The Power of Proximity to Coworkers

Training for Tomorrow or Productivity Today?[1]

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April 24, 2023

Abstract

In an increasingly digital world, how does sitting near coworkers affect collaboration, on-the-job training, and output? We study software engineers at a Fortune 500 firm, whose main campus has two buildings several blocks apart. When offices were open, engineers working in the same building as all their teammates received 23 percent more online feedback on their computer code than engineers with distant teammates. After offices closed for COVID-19, this advantage shrank by 17 percentage points. Sitting near coworkers increases how much junior engineers learn from their senior colleagues — not only in-person but also online. Proximity particularly increases feedback to female engineers and young engineers, who are more likely to quit the firm when proximity is lost. However, sitting together reduces senior engineers' programming output, suggesting a trade-off between short-term productivity and long-run human-capital development. Even pre-COVID, gaining one distant teammate reduced online feedback among coworkers sitting together: thus, remote-work policies may impact even workers who choose to go into the office.

Keywords: Remote work, on-the-job training, peer effects, telecommunication, gender, inclusion, worker retention

JEL: L23, L84, M54, J16, O31

[1]This project would not have been possible without the curiosity and commitment to research of our colleagues at the firm who shared data: Lauren and Susan. The findings and conclusions expressed are solely those of the authors and do not reflect the opinions or policy of our employers or the organizations that supported this work.

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For decades, despite advancing information and communication technologies, work remained centered around the office. Over 94 percent of workers commuted to the office in 2019, spending an average of nearly an hour per day in transit (Burd et al., 2021). The COVID-19 pandemic temporarily broke the link between work and the office for many people. Even as the pandemic fades, many workers have not returned to the office (Hansen et al., 2023). Yet relatively little is known about why the office was so central for so long and how the recent, seismic shift in remote work will impact work and workers. What are the consequences of the recent changes in work for collaboration, on-the-job training, and output, especially in complex tasks?

We study the impact of coworkers' physical proximity among software engineers at a Fortune 500 company, whose main campus has two buildings several blocks apart.[1] Software engineering is a seemingly 'best-case' scenario for purely digital collaboration: the software engineers produce digital output, have established online systems for giving one another required feedback, and meet daily in real-time even when remote.[2] Nonetheless, we find that sitting in the same building as coworkers increases digital collaboration, as well as in-person contact. Proximity is particularly integral to online feedback received by young engineers who have more to learn from their coworkers and female engineers in this predominantly male field. Young workers and women are substantially more likely to quit the firm when they lose proximity to coworkers.

The firm faces an intertemporal trade-off from workers' proximity. In the short run, proximity reduces programmers' output, particularly for senior engineers. Yet proximity increases on-the-job training, which is an input into longer-run productivity. We see this in promotions: sitting near coworkers decreases early promotions, but

[1] Software engineers compose an important segment of the labor market, accounting for 5 percent of labor income in 2020. Software engineering is also highly remotable, with 47 percent of engineers remote in 2020. Among those working remotely full-time in 2020, software engineers accounted for 11 percent of labor income (and 8 percent of employment).

[2] It is an industry standard to give code reviews in the online Github code management system and to have daily real-time meetings under the Agile management system.

increases longer-run promotions as workers build more human capital. This intertemporal trade-off can help explain the office's centrality before COVID-19, despite remote work's positive effects on short-run output (Bloom et al., 2015; Choudhury et al., 2020) and workers' high willingness to pay to work remotely (Mas and Pallais, 2017; Maestas et al., 2018; He et al., 2021). We find that a worker's location doesn't just impact their own interactions with coworkers, but, instead, has externalities for their coworkers' interactions, suggesting that an intertemporal tradeoff may arise even when only a subset of workers do not come into the office.

We study software engineers' comments on each others' computer code in the peer-review process, which is an industry standard for software engineers worldwide.[3] Reviewers collaborate to ensure code's functionality, efficiency, and clarity before it is deployed in a website or database. This iteration on the code not only improves the current program but also teaches engineers how to write better code in the future. Commenters often give frameworks for code-writing, by pointing engineers to code to emulate or giving guidance about restructuring the code. Code reviews are explicitly aimed at engineer development: as one engineering manager told us, "We ask senior, technical folks in promotion evaluations to make their code reviews a learning opportunity by, for example, including the reasoning behind suggested changes."

To identify the impact of physical proximity on online feedback, we leverage idiosyncrasies in engineers' pre-pandemic desk assignment. The firm has two buildings on its main engineering campus, several blocks apart. Which building a worker sat in was largely a function of what desks were available when she started. Prior to COVID-19, engineers whose teammates all worked in the same building held daily meetings in-person. Once a single engineer was in another building, this dynamic often changed: as one engineer noted, "[my team] would almost never book a room

[3] Code reviews are often part of the version control process, using git or similar software to track changes in the code base.

and held all of our meetings [online] since we had a remote team member." We consequently categorize engineers by whether they were part of one-building teams (N=637) or multi-building teams (N=418).

Before the pandemic, engineers on one-building teams collaborated more: they received 23 percent more comments on their programs than engineers on multi-building teams (p-value < 0.0001). The office closures of COVID-19 help us test whether this gap in collaboration is causal: if causal, then we would expect the gap to shrink once the buildings closed and all teams were physically distant. Empirically, we find that the gap shrank by 74 percent (17 percentage points, p-value $=$ 0.0008) after the buildings shut down. We find similar effects when estimating the difference-in-differences in the total length of peer-reviews and mentions of other online conversations (e.g., on Slack, Zoom, or email). We further find that proximity enhances the depth and speed of online collaborations.

Our difference-in-differences design relies on a parallel-trends assumption: namely that engineers on one- and multi-building teams were similarly shocked by the pandemic. We test this in several ways. Consistent with quasi-random assignment of desks, engineers had similar baseline characteristics regardless of their proximity to their teammates, conditional on their team's size and average tenure.[4] We do not detect differential pre-trends in feedback for engineers on one- and multi-building teams. Finally, engineers who sit near all their teammates do not receive significantly more feedback from engineers outside their own teams, suggesting that engineers on one-building teams do not simply have greater feedback needs.

We find that proximity decreases a particularly important component of team collaboration: on-the-job training. We use principal component analysis to identify the purpose of comments. Our difference-in-differences estimates are driven by de-

[4]Many teammates are mechanically less likely to all find desks in one building, and, over time, teams are more likely to end up spread over the two buildings.

creases in comments that teach engineers about how to test their code and verify that their functions are producing expected outputs. Before the pandemic, engineers on one-building team received more of this substantive feedback, but the gap closes when everyone is remote. Moreover, the main beneficiaries of the additional comments exchanged in proximate teams were less experienced engineers, measured by tenure or age. Thus, proximity's effects were particularly concentrated among those with the most to learn from their coworkers.

We also consider the gendered effects of close proximity. We find that proximity matters more for female engineers' collaboration and on-the-job training. Before the offices closed, female engineers who were in the same building as all their teammates received 38 percent more feedback on their work than female engineers with distant teammates. For male engineers, this advantage was less than half as large at 16 percent. When the offices shut down for COVID-19, lost proximity mattered more for the feedback of women than for men: the triple difference indicates a differential decline of 17 percentage point.

Firms face an important trade-off from proximity between coworkers: proximity decreases programmer output measured by code written. Our difference-in-differences estimate suggests that proximity reduces programs written per month by 21 percent. This is driven by senior engineers who may write fewer programs when sitting near coworkers because they give more feedback to junior colleagues. However, very junior engineers also write fewer programs when sitting near their coworkers, consistent with needing to respond to more feedback. These patterns suggest that reduced output may not reflect reduced productivity if proximity increases learning and code reliability. We also see an intertemporal trade-off in terms of promotions: engineers who sit near all their teammates are less likely to be promoted early but are more likely to be promoted eventually.

Workers' revealed preferences suggest that they value collaboration. As younger engineers and female engineers received less feedback, they were more likely to leave the firm.After the office closed, younger engineers ($<$ 30 years old) who had been in the same building as all of their teammates were five times as likely to quit as before the pandemic, while younger engineers on multi-building teams were twice as likely to quit as before the pandemic (p-value of difference-in-differences estimate = 0.016). Similarly, female engineers who had been in the same building as all of their teammates were four times as likely to quit as before the pandemic, while female engineers on multi-building teams were equally likely to quit as before the pandemic (p-value of difference-in-differences estimate = 0.0056). By contrast, the quit rates of older engineers and male engineers did not differentially change around the closures for those on one- and multi-building teams. Workers' revealed preferences show online communication cannot substitute for in-person collaboration, particularly for younger workers and female engineers.

We find that distant teammates impose negative externalities on the collaboration of teammates sitting together. Prior to COVID-19, having a teammate in a different building spilled over into the comments written by proximate teammates, reducing their length by 18 percent. These externalities can explain 30 percent of the initial gap in feedback between engineers on one- and multi-building teams.[5] Pre-pandemic, we find that when a one-building team hired an engineer in another building, feedback systematically declined between proximate teammates (who predated the hire). By contrast, new hires in the same building (or those added to already multi-building teams) did not affect the feedback exchanged between proximate teammates. Teams' attempts to accommodate distant teammates by, for example, moving in-person meetings online, have substantial negative externalities.[6]

[5]When the offices closed for COVID-19, these externalities largely disappeared, which can explain between 26 and 33 percent of the differential decline in feedback between engineers on one- and multi-building.

[6]This extends existing research that finds that the introduction of remote work increased absenteeism among coworkers who stayed in the office at the US Patent Office (Linos, 2018). These negative spillovers not only arise because remote work changes the interactions between remote workers and their on-site colleagues but also because it changes how on-site colleagues interact with one

Finally, relatively small distances deter collaboration as much as large ones. When we compare engineers whose teammates work in a different city, either at home or in a satellite campus, as opposed to on the same campus a mere 10-minute walk away, we find similar results.[7] When the offices were open, engineers whose teammates were spread across cities received 18 percent less collaboration than engineers whose teammates were all in their building. This gap was completely eliminated when the offices closed. The similarity of this estimate with the one that compares teammates at most a 10-minute walk apart underscores the out-sized effect of small frictions on face-to-face contact, and, conversely, that a work-from-anywhere approach may be no more costly than a work-from-home policy.

