998) points out that point out that despite the advances in information technology since the mid-1980s, business travel (a proxy for face-to-face meetings) has continued to increase.

[12]See Figure A.1 in Section A.1 of the Appendix for a photograph of the BRAC headquarters.

We focus on a sample of 130 employees from corporate HR working at the Dhaka headquarters. An additional 30 employees from the corporate microfinance team took part in the experiment but were excluded from our analyses as they did not consent to sharing email, our primary data source to measure work outcomes.

We ran our experiment for a total of nine weeks, from July 5 to September 3, 2020. Using a random number generator, we selected which employees should come to the office each day. Since the decision of who is supposed to come in is randomized over the nine weeks, some employees were randomly assigned to come to the office for only a few days, whereas others were assigned to come for a higher number of days. The nine-week treatment period included 35 work days, exclusive of weekends and a midsummer break during the religious festival of Eid.[13] This is the maximum number of days a worker could be in the workplace. Each of the 130 employees in the sample followed this schedule closely, and managers took attendance daily. At the end of each work week, the team lead verified their attendance. At the end of each weekend, they were also provided with the randomized attendance assignment sheet to follow for the upcoming work week.[14] Panel A in Figure 1 plots the distribution of days in the office across employees in the human resources department.[15] Panel B plots the distribution of the hyperbolic sine of the number of emails across all dyads, displaying substantial variation.

[13]Bangladesh has a work week that commences on Sunday and ends on Thursday, with Friday and Saturday comprising the weekend. The randomization protocol accounted for the dynamic quotas for the number of employees that BRAC wanted in the office, and we dynamically updated the quota across weeks (i.e., we flipped coins with replacement from week-to-week.)

[14]Given that we conducted this experiment within an actual firm with full-time employees, a few exceptions to adhering to the attendance schedule were made for emergency reasons, such as friends and family being sick. The results reported are based on identifying the intent to treat; there was also high compliance with the attendance schedule. Subjects were not aware of the experiment, so there is no chance that knowledge of it confounds behavior, such as emails and other performance. At the end of the experiment, employees were informed and asked if they give their consent for their email data to be used for research purposes. There was nearly complete consent, and we received the universe of all BRAC employee emails, including the text and attachments and all to/cc/bcc information.

[15]Figure A.3 in Section A.2 of the Appendix also presents a similar distribution of days for microfinance workers.

[INSERT FIGURE 1 HERE]

We categorize workers into three groups based on how many days they were exogenously assigned to work from the physical office: high WFH (0-8 days in the office), intermediate WFH (9-14), and low WFH (15+). The cutoffs for the three groups are determined to equalize the number of total (i.e., HR and microfinance) workers in the experiment within each of the three subgroups, but in Table A.9 of Section A.3.5 of the Appendix, we show that our results are qualitatively robust to an alternative classification based off of equally spaced bins within the HR unit (the unit for which we have email data).

Figure 2 summarizes the timeline of the experiment. We partition the time series into two periods: lockdown, consisting of 82 days starting March 26, 2020; and post-lockdown (the "treatment" period), consisting of 62 days starting July 5, 2020, and ending September 3, 2020. Again, owing to holidays and other common breaks, the 62-day treatment period contained 35 work days. In the bulk of the paper, we refer to the post-lockdown period, which contains the hybrid work arrangement, as the treatment period. We compare this to the lockdown period.[16]

[INSERT FIGURE 2 HERE]

2.2 Outcome Measures

To measure intrafirm communication across dyads, we count the number of emails sent between each individual sender and receiver, for the lockdown and treatment periods. Building on the distribution of emails across dyads in Panel B in Figure 1, Figure A.4 in Section A.2 of the

[16]Figure A.2 in Section A.2 of the Online Appendix documents summary statistics for the sample during the treatment period, which ran from July 5, 2020 to September 3, 2020. Tables A.1 and A.2 explore balancing in our demographic covariates across the three partitions of low, medium, and high WFH.

Appendix plots the distribution separately across both the lockdown and treatment periods.[17]

To measure the uniqueness of information individuals produce, we use two sets of measures. Our primary method is based on using the text of employee emails and email attachments and then measuring information uniqueness. We do this by first applying text analysis and machine learning methods, particularly Doc2vec (Le and Mikolov, 2014). We then measure information uniqueness using three methods. In the first, we operationalize the metric of "information uniqueness" proposed by Aral and Dhillon (2022). In the second, we apply BIRCH clustering (Zhang et al., 1997) and measure the cosine similarity of document vectors to a synthetic representative document. In a last, cruder check, we apply a simple hashing function to determine if the exact document has been seen before. See Section A.4 of the Appendix for details of these alternative methods.

We also code employee performance based on managerial ratings. These ratings were collected using survey instruments from the prior management literature on remote work, notably those employed by Greenhaus and Parasuraman (1993) and Touliatos et al. (1984). These surveys ask managers to rate their direct reports on a 7-point scale ranging from (1) unsatisfactory to (7) excellent on the following measures: ability, cooperation, job knowledge, creativity, productivity, and quality of work.

[17] In our setting, workers engaged in informal communication on multiple Whatsapp groups, while all formal communication is conveyed in emails. We did not have a complete dataset of all Whatsapp groups, so we focused on emails. Given this, our study should be thought of as an exploration of formal (not informal) workplace communication.

3 Hybrid Work and Employee Work-Life Balance

We begin by asking how the intensity of WFH affects employees' perceptions of their work-life balance. We build on prior literature that has argued that intermediate hybrid work could represent the "best of both worlds" in relation to two underlying mechanisms: flexibility and isolation. Remote work offers workers fewer distractions, less commuting, and more flexibility (Bloom et al., 2014a), and greater flexibility is related to employees generating novel and creative work (Hackman et al., 1975; Amabile et al., 1996). On the flip side, remote work has been shown to increase isolation from colleagues (Raghuram et al., 2001), and scholars have argued that isolation negatively affects work outcomes (Golden et al., 2008a). Intermediate hybrid might offer the best of both worlds—flexibility without isolation—and potentially impact employee productivity.

To test this, we draw on answers to several survey questions that we designed to understand employee attitudes about remote work. We designed this survey by leveraging prior organizational literature in remote work, notably Raghuram et al. (2001). Each question is ranked on a scale of one to seven (1 = strongly disagree, 7 = strongly agree). First, drawing on validated survey questions from Raghuram et al. (2001), we ask: (i) "Overall, I am satisfied with working from home;" (ii) "Working from home allows me to perform my job better than I ever could when I worked in the office;" (iii) "If I were now given the choice to return to a traditional office environment (i.e., no longer telework), I would be very unlikely to do so;" (iv) "Since I started working from home, I have been able to balance my job and personal life;" and (v) "Since I started working from home, my productivity has increased." These questions help us understand whether employee engagement and/or reallocation of tasks are major mechanisms. We also draw on validated survey questions from Golden et al. (2008b): (i) “I feel left out on activities and meetings that could enhance my career;” (ii) “I miss out on opportunities to be mentored;” (iii) “I feel out of the loop;” (iv) “I miss face-to-face contact with coworkers;” (v) “I feel isolated;” (vi) “I miss the emotional support of coworkers;” and (vii) “I miss informal interactions with others.” These questions help us understand whether social isolation is at play.

Because of our randomization strategy, we simply regress our measures of employee performance and attitudes. Table 1 documents these results and suggests that workers in the intermediate WFH group report greater satisfaction with working from home, greater work-life balance, and lower isolation compared to workers in both the high and low WFH categories.[18]

[INSERT TABLE 1 HERE]

4 Hybrid Work and Work-related Communication

Recent evidence from Yang et al. (2021) points to the fact that firm-wide WFH might lead to intra-firm communication patterns becoming static and siloed. However, we know little about how hybrid work affects patterns of intra-firm communication, so we turn to data on emails, including the volume of emails and the underlying text and attachments in them.[19]

To quantify the causal effect of hybrid on intra-firm communication, we create a dyadic pair between an employee i and every other employee j over the lockdown and treatment periods, subsequently regressing the number of emails sent from employee i on the intensity of hybrid work

[18] In addition, Table A.29 in Section A.6 of the Appendix reports similar results when we define the cutoff for remote work based on the set of employees in the human resources division alone (that is, excluding microfinance). Furthermore, Table A.30 replicates the main results using cutoffs that are unique to the HR employees.

[19] We also gathered data on WhatsApp, but discovered that nearly all the communication on this app is in their native language and focused on nonwork-related questions and activities. We are capturing formal work activities.

while controlling for individual characteristics and allowing for heterogeneity by group:[20]

$$y_{ijt} = \gamma^I WFH_i^I + \gamma^L WFH_i^L + \xi^I(WFH_i^I \times G_i) + \xi^L(WFH_i^L \times G_i) + \beta X_{it} + \epsilon_{ij} \qquad (1)$$

where y_{ijt} denotes the number of emails that the (i, j) dyad exchanged during the treatment, WFH^j for $j \in I, L$ denotes an indicator for whether the employee works an "intermediate" $(j = I)$ or a "low" $(j = L)$ amount from home, G denotes an indicator for whether an individual falls within a particular group (e.g., gender), and X denotes individual demographics, including an indicator for being male, being a non-manager, having a master's or PhD degree, being married, whether the spouse also works from home, and having to care for a child. While we do not need to control for these characteristics given our randomization strategy, they are nonetheless useful and help remove any unobserved heterogeneity that could be spuriously correlated with extent of WFH and email. We assign high work from home as the baseline category, given that in the pre-treatment period, i.e., the lockdown period, all employees were working in an all-remote arrangement. Table A.4 of the Appendix motivates our empirical setup: co-location (i.e., when both the sender and receiver are in the office) is not strongly correlated with email activity; most of the variation comes from the number of days the sender is in the office.

While our use of dyadic data here comes at a disadvantage of greater sparsity in the number of emails sent between any dyad, we address that limitation by using a negative binomial model (although our results are qualitatively similar using a standard least square estimator).[21] Moreover,

[20] Interactions within a dyad are not independent, since the number of emails that employee i sends to j is dependent in part on the number that i receives from j (Quintane and Kleinbaum, 2011). We focus on the number of messages exchanged within a directed dyad. However, since employee i exchanges messages with not only j, but also j', there is a common person effect that could cause us to underestimate standard errors (Kenny et al., 2006). We address this challenge by also testing robustness in Table A.7, with robust standard errors that are clustered on both members of a dyad (Cameron et al., 2011; Kleinbaum et al., 2013).

[21] The distribution is highly censored: the median number of emails across dyads is zero and the mean is 1.28

the dyadic data allows us to exploit pre-pandemic communication between any pair, meaning that we can test for preexisting communication ties—that is, whether communication prior to the pandemic governs the direction of communication during the treatment period.

Our identifying variation comes from the comparison of email communication among dyads, based on whether the sender of the email is in the low, intermediate, or high WFH group. We employ dummy variables for each, but our coefficients on the days in the office indicators are normalized to an indicator for the employee coming in 0-8 days. To justify this approach, Section A.3.2 of the Appendix presents results showing that the bulk of the relationship between emails and days in the office comes from days that the sender is in the office. We estimate Equation 1 using a negative binomial model to account for the excess of zero emails within dyads.

Panel A in Table 2 documents the results associated with Equation 1. Column 1 documents that non-managers, intuitively, have significantly fewer email exchanges: roughly 1.6 less for any given dyad. For perspective, the median is zero and the mean is 1.3. More importantly, intermediate WFH is associated with a 0.814 increase in the number of emails for a given dyad, and low WFH is associated with a 0.537 increase, relative to the baseline of high WFH. We conduct a t-test to examine whether the two are statistically different from one another. We can reject the null hypothesis that they are equal, with a p-value of 0.09. The difference becomes more precise as we add additional controls in the columns that follow.

We now proceed by sequentially adding additional demographic characteristics, including: an indicator for being male, an indicator for having a master's or PhD degree (normalized to having just a bachelor's degree), an indicator for being married, an indicator for whether their spouse also works from home, and an indicator for whether they have to care for a child. We find that

(the standard deviation is 7.19, skewness 17.5, and kurtosis 450).

men generally send more emails than women, but differences in educational attainment do not explain email communication. Married workers send fewer emails, but those who care for children send more. Importantly, however, our marginal effects of intermediate and low WFH remain economically and statistically significant. In our strictest specification (column 6), intermediate WFH is associated with 0.689 more emails in a dyadic pair, and low WFH is associated with 0.364 more emails, relative to high WFH. Furthermore, we can reject the null hypothesis that the two are equal to each other (p-value = 0.05).

[INSERT TABLE 2 HERE]

Our estimates are statistically significant, but how economically meaningful are they? We now consider a simple aggregation exercise where we ask how email traffic would change if both the low and high WFH groups came in as often as the intermediate WFH group. To start, we estimate the baseline regression again, but use the intermediate WFH group as the normalization, producing coefficients of -0.689 for high WFH and -0.325 for low WFH. Next, we sum the number of emails across both groups, yielding 5,070 emails for high WFH and 2,551 for low WFH; we take the sum of their product with the respective elasticities. In sum, this produces 4,322 emails, which is 63 percent of the total intermediate WFH number of emails (6,805). The aggregation exercise abstracts from the dynamic social adjustment that would occur if everyone had hybrid work, but it still provides a useful interpretation for the economic significance of the effect.

So far, we have examined the effects of WFH on overall email volumes. However, we are also interested in the broader democratizing effects: How many employees are receiving emails from others with whom they did not previously correspond? Panel B in Table 2 documents these results by using the logged average number of unique recipients as the outcome variable.

Starting in column 1, we see that intermediate WFH is associated with a statistically significant 58 percent (= exp(0.462)) increase in the number of unique email recipients relative to the high WFH baseline. While low WFH is also positively associated with unique email recipients, it is not statistically significant. Again, we see that non-managers send fewer emails to wider groups of people. We subsequently layer additional demographic controls, which do not alter the treatment effect in any meaningful way. In the strictest specification (column 6), we find that intermediate WFH is associated with a 50 percent increase in unique email recipients. However, because of the sample size, we cannot statistically reject the null hypothesis that the intermediate and low WFH categories have similar effects on the number of unique email recipients. Interestingly, however, we see that more educated employees send fewer emails to unique recipients, which could be consistent with a greater focus on cognitively intensive activities that require less teamwork.

We now discuss a handful of robustness exercises. First, Table A.6 in Section A.3.4 of the Appendix replicates the main results using an alternative cutoff for intermediate WFH, demonstrating that employees coming into the office 12-14 or 15-23 days in the treatment period send substantially more emails than their counterparts who come in 0-7 days (and the effect for 8-11 days is positive, but statistically insignificant). Table A.7 replicates the main results with the standard cutoff but uses two-way clustered standard errors on both the recipient and sender following Kleinbaum et al. (2013). Furthermore, Table A.9 allows for additional heterogeneity in the intensity of WFH by creating four equally spaced bins of days in the office using the standard cutoff of all employees. We find that the bulk of the variation is concentrated in the third quartile, or those with 13-15 days in the office.

Second, we explore several additional parametric assumptions about our estimator and the potential for nonlinearities in Section A.3.5 of the Appendix. Table A.10 replicates the main results using a Poisson distribution. Table A.11 investigates several dimensions of heterogeneity. Most of the variation in intermediate WFH arrangements is driven by non-managers. We also find that dyadic communication during the lockdown prior to the treatment is associated with fewer emails among those in intermediate and low WFH arrangements, relative to high WFH; this is significant since it suggests that hybrid work can democratize communication within the firm. Communication becomes less siloed among dyadic pairs that communicated prior to the treatment.

Next, Table A.12 documents qualitatively similar results when we collapse our data to the employee level. Because we are no longer working with dyadic pairs, we can now use the log number of emails sent as the outcome variable. These estimates suggest that intermediate WFH leads to 46.6 percent more emails relative to high WFH, whereas low WFH leads to only 10.8 percent fewer emails, although the difference is not statistically significant.[22] Finally, Table A.15 shows that there is no statistically significant difference in email activity depending on whether an individual works from home earlier versus later in the week, ruling out a task-planning mechanism.[23]

In the Appendix (Table A.15), we also attempt to rule out alternative mechanisms and report results that show cognate outcomes did not differ based on whether the worker went to the office earlier versus later in the work week, allowing us to rule out an alternative explanation of our results related to more efficient planning and management of time. Intermediate hybrid work may

[22]Table A.13 shows a similar pattern when focused on email recipients, rather than senders, but the estimates are not statistically significant. Table A.14 presents analogous results using the continuous number of days the employee comes into the office as the main independent variable, rather than the bins. We find no evidence of a nonlinear, quadratic fit, suggesting the semi-parametric approach is a better fit.

[23]Rather than computing the number of days that employees come into the office over the three different periods, we can exploit daily variation. Section A.3.1 of the Appendix presents regressions of email communication on an indicator for whether the sender is in the office. Unlike earlier with our negative binomial model, we estimate a linear probability model for whether the dyad emailed on a particular day as a function of WFH, controlling for dyad and day fixed effects. We find that WFH is associated with a 0.4 percentage point decline in the probability of whether the employee sent a particular recipient an email.

lead to more efficient planning and allocation of time toward heterogeneous tasks—those that require social interaction and others that require independent work and concentration.

While all workers were made aware of the randomized weekly schedule on Saturday night (i.e., prior to the work week commencing), workers who went to the office later in the week (i.e., on Wednesday and Thursday) arguably had more time to plan activities such as meetings with colleagues who were also in the office on the same days as they were, compared to workers who went to the office earlier in the work week (i.e., on Sunday and Monday). Yet we find no differences in the number of emails sent based on the day of the week the worker went to the office. We interpret this as evidence suggestive that better planning and more efficient time allocation to heterogeneous tasks were not in play in our setting.[24]

In summary, the set of results reported above shed light on how intermediate levels of hybrid work (i.e., intermediate WFH) might be more efficient than both low WFH and high WFH in maximizing the number of emails sent by employees and the number of unique recipients of emails (the span or reach of the sender's network). These results complement recent research on how firm-wide remote work affects email communication in the workplace, notably Yang et al. (2021). However, we do not interpret volume of email as a measure of productivity. Instead, we next turn to study how the extent of hybrid work affects qualitative patterns of work-related communication, as measured using the uniqueness of information (emails and email attachments) generated by individuals.

[24]In unreported results, we also detected no significant trends relating to the number of times an employee switches work modalities within the week.

5 Hybrid Work and Information Uniqueness in Work-related Communication

We now examine the effects of extent of hybrid work on uniqueness of information conveyed in work-related communication by using the text of emails and the text of work-related attachments to emails. Our examination is motivated by managerial concerns around the effectiveness of hybrid work in contexts that require creative and novel work-related communication.

As with "creativity," the measurement of "information uniqueness" depends on the context. Perhaps the closest theoretical proxy for this concept is "novelty." In past literature, scholars have measured novelty by quantifying the presence of new keywords and combinations of words that have not been seen in prior work products (Boudreau et al., 2016), and they generally have used the latent Dirichlet allocation (LDA) method. Barron et al. (2018) considered the relationship between novelty and transience, finding a positive "innovation bias" in how highly novel ideas resonate into future texts. Network science offers another perspective, where metadata on network flows can capture concepts such as diversity, non-redundancy, and uniqueness (Aral and Dhillon, 2022). Here, we adopt their concept of "information uniqueness" (see A.4.1 in the Online Appendix for details). Although we considered network measures, such as average number of unique recipients, in Section 4, here we consider only the content of employee communication.

We innovate using machine learning and text analyses methods to generate an approximation of information uniqueness by two measures. We first pre-process the text of emails and attachments sent by each employee. Next, we use Doc2vec paragraph embeddings to represent each document as a fixed-length, numeric vector, much as in principal component analysis. Doc2vec considers not only the rarity of particular words, but also the context, such as surrounding words, to determine the key components of each document. We then proceed with two methods: one based on the Aral and Dhillon (2022) metric for information uniqueness and another based on an additional clustering step.

In the first method, considering the treatment and control periods separately, we examine all intrafirm sender s and recipient r dyads. The average vector representations of all documents sent in each directed dyad $\langle s, r \rangle$ are computed as $\overline{m}_{sr}$. We also calculate $\overline{m}_{s\backslash r}$, the average vector representation of documents sent to r by every sender *excluding* s. We then compute the information uniqueness implied by this dyad as

$$InformationUniqueness_{sr} = \|\overline{m}_{sr} - \overline{m}_{s\backslash r}\| \tag{2}$$

where $\| \cdot \|$ is the L^2 Euclidean norm. Then, we compute the information uniqueness score for a given sender s:

$$InformationUniqueness_{s} = \overline{\sum_{r \neq s} InformationUniqueness_{sr}} \tag{3}$$

and standardize this measure (see Figure A.11 in the Online Appendix for a graphical depiction).

The results of this process indicate a striking rise in information uniqueness associated with intermediate WFH, significant at the 5 percent level. Consider the interpretation of the intermediate WFH coefficient in column (7) of Table 3. The regression indicates that intermediate WFH workers increase this measure by 1.073 standard deviations more than the high WFH workers would, even in the presence of demographic, behavioral, and co-location controls.[25]

[25] In unreported results, the effect also holds when we control for the amount of time between the first and last

[INSERT TABLE 3 HERE]

In the second method, we use a clustering algorithm (BIRCH, a computationally optimized version of K-means) to group these vectors into different clusters. For example, one cluster might retrospectively represent "strategy reports," although the labels are not predetermined. Finally, we calculate the cosine similarity between each document and a synthetic centroid document within each cluster, and we transform this into an information uniqueness measure by taking the additive inverse and mapping the range to [0, 1]. Thus, a very unusual or novel document would be given a high score for information uniqueness.

The clustering problem involves parametrizations similar to the well-known mean-variance trade-off. We want to categorize the type of each document so we can compare it to others of its type to determine information uniqueness. But as the number of document types increases, the variation in the information uniqueness scores is lost. Thus, we optimize the vector length and number of clusters to select the most appropriate parameters. Details of the calculation are found in Section A.4 of the Appendix. The results are consistent with those of the first method:

[INSERT TABLE 4 HERE]

We also considered similar metrics, such as "usefulness," in determining what information uniqueness is meant to capture. We present examples of text with their relative information uniqueness scores in Table 5.[26]

email sent on a given day, which is an unreliable proxy for time spent working. Also see Table A.26 for heterogeneity results. In a subsample analysis, we find similar results whether the information uniqueness scores are calculated only for days a sender is working from home (Table A.27) or from the office (Table A.28).

[26] An HR manager manually reviewed a sample of 100 emails, one drawn from each percentile of the information uniqueness distribution, and scored them for "usefulness" (as the manager interpreted the term) on a scale from 1–5. The correlation between our information uniqueness metric and the manager's usefulness score was 0.26. Additionally, Section A.4.2 in the Online Appendix reports the results of a supervised machine learning process to predict usefulness for every email, finding a positive correlation between predicted usefulness and information uniqueness for the intermediate WFH group.

[INSERT TABLE 5 HERE]

Table 6 in Section A.6 of the Appendix presents additional evidence on the positive productivity effects of intermediate WFH using managerial performance ratings.[27] We also apply a cruder, alternative uniqueness measure, detailed in Section A.5.2 of the Appendix, which considers only attachment text and is broadly consistent with these results.

6 Hybrid Work and Employee Performance Ratings

Next we attempt to study how patterns of hybrid work relate to employee performance. While we do not have a direct measure of employee productivity, we ask managers to rate their employees on a one to seven scale across seven measures, building on a literature from personnel economics that uses employee rating variables as a proxy for employee productivity (e.g., Hoffman and Tadelis (2020) and Cai and Wang (2022)). Table 6 documents these results by regressing managerial ratings on our treatment, exploiting our random assignment with our usual demographic characteristics for robustness.

We find suggestive evidence that intermediate WFH is positively associated with increases in managerial ratings of employee performance: a 0.095 unit increase in ability, a 0.259 unit increase in cooperation, a 0.103 unit increase in knowledge, a 0.155 unit increase in creativity, a 0.264 unit increase in productivity, and a 0.291 unit increase in quality, relative to high WFH. The marginal effects are larger for intermediate WFH than low WFH for all outcomes except ability

[27] In the preceding discussion within this section, we explicitly discourage an identification of "information uniqueness" with "productivity." This relationship could vary by job role, or a document may be labeled as "novel" as a consequence of the limited sample period, even if it is routinely produced at regular intervals. However, these managerial performance ratings supply some evidence that information uniqueness and productivity are positively correlated.

and knowledge. Notably, the effect is twice as large when the outcome is cooperation, which counters the view that intermediate WFH adversely affects teams.

While the coefficients are not statistically significant at conventional levels and, thus, we cannot reject the null that the coefficients on intermediate and low WFH are different from one another or the omitted case of high WFH, we view the point estimates as useful diagnostics. Tables A.31 and A.32 in Section A.6 of the Online Appendix present analogous results using alternative cutoffs for WFH with the human resources employees.

7 Conclusion

The COVID-19 pandemic has led to a fundamental transformation in the way work is organized, with hybrid work emerging as an option for organizing work within firms. While there is a vigorous debate around hybrid work between employees and some employers, there is thin causal evidence on how hybrid work affects outcomes relevant for employees, such as their self-reported work-life balance and isolation, as well as outcomes relevant for employers, such as patterns of work-related communication and workers' performance ratings.

We provide causal evidence on the effects of the extent of hybrid work on outcomes relevant for employees and report that intermediate hybrid is positively related to both higher self-reported work-life balance and lower self-reported isolation from colleagues. We also report evidence that intermediate hybrid is positively related to outcomes relevant for the firm (i.e., patterns of intra-firm communication and the uniqueness of information conveyed in such communication). Our results exploit a field experiment conducted in collaboration with a large firm in Bangladesh, randomizing the number of days that each employee comes into the office over a nine-week period.

Drawing on every email that was sent during the treatment period, as well as the pre-treatment (lockdown) period by workers in the experiment, we measure patterns of work-related communication, notably volume of emails and number of email recipients for individual workers. We also use a novel measure of information uniqueness of work-related communication, using the text of emails and email attachments and cutting-edge machine learning and textual analysis methods. To recap, we find that intermediate levels of WFH correlate with the highest number of emails sent, highest number of email recipients, more positive sentiment of emails, and greater information uniqueness expressed in the email text. We also report that workers with intermediate WFH received higher performance ratings from managers.

While our results are not without limitations (e.g., our study does not employ an objective measure of worker productivity, a limitation relevant not only for HR workers but a large population of workers engaged in creative and nonroutine tasks), they provide important guidance for the transition to hybrid work. Our study is also in the tradition of economists studying a single firm (Lazear, 2000) and conducting field experiments within firms (Bandiera et al., 2011), and our findings need to be replicated in other settings before the results can be generalized. Future research should explore the effects of hybrid work in a wide variety of contexts; study whether, and under what conditions, intermediate levels of WFH correlate with effective mentoring outcomes for workers; and explore how adoption of intermediate WFH might change the geography of work, the future of cities, and the future of the central business district.[28]

[28] Relevant work on this topic includes Gupta et al. (2022) and Ramani and Bloom (2021).

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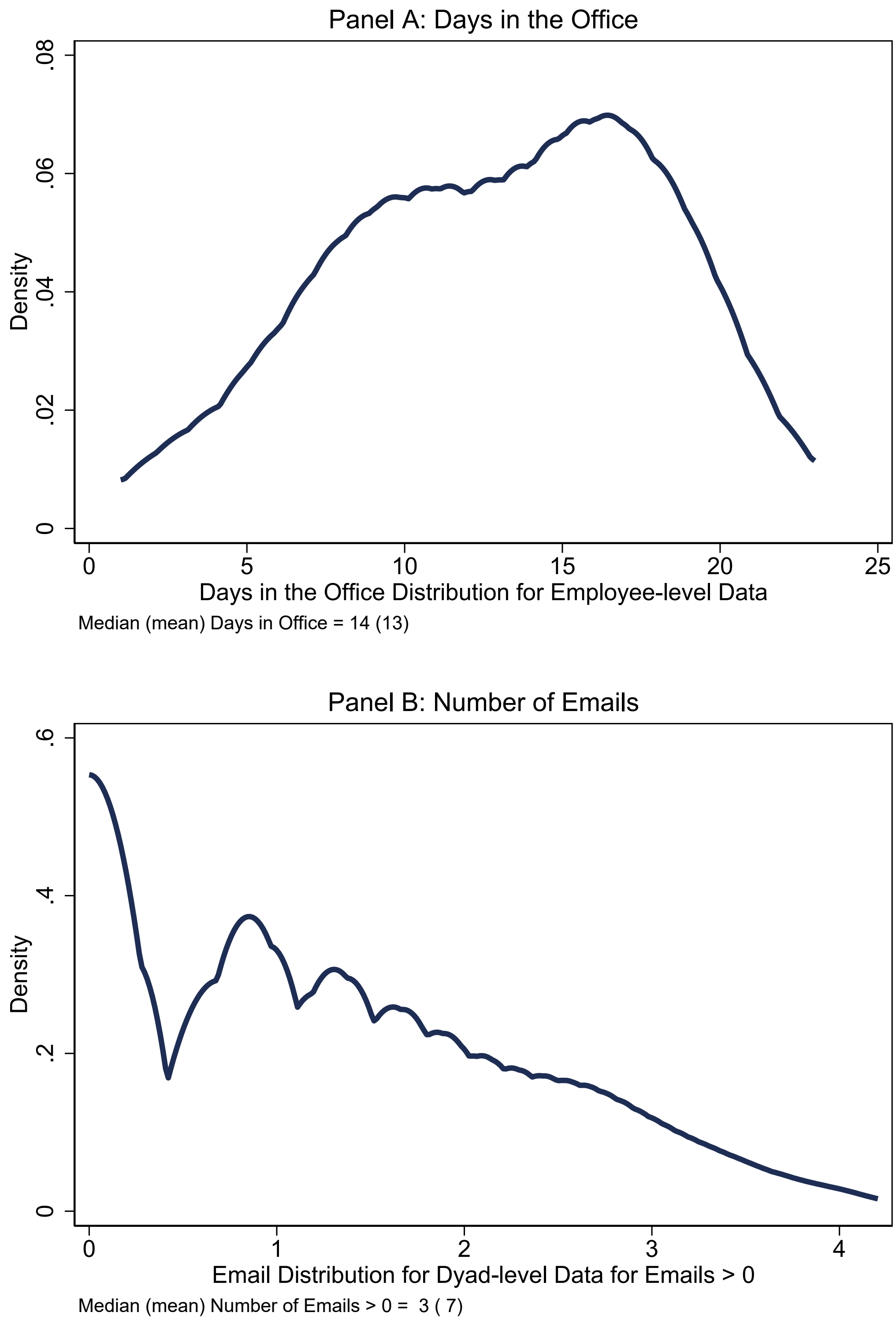

Figure 1: Distribution of Days in the Office and Emails

Notes: Source: Authors. Panel A in the figure plots the distribution of the number of days that a person comes into the office. Panel B in the figure plots the log number of emails sent in the dyadic data conditional on a dyad sending some non-zero amount of emails. Our sample is restricted to the employees in the human resources department.

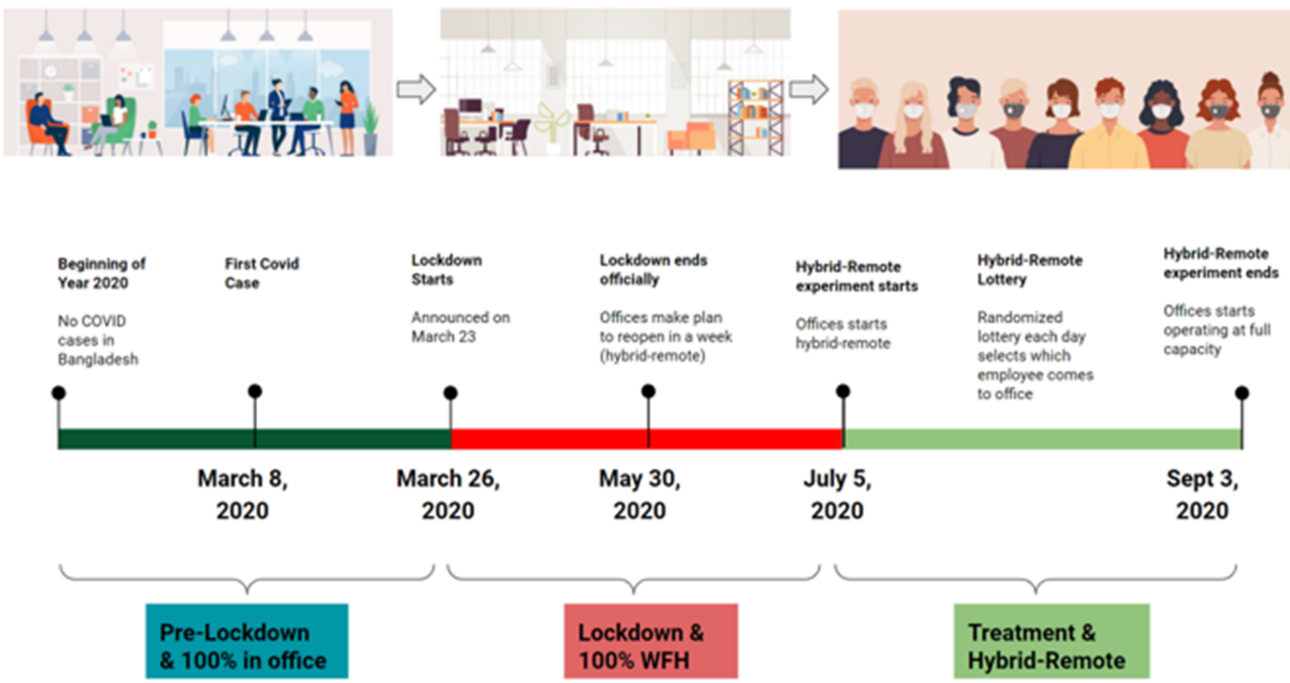

Figure 2: Timeline of the Experimental Design

Notes: Source: Authors. The figure plots the timeline of the experimental design, ranging from the pre-lockdown period to the hybrid work period.

Table 1: Intensity of WFH and Employee Work-life Balance and Isolation

	Job Satisfaction	Better Balance	Prefer WFH
	(1)	(2)	(3)
Panel A			
Intermediate WFH	.668**	.803**	-.168
	[.308]	[.355]	[.389]
Low WFH	-.199	-.215	-.116
	[.356]	[.393]	[.415]
R-squared	.16	.11	.12
Sample Size	143	143	143
	Feel Left Out	Miss Mentorship	Feeling Isolated
	(1)	(2)	(3)
Panel B			
Intermediate WFH	.287	-.018	-.784*
	[.388]	[.390]	[.434]
Low WFH	.446	.670	.262
	[.413]	[.429]	[.500]
R-squared	.08	.05	.11
Sample Size	143	143	143

Notes: Source: Authors. The table reports the coefficients associated with regressions of indices of employee preferences (ranging from one to seven) on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 days in the office (low WFH), controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. In Panel A, we draw on indices from Raghuram et al. (2001): "Overall, I am satisfied with working from home," "Since I started working from home, I have been able to balance my job and personal life," and "If I were now given the choice to return to a traditional office environment (i.e., no longer telework). In Panel B, we draw on indices from Golden et al. (2008b): "I feel left out on activities and meetings that could enhance my career," "I miss out on opportunities to be mentored," and "I feel isolated." Section A.6. in Appendix subject these results to a battery of controls and robustness checks. Standard errors are heteroskedasticity-robust.

Table 2: Intensity of Working-from-Home and Patterns of Email

	Dep. var. = Number of Emails Sent					
	(1)	(2)	(3)	(4)	(5)	(6)
Dyadic Data						
Intermediate WFH	.814***	.781***	.758***	.716***	.710***	.689***
	[.178]	[.182]	[.186]	[.171]	[.170]	[.171]
Low WFH	.537***	.493***	.457***	.421***	.379**	.364**
	[.151]	[.152]	[.162]	[.160]	[.161]	[.161]
Non-Manager	-1.608***	-1.558***	-1.555***	-1.563***	-1.538***	-1.419***
	[.217]	[.215]	[.217]	[.216]	[.209]	[.205]
Male		.185	.192	.259*	.260*	.334**
		[.136]	[.140]	[.134]	[.133]	[.137]
Masters/PhD			-.139	-.003	-.018	-.062
			[.180]	[.204]	[.203]	[.208]
Married				-.384	-.337	-.554*
				[.273]	[.274]	[.289]
Spouse WFH					-.127	-.111
					[.138]	[.138]
Caring for Child						.447***
						[.135]
Sample Size	10600	10600	10600	10600	10600	10600
	Dep. var. = log(Unique Recipients of Emails)					
Employee Data						
Intermediate WFH	.462***	.449***	.404**	.425***	.422**	.406**
	[.155]	[.162]	[.164]	[.160]	[.161]	[.164]
Low WFH	.299	.271	.212	.227	.262	.246
	[.200]	[.214]	[.209]	[.209]	[.207]	[.208]
Non-Manager	-.612**	-.587**	-.555**	-.554**	-.561**	-.502*
	[.275]	[.270]	[.272]	[.273]	[.268]	[.267]
Male		.096	.130	.104	.103	.144
		[.153]	[.152]	[.151]	[.152]	[.154]
Masters/PhD			-.357**	-.396**	-.394**	-.400**
			[.163]	[.176]	[.178]	[.175]
Married				.184	.133	.047
				[.214]	[.221]	[.219]
Spouse WFH					.141	.133
					[.159]	[.161]
Caring for Child						.180
						[.152]
Sample Size	99	99	99	99	99	99

Notes: Source: Authors. Panel A in the table reports the coefficients associated with negative binomial regressions of the number of emails sent during the treatment period on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 days in the office (low WFH), controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. Panel B in the table reports comparable models, but now using the log number of unique email recipients that a given employee has emailed with the same right-hand-side variables as Panel A. Standard errors are clustered at the dyad-level in the top panel and at the employee-level in the bottom panel. Since employee i exchanges with not only j, but also j', there is a common person effect that could cause us to underestimate standard errors (Kenny et al., 2006), so we use robust standard errors that are clustered on both members of a dyad (Cameron et al., 2011; Kleinbaum et al., 2013) in the top panel.