Our study makes three central contributions. First, it contributes to the remote work literature, potentially resolving a puzzle as to why remote work was rare before the pandemic despite workers' high willingness to pay for remote work (Mas and Pallais, 2017; Maestas et al., 2018; Mas and Pallais, 2020; He et al., 2021) and remote work's positive impacts on productivity in settings without much collaboration (Bloom et al., 2015; Choudhury et al., 2020). If remote work decreases collaboration and hampers on-the-job training, firms may still resist it. Relatively little of the remote-work research has investigated collaboration among knowledge workers.[8] We contribute by analyzing both collaboration and short-term output, while also considering remote work's impacts on workplace inequalities in the highly relevant

another.

[7]Our primary analysis focuses on engineers whose teammates all work on the main campus, where buildings are several blocks apart.

[8]Gibbs et al. (2021) finds reductions in coding output of IT professionals around the office closures of COVID-19, but their setting lacks a natural control group. Using a difference-in-difference design similar to our own, Yang et al. (2022) show that remote work reduced the breadth of workers' communication networks at Microsoft, but this study does not have data on coding conversations nor programmers' coding output.

Others have studied the effects of remote work using lab-based experiments (Brucks and Levav, 2022) and natural experiments in more specialized settings (Battiston et al., 2021). Battiston et al. (2021) find that when workers who answer 911 calls are in the same room as dispatchers who send police to the scene, they spend more time communicating with the dispatchers and the police get to the scene sooner. This parallels our findings of an intertemporal tradeoff from remote work: we find a similar tradeoff exists for knowledge workers on a longer time-scale.

setting of software engineering.

Second, the paper contributes to a robust literature on on-the-job training. It has long been known that coworkers are crucial for workers' human capital development, but the role of proximity has been hard to assess. This paper directly considers how proximity impacts on-the-job training inside firms. Finally, the paper contributes to the urban literature that has investigated whether information and communication technologies will complement or substitute for proximity. This paper contributes by finding complementarity between proximity and digital communication, even among coworkers whose interactions are not purely based on serendipity.

The rest of the paper is organized as follows. Section I situates our paper in the broader literature; Section II describes our data and setting. Section III details our empirical strategy. Section IV presents our results about the complementarity between physical proximity and online collaboration and explores who is most impacted. Section V documents the impact of proximity on output. Section VI considers the downstream implications for promotions and quits, particularly for younger workers and female engineers. Section VII opens up the black box of proximity by evaluating the externalities from having a single teammate located elsewhere. Section VIII concludes.

I Related Literature

A growing literature quantifies the importance of coworkers in on-the-job learning. Patenters who work in the same firm as better inventors subsequently patent more (Akcigit et al., 2018). Teachers in schools with other higher value-added teachers subsequently generate better educational outcomes (Jackson and Bruegmann, 2009). And sales workers who seek advice from their coworkers have higher sales thereafter (Sandvik et al., 2020).[9] More generally, working in a firm with cowork-

[9] A related literature studies the impacts of contemporaneous peer effects on productivity. While grocery store clerks (Mas and Moretti, 2009), envelope stuffers (Falk and Ichino, 2006), and fruit

ers with higher wages (or more education) is strongly correlated with higher subsequent wage growth in the US (Herkenhoff et al., 2018), Germany (Jarosch et al., 2021), and Sweden (Nix, 2020). Yet it is unclear whether physical proximity *per se* is necessary for these spillovers or instead whether being in the same firm, school, or intellectual community would suffice even at a distance.

Indeed, there is debate about the importance of physical proximity in how much coworkers learn from one another. Azoulay et al. (2010) and Waldinger (2012) find that physical distance is less important than intellectual distance in determining spillovers within the ivory tower. Yet Glaeser and Mare (2001); Roca and Puga (2017); Eckert et al. (2022) find that workers who work in large cities tend to have higher subsequent wage growth even after they leave large cities, suggesting that physical proximity might be central to human capital development.[10]

The role of proximity is even more contentious given the rise of digital communication technologies that could seemingly substitute for face-to-face contact. Indeed, with the rise of the internet, many predicted the death of distance (Cairncross, 2001; Friedman, 2005). Yet urban economists have long noted the possibility that online technologies would complement rather than substitute for physical proximity (Gaspar and Glaeser, 1998). Indeed, phone calls tend to be to others nearby. And denser places have been quicker to adopt phones historically. Further, internet connectivity tended to increase collaboration between researchers at physically proximate universities (Agrawal and Goldfarb, 2008).[11] Relatedly, Chen et al. (2022) show that

pickers (Bandiera et al., 2010) are all significantly more productive if they work near faster peers, Cornelissen et al. (2017) estimate small contemporaneous impacts of coworkers on workers' wages in the economy overall. Cornelissen et al. (2017) argue that the micro-findings of large contemporaneous peer effects on output depend on having a context where output is observable and the task is relatively routine.

[10]A related literature has investigated the relationship between physical proximity and knowledge flows across firms (e.g. Jaffe et al., 1993; Atkin et al., 2019). Ex-ante, it is unclear that face-to-face interactions would be pivotal *within firms* since technological systems can track and facilitate knowledge flows and serendipity is not the only way that coworkers interact. Our study thus shows that physical proximity is an even more powerful force than previously theorized.

[11]Similarly, funders of new creative pursuits on an online crowdsourcing platform disproportion-

when research teams become distributed across universities, the likelihood of producing 'disruptive' research falls.[12] Yet they find that the costs of being distributed have fallen over time with the rise of better communication technologies.

It is unclear, however, that the complementarity between online technology and face-to-face interaction in the research world would also hold in more structured workplace settings where coworkers must interact and meetings do not rely on serendipity. We provide evidence that even within a modern workplace, face-to-face interactions complement online ones.

II Data and Setting

Our data include peer code reviews of software engineers at a Fortune 500 firm between August 2019 and December 2020. Personnel data identifies each engineer's office building and teammates.[13] We first characterize our sample of engineers and then detail how we measure online feedback in code reviews and proximity to teammates in personnel records.

II.A Characterizing the Sample of Software Engineers

Personnel records from the firm's human-resources (HR) department provide information on each engineer's job title, hire date, termination date (if applicable), pay rate, age, gender, and parental status (from a June 2020 firm-wide survey).[14]

Engineers at the firm are predominantly male (81 percent) and highly paid ($56/hour on average), which is representative of software engineers nationally (75 percent are male with an average wage of $47.40/hour).[15] Engineers at the firm tend to be

ately live close to the funded artists (Agrawal et al., 2015).

[12]As in our study, they find fixed costs of becoming distributed with little additional penalty for more mileage between coauthors.

[13]We are able to match 99 percent of engineers across the peer-review and personnel datasets.

[14]A third of engineers participated in the June 2020 parenthood survey, with a comparable 30 percent in one-building teams and 35 percent in multi-building teams.

[15]Data comes from the 2019 American Community Survey. We define software engineers as the three Census occupational codes: Computer Scientists and Systems Analysts, Network systems An-

young, with an average age of twenty-nine compared to forty nationally. Consistent with their youth, only 16 percent the firm's engineers are parents.

Software engineers compose an important and growing segment of the labor market, accruing 5 percent of total labor income in 2020 (Figure A.1 shows the trajectory). Software engineering is also a highly remotable occupation. Before the pandemic, 13 percent of software engineers worked full-time from home — over twice the rate as other occupations — and in 2020, nearly half of software engineers reported working from home (47 percent) compared to just 16 percent of workers in other occupations (Figure A.2).

II.B Online Feedback in Code Reviews

Our data includes reviews of code that runs the firm's front-end website and back-end databases.To maintain code quality, every piece of code is reviewed by at least one other engineer before it is committed to the code-base. This is standard practice in software engineering, often as part of the Github code management system.

Code-Review Data. Our data describes the initial piece of code — including its author, its time-stamp, how many files it changed, and how many lines were added/deleted — and every peer comment — including its author, text, and time-stamp. The 1,055 engineers in our main analysis wrote 29,959 pieces of code and received 174,424 peer comments. On average, engineers submitted two programs per month to this (primary) code-base, each of which changes nearly 500 lines of code and affects seven different files. The typical engineer also submits code to other code-bases that handle more specialized tasks (e.g., support for the sales and service teams), which are outside the scope of our data.[16]

alysts, and Web Developers (Occupation 1000 in the 2010 Census), Computer Programmers (1010), and Software Developers, Applications and Systems Software (1020). We use Census sampling weights for these averages.

[16] Approximately half of the firm's engineers contribute to this code-base. We omit the total number of engineers at the firm to protect the firm's anonymity.

Before each piece of code is committed to the code-base, it is peer reviewed. Engineers typically receive feedback from one commenter but sometimes receive feedback from multiple commenters, who have different expertise (e.g., on the programming language versus the part of the code-base). It typically takes nearly a day (sixteen hours) to receive the first comment on the engineer's program.

Goal of Peer Reviews. Reviewers' comments often aim to improve a program's reliability or readability and give engineers general advice that can improve their subsequent coding. Reviewers average six comments per program, each of which averages eighty characters long.

Figure 2(a) identifies common themes in the comments on engineers' code. We use principal component analysis (PCA) to identify these themes. Intuitively, PCA recognizes that certain words often appear together in comments and so identifies the groupings of words that explain maximal variation in the data (Appendix Section I.A provides more details on the approach). The first principal component identifies comments that are about interacting with databases, often in the structured query language, *SQL*.[17] Particular attention is often paid to the *execution time* of these queries and their underlying *logic*. The second component has identified two, typically non-overlapping groups of comments. One group is about getting approval from *teams* that *own* code on *Github*.[18] The second group identifies comments that are about *function* output, which often concern edge cases for *null* or *empty* values. The last component has identified comments about how to *test* code, often use the testing suite of the firm's primary programming language, PHP, called *PHPUnit* tests. Making code testable often requires that the programmer rewrite to have separable components and clearly-articulate the expected behaviors of their program.[19] Table A.1 provides five illustrative examples for each theme in the comments.

[17] SQL operations including *SELECT*ing variables, *COUNTING*ing *row*s, and *JOIN*ing datasets (SQL's terminology for merging data).

[18] Owners of code often codify their programming *conventions* in an internal wiki (*Infohub*).

[19] Nexus automatically tests for security issues in open source code used by the software.

Peer reviews often involve a back-and-forth conversation between the commenter and the engineer. For the typical review, a commenter gives an initial set of comments on the code. The engineer can then respond to these comments to ask for further clarification or check whether the changes that she made were sufficient. The commenter often then replies with a clarification, additional feedback, or acknowledgement of the changes. Seventy-one percent of reviews have a back-and-forth between the commenter and coder. Below is an example of such an interchange where the back-and-forth helps the coder clarify what was missing in her program and what could be improved in subsequent code:

> Commenter at 3:14pm: Can you please add testing details to this program?
> Coder at 3:32pm: What do you mean by testing details? I added more information on the description if that helps. Let me know if you need further information.
> Commenter at 3:40pm: [I meant] what you did to validate that your changes are working as expected. Here is an example testing doc I made for a ticket in the past: {link to example}.
> Coder at 4:18pm: [I added a] document in description: {link to documentation}.