Table 3: Intensity of Working-from-Home and Information Uniqueness (Aral and Dhillon (2022) Method)

	Change in Information Uniqueness						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate WFH	0.436**	0.465***	0.491**	0.520***	0.517***	0.517***	1.073***
	(0.175)	(0.174)	(0.191)	(0.176)	(0.177)	(0.176)	(0.215)
Low WFH	−0.448	−0.336	−0.276	−0.273	−0.236	−0.239	0.991**
	(0.392)	(0.372)	(0.382)	(0.386)	(0.384)	(0.384)	(0.467)
Non-Manager	−0.084	−0.136	−0.193	−0.173	−0.182	−0.163	−0.201
	(0.189)	(0.190)	(0.197)	(0.203)	(0.203)	(0.200)	(0.186)
Male		−0.312*	−0.326*	−0.353**	−0.352**	−0.335**	−0.420**
		(0.168)	(0.176)	(0.164)	(0.165)	(0.169)	(0.169)
Masters/PhD			−0.147	−0.190	−0.192	−0.193	−0.120
			(0.346)	(0.372)	(0.374)	(0.377)	(0.378)
Married				0.221	0.172	0.138	0.111
				(0.376)	(0.387)	(0.388)	(0.363)
Spouse WFH					0.124	0.119	0.043
					(0.163)	(0.164)	(0.162)
Caring for Child						0.078	0.040
						(0.198)	(0.195)
Co-location Intensity							−0.562***
							(0.192)
Sample Size	105	105	99	99	99	99	99

Notes: Source: Authors. This table reports the coefficients associated with OLS regressions of the change in the information uniqueness measure (Equation 3, based on Aral and Dhillon (2022)) on an indicator for whether the email sender came to the office 9-14 days (intermediate WFH), 15-23 days (low), or fewer than nine days (high, omitted category) controlling for the following demographic characteristics: male, non-manager (employee), education (masters/PhD–normalized to having a bachelor's), married, spouse works from home, employee has to care for a child, and standardized co-location intensity (the standardized number of days a person is physically co-located in the office with another team member). The dependent variable represents the change in standard deviations from the baseline to the experimental period. Section A.5.1 of the Appendix for a discussion of the choice of number of clusters for Doc2vec.

Table 4: Intensity of Working-from-Home and Information Uniqueness (BIRCH/Cosine Similarity Method)

	Dep. var. = Change in Cosine Similarity-Based Work Product Index						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate WFH	0.497**	0.472**	0.565**	0.563**	0.564**	0.565**	0.653***
	(0.203)	(0.197)	(0.226)	(0.248)	(0.249)	(0.248)	(0.204)
Low WFH	0.262	0.165	0.247	0.247	0.228	0.224	0.420
	(0.219)	(0.222)	(0.236)	(0.237)	(0.253)	(0.260)	(0.541)
Non-Manager	−0.722***	−0.676***	−0.791***	−0.793***	−0.788***	−0.758***	−0.764***
	(0.253)	(0.246)	(0.244)	(0.244)	(0.249)	(0.264)	(0.268)
Male		0.270	0.193	0.196	0.195	0.222	0.208
		(0.182)	(0.180)	(0.172)	(0.171)	(0.183)	(0.200)
Masters/PhD			0.035	0.039	0.040	0.040	0.051
			(0.343)	(0.312)	(0.314)	(0.315)	(0.295)
Married				−0.020	0.005	−0.049	−0.054
				(0.319)	(0.338)	(0.314)	(0.311)
Spouse WFH					−0.063	−0.073	−0.085
					(0.201)	(0.211)	(0.204)
Caring for Child						0.124	0.118
						(0.211)	(0.220)
Co-location Intensity							−0.089
							(0.216)
Sample Size	105	105	99	99	99	99	99

Notes: Source: Authors. This table reports the coefficients associated with OLS regressions of the change in the information uniqueness measure (BIRCH/cosine similarity-based) on an indicator for whether the email sender came to the office 9-14 days (intermediate WFH), 15-23 days (low), or fewer than nine days (high, omitted category), controlling for the following demographic characteristics: male, non-manager (employee), education (masters/PhD–normalized to having a bachelor's), married, spouse works from home, employee has to care for a child, and standardized co-location intensity (the standardized number of days a person is physically colocated in the office with another team member). The dependent variable represents the change in standard deviations from the baseline to the experimental period. Text data was classified into eight clusters (BIRCH-based) from a Doc2vec vector length of four; see Section A.5.1 of the Appendix for a discussion of the parameter fit.

Table 5: Validation of the Information Uniqueness Metric

Uniqueness Percentile	**Usefulness Score**	**Text**
1	2	Dear [name] As per conversation, here I attached the screenshot. Kindly see the attachment
10	2	PIease correct accordingly, thanks
43	3	Whats the update on this issue? Please check with [vendor] and solve the issue by today. Also give a reply to the Field Office. Thank you.
46	3	Not match experience. Need at least 3 years' experience for lab technician position. Thanks
83	5	Dear [name] Greetings! I think it's all good to me ,just adding one observation-Expected joining date can be written in a specific date in lieu of as early as possible.You can proceed with this approval. Best,
95	4	Dear [name], These items were marked by budget change areas. PRL is requiring the percentage changed of these areas. * Salary & Benefits * Travelling & Transportation * Office supplies, Postage & Stationery * Maintenance, General Expenses and support cost * Fooding expenses ([company] and other) * Meeting and Workshop * Staff training and development * Advertisement and publicity expenses * Audit, Consultancy and Legal fees * Capital Expenditure

Table 6: Intensity of Working-from-Home and Managerial Performance Ratings

	Ability	Cooperation	Knowledge	Creativity	Productivity	Quality	Overall
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate WFH	.105	.281	.124	.164	.267	.291	.205
	[.164]	[.237]	[.197]	[.174]	[.207]	[.184]	[.154]
Low WFH	.222	.165	.108	.013	.039	.217	.127
	[.212]	[.248]	[.238]	[.248]	[.239]	[.233]	[.183]
Non-manager	-.015	-.640***	-.118	-.037	-.386	.039	-.193
	[.219]	[.223]	[.226]	[.205]	[.254]	[.269]	[.171]
Male	.182	-.037	.231	.346*	.283	.151	.192
	[.141]	[.186]	[.177]	[.183]	[.192]	[.176]	[.133]
Masters/PhD	-.174	-.199	.216	-.449	.023	.012	-.095
	[.220]	[.309]	[.283]	[.278]	[.266]	[.251]	[.219]
Married	.310	.158	.760***	-.173	-.306	.032	.130
	[.261]	[.290]	[.285]	[.255]	[.273]	[.249]	[.222]
Spouse WFH	-.014	.073	.102	.013	.043	.226	.074
	[.145]	[.196]	[.171]	[.160]	[.180]	[.170]	[.123]
Cares for Child	.149	.239	-.014	.174	.265	.155	.161
	[.134]	[.191]	[.170]	[.191]	[.195]	[.179]	[.137]
R-squared	.07	.10	.15	.09	.09	.06	.09
Sample Size	118	118	118	118	118	118	118

Notes: Source: Authors. The table reports the coefficients associated with regressions of managerial productivity ratings (ranging from one to seven) on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 days in the office (low WFH), controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. The sample is restricted to employees in the human resources department. While we do not have a direct measure of employee productivity, we ask managers to rate their employees on a one to seven scale across seven measures, building on a literature from personnel economics that uses employee rating variables as a proxy for employee productivity (e.g., Hoffman and Tadelis (2020) and Cai and Wang (2022)). Standard errors are heteroskedasticity-robust.

A Online Appendix

Contents

A.1 Data Preparation

BRAC is the world's largest non-governmental organization, headquartered in Bangladesh. Founded over four decades ago, the firm has over 35,000 staff as of September 2020 and over $1 billion in total income. In fact 81% of BRAC's revenues came from earned income in 2019 (Khanna and Ramachandran, 2021). While it is headquartered in Dhaka, BRAC has operations in multiple countries including Myanmar, Liberia, Sierra Leone, Uganda, and Rwanda. BRAC headquarters workers, the focus of our study, work in a modern office in Dhaka. Figure A.1 gives a visual representation of the entry to the BRAC headquarters.

Figure A.1: BRAC Headquarters

Notes.—The figure plots the entry to the BRAC headquarters.

Email data was provided by the firm's IT department. Because users frequently manipulate their inboxes and other incoming mail folders, we looked exclusively at emails in the sent mailbox—that is, emails sent by a given employee. In addition to being generally more reliable, this also prevented any accidental duplicate-counting of a given message. The email text was then processed to remove disclaimers and boilerplate text, individual employees' email signatures, and inline replies. Consequently, the word counts reported in this paper represent substantive text in the body of each message. In the case of multipart messages (e.g., with messages containing both HTML and text representations of the body), we utilized a common Python library that selects the part most likely to contain the true body. The small number of emails containing Bangla text, identified by the character set, were translated to English using Google Translate APIs.

Generally speaking, email counts and other metrics reported at the level of a sender (employee) count each email message only once, regardless of the number of recipients. Because emails can contain multiple recipients within and across the To, CC, and BCC fields, the dyadic data multiply counts single emails if they are sent to multiple recipients (although, within a given dyad, no individual message is ever counted more than once).

A.2 Descriptive Statistics

Figure A.2 documents summary statistics for the sample during the treatment period, which ran from 7/5/20 until 9/3/20. We see that 53% of the sample is male. We also find an average of 136 emails. However, the standard deviation is nearly as large as the mean, showing that there is significant heterogeneity across employees. The mean number of days an employee is in the office is 9.86 (and the median is 10). Most employees are married and highly educated, but fewer have a spouse who also works from home. We also show the correlations across the variables.

Figure A.2: Summary Statistics in Email Data over Lockdown

	Mean	SD	Male	Non-Manager	Masters/ PhD	Married	Spouse WFH	Care for Child	Email Novelty	No. of Emails	Unique Recipients	Days in Office	High WFH	Intermediate WFH	Low WFH
Male	0.53	0.5	1												
Non-Manager	0.87	0.34	-0.12	1											
Masters/PhD	0.86	0.35	0.08	0.012	1										
Married	0.86	0.35	0.2	-0.07	0.25	1									
Spouse WFH	0.29	0.49	0.028	-0.01	0.07	0.26	1								
Care for Child	0.45	0.5	-0.14	-0.19	0.07	0.31	0.13	1							
Email Novelty	-0.018	0.96	0.05	-0.19	-0.14	-0.13	-0.1	0.04	1						
No. of Emails	136	138	0.15	-0.43	-0.03	-0.05	-0.09	0.19	0.51	1					
Unique Recipients	21.5	15	0.05	-0.26	-0.18	-0.01	0.05	0.19	0.49	0.69	1				
Days in Office	9.86	4.55	0.17	0.22	-0.16	-0.18	-0.24	-0.14	0.18	0	0.06	1			
High WFH	0.4	0.49	-0.15	-0.29	0.15	0.15	0.11	0.06	-0.18	-0.06	-0.13	-0.85	1		
Intermediate WFH	0.4	0.49	0.013	0.19	-0.08	-0.14	0.06	-0.02	0.25	0.1	0.12	0.32	-0.66	1	
Low WFH	0.2	0.4	0.17	0.12	-0.08	-0.01	-0.22	-0.05	-0.08	-0.05	0.02	0.64	-0.41	-0.41	

Notes.—Source: Authors' experimental design. Using the individual-level (during the intervention period), the table reports the mean and standard deviation for demographic characteristics, as well as the correlations, across all the variables: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child, the number of emails, unique recipients, the number of days in the office (from the sender), and the share under high WFH (1-8 days in the office), intermediate WFH (9-14 days in the office), and low WFH (15-23 days in the office).

We also explore the sample characteristics across the three partitions of the WFH distribution to check for balancing. Table A.1 reports these. We find statistically insignificant differences. While there are some differences among the share of males, we note that the standard deviation is large and we cannot rule out the null that the means for high and intermediate are the same. The share of males between high and low WFH are slightly different, but we again recognize the sample sizes are small. Table A.2 presents analogous means and standard deviations using the cutoff when we apply just to human resources workers.

Next, Figure A.3 builds on the results from Figure 1 in the main text, but presents the distribution of days in the office for both microfinance and human resources departments. Importantly,

Table A.1: Examining Balancing Across Treatment Groups

	High WFH		Intermediate WFH		Low WFH	
	Mean	SD	Mean	SD	Mean	SD
Male	0.44	0.50	0.54	0.51	0.70	0.47
Non-Manager	0.74	0.44	0.95	0.22	0.95	0.22
Masters/PhD	0.92	0.27	0.82	0.39	0.80	0.41
Married	0.92	0.27	0.79	0.41	0.85	0.37
Spouse WFH	0.36	0.49	0.33	0.48	0.10	0.31
Caring for Child	0.49	0.51	0.44	0.50	0.40	0.50
Observations	39		39		20	

Notes.—Source: Authors. The table reports the means and standard deviations across the three partitions of the WFH distribution: high WFH (1-8 days in the office), intermediate WFH (9-14 days in the office), and low WFH (15-23 days in the office).

Table A.2: Examining Balancing Across Treatment Groups (Alternative Cutoff)

	High WFH		Intermediate WFH		Low WFH	
	Mean	SD	Mean	SD	Mean	SD
Male	0.43	0.50	0.56	0.50	0.67	0.48
Non-Manager	0.76	0.43	0.94	0.25	0.96	0.20
Masters/PhD	0.93	0.26	0.81	0.40	0.79	0.41
Married	0.93	0.26	0.81	0.40	0.79	0.41
Spouse WFH	0.36	0.48	0.34	0.48	0.13	0.34
Caring for Child	0.52	0.51	0.41	0.50	0.38	0.49
Observations	42		32		24	

Notes.—Source: Authors. The table reports the means and standard deviations across the three partitions of the WFH distribution: high WFH (1-8 days in the office), intermediate WFH (9-13 days in the office), and low WFH (14-23 days in the office).

the distributions overlap significantly, mitigating concerns about differential selection and/or lack of external validity for our treatment effects between the two sets of w orkers.

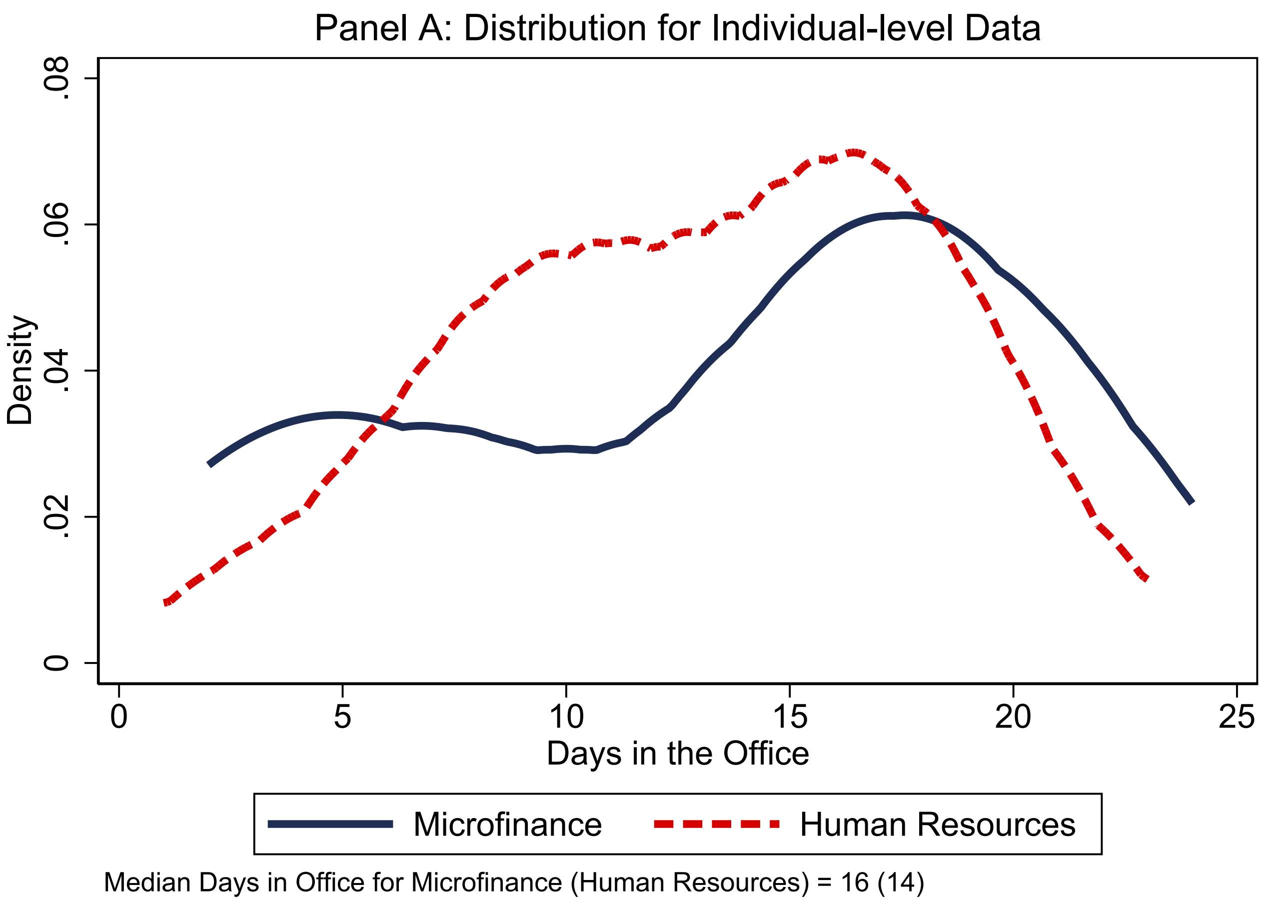

Figure A.3: Distribution of Days in the Office

Notes.—Sources: The figures plot the distribution of the number of days that a person comes into the office in the individual-level data for both microfinance and human resources departments.

Next, Figure A.4 plots the distribution separately across our three major time periods. We see that there are substantially more emails sent by the average employee during the lockdown versus pre-lockdown period, but almost as many post-lockdown as during. We also observe a much larger variance across employees during the lockdown (129) versus before or after (121 and 89).

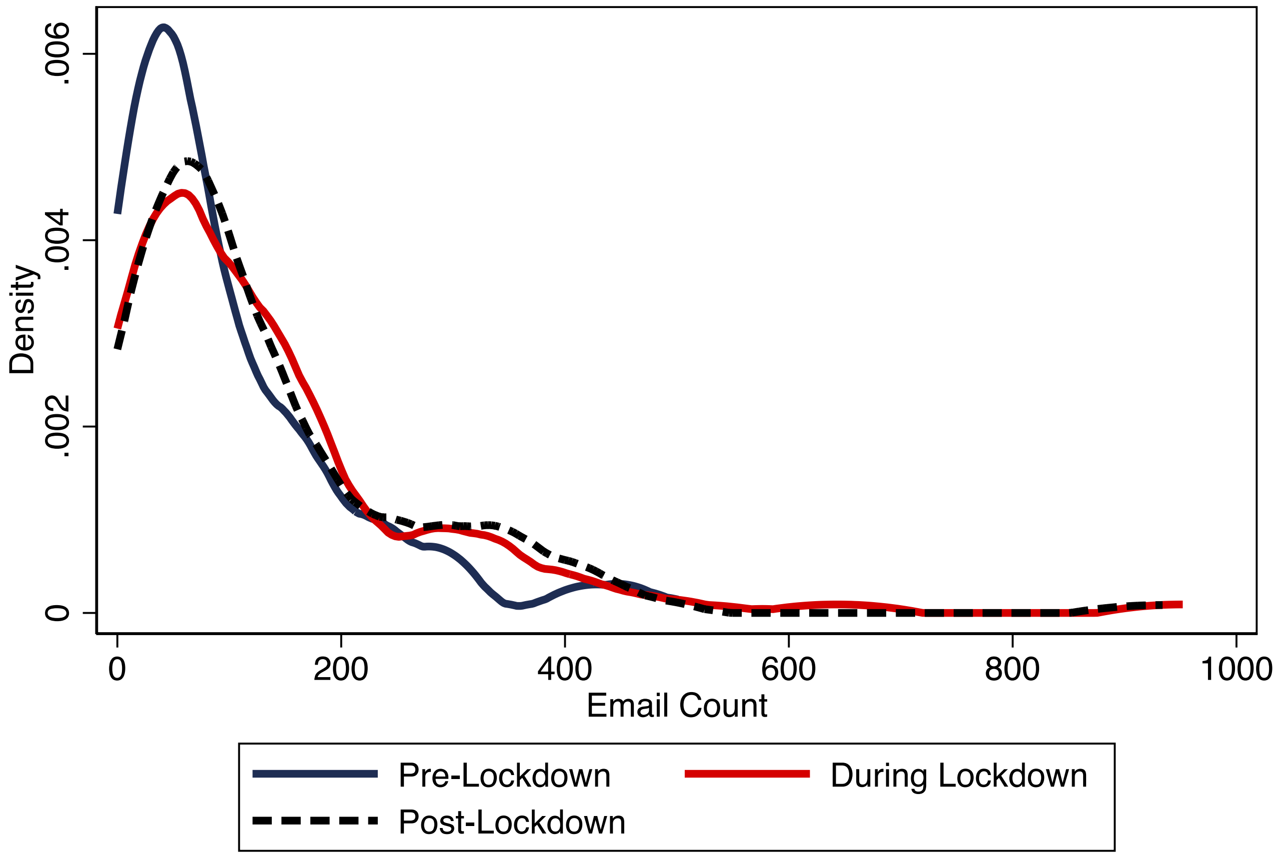

Figure A.4: Distribution of Emails Across Employees Over Time

Notes.—Source: Authors. The figure plots the distribution of emails sent pre-, during, and post-lockdown.

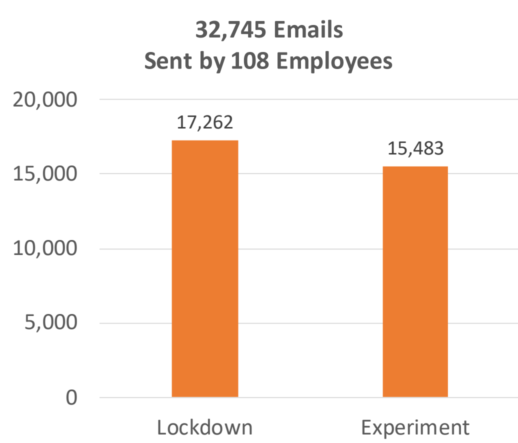

Figure A.5: Email Count

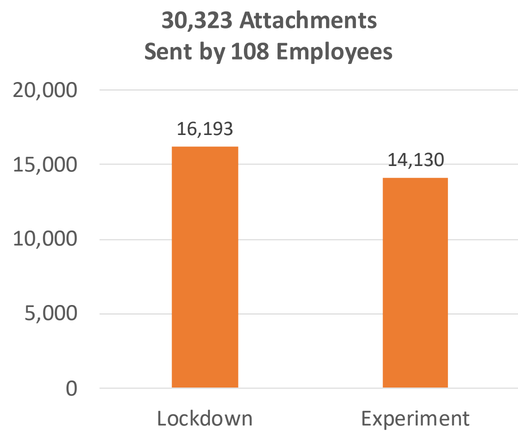

Figure A.6: Attachment Count

*Omits 128 malformed attachments (garbled or unrecognizable type)

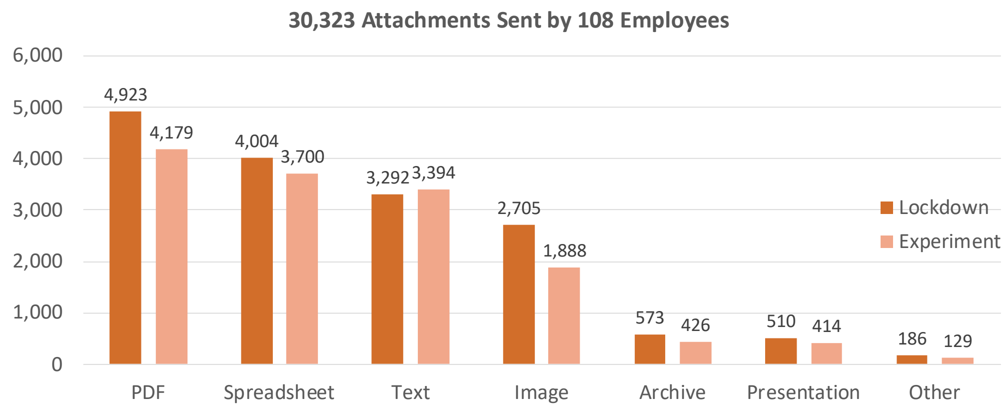

Figure A.7: Attachment Types

*Text analysis was performed only on extractable content from PDF, spreadsheet (e.g., Excel), text (e.g., Word), and presentation (i.e., PowerPoint) files. No OCR was attempted on images or embedded images.

A.3 Supplement to the Main Results with Email Traffic

A.3.1 Daily Patterns in Remote Work and Emails

While the main text focuses on remote work patterns over the entire treatment period, we now explore how remote work and email communication vary on a daily basis. In particular, we create a dyadic pair between each employee i and every other employee j, subsequently regressing an indicator for whether a dyadic pair interact on a given day on an indicator for whether the sender is working remotely that day, controlling for dyadic and time fixed effects:

$$y_{ijt} = \gamma r_{it} + \eta_{ij} + \lambda_t + \epsilon_{ijt} \tag{4}$$

where y_{ijt} denotes an indicator for whether the (i, j) dyad has exchanged emails on day t during the intervention, r denotes an indicator for whether the sender is working remotely, and η and λ denote fixed effects on dyad and time. Because of the randomization that we have built into our experiment, our estimate of γ has a causal interpretation. The identifying variation comes from the comparison of employees who were randomly assigned to come in on certain days over others, inducing variation in the pairs of employees that entered jointly as well.

Table A.3 documents these results. Starting with column 1, which presents the raw correlation, we see that employees are 0.4 percentage points less likely to send an email on a day that they are working remotely, suggesting that in-person work and email communication are complements, rather than substitutes. Column 2 introduces dyad and time fixed effects, thereby exploiting variation among pairs of employees who do not communicate via email on some days, but do on others. Here, we find a 0.2 p.p. decline in the probability of sending an email. Column 3 allows for heterogeneity in the gender of the sender, but there are no statistically significant differences between men and women. Column 4 allows for heterogeneity in the recipient of the email, specifically whether the email is sent to a manager. While managers are much more likely to receive emails in general, we find an 8 p.p. lower probability of sending an email among employees when they work remotely. In contrast, column 5 shows that email communication is slightly higher towards direct reports on remote work days, but the coefficient is not statistically significant.

Table A.3: Relationship Between Daily Email Communication and Remote Work

	Sent Emails Today				
	(1)	(2)	(3)	(4)	(5)
Sent to Manager				.292***	
				[.032]	
Sent to Direct Report					.112***
					[.036]
Remote Day	-.004***	-.002***	-.003***	-.001***	-.002***
	[.001]	[.000]	[.001]	[.000]	[.000]
× Male			.002		
			[.001]		
× Sent to Manager				-.082***	
				[.021]	
× Sent to Direct Report					-.005
					[.025]
R-squared	.00	.01	.01	.05	.02
Sample Size	648570	648570	648570	648570	648570
Dyad FE	No	Yes	Yes	Yes	Yes
Day FE	No	Yes	Yes	Yes	Yes

Notes.—Source: Authors. The table reports the coefficients associated with regressions of an indicator for whether person i and recipient j traded emails on day t on an indicator for whether the employee came into the office on day t and dyad and day-of-the-year fixed effects. The sample is restricted to the dates of the experiment in July and August. Since employee i exchanges with not only j, but also j', there is a common person effect that could cause us to underestimate standard errors (Kenny et al., 2006), so we use robust standard errors that are clustered on both members of a dyad (Cameron et al., 2011; Kleinbaum et al., 2013).

A.3.2 Examining the Role of the Sender and Recipient of Emails

The main text presents the baseline results that allow non-linearities between the number of days the sender is in the office and emails sent. We now provide two alternative measurement strategies: (a) the number of days that employee i is in the office with employee j during the treatment period, and (b) the number of days that the sender is in the office. We argue that both these results point towards the focus on non-linearities through our three-bin approach.

Table A.4 documents these results. Starting with demographics, we see that men tend to send an additional 0.49 more emails within a dyadic pair, whereas non-managers tend to send 1.06 fewer emails within a dyadic pair. Those with a master's or PhD degree are not statistically more likely to send more emails, but those who are married send 0.82 fewer emails. Interestingly, caring for a child is associated with 0.53 *more* emails between any dyadic pair.

We now focus on our main remote work variables. Starting with our measure of co-location, increases in the number of days that a dyad is jointly in the office is negatively associated with the number of emails exchanged, but just barely and not in a statistically significant way. We find a slight positive interaction effect between co-location and male gender, but again it is not statistically significant. We find a positive interaction between co-location for non-managers, but it is only statistically significant at the 10% level. We find no meaningful variation when we allow for heterogeneity between the treatment (post-lockdown) and pre-treatment (lockdown) periods, but we do find a strong negative interaction effect for co-location among dyads that had talked prior to the pandemic, which is again consistent with a democratizing effect of remote work on email communication. These results are in contrast to what we might normally expect based on theories of homophily whereby similar individuals associate more (e.g., those who communicated prior to the treatment) (Bramoulle et al., 2012; Golub and Jackson, 2012).

Next, we turn towards the number of days the sender is in the office. Unlike our measure of co-location, we generally find a strong positive interaction effect across our specifications. For example, an additional day in the office is associated with an additional 0.038 emails sent. We find no heterogeneity between men and women or between the lockdown and post-lockdown periods. However, we find a strong positive interaction effect between our non-manager indicator and days the sender was in the office. In short, these results suggest that the number of days the sender is in the office matters much more than the number of days a dyad co-locates.

Table A.4: The Effects of Co-location and Days Sender in the Office on Email Communication

	Number of Emails Sent									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
# Days Jointly in Office	-.011	-.039	-.162**	.006	.063*					
	[.031]	[.049]	[.082]	[.030]	[.038]					
× Male		.057								
		[.063]								
× Non-Manager			.161*							
			[.088]							
× Post-Lockdown				-.017						
				[.018]						
× Emailed Pre-Lockdown					-.173***					
					[.057]					
# Days Sender in Office						.038**	.033	-.067*	.057***	.009
						[.016]	[.023]	[.035]	[.017]	[.017]
× Male							.009			
							[.028]			
× Non-Manager								.123***		
								[.041]		
× Post-Lockdown									-.005	
									[.010]	
× Emailed Pre-Lockdown										-.036
										[.025]
Male	.492***	.283	.490***	.627***	-.140	.428***	.332	.405***	.569***	-.104
	[.145]	[.285]	[.145]	[.147]	[.145]	[.146]	[.328]	[.144]	[.150]	[.151]
Non-Manager	-1.061***	-1.081***	-1.548***	-1.017***	-.344**	-1.246***	-1.259***	-2.263***	-1.273***	-.324**
	[.181]	[.183]	[.359]	[.179]	[.152]	[.195]	[.193]	[.440]	[.195]	[.162]
Masters/PhD	-.098	-.086	-.107	.100	-.652***	-.010	-.005	-.032	.221	-.673***
	[.211]	[.211]	[.210]	[.193]	[.191]	[.219]	[.219]	[.211]	[.203]	[.208]
Married	-.820**	-.836**	-.828**	-.659**	-.260	-.791**	-.801**	-.780**	-.611*	-.285
	[.331]	[.330]	[.335]	[.306]	[.227]	[.339]	[.340]	[.334]	[.313]	[.236]
Spouse WFH	-.060	-.048	-.026	-.032	.091	.018	.023	.157	.085	.069
	[.144]	[.144]	[.147]	[.149]	[.150]	[.150]	[.149]	[.161]	[.158]	[.150]
Caring for Child	.530***	.530***	.520***	.497***	.216	.525***	.524***	.475***	.466***	.233
	[.141]	[.141]	[.141]	[.140]	[.146]	[.144]	[.145]	[.141]	[.142]	[.148]
Post-Lockdown				.045					.055	
				[.085]					[.125]	
Emailed Pre-Lockdown					4.678***					4.443***
					[.396]					[.430]
Sample Size	10176	10176	10176	20352	10176	10176	10176	10176	20352	10176

Notes.—Source: Authors. The table reports the coefficients associated with negative binomial regressions of the number of emails sent during the treatment period on an indicator for being male, a non-manager (employee), the post-lockdown period, whether the (i, j) dyad exchanged at least one email prior to the treatment, the number of days dyad (i, j) is jointly in the office, the number of days the sender is in the office, and their interactions. We also control for whether an individual has a masters/PhD (normalized to having a bachelor's), married, the spouse works from home, and the employee has to care for a child. Since employee i exchanges with not only j, but also j', there is a common person effect that could cause us to underestimate standard errors (Kenny et al., 2006), so we use robust standard errors that are clustered on both members of a dyad (Cameron et al., 2011; Kleinbaum et al., 2013).

A.3.3 Sentiment Analysis

Additionally, we study how extent of hybrid work relates to characteristics of emails sent by workers, notably the length and sentiment of email text. Table A.5 documents these results. These results show that employees spending significant time at the office are more parsimonious in their emails, with an additive effect when co-located in the office with a recipient.

We assess sentiment using a simple algorithm from a widely-used open-source software package (Hutto and Gilbert, 2014). After preprocessing the email bodies to remove extraneous elements, such as email signatures, we assigns proportions of positive, negative, and neutral sentiment to each email body. This analysis finds that in-person attendance is strongly associated with an increase in the average sentiment of emails, with positive sentiment increasing significantly and neutral sentiment decreasing somewhat; there is little effect on negative sentiment. Though we do not explore the mechanisms by which co-location affects sentiment, such a reading is consistent with co-location engendering more collegiality.

Table A.5: Relationship Between Email Metrics and Remote Work

	Word Count	Positive	Negative Sentiment	Neutral
	(1)	(2)	(3)	(4)
Days Sender in Office	-2.829^{**}	0.003	-0.0001	-0.003
	(1.347)	(0.003)	(0.0002)	(0.003)
Non-Manager	6.466	-0.091^{***}	-0.0002	0.092^{***}
	(13.424)	(0.035)	(0.002)	(0.035)
Post-Lockdown	3.340	0.007	-0.001	-0.005
	(7.396)	(0.021)	(0.001)	(0.021)
Gender FE	Yes	Yes	Yes	Yes
R^2	0.050	0.039	0.035	0.039
Adjusted R^2	0.032	0.020	0.016	0.020

Notes: Notes.—Source: Authors. The table reports the coefficients associated with regressions of word count and sentiment metrics against the number of days the sender is in the office. Standard errors are clustered at the sender-level.

A.3.4 Robustness Over the Intermediate Work Cutoff Threshold

Our baseline results partition employees into one of three bins based on the overall distribution of days in the office—that is, drawing from the distributions for both the microfinance and human resources departments. However, since our email data consists only of messages sent by HR employees, we replicate our main results from Table 2 in an additional series of results below, Table A.6. In reality, there is no statistically significant differenc. The intermediate cutoff changes to 9-13 days, rather than 9-14 days, which is not surprising given the overlap in the distribution of days in the office we presented earlier in Figure A.3.

Next, Table A.7 presents the main results (using the original cutoffs from the full sample) using two-way clustering from Kleinbaum et al. (2013). The standard errors increase, but the main effects remain statistically significant.

Next, Table A.8 replicates the results from the main text by altering the cutoff on the remote work classifications using only the employees in human resources. Again, there is no statistically difference between these two sets of results.

Next, we allow for even greater heterogeneity in the intensity of WFH by classifying employees into four bins: 0-7 days in the office, 8-12 days, 13-15 days, and 16-23 days. Our goal here is to allow for greater heterogeneity. We also estimate our regressions separately by group to ease the interpretation of marginal effects, rather than having to present many interaction effects.

Table A.9 documents these results. We see, in the pooled sample, that the results are clustered among those who come into the office 13-15 days: they send 0.914 more emails for a given dyad.