Without this iteration on the code, the coder may not have identified and rectified the omission and learned how to write better code going forward.

As in this example, most comments are given during standard work hours (between 8 AM and 6 PM on the weekdays). When the offices were open, 96% of comments were given during standard work hours, which only marginally declined by 0.8 percentage points when the offices closed (Figure A.3).[20]

[20]Our results are comparable when only considering interactions that occur during standard business hours (Figure A.6).

Requesting Feedback. Engineers are responsible for asking coworkers to review their code. While engineers can request feedback in the code-review system, they typically ask first outside the system, either in person or in a direct message (e.g., on Slack). Engineers can ask for feedback from teammates or from engineers outside of their own small five- to six-person teams. Engineers might ask for feedback from a non-teammate with relevant expertise in the part of the code-base, the programming language, and/or the type of problem being solved. About two-thirds of engineers' feedback comes from teammates. There are no explicit incentives to give peer reviews, but there are strong norms (and managerial expectations) to give feedback when asked.

Engineers often ask teammates for feedback before or after daily team meetings. Teams have daily fifteen-minute "stand-up" meetings and longer one- to two-hour meetings each week. The nature and frequency of meetings both follow a set routine under Agile management, which is common in the industry.[21] Teams use this meeting schedule before and after the office closures and regardless of their proximity to one another. Thus, teammates' proximity does not typically affect the frequency of meetings but often does affect their medium (i.e., Zoom versus in-person).

II.C Proximity in Personnel Records

Personnel records detail each engineer's office building and manager.

Identifying Teams. Two features of the firm's organizational structure mean that the engineer's manager allows us to identify her teammates. First, workers at the firm always directly report to a single manager rather than to multiple managers according to one of the firm's HR directors. Second, managers can only oversee

[21]At the firm, engineers' work is organized around two-week sprints in an "Agile" workflow. At the beginning of a sprint, the team meets to plan what work will get done. In daily "scrum" meetings, engineers discuss their progress and what others could do to help, including offering feedback on code. Each sprint includes a backlog meeting to review outstanding tasks and a retrospective to debrief about the sprint. There are also regular meetings to discuss the products being built.

multiple teams once they reach a certain level in the company. We limit the main analysis sample to engineers under mid-level managers. We also limit to teams where all engineers sit in the main campus – either in the main building or the auxiliary building, several blocks away.[22]

Proximity to Teammates. Because of limited desk availability, some engineers sit in the same building as all of their teammates, while others have at least one teammate in another building. Once one engineer is in a different building, daily meetings are held online since a ten- to fifteen-minute meeting does not justify a twenty-minute walk (round-trip). Distributed teams may also hold longer meetings online to reduce commuting. As a result, engineers on one-building teams may more easily discuss their work face-to-face than engineers on multi-building teams before, during, and after meetings.

Before the pandemic, 637 engineers were on teams where all of the members worked together in one building while the remaining 419 engineers were on teams that spanned the two office buildings. For engineers on multi-building teams, 30 percent of their team — or one to two teammates — were in the other building. We exclude the small number of engineers hired after the offices closed in March 2020. We define engineers as being in one-building teams if we always observe them in the same building as all of their teammates during the pre-period from August 2019 through February 2020. During the pre-period, only 14 percent of engineers switched teams, and only 2 percent of engineers switched buildings.[23]

[22]Eighty five percent of the firm's engineers worked in the main campus. We drop the 7 percent of engineers whose managers and teammates we cannot identify and the 14 percent of engineers who are not managed by mid-level managers at the firm. We limit to the 1,055 engineers whose teammates all worked in the firm's main campus. We separately consider the 215 engineers whose teammates worked remotely or in satellite campuses in Section VII.A.

[23]By construction, everyone who is categorized as being on a one-building team was always categorized as being on a one-building team in every month in the pre-period; 75 percent of engineers who we categorize as being on multi-building teams were categorized as being on multi-building teams in every month of the pre-period and 25 percent were categorized as being on a one-building team in at least one month. With our preferred specification, our results are similar when we use whether engineers were in one- versus multi-building in any given month rather than at baseline

COVID-19 Closures. The office closures of COVID-19 eliminated differences in coworkers' proximity. On Friday March 6th, most engineers went home from the office expecting to return the following Monday. Almost no engineers came into the office come Monday, though the firm did not officially close the campus immediately. Engineers had an opportunity to collect any belongings that they may have left in the office. After the closures, engineers continued to work on the same laptops, VPN into the same systems, and work on the same code-bases as they had before the pandemic. Engineers continued to work from home during the entire post-period in our sample: the return to the office is beyond the scope of our data. Thus, during the entire post-period, all engineers were physically separated from their coworkers.

III EMPIRICAL DESIGN

To identify proximity's impact on collaboration and programming output, we compare engineers on one- and multi-building teams. Because pre-pandemic building assignment depended on what desks were free at the time that engineers started, much of the pre-pandemic difference in online feedback is likely due to the causal effect of proximity. Yet some of the differences might reflect unobservable differences between the two groups of engineers. To net out unobservable differences, we utilize the building closures of COVID-19, which forced all teammates to work separately. In a difference-in-differences design, we assess how the greater loss of proximity for engineers on one-building teams translates into the change in the online feedback that they receive and the number of programs that they write.

Specifically, we estimate the following equation:

$$\begin{aligned} \text{\# Online Comments/Program}_{i,t} =& \beta \text{Post}_t \cdot \text{One-Building Team}_i + \alpha \text{Post}_t + \\ & \psi \text{One-Building Team}_i + X'_{i,t}\psi + \epsilon_{i,t}, \end{aligned} \tag{1}$$

over the entire pre-period.

where each observation represents a given programmer i in month t. We cluster standard errors at the team level since that is the unit of treatment assignment. This design considers a single focal event — the pandemic-related office closures in March 2020 — so does not run into the problems that can arise when treatment is staggered over time (e.g. Goodman-Bacon, 2021).

We also estimate a dynamic version of Equation 1 that allows the difference between engineers on one- and multi-building teams to vary flexibly by month m:

$$\begin{aligned}\text{\# Online Comments/Program}_{i,t} = \sum_{m \neq \text{Feb 2020}} \alpha_m \text{One-Building Team}_i \cdot \mathbb{1}[t = m] + \\ \sigma \text{One-Building Team}_i + \mu_t + X'_{i,t}\gamma + u_{i,t}, \qquad (2)\end{aligned}$$

where the month before the office closures, February 2020, is held out as the reference month and μ_t denotes month fixed effects.

Our difference-in-differences design relies on the parallel-trends assumption — namely, that engineers who were initially proximate to all of their teammates faced similar pandemic shocks as those who were distant from some teammates. We probe the robustness of this parallel-trends assumption in a few ways. First, we test for imbalances in baseline characteristics and assess robustness to adding controls in $X_{i,t}$, which condition the parallel-trends assumption on covariates. Second, we assess placebo checks, using the source of feedback and the timing of treatment. Third, we test for differential pre-trends between engineers on one- and multi-building teams.

III.A Balance in Engineer Characteristics

Table 1 describes the sample, comparing engineers whose teams are all in one building with those whose teams span the two buildings. Engineers' baseline characteristics are well-balanced after accounting for differences in team-size and average team tenure (Columns 5 and 9). Mechanically, engineers on smaller teams were more likely to all find desks in one building (Row 2). It was also easier to find desks for the whole team in the larger main building (Row 3). Engineers who had been at the company longer were more likely to end up physically separated from at least one teammate (so averaged an additional 4.1 months at the firm, Row 7). Once we account for the size and average tenure of their teams, engineers on one- and multi-building teams have similar demographics (Rows 4−6) as well as tenure, job-level, and pay (Rows 7−9).

III.B Controls

Preferred controls: Team-composition controls account for the team's size quintile interacted with the team's average-tenure quintile. Team composition is allowed to have time-varying effects before versus after the COVID-19 office closures. For online feedback, we also control for program scope — quartics in the number of files changed, the number of lines added,[24] and the number of lines deleted — all of which might mediate the feedback that an engineer receives.

Full set of controls: Our full set of controls also includes indicators for the engineer's age (in years), tenure (in months), gender, home zipcode, job-level, and initial building. We allow all these coefficients to differ before and after the COVID-19 closures to allow different types of engineers to face different pandemic shocks. We further include engineer fixed effects to handle any changes in the composition of engineers who submit programs to the main code-base.

III.C Placebo Checks

Placebo Check Using the Source of Feedback. Being on a one-building team does not affect comments from non-teammates. This null effect makes us more confident that proximity to teammates is not related to the latent quality of engineers' code, which would affect feedback from all coworkers, not just proximate ones. Con-

[24]Writing longer, more complicated programs often conflicts with best programming practice to write concise, self-contained programs that can be more easily checked and succinctly reviewed.

versely, we find complementary evidence that proximity to non-teammates impacts feedback from non-teammates, but not from teammates.

Placebo Checks around Alternative Dates. We consider the treatment effects that would arise if the office closure happened in any month in our data. Using a 2-month bandwidth and our preferred set of controls, no other month shows changes of magnitude or statistical significance (Figure A.4).

III.D Testing Pre-trends

There was no significant differential trend in peer comments in the pre-period across engineers in one- and multi-building teams (p-value = 0.26 for the raw and p-value = 0.33 for our full set of controls).[25] Indeed, in the months leading up to the office closures, peer commenting did not systematically change for either group of engineers.[26] Further, a Wald test considering whether the difference between one- and multi-building teams' slope is the same in each month before office closures also finds no significant differences (p-value = 0.43 for the raw and p-value = 0.71 for our full set of controls).

IV Proximity's Impact on Online Collaboration

We find that the opportunity for face-to-face collaboration in the office is complementary with receiving more online feedback. Thus, physical proximity likely has an out-sized effect on how much workers can learn from their coworkers, by facilitating online feedback and guidance in addition to in-person advice.

Engineers who sat in the same building as all their teammates had more online collaboration than engineers on distributed teams when the offices were open but

[25]Our results are also robust to including local-linear time-trends for engineers on one- and multi-building teams on both sides of the office closures.