Table A.6: Intensity of Working-from-Home and Number of Emails Sent (Alternative Cutoff)

	Number of Emails Sent					
	(1)	(2)	(3)	(4)	(5)	(6)
8-11 Days in Office	.193	.113	.105	.081	.079	.084
	[.197]	[.196]	[.200]	[.198]	[.197]	[.200]
12-14 Days in Office	1.046***	1.002***	.985***	.929***	.937***	.887***
	[.208]	[.212]	[.218]	[.198]	[.201]	[.200]
15-23 Days in Office	.562***	.490***	.466***	.423**	.438**	.406**
	[.160]	[.161]	[.171]	[.171]	[.178]	[.177]
Non-Manager	-1.611***	-1.534***	-1.533***	-1.525***	-1.535***	-1.414***
	[.224]	[.219]	[.221]	[.218]	[.218]	[.212]
Male		.252*	.258*	.302**	.300**	.364***
		[.135]	[.138]	[.137]	[.136]	[.141]
Masters/PhD			-.091	-.009	-.005	-.047
			[.170]	[.195]	[.196]	[.199]
Married				-.249	-.260	-.455
				[.263]	[.268]	[.283]
Spouse WFH					.038	.036
					[.141]	[.140]
Caring for Child						.398***
						[.139]
Sample Size	10600	10600	10600	10600	10600	10600

Notes.—Source: Authors. The table reports the coefficients associated with negative binomial regressions of the number of emails sent during the treatment period on an indicator for whether the email sender came in between 8-11, 12-14, and 15-23 days in the office, normalized to 1-7 days in the office, controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. Here, cutoff for the number of days in the office is generated based off the employees in the human resources department. Since employee i exchanges with not only j, but also j', there is a common person effect that could cause us to underestimate standard errors (Kenny et al., 2006), so we use robust standard errors that are clustered on both members of a dyad (Cameron et al., 2011; Kleinbaum et al., 2013).

Table A.7: Intensity of Working-from-Home and Number of Emails Sent (Two-way Clustering)

	Number of Emails Sent					
	(1)	(2)	(3)	(4)	(5)	(6)
Intermediate WFH	.814**	.781**	.758**	.716**	.710**	.689**
	[.337]	[.340]	[.340]	[.322]	[.318]	[.313]
Low WFH	.537	.493	.457	.421	.379	.364
	[.364]	[.371]	[.360]	[.355]	[.345]	[.318]
Non-Manager	-1.608***	-1.558***	-1.555***	-1.563***	-1.538***	-1.419***
	[.454]	[.435]	[.439]	[.434]	[.408]	[.370]
Male		.185	.192	.259	.260	.334
		[.228]	[.224]	[.240]	[.238]	[.230]
Masters/PhD			-.139	-.003	-.018	-.062
			[.294]	[.266]	[.265]	[.266]
Married				-.384	-.337	-.554
				[.404]	[.420]	[.419]
Spouse WFH					-.127	-.111
					[.206]	[.193]
Caring for Child						.447*
						[.241]
Sample Size	10600	10600	10600	10600	10600	10600

Notes.—Source: Authors. The table reports the coefficients associated with negative binomial regressions of the number of emails sent during the treatment period on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 days in the office (low WFH), controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. Since employee i exchanges with not only j, but also j', there is a common person effect that could cause us to underestimate standard errors (Kenny et al., 2006), so we use robust standard errors that are clustered on both members of a dyad (Cameron et al., 2011; Kleinbaum et al., 2013).

Table A.8: Intensity of Working-from-Home and Number of Unique Recipients (Alternative Cutoff)

	log(Unique Recipients of Emails)					
	(1)	(2)	(3)	(4)	(5)	(6)
8-11 Days in Office	.210	.194	.152	.173	.160	.149
	[.191]	[.191]	[.193]	[.194]	[.192]	[.199]
12-14 Days in Office	.605***	.590***	.540***	.615***	.629***	.611***
	[.183]	[.190]	[.192]	[.181]	[.183]	[.186]
15-23 Days in Office	.332	.300	.236	.276	.328	.311
	[.214]	[.228]	[.223]	[.225]	[.219]	[.221]
Non-Manager	-.603**	-.577**	-.543**	-.547**	-.559**	-.502*
	[.270]	[.263]	[.267]	[.268]	[.261]	[.259]
Male		.103	.136	.091	.087	.128
		[.150]	[.148]	[.145]	[.147]	[.150]
Masters/PhD			-.352**	-.412**	-.409**	-.414**
			[.154]	[.173]	[.176]	[.174]
Married				.305	.242	.157
				[.213]	[.218]	[.224]
Spouse WFH					.193	.185
					[.159]	[.161]
Caring for Child						.174
						[.150]
Sample Size	99	99	99	99	99	99

Notes.—Source: Authors. The table reports the coefficients associated with regressions of the logged number of unique recipients during the treatment period on an indicator for whether the email sender came in between 8-11, 12-14, and 15-23 days in the office, normalized to 1-7 days in the office, controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. Standard errors are clustered at the employee-level.

The other two indicators are both positive, but not statistically significant, relative to the omitted group of high WFH (0-7 days in the office). Next, we see that the marginal effect is greater for men than for women on the 13-15 days in the office indicator, but a high number of days in the office is negatively associated with emails sent by women. Next, we see that our effects are roughly as large for employees with a spouse who works from home, relative to their counterparts. However, we do find important heterogeneity when we split on caring for a child. For them, the 13-15 days category is strongly associated with more sent emails. Our other effects are not statistically significant at this level of granularity.

Table A.9: Intensity of Working-from-Home and Emails Sent (Four-Bins)

	Number of Emails Sent						
	All	Male	Female	Spouse WFH	No Spouse WFH	Care for Child	No Care for Child
8-12 Days in Office	.259	.575*	-.022	.193	.233	-.625*	.577**
	[.206]	[.306]	[.243]	[.262]	[.314]	[.358]	[.258]
13-15 Days in Office	.914***	1.391***	.758***	.942***	1.069***	1.275***	.761***
	[.189]	[.378]	[.209]	[.322]	[.312]	[.365]	[.221]
16-23 Days in Office	.107	.606*	-.752*	.370	.229	.105	.005
	[.224]	[.324]	[.457]	[.474]	[.354]	[.444]	[.289]
Sample Size	10176	5618	4558	3074	7102	4452	5724

Notes.—Source: Authors. The table reports the coefficients associated with Poisson regressions of the number of emails sent during the treatment period on an indicator for whether the email sender came in between 8-12 days in the office, an indicator for 13-15 days in the office, and 16-23 days in the office, normalized to 1-7 days in the office, separately by group. We also control for whether an individual is male, is an employee (versus a manager), has a masters/PhD (normalized to having a bachelor's), married, the spouse works from home, and the employee has to care for a child. Since employee i exchanges with not only j, but also j', there is a common person effect that could cause us to underestimate standard errors (Kenny et al., 2006), so we use robust standard errors that are clustered on both members of a dyad (Cameron et al., 2011; Kleinbaum et al., 2013).

A.3.5 Robustness Exercises Over Main Non-linearity Results

The main text presents the coefficients associated with negative binomial regressions of number of emails exchanged with dyadic data in Table 2. Now, we examine whether these results are robust to using a Poisson distribution, rather than a negative binomial distribution.

Table A.10 documents these results. Generally speaking, we see less statistically significant results. For example, while the baseline marginal effects of intermediate and low WFH were 0.814 and 0.537, here they are 0.657 and 0.393, respectively. As we add additional controls, the marginal effect on low WFH becomes less statistically significant, but remains positive. Importantly, the marginal effect on intermediate WFH remains economically and statistically significant across every specification. The rationale for the decline in significance stems from the large share of zero email communication across dyads, making the negative binomial a better fit.

Table A.10: Intensity of Working-from-Home and Emails Sent (Poisson Robustness)

	Number of Emails Sent					
	(1)	(2)	(3)	(4)	(5)	(6)
Intermediate WFH	.657***	.614***	.599***	.576***	.595***	.538***
	[.152]	[.156]	[.161]	[.155]	[.155]	[.157]
Low WFH	.393***	.324**	.312**	.294*	.278*	.268*
	[.140]	[.147]	[.151]	[.151]	[.153]	[.158]
Non-Manager	-1.456***	-1.395***	-1.387***	-1.403***	-1.406***	-1.273***
	[.176]	[.174]	[.179]	[.181]	[.183]	[.182]
Male		.215	.221	.280*	.264*	.353**
		[.146]	[.152]	[.155]	[.156]	[.160]
Masters/PhD			-.075	-.009	-.044	-.051
			[.182]	[.189]	[.188]	[.187]
Married				-.331	-.241	-.497*
				[.250]	[.253]	[.264]
Spouse WFH					-.220	-.195
					[.140]	[.140]
Caring for Child						.429***
						[.141]
Sample Size	10600	10600	10600	10600	10600	10600

Notes.—Source: Authors. The table reports the coefficients associated with Poisson regressions of the number of emails sent during the treatment period on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 days in the office (low WFH), controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. Since employee i exchanges with not only j, but also j', there is a common person effect that could cause us to underestimate standard errors (Kenny et al., 2006), so we use robust standard errors that are clustered on both members of a dyad (Cameron et al., 2011; Kleinbaum et al., 2013).

Next, we allow for heterogeneity across several different dimensions in Table A.11. Column 1 begins by replicating the main result. We subsequently interact each of our demographic characteristics with our two WFH indicators, as well as an indicator for whether the dyad communicated at all during the lockdown (prior to the treatment).

We document these results in Table A.11. Column 1 begins by replicating our main result. Column 2 shows that there is not much heterogeneity between male versus female employees; the interactions are statistically insignificant. Column 3 shows that there is significant heterogeneity among employees and non-managers: all of the effect of intermediate WFH on emails is driven by employees, although there is not much heterogeneity on low WFH. Turning towards heterogeneity in educational attainment, column 4 shows that those with a master's or PhD degree are less likely to email, which may reflect their focus on more cognitively-demanding tasks (which may require less coordination and involve more independent work). Columns 5, 6, and 7 show that there is little heterogeneity across marital status, whether the spouse also works from home, and whether the respondent has to care for a child. If anything, the spouse WFH exhibits complementarity for those in intermediate WFH arrangements and substitutability for those in low WFH arrangements, whereas caring for a child interacts negatively for both intermediate and low WFH. Furthermore, those who are married send fewer emails when they are in low WFH arrangements.

Finally, column 8 allows for an interaction with whether the dyad communicated during the lockdown prior to the treatment. Perhaps most importantly, we find a negative interaction effect on the interaction effect for both intermediate and low WFH arrangements, meaning that intermediate and low levels of WFH helps democratize the workplace and break temporally static patterns in workplace communication (Bramoulle et al., 2012; Golub and Jackson, 2012). Given that one of the major concerns about WFH is that it will cause more siloes to emerge relative to workplace communication (Yang et al., 2021), these results suggest that intermediate levels of hybrid work is a potential panacea because it balances between the two extremes.

Additionally, we examine whether our results are robust to conducting regressions at the employee level, rather than dyad level presented in the main text. We did so at the dyad level for two reasons. First, it provides us with additional variation since we can exploit differences in connectivity for the same sender towards many recipients. Second, it allows us to exploit pre-pandemic connectivity to examine the role of homophily. Nonetheless, other results (especially performance ratings) are based on employee-level data, so we want to ensure that our results are robust to this alternative specification.

Table A.12 documents these results. Starting with column 1, we see that intermediate WFH leads to 44.5% higher emails sent, whereas low WFH leads to 8.6% fewer emails sent, although it is not statistically significant at the 10% level. Next we begin partitioning based on different dimensions of demographic heterogeneity. We find that intermediate WFH is most associated with increases in emails sent, although the marginal effects are not always statistically significant because of the small sample size. Men tend to have larger marginal effects for intermediate WFH, but women have larger marginal effects for low WFH.

Next, Table A.13 reports the results associated with regressions of the logged number of emails on WFH indicators for the recipient, *rather than the sender*. While the coefficient on intermediate WFH is statistically significant at the 10% level, it is lower in magnitude and not statistically different from low WFH, which is not statistically significant at conventional levels. This is not surprising: recipients should be less affected by these choices.

Next, Table A.14 presents the results for an analogous specification where we instead use the number of days the individual was in the office, rather than an indicator for different bins, and its square. This approach is less flexible because it assumes that there is a linear, or possibly

Table A.11: Heterogeneity in the Intensity of Working-from-Home and Emails Sent

	Number of Emails Sent							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intermediate WFH	.689***	.671***	-.095	1.571***	1.295**	.656***	.881***	.863***
	[.171]	[.242]	[.357]	[.419]	[.568]	[.219]	[.240]	[.190]
× Male		.044						
		[.295]						
× Non-Manager			.838**					
			[.393]					
× Masters/PhD				-.929**				
				[.425]				
× Married					-.644			
					[.562]			
× Spouse WFH						.147		
						[.310]		
× Care for Child							-.413	
							[.296]	
× Emailed Pre-Lockdown								-.554**
								[.235]
Low WFH	.364**	.583**	.326	1.635***	1.429***	.424**	.512**	.332
	[.161]	[.250]	[.406]	[.355]	[.443]	[.192]	[.212]	[.202]
× Male		-.317						
		[.302]						
× Non-Manager			.065					
			[.456]					
× Masters/PhD				-1.447***				
				[.388]				
× Married					-1.214***			
					[.462]			
× Spouse WFH						-.556		
						[.403]		
× Care for Child							-.351	
							[.309]	
× Emailed Pre-Lockdown								-.510**
								[.251]
Male	.334**	.366*	.338**	.319**	.357**	.343**	.326**	-.438***
	[.137]	[.195]	[.135]	[.137]	[.141]	[.139]	[.136]	[.149]
Non-Manager	-1.419***	-1.417***	-1.532***	-1.444***	-1.411***	-1.483***	-1.358***	-.774***
	[.205]	[.201]	[.240]	[.199]	[.201]	[.221]	[.200]	[.167]
Masters/PhD	-.062	-.033	-.103	.873**	-.049	-.018	-.086	-.342**
	[.208]	[.202]	[.207]	[.359]	[.205]	[.211]	[.205]	[.151]
Married	-.554*	-.519*	-.532*	-.547*	.091	-.590**	-.450	-.196
	[.289]	[.300]	[.287]	[.286]	[.444]	[.294]	[.287]	[.193]
Spouse WFH	-.111	-.116	-.094	-.135	-.135	-.129	-.166	.136
	[.138]	[.138]	[.144]	[.139]	[.139]	[.199]	[.145]	[.140]
Caring for Child	.447***	.451***	.461***	.412***	.478***	.446***	.673***	.205
	[.135]	[.135]	[.137]	[.135]	[.135]	[.141]	[.203]	[.132]
Emailed During Lockdown								4.705***
								[.333]
Sample Size	10600	10600	10600	10600	10600	10600	10600	10600

Notes.—Source: Authors. The table reports the coefficients associated with negative binomial regressions of the number of emails sent during the treatment period on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 days in the office (low WFH), an indicator for being male, a non-manager (employee), the post-lockdown period, whether the (i, j) dyad exchanged at least one email prior to the treatment during the lockdown, and their interactions. We also control for whether an individual has a masters/PhD (normalized to having a bachelor's), whether married, whether the spouse works from home, and whether the employee has to care for a child. Since employee i exchanges with not only j, but also j', there is a common person effect that could cause us to underestimate standard errors (Kenny et al., 2006), so we use robust standard errors that are clustered on both members of a dyad (Cameron et al., 2011; Kleinbaum et al., 2013).

Table A.12: Intensity of Working-from-Home and Logged Emails Sent (Employee-level)

	log(Number of Emails Sent)						
	All	Male	Female	Spouse WFH	No Spouse WFH	Care for Child	No Care for Child
Intermediate WFH	.445**	.498**	.340	.531	.491*	.314	.579**
	[.213]	[.231]	[.397]	[.447]	[.291]	[.420]	[.239]
Low WFH	.086	-.058	.378	.205	.105	-.047	.219
	[.270]	[.352]	[.483]	[.462]	[.332]	[.560]	[.335]
Male	.518***			.542	.392	.670**	.365
	[.193]			[.454]	[.245]	[.326]	[.273]
Non-Manager	-1.226***	-1.164***	-1.369***	-1.194**	-1.312***	-1.200***	-1.204***
	[.206]	[.259]	[.437]	[.433]	[.305]	[.319]	[.284]
Masters/PhD	-.135	-.304	.144	.140	-.281	.297	-.375
	[.230]	[.246]	[.377]	[.490]	[.295]	[.352]	[.322]
Married	-.355	-.636	-.209			-.588	-.183
	[.337]	[.379]	[.461]			[.465]	[.377]
Spouse WFH	-.088	-.047	-.128			-.287	.033
	[.201]	[.236]	[.428]			[.376]	[.229]
Caring for Child	.321	.468*	.123	.112	.318		
	[.196]	[.256]	[.365]	[.479]	[.255]		
R-squared	.28	.41	.14	.28	.28	.34	.24
Sample Size	94	51	43	29	65	40	54

Notes.—Source: Authors. The table reports the coefficients associated with regressions of the logged number of emails sent during the treatment period on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 (low WFH), separately by group. We also control for whether an individual is male, is an employee (rather than manager), has a masters/PhD (normalized to having a bachelor's), married, the spouse works from home, and the employee has to care for a child. Standard errors are heteroskedastic-robust.

higher-order, relationship between emails and remote work, whereas the prior approach treated the relationship semi-parametrically. While we see a positive association for the linear term between days in the office and emails sent, we find no evidence of a statistically significant effect on the quadratic term. If anything, it is slightly negative (i.e., column 2), but small. This is consistent with our view that the semi-parametric approach is a better fit for the data.

Finally, we ask whether it matters if a person works from home on a particular day over another—for example, earlier in the week versus later in the week. Here, we exploit our daily variation, regressing the log number of emails and words per email on an indicator for whether the employee is WFH, whether it is a Wednesday or Thursday (the end of the Bangladesh work week), their interaction, and day-of-month and person fixed effects. While columns 1 and 4 report the raw correlations for completeness, columns 2 and 5 include the fixed effects. We find no statistically

Table A.13: Intensity of Working-from-Home and Recipient Emails (Employee-level)

	log(Number of Emails Received)				
	(1)	(2)	(3)	(4)	(5)
Intermediate WFH	.300*	.298*	.287*	.287*	.269*
	[.152]	[.155]	[.158]	[.158]	[.155]
Low WFH	.210	.207	.198	.182	.168
	[.198]	[.200]	[.199]	[.205]	[.201]
Non-Manager	-1.530***	-1.529***	-1.529***	-1.526***	-1.471***
	[.182]	[.184]	[.184]	[.182]	[.184]
Male	.222	.223	.240	.240	.277*
	[.136]	[.140]	[.149]	[.149]	[.154]
Masters/PhD		-.014	.006	.002	-.010
		[.156]	[.152]	[.152]	[.152]
Married			-.105	-.082	-.162
			[.196]	[.211]	[.226]
Spouse WFH				-.065	-.071
				[.148]	[.148]
Caring for Child					.168
					[.150]
R-squared	.39	.39	.39	.40	.40
Sample Size	100	100	100	100	100

Notes.—Source: Authors. The table reports the coefficients associated with regressions of the logged number of emails for the recipient during the treatment period on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 (low WFH), separately by group. We also control for whether an individual is male, is an employee (rather than manager), has a masters/PhD (normalized to having a bachelor's), married, the spouse works from home, and the employee has to care for a child. Standard errors are heteroskedastic-robust.