[26]When we use our full set of controls, peer comments of engineers in multi-building teams insignificantly declined by 3 percent per month (or 0.11 comments), while peer comments of engineers in one-building teams insignificantly increased by 0.2 percent per month.

not once they were closed. Figure 1(a) shows this, plotting the average number of comments received per program without controls. Initially, there is a sizeable gap in feedback between engineers on one- and multi-building teams. If the gap reflects a causal effect of proximity as opposed to latent differences across teams, then it will close when all workers go remote due to COVID-19's office closures. We find the gap between one- and multi-building teammates disappears when the offices close, suggesting that physical proximity to teammates explained the initial gap.

While the offices remain closed, engineers on one-building teams never regain the advantages conferred by physical proximity. The persistence suggests it is hard to substitute for face-to-face interactions and that our effects are not a fleeting byproduct of transitioning to new technologies for engineers accustomed to in-person interactions with their teammates.[27]

We find the same complementarity between face-to-face and online interaction when we compare engineers on similar teams (based on their size and average seniority) who write similar programs (based on the number of files changed, lines added, and lines deleted) in Column 3 of Table 2. When the offices were open, engineers on one-building teams received 1.8 additional comments, or 22.9 percent more comments per program (p-value < 0.0001) than engineers on multi-building teams. This gap narrowed to only 0.49 additional comments or 6.1 percent after the offices closed. Our difference-in-differences estimate indicates that losing physical proximity decreased comments per program by 1.35 comments or 16.8 percentage points for engineers on one-building teams vs. multi-building teams (p-value $= 0.0008$). This result is robust to including a variety of controls, a stability which is marked given

[27]When the offices closed, engineers on multi-building teams might have been more comfortable with Zoom and other online tools. Yet such a difference would likely have a transitory effect not a persistent one. Instead, Figure A.5 shows our results are similar across different post-period windows. Moreover, it is worth noting that all engineers were familiar with git, the online software used for giving comments on updated code. On the other hand, pre-pandemic proximity and a habit of increased online collaboration could have led to more online collaboration in one-building teams even once the offices closed. But we do not see this type of lasting effect of proximity.

the increase in the R^2 from 1.5 percent to 49.1 percent across Table 2.[28]

The differential decline in feedback for engineers on one-building teams vs. multi-building teams is closely tied to the timing of the office closures, as illustrated in the event study in Figure 1(b). Indeed, in a placebo check, we do not find any economically or statistically significant differential changes in feedback around untreated months (Figure A.4). We find no evidence of deviations from parallel trends in the pre-period, and our results are robust to including local-linear time-trends for engineers on one- and multi-building teams on either side of the closures (Table A.3).[29]

The differential declines in feedback are driven by comments given during standard work hours (8AM $-$ 6PM, Monday through Friday), when teammates on one-building teams would have been proximate to one another before the offices closed but not afterwards (Figure A.6).

The differential decline in collaboration comes from the expected source: losing proximity to teammates affects collaboration with teammates but not collaboration with other engineers (Columns 8$-$9 in Table 2 and Figure A.7(a)). The null effect for non-teammate comments is inconsistent with an alternative explanation based on engineers' need for collaboration: if engineers on one-building teams simply needed more help before the offices closed but not afterwards, this change would impact reviews from both teammates and non-teammates.

We also find complementary evidence that proximity to non-teammates impacts feedback from non-teammates but not from teammates. Engineers who sat in the main building — near 71 percent of the main campus's engineers and near the

[28]Our results are also robust to comparing engineers who are in the same part of the engineering department (i.e., who have the same "grandparent" in the management hierarchy) in Table A.2.

[29]When we estimate the difference in slopes in the pre-period, we find an insignificant differential *increase* in 0.17 comments per month for engineers on one-building versus mult-building teams (p-value = 0.19 of the difference in slopes). When we estimate whether the difference in the one- and multi-building teams' slopes changes from month to month, our Wald test yields a p-value of 0.79 in our preferred specification.

main campus's lunch room — saw larger declines in feedback from non-teammates around the office closures but not from teammates (Figure A.7(b)).[30] Particularly, engineers in the main building saw larger declines in feedback from non-teammates who also sat in the main building (Figure A.8).

IV.A Depth of Collaboration

We find that proximity leads to both more extensive and deeper conversations. Proximity enhances not only the number of comments (Table 3(a), Column 1) but also the total number of characters (Column 2). Proximity also leads to timelier feedback, with shorter delays between program submission and the receipt of the first comment (Column 3). We also find complementary evidence when we consider references to other online conversations — over email, Slack, or Zoom — which commenters flag to document the source of coding decisions. Mentions of these other forms of online communication decline more precipitously around the office closures for engineers who were initially in the same building as all of their teammates (Column 4). This further suggests that collaboration did not simply go to another means of digital communication when offices closed.

Engineers on one-building teams receive more initial feedback from commenters and have richer digital conversations about their code.[31] When the offices were open, engineers on one-building teams received 23 percent more initial feedback, a gap which narrows when the offices close (Column 1 of Table 3(b)). In response to initial feedback, engineers on one-building teams also replied 19.7 percent more and asked 24 percent more follow-up questions when the offices were open but not once they were closed (Columns 2 and 3). In response to these questions, com-

[30] The declines in teammate feedback were similar in the main and auxiliary buildings (Figure A.9).

[31] Much of the increase in feedback comes from the intensive margin. When the offices were open, engineers on one-building teams received 14 percent more feedback from each commenter, a gap that disappeared when the offices closed. This intensive margin difference explains 71 percent of the initial feedback gap (Column one of Table 3(b)), with the rest attributable to receiving feedback from more people.

menters also offer 23 percent more reply comments after the author has engaged with their feedback on one-building teams when the offices were open (Column 4). These findings suggest that face-to-face interactions complement online interactions by not only encouraging commenters to offer more initial feedback but also emboldening engineers to ask more follow-up questions: this iterative back-and-forth may be especially useful in engineers' learning by zeroing in on pain-points in their programming.

IV.B On-the-job Training

While proximity increases all digital collaboration, of particular concern is on-the-job training. Based both on the content of the communication and the recipients of feedback, we find that physical proximity increases on-the-job training.

Comment Content. Proximity increases substantive comments about testing code and ensuring functions produce their expected outputs. Figure 2(b) shows this, illustrating the thematic content of feedback received by engineers on one- and multi-building teams. While the offices were open, the most pronounced difference in feedback between engineers on one- and multi-building was in comments about testing code (in green in the bottom right plot). This gap closed when the offices shut down. We see similar although smaller effects for comments about function output (in blue in the bottom left plot).

Both of these themes capture substantive feedback that may be time-consuming to give, would often be broadly applicable to other programs, and would likely impact the reliability of the code in the long run rather than its performance in the short run. Proximity has less of an impact on comments about interacting with databases (in pink in the top left) and who owns files (in orange in the top right) — which are likely less discretionary and more immediate in their impacts on the code.

Comment Recipients: Less Experienced Engineers. Young engineers with less experience in the labor market and junior engineers with less experience in the firm are by and large the beneficiaries of on-the-job training. The feedback received by these engineers is also the most sensitive to proximity to their coworkers in the office.

Pre-pandemic, engineers 29 and under (the firm's median age) received 13 percent more comments per program than older engineers (p-value $= 0.004$).[32] However, younger engineers only receive more feedback than their older teammates when teams sit together in the office. Comparing across Panel (a) and (b) of Figure 3 reveals that younger engineers on one-building teams received significantly more feedback than their older teammates when the offices were open (the blue solid line in Panel (a) is higher than in Panel (b) before March 2020). Yet engineers on one-building teams ceased to receive more feedback than their older coworkers once they were working remotely (the blue solid line in Panel (a) is at a similar level to the one in Panel (b) after March 2020). Further, younger engineers on multi-building teams never received more feedback than their older teammates (the orange dashed lines are always at similar levels across the two panels). This finding suggests that face-to-face interaction facilitates knowledge flows from older, more experienced engineers to younger, less experienced engineers. Given the importance of senior workers for mentorship, it is then particularly notable that among college educated workers in the US, older workers are much more likely to be working from home than those fresh out of college in 2021 (Figure A.11).

We similarly find that engineers who had less than the median firm-tenure of 16 months prior to the closures tended to receive more comments on their programs, especially when sitting near their teammates in the office. When the offices were open, junior engineers who sat in the same building as all of their teammates re-

[32]While younger engineers are the main beneficiaries of coworker training, older engineers tend to make the human capital investments. Program writers are on average 29.8 years old while program commenters are 31.2 years old (p-value of difference < 0.0001, see Figure A.10).

ceived 28 percent more feedback than junior engineers on distributed teams (Figure 3(c) and Column 3 of Table 4). Once the offices closed, this gap in feedback quickly narrowed. By contrast, for more experienced engineers in Figure 3(d), proximity did not impact the volume of feedback before or after the offices closed.[33]

Age and tenure at the firm are independently important determinants of proximity's impacts on online feedback (Figure 3(e)). These findings indicate that proximity increases feedback for workers with the most to learn from their coworkers, both because they are younger so have less general human capital and newer to the firm so have less firm-specific human capital.

IV.C Gendered Consequences of Proximity

Software engineering is a predominantly male occupation, both at this firm and more broadly. Indeed, 81 percent of the engineers in our sample are male (and 75 percent of programmers in the US are male).[34] Ex-ante it is unclear whether the minority of female engineers would benefit more or less from physical proximity.

We find that physical proximity is particularly complementary with online interactions for female engineers. Before offices closed, female engineers received 38 percent more comments when they sat near all their teammates than when they were on a dispersed team (Figure 4(a)). Male engineers working near all their colleagues received only 16 percent more feedback than male engineers on multi-building teams – less than half the gap that female engineers experienced.[35] After offices closed, the advantage in feedback for engineers on one-building teams shrank by 28 percentage points for female engineers (p-value = 0.0006) and 11 percentage points for

[33]Figure A.13 shows the raw patterns of feedback as a function of engineers' tenure at the firm for engineers on one- and multi-building teams before and after the pandemic.

[34]Our data on engineers' gender in the firm come from HR, which are based on employees' self-reported gender. National demographics come from the US Census, which also uses respondents' self-reported gender.

[35]Female engineers on multi-building teams received 16 percent *less* feedback than male engineers. This suggests that underlying differences in the quality of code produced by female and male engineers are unlikely to account for gender differences in feedback among one-building team members.

male engineers (p-value = 0.021). The triple difference indicates that losing proximity decreased feedback by 17 percentage points more for female engineers than male engineers (p-value = 0.1).