Table A.14: Robustness Using Quadratic in Number of Days

	Number of Emails		log(Number of Emails)	
	(1)	(2)	(3)	(4)
Days in Office	3.257	5.323	.056*	.109
	[3.022]	[14.243]	[.029]	[.112]
Days in Office Squared		-.098		-.003
		[.574]		[.005]
Non-Manager	-124.117***	-124.216***	-1.015**	-1.014**
	[28.187]	[27.915]	[.454]	[.456]
Male	41.081	40.871	.123	.112
	[28.858]	[29.481]	[.288]	[.289]
Masters/PhD	-12.234	-11.275	-.215	-.191
	[28.184]	[29.299]	[.257]	[.265]
Married	-58.530	-57.583	-.225	-.201
	[39.426]	[40.450]	[.353]	[.355]
Spouse WFH	-13.759	-14.292	.267	.257
	[24.605]	[23.506]	[.268]	[.272]
Caring for Child	51.391**	51.150**	.008	.006
	[25.165]	[25.721]	[.286]	[.288]
R-squared			.11	.12
Sample Size	99	99	99	99

Notes.—Source: Authors. The table reports the coefficients associated with regressions of the number of emails (estimated with a Poisson count model) and the logged number of emails (estimated using least squares) sent during the treatment period on the number of days the employee was in the office and its square. We also control for whether an individual is male, is an employee (rather than manager), has a masters/PhD (normalized to having a bachelor's), married, the spouse works from home, and the employee has to care for a child. Standard errors are heteroskedastic-robust.

significant interaction effect between the latter part of the week and WFH. For completeness, we also omit the interaction effect in columns 3 and 6, showing that employees send fewer emails on days that they are working from home. We conduct all our analysis using least squares regressions, rather than negative binomial, because of the importance of including person and time fixed effects.

Table A.15: Evaluating Heterogeneous Treatment Effects by Day-of-Week

	log(Number of Emails)			log(Words/Emails)		
	(1)	(2)	(3)	(4)	(5)	(6)
Working from Home (WFH)	-.128*	-.041	-.072*	.101	.021	-.013
	[.066]	[.047]	[.038]	[.068]	[.043]	[.029]
Wednesday/Thursday	-.065			.076		
	[.061]			[.058]		
WFH × Wednesday/Thursday	.075	-.073		-.075	-.081	
	[.080]	[.059]		[.072]	[.071]	
R-squared	.00	.43	.43	.00	.46	.46
Sample Size	2710	2710	2710	2632	2632	2632
Person FE	No	Yes	Yes	No	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes

Notes.—Source: Authors. The table reports the coefficients associated with least squares regressions of the number of emails and words in emails at a daily frequency on an indicator for working from home (WFH), an indicator for whether we see a Thursday or Friday, their interaction, conditional on person and day by month fixed effects. Standard errors are clustered at the person-level.

A.4 Methodology for the Information Uniqueness Measure

We apply a new procedure to generate an approximation of information uniqueness. We first preprocess all email text to remove email signature, inline replies, and the like. Then, we combine this text with the plaintext extracted from document attachments[29]. We then generate word vectors for each document (email text or attachment text) using Doc2vec (Le and Mikolov, 2014), a nat-

[29] Specifically, we examine Word documents, PowerPoint presentations, and PDF files.

ural language processing model implementing in Gensim and extended from Word2vec. Doc2vec makes use of neural networks to produce a numeric vector representing a document (Figure A.8). Beyond a mere bag-of-words approach, this attempts to leverage semantic relationships. Thus, each document admits a fixed-length, numeric vector representation.

We then apply the BIRCH (Balanced Iterative Reducing and Clustering Using Hierarchies) algorithm (Zhang et al., 1997), an unsupervised learning process in the scikit-learn package, to cluster all such vectors into document types. Then, returning to the original vectors, we generate a "representative" document for each sender $\times$ document type by taking the simple average. For example, this would generate a synthetic "representative salary report sent by employee A." Next, for each document, we compute the cosine similarity against this synthetic representative document (Figure A.9). The cosine similarity measure ranges from -1 to 1 for documents orthogonal or identical, respectively, to the synthetic representative document. By halving this value and subtracting from 0.5, we produce an information uniqueness measure between 0 and 1, with 1 indicating more uniqueness.[30]

To collapse these values into a tractable form, we take the mean of all information uniqueness measures per sender during the lockdown and treatment periods (Figure A.10). Finally, we take the difference in each sender's scores from the lockdown to the treatment period and standardize this value.

To interpret these as a measure of productivity, we would need an additional identifying as-

[30]For example, the following string received an information uniqueness score of 0.013 (low uniqueness): "Dear [Name] As per your requirement here I have attached the documents. Regards [Name]". This string received a higher score of 0.315: "i) Staff reflection/comments on overall actual achievements made so far including challenges and areas to be improved based on objectives (MID-YEAR):... In this pandemic situation i ensured virtual communication with [#] field staffs regarding COVID awareness and positive case identify and regular HR service. It could have been better if I could give more attention to develop my team members. Rest of the year I will focus on building a productive and high performing team through proper guideline and involvement in this pandemic situation..."

sumption is that producing more novel documents implies that an employee has produced more work; we do not do so here, leaving it as simply "information uniqueness." Although the details of the calculation outlined above are involved, the interpretation of this information uniqueness measure is natural. Consider the case in which an employee simply attaches the same document to many emails. The cosine similarity of these documents will be very high, and so the information uniqueness measure will be low. Therefore, we interpret the value of the difference index to mean that little productive work was required for this document. Now, consider a case where an employee creates a salary report each week. Although the documents are broadly similar, and therefore would be classified as the same document types, we would anticipate deviations in the content of each document. Therefore, the cosine similarity index would be lower, and the information uniqueness measure higher. One potential interpretation is that this represents more work performed by the sender.

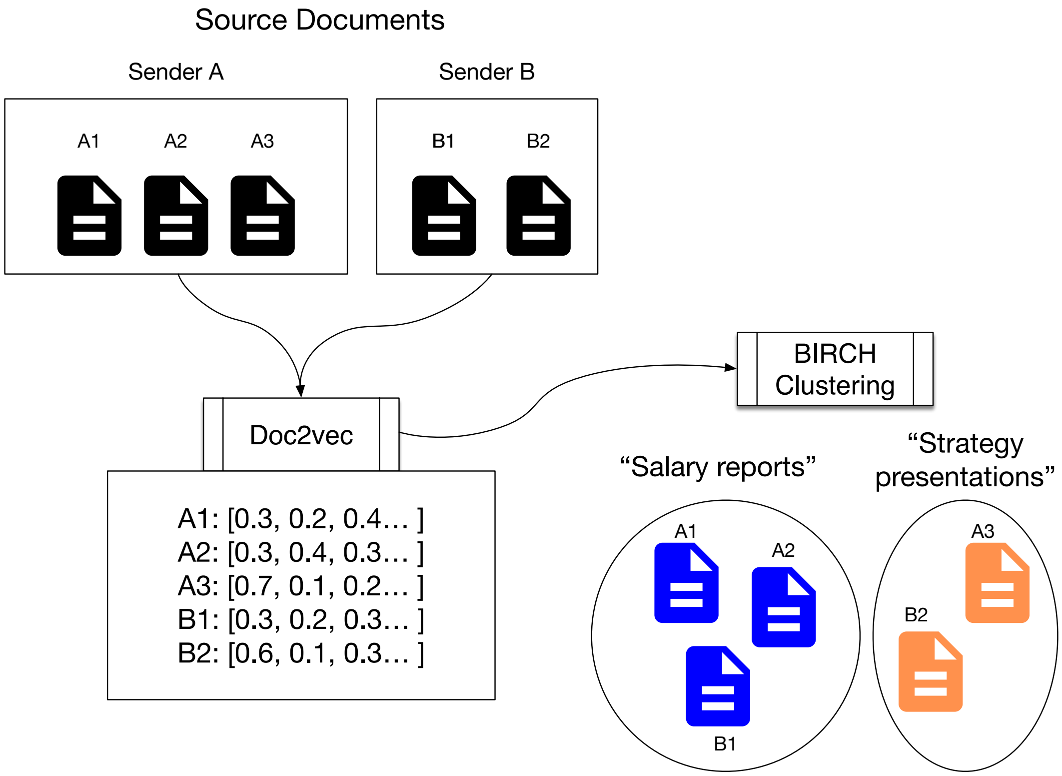

Figure A.8: Clustering Process

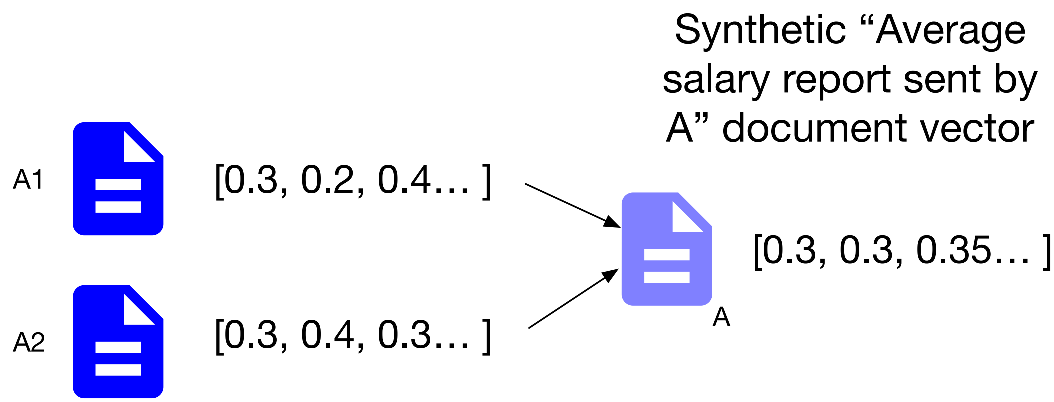

Figure A.9: The Synthetic Document

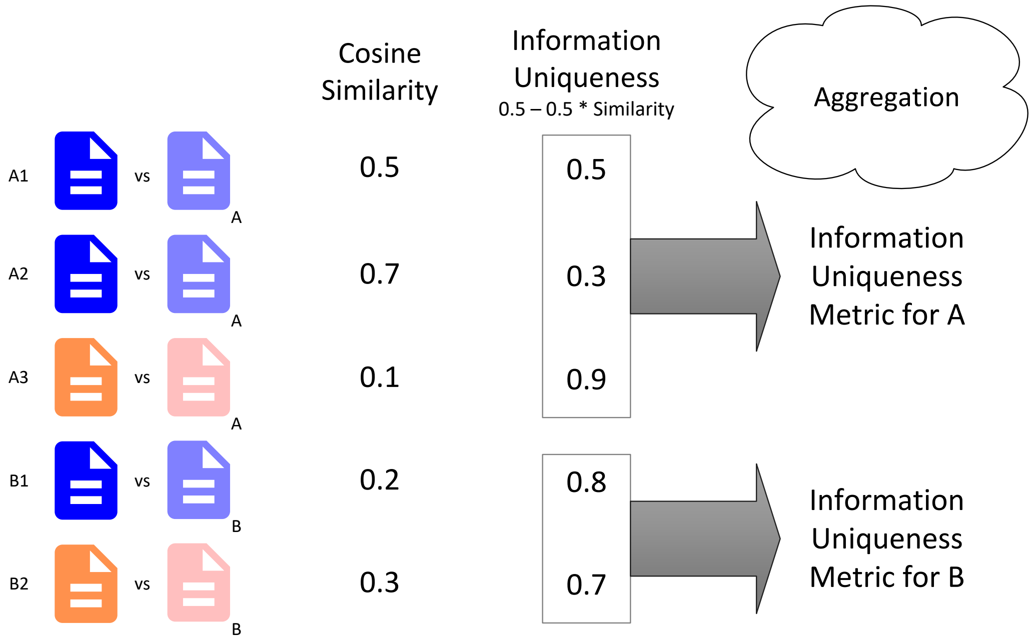

Figure A.10: Information Uniqueness Measure

A.4.1 The Aral-Dhillon Measure

As described in Section 5 in the main text, we adapted the information uniqueness measure of Aral and Dhillon (2022) to focus primarily on individual senders, rather than dyadic interactions *per se*. Specifically, we adapted the process to calculate a sender-level measure (Figure A.11):

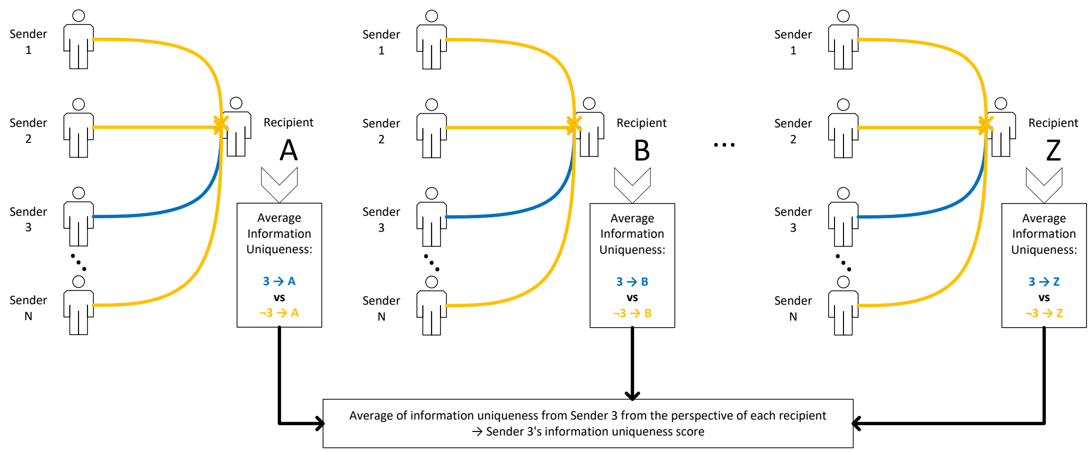

Figure A.11: Calculation of the information uniqueness score for sender 3 (without loss of generality).

The Aral-Dhillon measure of information uniqueness is a dyad- or tie-level measure which "quantifies how similar the information conveyed to an ego v by one contact r is to the information received from all their other contacts $r'(\forall r' \neq r)$." Each message has a particular topic distribution; the measure essentially measures the distance between the average topic distribution of messages received by r from v and that of all messages received by r from all non-v senders:

$$InformationUniqueness_{vr} = \mathbf{Distance}\left[\overline{m}_{vr}^{\{\cdot\}}, \overline{m}_{v\backslash r}^{\{\cdot\}}\right]$$

Although the idealized equation leaves the distance metric unspecified, Aral and Dhillon use a cosine similarity-based measure and show that their results are robust to alternative methods (viz., Hellinger distance and Kullback-Liebler divergence).

A.4.2 "Usefulness" and Information Uniqueness

In Section 5, we discussed the relationship between manager-assessed "usefulness" and the information uniqueness score. Although the training data consisted of only 100 manager-labeled pairs, we applied a supervised learning process to predict the expected level of "usefulness" for each out-of-sample document. Specifically, we trained a support vector machine classifier, using a sigmoid kernel, with the Doc2vec representations as the feature set and the manually-scored usefulness as the label. Next, we predicted the usefulness scores of all documents. Finally, looking only at the treatment period and at intermediate WFH workers, we took the average usefulness score at the employee level and plotted it against the employee's average information uniqueness score (Figure A.12). Because the training set is so small, caution should be exercised in interpreting this figure. However, the positive correlation between usefulness and information uniqueness is consistent with an interpretation of information uniqueness being a desirable trait in determining usefulness.

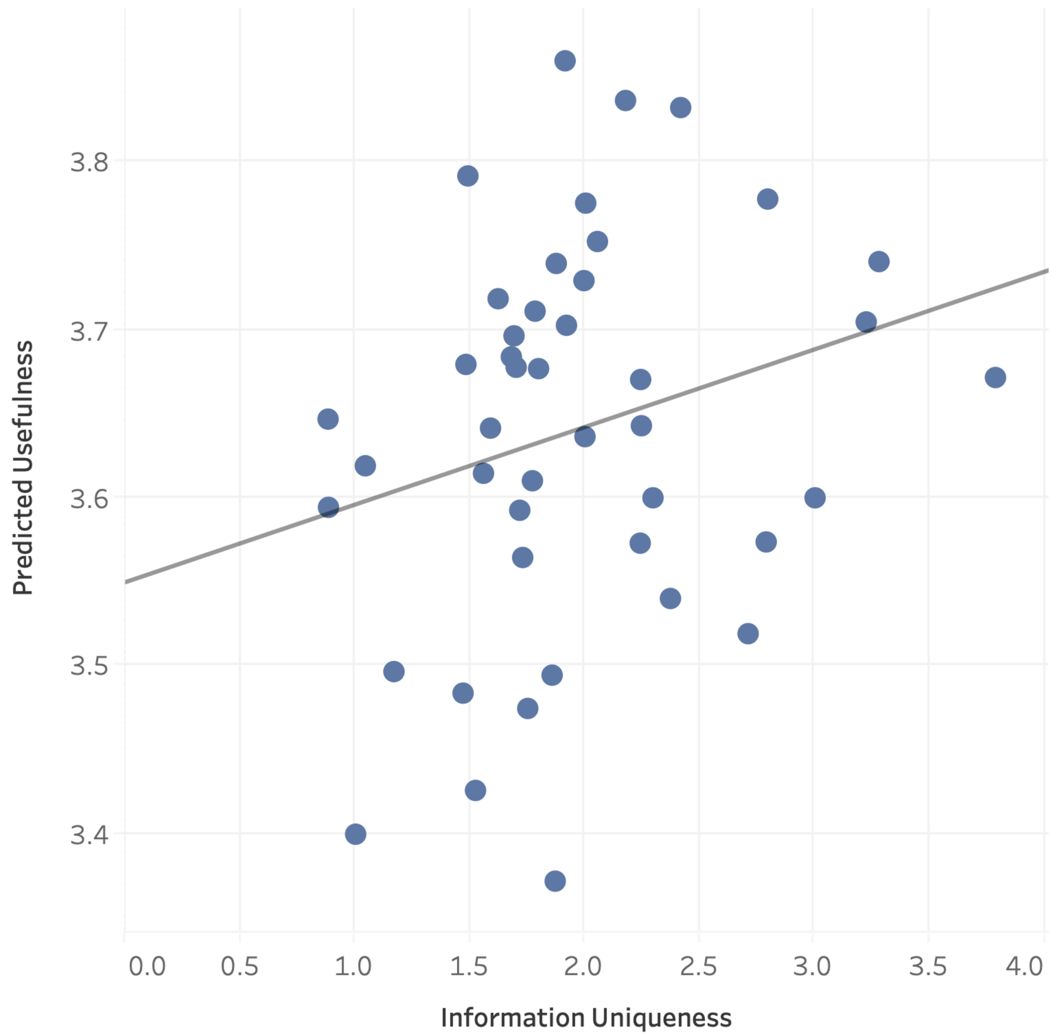

Figure A.12: SVM classifier-predicted usefulness vs. information uniqueness score for intermediate WFH workers, experimental period

A.5 Robustness of the Information Uniqueness Measure

A.5.1 Parametrization of the Clustering Model

As Doc2vec and BIRCH leverage unsupervised machine learning methods, the choice of appropriate parameters is critical to deriving robust and useful results. For example, increasing the number of epochs may improve the fit of a model while increasing computational time; similarly, modifying the learning rate can dampen the influence of outliers. Beyond these computational considerations, two parameters are particularly salient: the length of the vector Doc2vec uses to represent a document (akin to the number of principal components), and the number of clusters BIRCH returns.