To better understand the mechanisms underpinning the gap, we decompose the gap in collaboration based on the type of comment. We find no differential effect in the initial comments offered on code written by female or male engineers. However, proximity was helpful for encouraging female engineers to engage in followup conversation, where female engineers might ask questions or post replies and commenters would respond. This is visible by zeroing in on the follow-up comments received by female and male engineers, where female program writers are more likely to engage in back-and-forth conversation when in-person, but not when working remotely (Figure 4(c)-(d)).

We also find that the effect of proximity comes from both female and male commenters (Table **??**). This suggests that the additional comments are not solely driven by male colleagues mansplaining nor female colleagues taking other female engineers under their wing.

V Physical Proximity's Impact on Programmer Output

When engineers sit near their coworkers, junior engineers receive more on-the-job training, but senior engineers get less done. Thus, proximity creates a trade-off between long-run human capital development and short-run output.

Proximity reduces the *volume* of programs submitted, particularly for senior engineers (Figure 5(a)). When the offices were open, senior engineers on distributed teams submitted more programs than engineers whose teammates all sat together in one building, with an average difference of 0.67 programs per month or 39 percent (p-value = 0.003). When the offices closed for COVID-19, this gap immediately narrowed. The programming output of all senior engineers fell — likely due to the pandemic's many stressors — but the decline is less precipitous for senior engineers who had been proximate to all of their junior colleagues in the office. Thus, our difference-in-differences estimate indicates that losing proximity to teammates increases the programming output of senior engineers who had sat near all their teammates in the office by 0.52 programs per month (p-value = 0.0007) compared to senior engineers whose teammates were already distributed. This result is consistent with senior engineers having more time to work on their own programs when they are spending less time mentoring junior engineers.

Junior engineers on distributed teams also submit slightly more programs before the offices closed but not afterwards (the left plot of Figure 5(a)). This negative effect of proximity on junior engineers' programming output is driven by the most junior engineers who also see the largest declines in feedback when proximity is lost (Panel (c)). This pattern is consistent with the most inexperienced engineers being able to submit a greater *quantity* of programs when there are fewer checks on the *quality* of those programs.

VI Downstream Consequences

Both firms and workers see longer term consequences arising from the decision to work proximately or remotely.

VI.A Promotions

The trade-off between short-term output and long-run human capital development can also be seen in the promotion trajectories of engineers on one- and multi-building teams in Figure 6. Engineers who sit in the same building as all of their teammates are less likely to be promoted early in their time at the firm than engineers on multi-building teams. Junior engineers — with less than 16 months of experience — are 0.48 percentage points *less* likely to be promoted on one-building teams than multi-building teams (p-value = 0.052). Yet over time, the gap in promotions flips as engineers on one-building teams become *more* likely to be promoted than engineers on distributed teams: senior engineers — with more than 16 months of experience — are 1.44 percentage points more likely to be promoted each month if they are on one-building teams than on multi-building teams (p-value = 0.0004). As engineers gain experience, the initial investments in their human capital may start to pay dividends in the quality of their code.

VI.B Quits

The evidence so far suggests that distance diminishes on-the-job training. To understand how employees react to an increase in distance, we consider a measure of employees' revealed preference: quitting the firm.

In person, quit rates are low and insignificantly larger for engineers on multi-building teams.[36] After the offices closed, quit rates rose for all engineers, but they increased more for engineers on one-building teams who lost proximity to their teammates (from 0.44 to 1.52 percent per month) than engineers on multi-building teams (from 0.45 to 0.99 percent per month).

Quits were concentrated among those engineers for whom the loss of proximity most impacted the on-the-job training they received: younger engineers and female engineers. Younger engineers who had been in one-building teams were not more likely to quit than those in multi-building teams pre-pandemic (Figure 7(a)). However, after losing teammate proximity, the quit rates among young engineers increased by 0.93 percentage points (p-value = 0.021, Column two of Table 5). Older engineers on one-building teams, whose on-the-job training was not differentially affected relative to other older engineers, are no more likely to quit than their multi-building counterparts. Table 5 shows that these results are robust to adding time-varying team composition controls (Column two).

[36] To some extent, quit rates are mechanically low in the pre-period since engineers are only included in the sample if they contribute to the code-base during our sample period.

Likewise, female engineers who lost proximity to teammates were more likely to quit. Female engineers from one-building teams who were no longer near their teammates were more likely to quit after the pandemic (from 0.57 to 2.5 percent per month, Figure 7(b)). By contrast, male engineers' quits increased less with office closures and with limited differential based on the location of teammates. Losing teammate proximity increases quit rates among female engineers by 2.1 percentage points (p-value = 0.0056, Column three of Table 5) but had a more limited impact on male engineers' quits 0.20 percentage points (p-value = 0.52). The triple difference indicates that losing proximity increased the quit rates of female engineers by 1.6 percentage points more than that of male engineers (p-value = 0.052). As with age, these results are robust to include time-varying engineer controls. Moreover, when we include both age and gender, we find that the triple differences indicate an increase in quits among both younger and female engineers (Columns five and six of Table 5).

VII Externalities from Distant Teammates

Even a single remote colleague decreases the on-the-job training among proximate teammates. This may be because teams that are spread across buildings substitute online meetings for in-person ones.

We measure the impact of a distant teammate in two ways. First, we compare the interactions of *same-building* teammates on one- and multi-building teams (Figure 8). Before the office closures, engineers with distant teammates received 18 percent fewer comments per review from a *proximate* teammate than did engineers whose teammates were all in their building. This gap largely closed once the offices shut down for the pandemic (Column two of Table A.8). These externalities are concentrated among engineers who are new to the firm (see Figure A.12). Engineers who are new to the firm may have more to learn from their coworkers and less confidence asking for help online, accentuating the externalities from having in-person meetings move online.

A sizable fraction of the pre-pandemic gap in online feedback between one- and multi-building teams stems from these externalities. Even on multi-building teams, engineers received much of their feedback from proximate teammates, averaging 0.67 proximate teammate commenters per program (out of 1.7 total commenters) pre-pandemic. Thus, the externalities alone would suggest that engineers on multi-building teams would receive 6 percent less feedback on their programs when the offices were open.[37] The externalities thus account for 30 percent of the initial 21 percent gap in feedback between one- and multi-building teams. By a similar logic, these externalities can explain between 26 and 33 percent of the differential decline in feedback around the closures (Table A.8).

Second, we examine team dynamics around a new hire. We compare teams where the new hire converted the team from being a one-building team into a multi-building team to teams where the new hire did not affect whether the team was centrally located. Empirically, we estimate

$$\begin{aligned}\text{\# Comments/Program}_{i,j,t} =& \gamma \text{Post Hire}_t \cdot \text{One- to Multi-building Team}_i + \\ &+ \sigma \text{Post Hire}_t + \mu_{i,j} + v_{i,j,t}\end{aligned} \tag{3}$$

where i indexes the coder and j indexes the commenter. As in our prior analysis, we only consider coders and commenters who are in the same building. And we only consider workers who were hired before the 6-week window.

Figure 9(a) shows that one-building teams with a new hire in another building see a sharp decline in online feedback between same-building teammates. Teams that were always in one building or multiple buildings do not. The estimated decrease is 1.7 comments per review when the team converts to a multi-building team relative

[37]The externalities would lead to 0.67 comments/commenter $\times 0.73$ commenters/program $= 0.51$ comments/program fewer relative to a baseline mean of 8.04 comments per program.

to other teams with a new hire (p-value=0.05), with similar estimates controlling for program scope (Table A.9). This effect is concentrated among engineers who are new to the firm and, thus, may be particularly sensitive to the change in the team's dynamics.[38]

Together, these estimates suggest that having even one teammate in another location diminishes coworkers' online feedback among same-building colleagues. This finding suggests that even as workers come back to the office after the pandemic, their interactions will be affected by coworkers who continue to work remotely.

VII.A Externalities from the Marginal Mile?

We find that having a teammate a thousand miles away is not appreciably different than having a teammate a mile away. While we focus on teams entirely in the firm's main campus, we find similar effects when we consider engineers whose teammates worked remotely or in an satellite campus. As illustrated in Figure 10(a), engineers whose teammates worked many miles away received the fewest comments on their programs before the pandemic, but these differences closed when the offices closed. After including our full set of controls in Figure 10(b), engineers on one-building teams saw 17.5 percent point larger declines in feedback (1.41 comments) around the office closures than engineers whose teammates were already spread across multiple cities before the pandemic. These differential effects are similar to those using engineers whose teammates are just a few blocks away.

One mechanism that could explain the two sets of externality results is the meeting modality. Even the small friction of a 10-minute walk, or the comparably smaller impact of a single remote teammate, would transform in-person meetings to on-

[38]On average, the half of engineers who were in their first year lost 2.7 comments per program from proximate teammates when there was a new hire in another building versus the same one (p-value = 0.067). By contrast, the half of engineers who had been at the firm for at least a year lost 0.6 comments per program from proximate teammates when there was a new hire in another building (p-value = 0.42).

line meetings. One implication is that attention to workers' locations within a campus matters and conversely that work-from-anywhere may not be more costly than work-from home policies.

VIII CONCLUSION

Remote work provides firms with a tradeoff. It increases output today, particularly from more senior workers. But, it decreases collaboration and training of more junior workers. Young workers and women, who may feel less included at the firm to begin with, see a particularly large decrease in their ability to collaborate with other workers and they quit more often in response.

A key finding is that one worker's choice to work remotely impacts her peers. Older workers are much more likely to work remotely than young workers. Their not coming back to the office can depress younger workers' skill accumulation. This may be particularly important as young workers learn the most on the job. And even one remote worker can have an outsized impact, depressing collaboration between co-located coworkers.

This suggests policies coordinating workers' locational choices may yield benefits. For example, coordinating which days teams spend in the office may lead to more fully in-person meetings. This raises the question of whether a few days in the office are enough to spur online interactions. Similarly, it may be more efficient to have firms or teams sort into being fully in-person or fully remote than to have hybrid teams where a few remote workers affect their in-person colleagues. It will be interesting to see whether we see segregation of in-person and remote workers across or within firms as workers return to the office.

If there is a permanent increase in remote work post-pandemic, can alternative management practices substitute for the decrease of coworkers' online feedback and guidance? Interventions to increase informal training for young workers even when they are remote may reap dividends for workers' skills and retention.

More broadly, our results suggest that space will remain an important organizing force in the economy. Understanding what about in-person interactions is so unique that it cannot be replicated online will be an important area of research, allowing us to diagnose whether digital interactions will ever be able to substitute for in-person ones.

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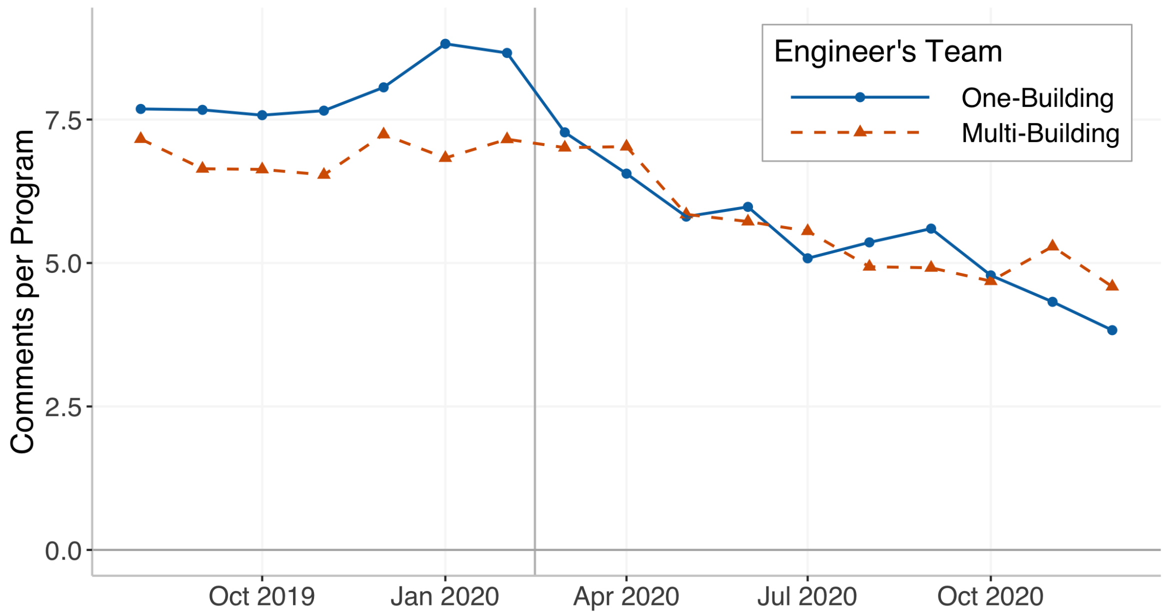
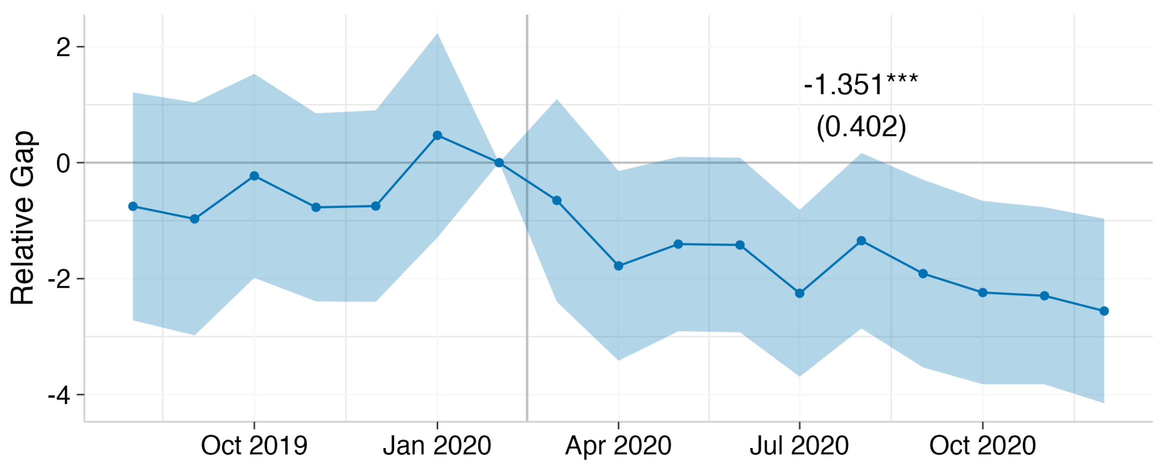
IX Figures & Tables

Figure 1: Proximity to Teammates and Online Feedback

Panel (a): Raw Averages of Comments Per Program



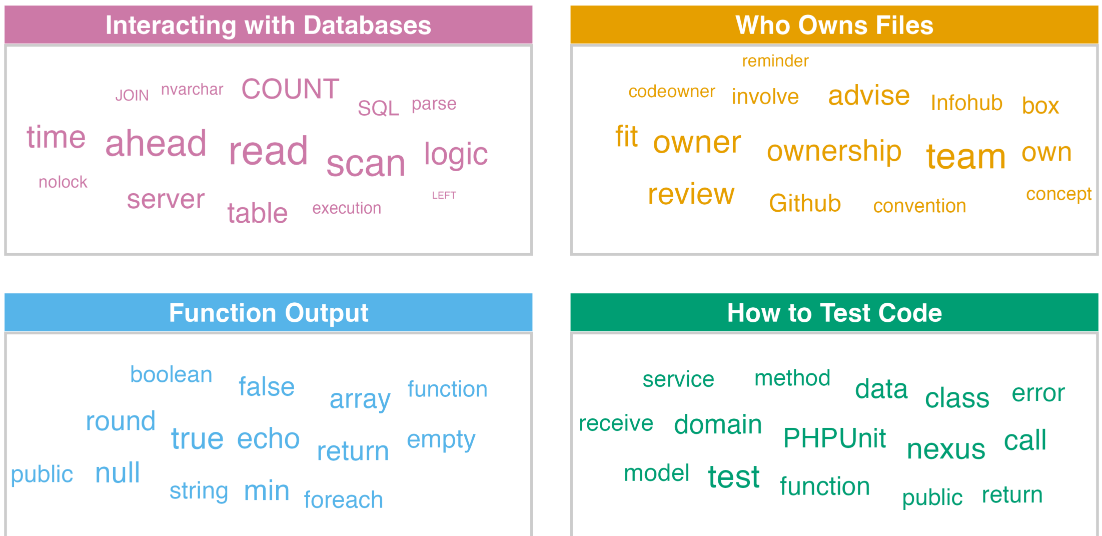
Panel (b): Dynamic, Conditional Differences in Comments Per Program



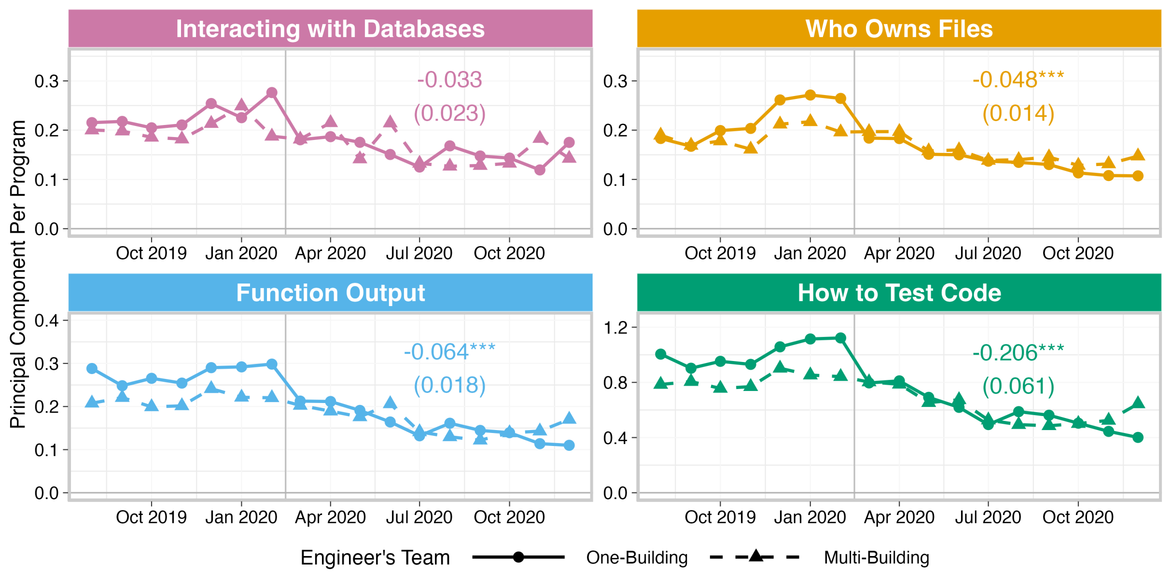
Notes: This figure illustrates the online feedback received by engineers in one-building teams (N=637) and engineers on multi-building teams (N=418) before and after the offices closed for COVID-19 (the grey vertical lines). Panel (a) plots the raw averages, while Panel (b) plots the differences from Equation 2, conditional on our preferred controls for program scope, team size, and team average tenure as in column two of Table 2. The ribbon is a 95% confidence interval with clustering by engineering team. The annotated coefficient is the difference-in-differences estimate from Equation 1. The sample is limited to engineers whose teammates all worked in the main campus. *p<0.1; **p<0.05; ***p<0.01.