Because our data are unlabeled—we do not manually tag or cluster documents, but rather use these unsupervised methods—we must rely on heuristics to determine an appropriate parametrization. One such heuristic is the "silhouette score," which ranges from -1 to 1 and is implemented in scikit-learn. A higher value indicates that 1) clusters are clearly separated from each other in the metric space and 2) clusters are relatively tight relative to the distance between clusters overall. By ranging both the vector size and number of clusters from 4 to 20, inclusive, and running the Doc2vec/BIRCH process, we observe the range of silhouette scores reported in Figure A.13. Note that increasing granularity (that is, increasing the vector size or number of clusters) is generally detrimental for this silhouette score, given our data. Although this may appear counterintuitive, increasing granularity can result in "overfitting" the data and thereby undermining the clusters.

This process results in the cluster distribution illustrated by Figures A.14 and A.15.

We also ran several other variations of the model in Table A.16, all of which are broadly consistent with our reported results. Specifically, we examine using (1) only attachment text, (2) only email text, (3) K-means rather than BIRCH clustering, and (4) a sender $\times$ cluster-level synthetic document used as the centroid, rather than a common cluster-level synthetic document. (Note that, in all cases, individual clusters are calculated on a universal basis, not on a per-sender basis.) Additionally, we applied alternate bin specifications in Table A.17 and found robust results for an intermediate WFH category. We tested for non-linearity by using the number of days in

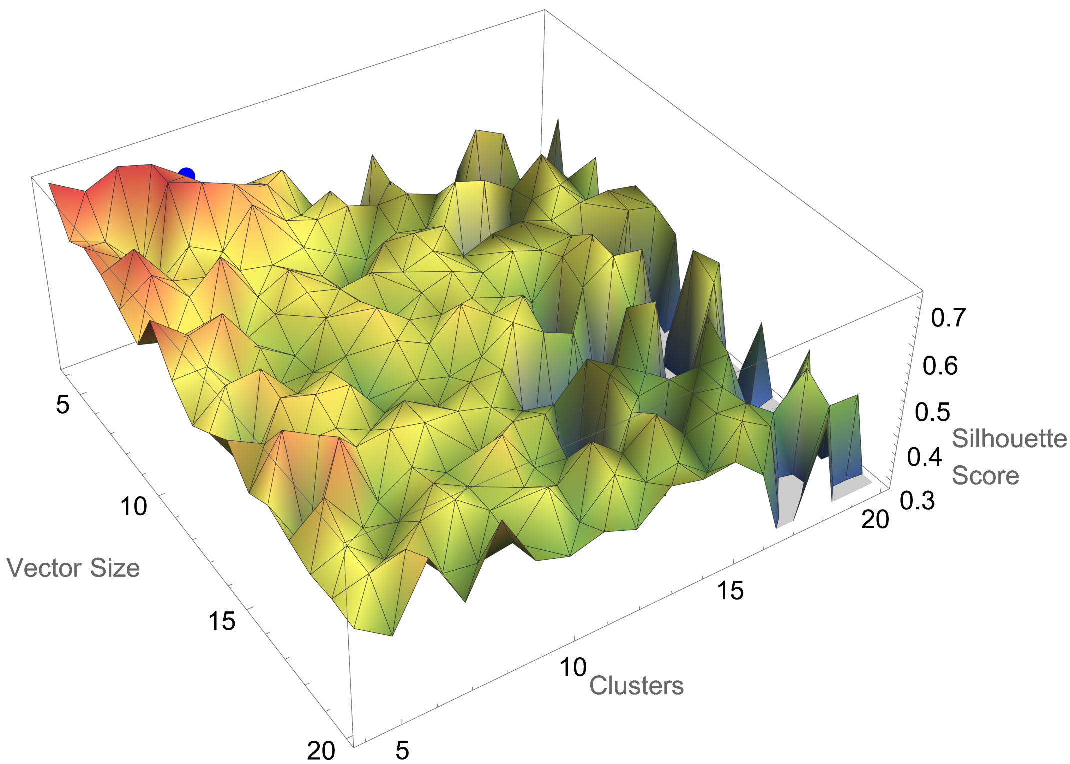

Figure A.13: Silhouette scores for various possible parameters for the vector size and number of clusters. The blue dot represents the parametrization used in Table 4.

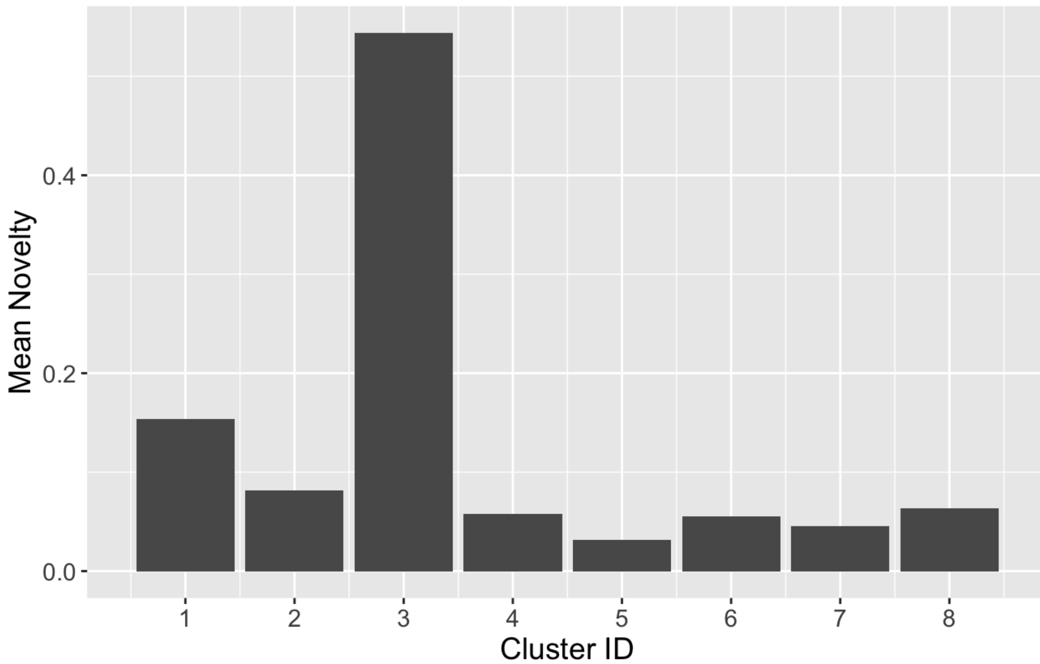

Figure A.14: Distribution of mean information uniqueness scores per cluster (treatment period only)

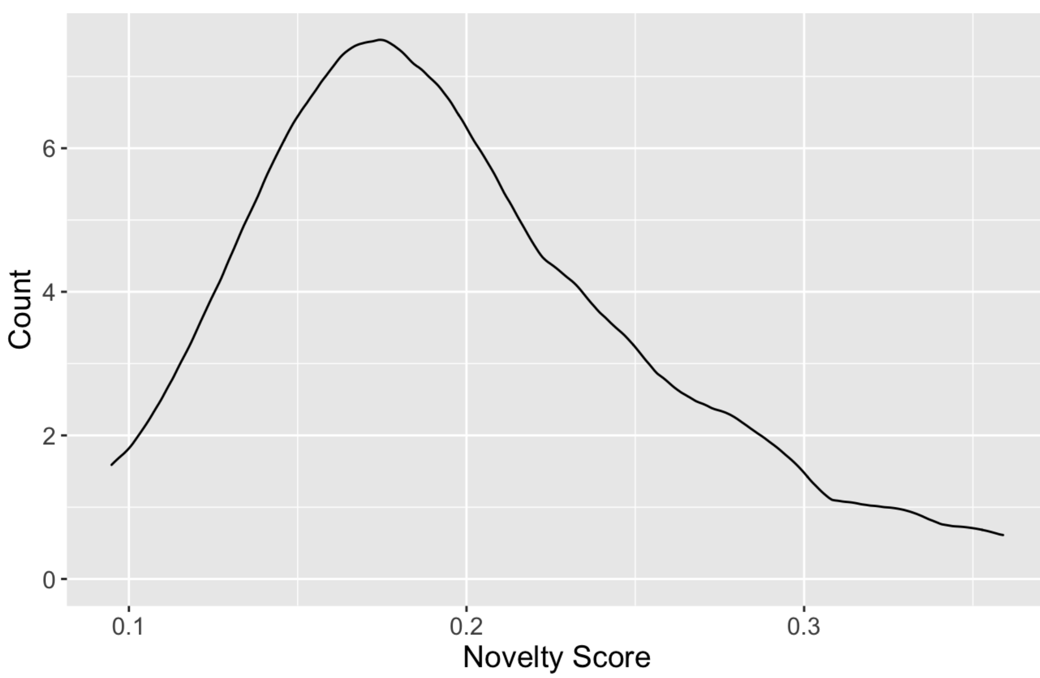

Figure A.15: Distribution of mean information uniqueness scores, across all clusters, by sender (treatment period only) the office, rather than the bin, directly in Tables A.23 and A.24. We also tested the effect of email counts, as the information uniqueness measure indirectly captures both volume and uniqueness; our results remain robust, although slightly less significant (Table A.18). Next, rather than examining the standardized change in information uniqueness from the lockdown to treatment period, we look at the standardized value during the treatment period only in Table A.19. Finally, we also examine heterogeneity within specific clusters in Table A.22, as each document is tagged with a single cluster from 1 to 8. The subsample analysis is somewhat noisy as it ignores the aggregation at a per-sender level across all documents. The effect is most strongly pronounced in cluster 2 and 3, with the coefficients in other clusters statistically insignificant from zero. Assigning an intuitive meaning to these labels is inherently subjective, but a review of the data reveals that cluster 2 is primarily related to "salary adjustment reports" and cluster 3 to "policy clarifications."

Table A.16: Relationship Between Information Uniqueness and the Intensity of Working-from-Home, Alternate Specifications

	Change in Cosine Similarity-Based Information Uniqueness Measure			
	(1)	(2)	(3)	(4)
Intermediate WFH	0.619***	0.094	0.380*	0.634***
(9-14 days in office)	(0.224)	(0.223)	(0.217)	(0.225)
Low WFH	0.099	−0.302	0.130	0.303
(15+ days in office)	(0.232)	(0.241)	(0.249)	(0.551)
Gender FEs	Yes	Yes	Yes	Yes
Manager/Worker FEs	Yes	Yes	Yes	Yes
Other Demographic FEs	Yes	Yes	Yes	Yes

Notes: See Table 4 for a discussion of the information uniqueness measure. The specific robustness checks represented above involve using (1) only attachment text, (2) only email text, (3) K-means rather than BIRCH clustering, and (4) a sender $\times$ cluster-level synthetic document used as the centroid, rather than a common cluster-level synthetic document.

Table A.17: Relationship Between Information Uniqueness and the Intensity of Working-from-Home, Alternative WFH Classifications

	Change in Cosine Similarity-Based Information Uniqueness Measure	
	(1)	(2)
8-11 Days in Office	0.345	0.334
	(0.227)	(0.227)
12-14 Days in Office	0.736***	0.673***
	(0.226)	(0.239)
15+ Days in Office	0.044	0.037
	(0.204)	(0.236)
Gender FEs	Yes	Yes
Manager/Worker FEs	Yes	Yes
Other Demographic FEs	No	Yes
N	105	99

Notes: Source: Authors. See text for discussion of the construction of the similarity measure. The dependent variable measures the change in the information uniqueness measure from the baseline to treatment period. "Other Demographic FEs" are controls for education (bachelor's, master's/PhD), marriage status, whether the employee's spouse works from home, and whether the employee cares for a child at home. Text data was classified into eight clusters from a Doc2vec vector length of four; see Section A.5.1 of the Appendix for a discussion of the parameter fit.

Table A.18: Relationship Between Information Uniqueness and the Intensity of Working-from-Home, Controlling for Email Volume

	Change in Cosine Similarity-Based Information Uniqueness Index	
	(1)	(2)
Intermediate WFH	0.373**	0.329*
(9-14 days in office)	(0.184)	(0.200)
Low WFH	−0.114	−0.115
15+ days in office	(0.196)	(0.217)
Email Volume	0.002***	0.003**
	(0.001)	(0.001)
Gender FEs	Yes	Yes
Manager/Worker FEs	Yes	Yes
Other Demographic FEs	No	Yes

Notes: Source: Authors. See text for discussion of the construction of the similarity measure. The dependent variable measures the change in the information uniqueness measure from the baseline to treatment period. "Other Demographic FEs" are controls for education (bachelor's, master's/PhD), marriage status, whether the employee's spouse works from home, and whether the employee cares for a child at home. Text data was classified into eight clusters from a Doc2vec vector length of four; see Section A.5.1 of the Appendix for a discussion of the parameter fit.

Table A.19: Relationship Between Information Uniqueness and the Intensity of Working-from-Home, Treatment Period Only

	Standardized Cosine Similarity-Based Information Uniqueness During Treatment Period	
	(1)	(2)
Intermediate WFH	0.505***	0.570**
(9-14 days in office)	(0.192)	(0.235)
Low WFH	0.152	0.269
(15+ days in office)	(0.211)	(0.237)
Gender FEs	Yes	Yes
Manager/Worker FEs	Yes	Yes
Other Demographic FEs	No	Yes

Notes: Source: Authors. The dependent variable reflects the standardized score of each sender's information uniqueness measure with reference to the treatment period only (not a change from the control to treatment period).

Table A.20: Relationship Between Information Uniqueness and the Intensity of Working-from-Home

	Dep. var. = Change in Cosine Similarity-Based Work Product Index (K-Means)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate WFH	0.392*	0.373*	0.351	0.352	0.347	0.347	0.380*
	(0.209)	(0.204)	(0.231)	(0.254)	(0.254)	(0.253)	(0.217)
Low WFH	0.155	0.080	0.075	0.075	0.137	0.130	0.146
	(0.214)	(0.217)	(0.242)	(0.243)	(0.245)	(0.249)	(0.481)
Non-Manager	−0.855***	−0.820***	−0.910***	−0.909***	−0.925***	−0.876***	−1.001***
	(0.309)	(0.303)	(0.296)	(0.295)	(0.283)	(0.283)	(0.342)
Male		0.210	0.201	0.200	0.203	0.246	0.284
		(0.181)	(0.183)	(0.178)	(0.178)	(0.185)	(0.233)
Masters/PhD			−0.274	−0.275	−0.278	−0.279	−0.249
			(0.375)	(0.345)	(0.340)	(0.340)	(0.322)
Married				0.005	−0.079	−0.169	−0.161
				(0.320)	(0.330)	(0.312)	(0.317)
Spouse WFH					0.212	0.197	0.248
					(0.204)	(0.210)	(0.245)
Caring for Child						0.203	0.141
						(0.199)	(0.250)
Co-location Intensity							−0.067
							(0.215)

Notes:Source: Authors. The same notes as in Table 4 apply, except that K-Means, rather than BIRCH, was used for the clustering.

Table A.21: Relationship Between Information Uniqueness and the Intensity of Working-from-Home

	Dep. var. = Change in Central Cluster, Cosine Similarity-Based Uniqueness Index						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate WFH	0.497**	0.472**	0.565**	0.563**	0.564**	0.565**	0.634***
	(0.203)	(0.197)	(0.226)	(0.248)	(0.249)	(0.248)	(0.225)
Low WFH	0.262	0.165	0.247	0.247	0.228	0.224	0.303
	(0.219)	(0.222)	(0.236)	(0.237)	(0.253)	(0.260)	(0.551)
Non-Manager	−0.722***	−0.676***	−0.791***	−0.793***	−0.788***	−0.758***	−0.787**
	(0.253)	(0.246)	(0.244)	(0.244)	(0.249)	(0.264)	(0.314)
Male		0.270	0.193	0.196	0.195	0.222	0.287
		(0.182)	(0.180)	(0.172)	(0.171)	(0.183)	(0.238)
Masters/PhD			0.035	0.039	0.040	0.040	0.091
			(0.343)	(0.312)	(0.314)	(0.315)	(0.304)
Married				−0.020	0.005	−0.049	−0.030
				(0.319)	(0.338)	(0.314)	(0.320)
Spouse WFH					−0.063	−0.073	−0.049
					(0.201)	(0.211)	(0.242)
Caring for Child						0.124	0.099
						(0.211)	(0.264)
Co-location Intensity							−0.088
							(0.233)

Notes: Source: Authors. The same notes as in Table 4 apply, except that the synthetic document is calculated at the cluster level (i.e., "Cluster 1" uses the same synthetic document for all users).

Table A.22: Relationship Between Information Uniqueness and the Intensity of Working-from-Home

	Cosine Similarity-Based Uniqueness Index Subsample Analysis (Cluster ID)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intermediate WFH	0.174	2.320***	0.659***	0.521	−0.488	0.253	0.322	0.250
	(0.158)	(0.381)	(0.221)	(0.381)	(0.433)	(0.314)	(0.399)	(0.354)
Low WFH	−0.069	4.088***	0.282	0.248	−0.350	−1.772	0.550	−0.536
	(0.360)	(0.595)	(0.532)	(0.604)	(0.476)	(1.243)	(0.858)	(0.676)
Non-Manager	−0.724**	−0.630***	−0.847***	−0.130	−0.210	−0.236	−0.702	0.068
	(0.336)	(0.222)	(0.322)	(0.256)	(0.446)	(0.344)	(0.587)	(0.360)
Male	0.194	−1.664***	0.267	0.257	−0.006	0.133	0.181	0.124
	(0.174)	(0.325)	(0.235)	(0.252)	(0.435)	(0.456)	(0.257)	(0.287)
Masters/PhD	0.221	−1.919***	0.036	−0.259	2.075	−0.708*	0.550*	0.176
	(0.156)	(0.302)	(0.305)	(0.607)	(1.534)	(0.363)	(0.328)	(0.230)
Married	−0.239	2.650***	−0.051	0.295	−2.308	0.374	−0.132	−0.132
	(0.224)	(0.539)	(0.312)	(0.459)	(1.535)	(0.464)	(0.285)	(0.312)
Spouse WFH	−0.215	0.481**	−0.064	0.729	−0.248	−0.356	−0.347	−0.532*
	(0.174)	(0.230)	(0.237)	(0.533)	(0.212)	(0.469)	(0.522)	(0.275)
Caring for Child	0.192	−2.246***	0.138	−0.126	0.212	0.580*	0.368	−0.046
	(0.191)	(0.400)	(0.261)	(0.303)	(0.381)	(0.339)	(0.519)	(0.312)
Co-location Intensity	−0.009	−1.312***	−0.083	0.056	−0.137	0.545	−0.543	−0.055
	(0.121)	(0.308)	(0.227)	(0.226)	(0.183)	(0.364)	(0.497)	(0.255)

Table A.23: Relationship Between Information Uniqueness and the Intensity of Working-from-Home

	Change in Information Uniqueness						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Days in Office	−0.010	−0.010	−0.010	−0.010	−0.010	−0.010	−0.008
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)
Days in Office Squared	0.177	0.187	0.195	0.201	0.197	0.197	0.269^{*}
	(0.143)	(0.139)	(0.145)	(0.146)	(0.146)	(0.145)	(0.138)
Non-Manager	0.039	−0.026	−0.087	−0.076	−0.095	−0.082	−0.108
	(0.213)	(0.218)	(0.224)	(0.231)	(0.230)	(0.232)	(0.270)
Male		-0.361^{**}	-0.360^{*}	-0.379^{**}	-0.377^{**}	-0.366^{*}	-0.449^{**}
		(0.184)	(0.198)	(0.185)	(0.185)	(0.195)	(0.211)
Masters/PhD			−0.188	−0.213	−0.213	−0.214	−0.072
			(0.366)	(0.390)	(0.389)	(0.392)	(0.375)
Married				0.132	0.074	0.050	0.142
				(0.364)	(0.381)	(0.372)	(0.348)
Spouse WFH					0.173	0.169	0.190
					(0.180)	(0.184)	(0.211)
Caring for Child						0.053	0.006
						(0.204)	(0.225)
Co-location Intensity							-0.689^{***}
							(0.187)

Notes: Source: Authors. See text for discussion of the construction of the information uniqueness measure. The dependent variable represents the change in standard deviations from the baseline to the experimental period.

Table A.24: Relationship Between Information Uniqueness and the Intensity of Working-from-Home

	Change in Central Cluster, Cosine Similarity-Based Information Uniqueness						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Days in Office	-0.005^{*}	-0.005^{*}	-0.005^{**}	-0.005^{**}	-0.005^{**}	-0.005^{**}	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Days in Office Squared	0.140^{**}	0.133^{**}	0.148^{**}	0.147^{**}	0.147^{**}	0.145^{**}	0.174^{***}
	(0.057)	(0.056)	(0.058)	(0.060)	(0.061)	(0.059)	(0.063)
Non-Manager	-0.702^{***}	-0.661^{***}	-0.765^{***}	-0.767^{***}	-0.769^{***}	-0.742^{***}	-0.789^{**}
	(0.260)	(0.252)	(0.255)	(0.258)	(0.258)	(0.269)	(0.330)
Male		0.229	0.165	0.169	0.169	0.193	0.238
		(0.180)	(0.182)	(0.176)	(0.176)	(0.185)	(0.237)
Masters/PhD			0.029	0.035	0.035	0.034	0.118
			(0.311)	(0.288)	(0.288)	(0.289)	(0.262)
Married				-0.028	-0.033	-0.083	-0.039
				(0.292)	(0.301)	(0.285)	(0.271)
Spouse WFH					0.012	0.005	0.056
					(0.188)	(0.196)	(0.227)
Caring for Child						0.111	0.070
						(0.213)	(0.267)
Co-location Intensity							-0.216
							(0.272)

Notes: Source: Authors. See text for discussion of the construction of the similarity index. The dependent variable represents the change in standard deviations from the baseline to the experimental period.

A.5.2 Hash-Based Information Uniqueness Measure

As a third robustness check, we apply a cruder information uniqueness measure and find broadly consistent results. This measure is based on the count of novel work related email attachments sent by workers, determined by a unique hexadecimal string calculated from each attachment. Specifically, we use a hashing function—MD5 (Rivest, 1992)—to code the number of novel work-related attachments from individual emails and treat this variable as a proxy for individual productivity.

To generate this measure, we first extract each email attachment from all emails sent by the individual and classify the attachment by file types, i.e., PDF files, Excel files, Word files, etc. Next, we apply the MD5 hash function to determine whether the attachment is unique for the given employee, i.e., whether the employee sent the attachment for the first time ever. Each hash is represented as a fixed-length hexadecimal string, such as "5e8c7faa7914883775d4009c1850e67e". Changing even a single bit of data in a file will produce a different hash value, so this hashing process allows us to determine whether an attachment is truly unique. We then tag each sent email as containing a novel work product if at least one of the attachments has never been sent before by a given employee. The results are reported in Table A.25. Of particular note are regressions (2) and (4), which show evidence that this measure of information uniqueness is highest for employees in the intermediate WFH category.[31] These results suggest that individuals with intermediate WFH send roughly 19 more novel email work products compared to those in the high WFH group.

[31]For this table, the sample size is determined by the fact that we have 107 employees for whom we have email data and two periods (lockdown, treatment). Some of the regressions have fewer observations because we don't have survey data for every person.

Table A.25: Relationship Between Information Uniqueness and the Intensity of Working-from-Home

	Count of Novel Email Attachments			
	(1)	(2)	(3)	(4)
Intermediate WFH		0.421**		0.278*
		(0.168)		(0.155)
Low WFH		0.287*		0.202
		(0.171)		(0.137)
Male	0.389***	0.309***	0.374***	0.312***
	(0.104)	(0.101)	(0.117)	(0.118)
Non-manager	−0.595***	−0.695***	−0.499***	−0.575***
	(0.135)	(0.129)	(0.134)	(0.145)
Bachelor's Degree	−0.157	0.047		
	(0.228)	(0.275)		
Master's/PhD	−0.185	−0.016		
	(0.169)	(0.194)		
Married	−0.326*	−0.335		
	(0.179)	(0.230)		
Spouse WFH	−0.022	−0.005		
	(0.118)	(0.114)		
Cares for Child	0.105	0.129		
	(0.106)	(0.101)		
N	202	198	214	210

Notes: Source: Authors. The parameters were estimated by a negative binomial model. An attachment is considered "novel" if it has never been sent before by a given sender. We use a hash function, which varies based on the content (rather than name) of the attachment, to determine information uniqueness. The coefficients for the treatment period and constant are omitted from the table. Standard errors are clustered at the sender level.

Table A.26: Heterogeneity in the Intensity of Working-from-Home and Information Uniqueness (Aral and Dhillon (2022) Method)

	Change in Information Uniqueness						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate WFH	0.517***	0.423	0.409	0.373	−0.034	0.498**	0.660***
	(0.176)	(0.302)	(0.275)	(0.532)	(0.625)	(0.232)	(0.227)
× Non-Manager		0.104					
		(0.336)					
× Male			0.203				
			(0.354)				
× Masters/PhD				0.136			
				(0.576)			
× Married					0.665		
					(0.677)		
× Spouse WFH						0.047	
						(0.350)	
× Caring for Child							−0.325
							(0.322)
Low WFH	−0.239	−0.081	0.350	−2.127	1.372**	−0.269	0.106
	(0.384)	(0.329)	(0.281)	(1.631)	(0.547)	(0.434)	(0.521)
× Non-Manager		−0.171					
		(0.568)					
× Male			−0.725				
			(0.595)				
× Masters/PhD				2.169			
				(1.659)			
× Married					−1.729***		
					(0.661)		
× Spouse WFH						0.229	
						(0.537)	
× Caring for Child							−0.853
							(0.823)
Non-Manager	−0.163	−0.173	−0.175	−0.121	−0.183	−0.139	−0.072
	(0.200)	(0.290)	(0.193)	(0.191)	(0.203)	(0.210)	(0.197)
Male	−0.335**	−0.336**	−0.345	−0.350**	−0.381**	−0.331*	−0.299*
	(0.169)	(0.167)	(0.222)	(0.167)	(0.167)	(0.174)	(0.168)
Masters/PhD	−0.193	−0.200	−0.138	−0.617	−0.195	−0.192	−0.297
	(0.377)	(0.379)	(0.380)	(0.534)	(0.391)	(0.379)	(0.331)
Married	0.138	0.145	0.049	0.223	−0.132	0.133	0.208
	(0.388)	(0.392)	(0.395)	(0.388)	(0.552)	(0.395)	(0.378)
Spouse WFH	0.119	0.109	0.144	0.092	0.083	0.085	0.069
	(0.164)	(0.173)	(0.172)	(0.164)	(0.162)	(0.225)	(0.166)
Caring for Child	0.078	0.083	0.106	0.183	0.052	0.087	0.347
	(0.198)	(0.202)	(0.195)	(0.163)	(0.196)	(0.203)	(0.230)
Sample Size	99	99	99	99	99	99	99

Notes.—See Table 3 for notes.

Table A.27: Relationship Between Information Uniqueness and the Intensity of Working-from-Home, Only Days Sender is Working from Home

	Change in Information Uniqueness						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate WFH	0.301	0.303	0.382*	0.440**	0.433**	0.434**	1.023***
	(0.184)	(0.186)	(0.209)	(0.194)	(0.194)	(0.194)	(0.246)
Low WFH	−0.660*	−0.651*	−0.597	−0.590	−0.509	−0.513	0.790
	(0.361)	(0.358)	(0.366)	(0.379)	(0.371)	(0.370)	(0.498)
Non-Manager	0.008	0.003	−0.014	0.029	0.008	0.036	−0.005
	(0.177)	(0.179)	(0.192)	(0.197)	(0.189)	(0.187)	(0.186)
Male		−0.027	−0.055	−0.110	−0.107	−0.082	−0.172
		(0.177)	(0.188)	(0.178)	(0.178)	(0.183)	(0.182)
Masters/PhD			0.168	0.080	0.075	0.075	0.152
			(0.295)	(0.324)	(0.327)	(0.333)	(0.332)
Married				0.447	0.337	0.286	0.258
				(0.375)	(0.387)	(0.393)	(0.347)
Spouse WFH					0.278	0.270	0.190
					(0.195)	(0.195)	(0.201)
Caring for Child						0.116	0.076
						(0.198)	(0.197)
Co-location Intensity							−0.595***
							(0.176)
N	105	105	99	99	99	99	99

Notes: Source: Authors. See text for discussion of the construction of the information uniqueness measure. The dependent variable represents the change in standard deviations from the baseline to the experimental period.

Table A.28: Relationship Between Information Uniqueness and the Intensity of Working-from-Home, Only Days Sender is Working from the Office

	Change in Information Uniqueness						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate WFH	0.592***	0.618***	0.619***	0.602***	0.603***	0.598***	0.917***
	(0.187)	(0.189)	(0.202)	(0.185)	(0.184)	(0.184)	(0.216)
Low WFH	0.039	0.156	0.265	0.265	0.257	0.247	1.006**
	(0.300)	(0.291)	(0.294)	(0.292)	(0.297)	(0.304)	(0.421)
Non-Manager	−0.606*	−0.645**	−0.781**	−0.799**	−0.798**	−0.764**	−0.771**
	(0.312)	(0.322)	(0.341)	(0.341)	(0.338)	(0.316)	(0.300)
Male		−0.354*	−0.375**	−0.355**	−0.355**	−0.326*	−0.397**
		(0.187)	(0.190)	(0.171)	(0.171)	(0.180)	(0.176)
Masters/PhD			−0.372*	−0.336	−0.336	−0.336	−0.282
			(0.224)	(0.260)	(0.260)	(0.261)	(0.250)
Married				−0.170	−0.159	−0.220	−0.233
				(0.416)	(0.417)	(0.411)	(0.405)
Spouse WFH					−0.028	−0.038	−0.073
					(0.156)	(0.159)	(0.167)
Caring for Child						0.145	0.153
						(0.171)	(0.174)
Co-location Intensity							−0.360
							(0.227)
N	100	100	94	94	94	94	94

Notes: Source: Authors. See text for discussion of the construction of the information uniqueness measure. The dependent variable represents the change in standard deviations from the baseline to the experimental period.

A.6 Robustness Over Results Related to Employee Work-life Balance, Isolation and Performance Ratings

Table A.29 begins by replicating the main results from Table 1 in the main text using only the employees in the human resources division. We see a broad similarity between the two—even slightly larger in absolute value coefficient estimates in certain cases. This shows that our results are not a remnant of composition effects and who is specifically included in our sample.

Next, Table A.30 replicates the main results, but this time using only human resources employees to determine the cutoff; each employee is assigned to one of four bins. As before, we find that intermediate WFH (here, between 12-14 days in the office) is linked with higher job satisfaction and better work-life balance.

Table A.31 replicates these results using only the set of employees in the human resources department. We see similar positive effects, although they remain statistically insignificant. Furthermore, Table A.32 replicates these results using the four-bin cutoff for human resources employees. Here, we generally see larger positive effects for those who come in 12-14 days. For example, the gradients when the outcome variables are scores for creativity or productivity are especially large and greater than the other indicators for 8-11 or 15-23 days in the office, relative to those who come in 1-7 days.

Table A.29: Intensity of Working-from-Home and Employee Attitudes and Engagement for Human Resources Employees Only

	Job Satisfaction	Better Balance	Prefer WFH
	(1)	(2)	(3)
Panel A			
Intermediate WFH	.726**	.827**	-.410
	[.354]	[.383]	[.421]
Low WFH	-.168	-.167	-.682
	[.486]	[.477]	[.484]
R-squared	.12	.10	.14
Sample Size	118	118	118
	Feel Left Out	Miss Mentorship	Feeling Isolated
	(1)	(2)	(3)
Panel B			
Intermediate WFH	.332	.062	-.631
	[.436]	[.423]	[.470]
Low WFH	.536	.669	.829
	[.546]	[.540]	[.585]
R-squared	.05	.05	.11
Sample Size	118	118	118

Notes.—Source: Authors. The table reports the coefficients associated with regressions of indices of employee preferences (ranging from one to seven) on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 days in the office (low WFH), controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. In Panel A, we draw on indices from Raghuram et al. (2001): "Overall, I am satisfied with working from home," "Since I started working from home, I have been able to balance my job and personal life," and "If I were now given the choice to return to a traditional office environment (i.e., no longer telework). In Panel B, we draw on indices from Golden et al. (2008b): "I feel left out on activities and meetings that could enhance my career," "I miss out on opportunities to be mentored," and "I feel isolated." Standard errors are heteroskedasticity-robust.

Table A.30: Intensity of Working-from-Home and Employee Attitudes and Engagement (Alternative Cutoffs)

	Job Satisfaction	Better Balance	Prefer WFH
	(1)	(2)	(3)
8-11 Days in Office	.390	.464	-.403
	[.434]	[.476]	[.539]
12-14 Days in Office	.717*	.847*	.117
	[.416]	[.470]	[.513]
15-23 Days in Office	-.167	-.062	-.488
	[.541]	[.518]	[.551]
R-squared	.11	.08	.14
Sample Size	117	117	117
	Feel Left Out	Miss Mentorship	Feeling Isolated
	(1)	(2)	(3)
8-11 Days in Office	.444	.395	-.232
	[.559]	[.562]	[.608]
12-14 Days in Office	.050	.301	-.501
	[.485]	[.489]	[.550]
15-23 Days in Office	.321	.700	.856
	[.576]	[.581]	[.637]
R-squared	.04	.05	.10
Sample Size	117	117	117

Notes.—Source: Authors. The table reports the coefficients associated with regressions of indices of employee preferences (ranging from one to seven) on an indicator for whether the email sender came in between 8-11, 12-14, and 15-23 days in the office, normalized to 1-7 days in the office, controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. In Panel A, we draw on indices from Raghuram et al. (2001): "Overall, I am satisfied with working from home," "Since I started working from home, I have been able to balance my job and personal life," and "If I were now given the choice to return to a traditional office environment (i.e., no longer telework). In Panel B, we draw on indices from Golden et al. (2008b): "I feel left out on activities and meetings that could enhance my career," "I miss out on opportunities to be mentored," and "I feel isolated." Standard errors are heteroskedasticity-robust.

Table A.31: Intensity of Working-from-Home and Managerial Performance Ratings (Human Resources Only)

	Ability	Cooperation	Knowledge	Creativity	Productivity	Quality	Overall
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate WFH	.095	.259	.103	.155	.264	.291	.194
	[.168]	[.238]	[.198]	[.177]	[.208]	[.184]	[.155]
Low WFH	.163	.129	.113	-.005	.024	.216	.107
	[.222]	[.252]	[.244]	[.261]	[.248]	[.241]	[.189]
Non-manager	.013	-.642***	-.118	-.020	-.382	.039	-.185
	[.225]	[.223]	[.225]	[.206]	[.255]	[.269]	[.173]
Male	.173	.001	.272	.389**	.293	.151	.213
	[.145]	[.189]	[.184]	[.191]	[.198]	[.182]	[.137]
mastersPhD	-.248	-.138	.286	-.457	.019	.011	-.088
	[.242]	[.318]	[.273]	[.276]	[.266]	[.251]	[.219]
Married	.344	.106	.730**	-.186	-.315	.032	.118
	[.266]	[.291]	[.287]	[.261]	[.276]	[.254]	[.224]
Spouse WFH	-.051	.102	.123	.013	.045	.226	.076
	[.150]	[.197]	[.171]	[.162]	[.181]	[.171]	[.124]
Cares for Child	.165	.236	-.035	.185	.272	.156	.163
	[.141]	[.193]	[.173]	[.195]	[.198]	[.181]	[.139]
R-squared	.07	.09	.16	.09	.09	.06	.09
Sample Size	117	117	117	117	117	117	117

Notes.—Source: Authors. The table reports the coefficients associated with regressions of managerial productivity ratings (ranging from one to seven) on an indicator for whether the email sender came in between 9-14 days in the office (intermediate WFH), an indicator for 15-23 days in the office (low WFH), controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. The sample is restricted to employees in the human resources department. Standard errors are heteroskedasticity-robust.

Table A.32: Intensity of Working-from-Home and Managerial Performance Ratings (Alternative Cutoffs)

	Ability	Cooperation	Knowledge	Creativity	Productivity
	(1)	(2)	(3)	(4)	(5)
8-11 Days in Office	.063	.199	.182	.140	.237
	[.205]	[.256]	[.238]	[.213]	[.227]
12-14 Days in Office	.228	.305	.230	.261	.404
	[.192]	[.296]	[.242]	[.182]	[.249]
15-23 Days in Office	.242	.145	.194	.030	.090
	[.234]	[.270]	[.269]	[.256]	[.271]
R-squared	.08	.10	.15	.10	.11
Sample Size	117	117	117	117	117

Notes.—Source: Authors. The table reports the coefficients associated with regressions of managerial productivity ratings (ranging from one to seven) on an indicator for whether the email sender came in between 8-11 days in the office, 12-14, and 15-23, normalized to 1-7 days in the office, controlling for the following demographic characteristics: male, a non-manager (employee), education (masters/PhD - normalized to having a bachelor's), married, spouse works from home, and employee has to care for a child. The sample is restricted to employees in the human resources department. Standard errors are heteroskedasticity-robust.