Figure 2: Themes in Programmers' Online Peer Feedback

Panel (a): Word Loadings in Principal Components



Panel (b): Proximity and Themes in Feedback

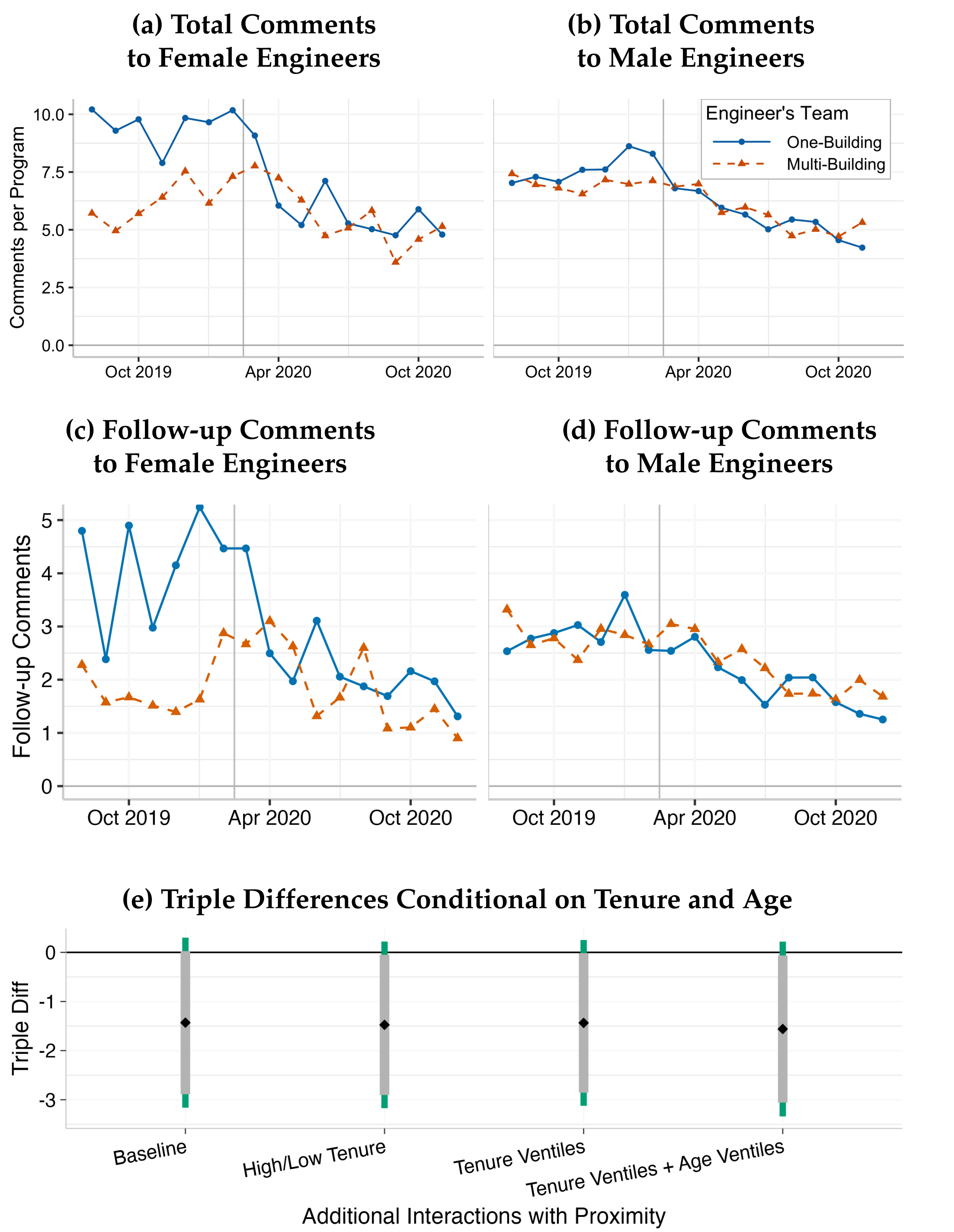


Notes: This figure illustrates the common themes in programmers' online feedback to one another, and how proximity impacts these themes. These themes are identified using principal component analysis (see Section I.A for details and Table A.1 for emblematic, example comments). Panel (a) presents the words with the highest loading for each component, with the size reflecting the loading. The first component identifies comments that are about how to *read* data from databases often in the structured query language, *SQL*. The second component identifies two, typically non-overlapping groups of comments. One is about asking *owners* of code on *Github* to *review* suggested changes. The other is about what *functions return*, with special attention to edge cases, like *null* values and *empty arrays*. The final component shown here is about *test*ing code, often using the testing suite *PHPUnit*. Panel (b) replicates the analysis in Figure 1 for these components in the comments on each program. The annotated coefficient is the difference-in-differences estimate conditional on our preferred controls. Standard errors are clustered by engineering team. *p<0.1; **p<0.05; ***p<0.01.

Figure 3: Feedback by Engineer Experience

Notes: This figure illustrates the effects of proximity on the online feedback received by engineers of different ages and tenures. Panels (a)-(b) show the raw monthly averages of comments received per program for engineers on one-building and multi-building teams, separately by those below and above the mean age of 29. Panel (c)-(d) does this separately for engineers who are more junior and more senior (above or below the median tenure of 16 months). Panel (e) shows the triple-difference estimates with our preferred set of controls. Additional triple-difference interactions are included to isolate the role of age, tenure and gender. The lighter bars show 90% confidence intervals, and the darker, narrower bars show 95% confidence intervals. Standard errors are clustered by engineering team.

Figure 4: Collaboration by Program-writer Gender

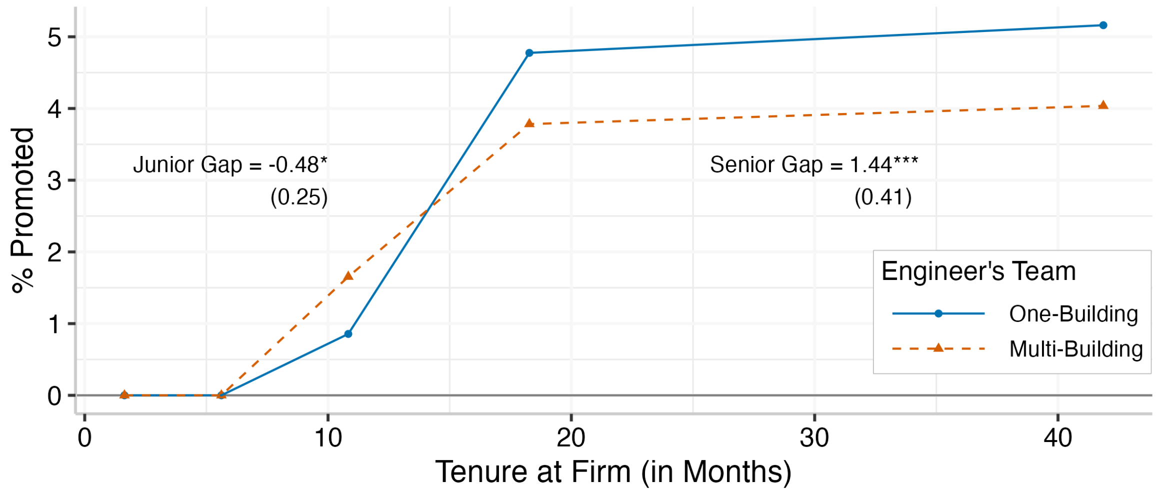


Notes: This figure illustrates the effects of proximity on the online feedback received by engineers of different genders. Panels (a)-(b) show the raw monthly averages of comments received per program for engineers on one-building and multi-building teams, separately for engineers who identify as female and male. Panel (c)-(d) zeros in on follow-up comments after the program writer has replied to initial comments. Panel (e) shows the triple-difference estimates on all comments/program with our preferred set of controls. Additional triple-difference interactions are included to isolate the role of age, tenure and gender. The lighter bars show 90% confidence intervals, and the darker, narrower bars show 95% confidence intervals. Standard errors are clustered by engineering team.

Figure 5: Trade-offs Between Feedback and Output

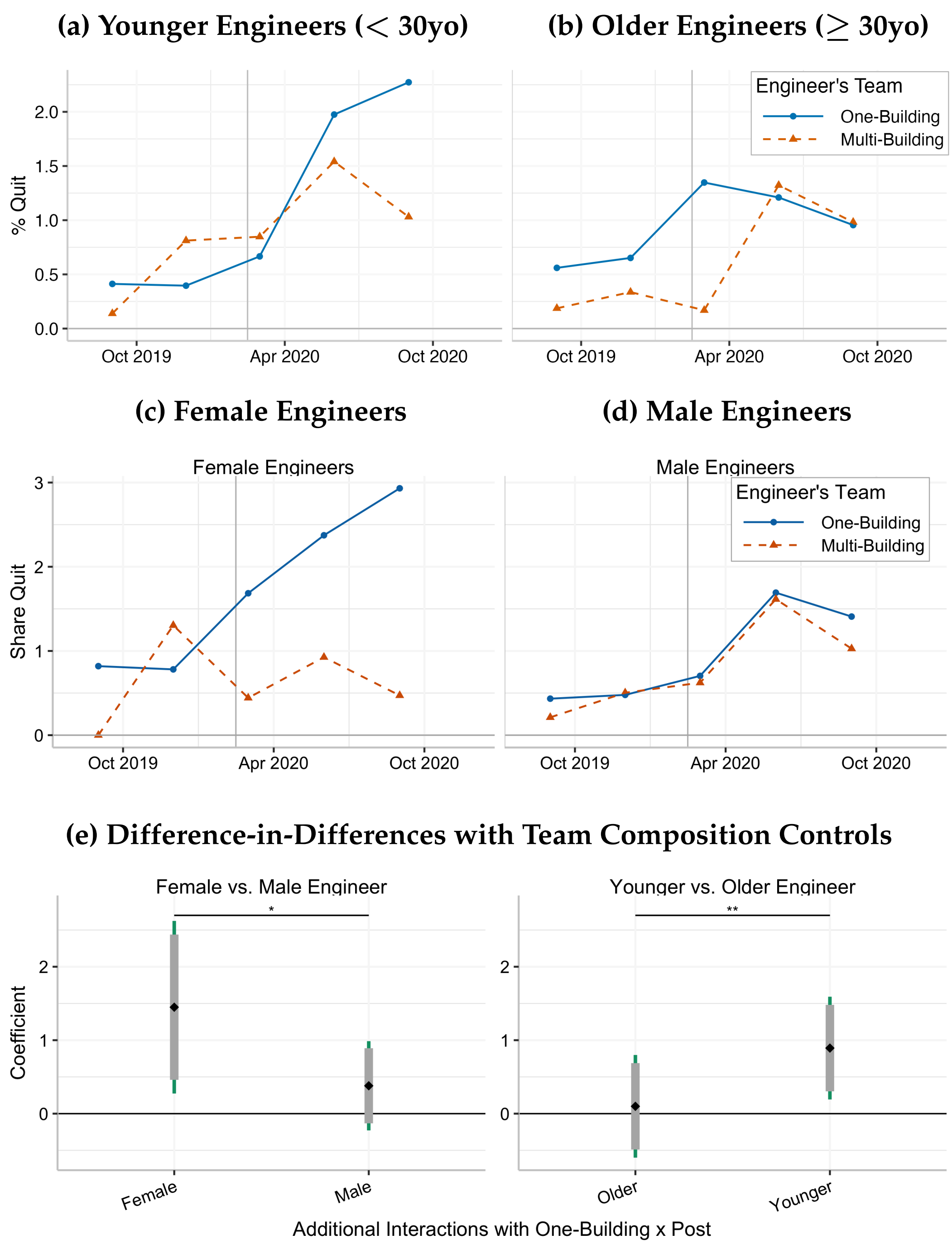
Notes: This figure illustrates the tradeoffs from proximity between long-term training and short-term output. Panels (a)-(b) show the raw monthly averages of the number of programs submitted per month for engineers on one-building and multi-building teams, separately by those who were relatively new to the company before the offices closed and those who were more experienced. Panel (c) shows the difference-in-differences estimates in percentage terms for quintiles of tenure with our preferred set of controls. Standard errors are clustered by engineering team.

Figure 6: Engineers' Promotion Trajectories



Notes: This figure illustrates the differences in promotions of engineers on one- and multi-building teams as a function of their tenure at the firm. The sample is limited to engineers whose teams are all in the firm's main campus and to promotions that occur before June 2020 and so are primarily based on pre-pandemic performance. The points reflect raw promotion rates by the engineer's tenure. The annotated coefficients condition on the size and average tenure of the engineer's team as quintiles. Standard errors are clustered by engineering team.

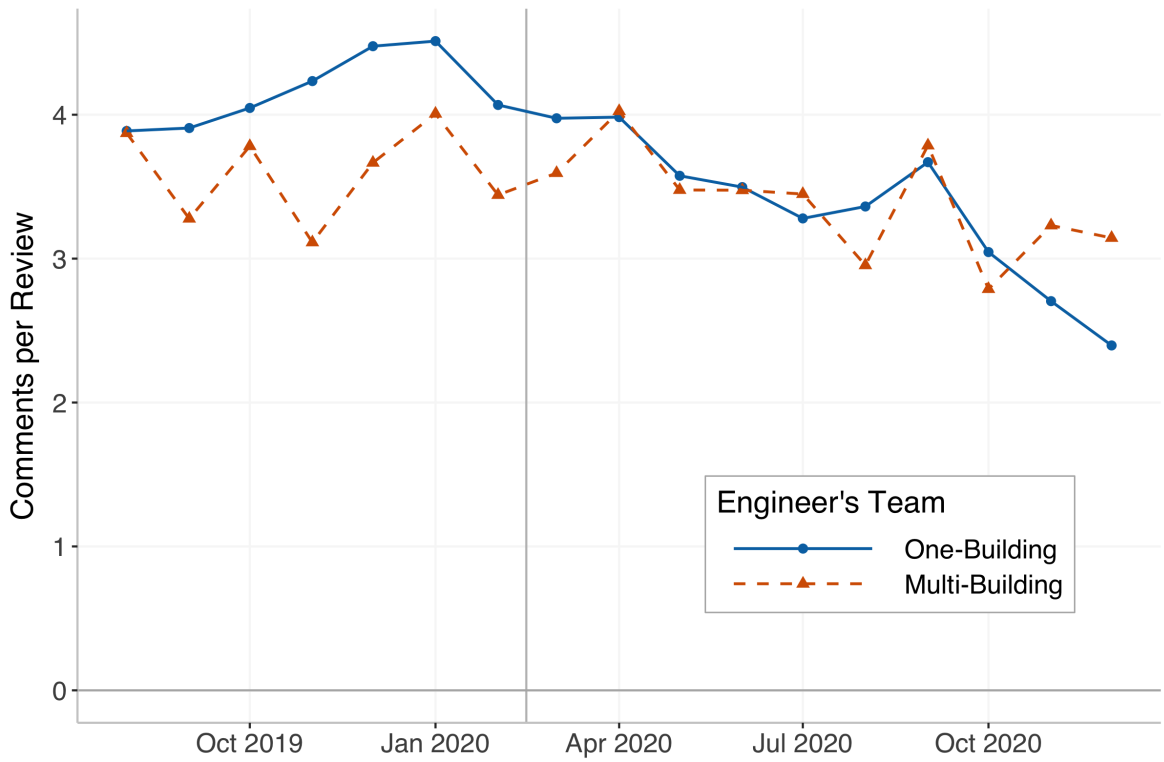
Figure 7: Impacts of Proximity on Quits



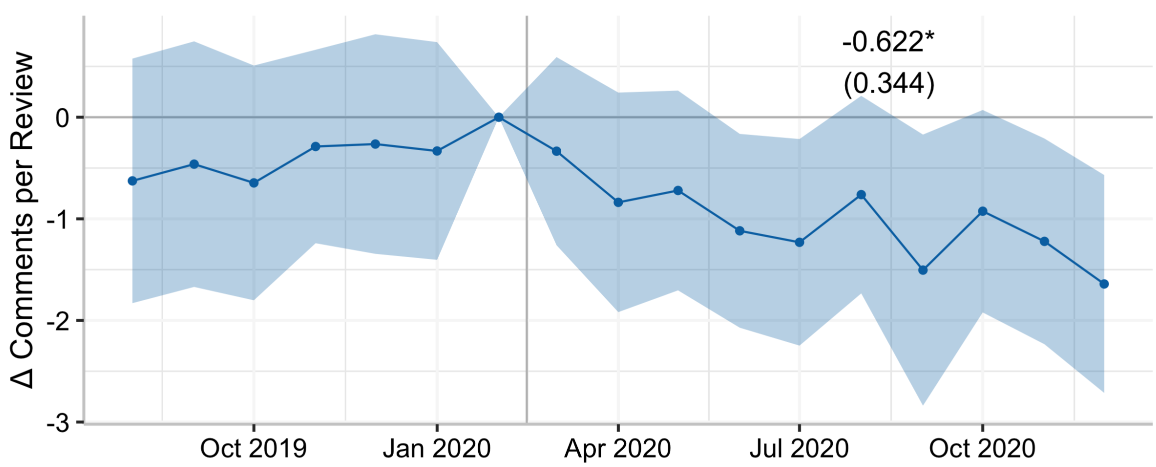
Notes: This figure illustrates the effects of proximity on quits among engineers of different ages and genders. Panels (a)-(b) show the raw quit rates for engineers on one-building and multi-building teams, separately by those below and above the mean age of 30. Panel (c)-(d) does the same for engineers who identify as male and female. Panel (e) shows the difference-in-difference estimates for each group with of controls for team composition. The lighter bars show 90% confidence intervals, and the darker, narrower bars show 95% confidence intervals. The stars show the significance of the triple difference estimates. Standard errors are clustered by engineering team.

Figure 8: Externalities from Distant Teammates

Panel (a): Raw Comments in Reviews from Same-Building Teammates

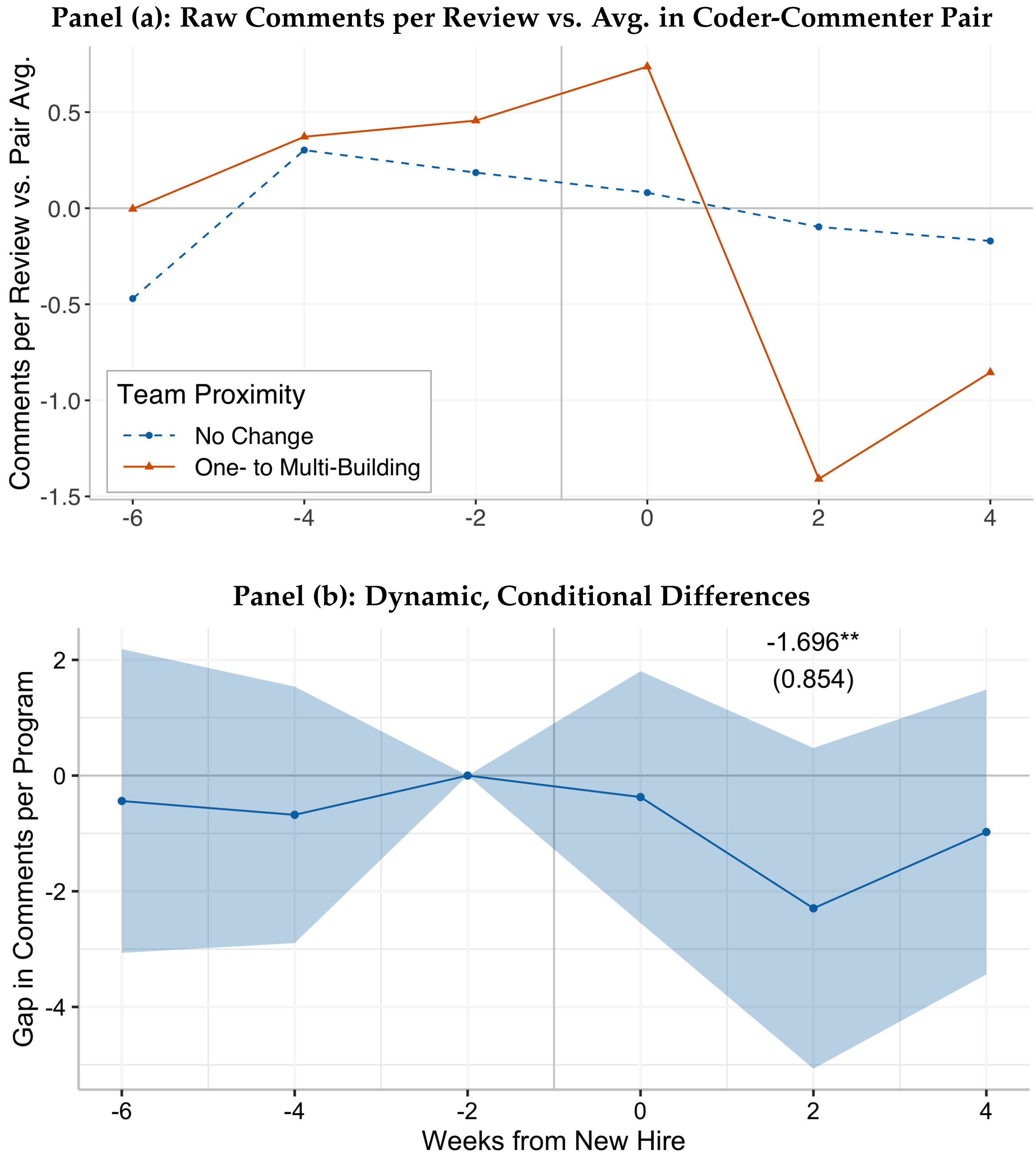


Panel (b): Dynamic, Conditional Differences in Comments per Reviews from Same-Building Teammates



Notes: This figure investigates the externalities from having a distant teammate on the feedback an engineer receives from teammates *in the same building*. Panel (a) plots the monthly averages of comments received per peer-review from same-building teammates, separately for engineers in one- and multi-building teams. Panel (b) plots the differences from Equation 2 conditional on program scope and team size and average tenure as in column two of Table A.8. The ribbon reflects 95% confidence intervals with standard errors clustered by engineer. The annotated coefficient is the difference-in-differences estimate from Equation 1. Only engineers whose teammates all worked in the main campus are included. The grey vertical lines mark the COVID-19 office closures. *p<0.1; **p<0.05; ***p<0.01.

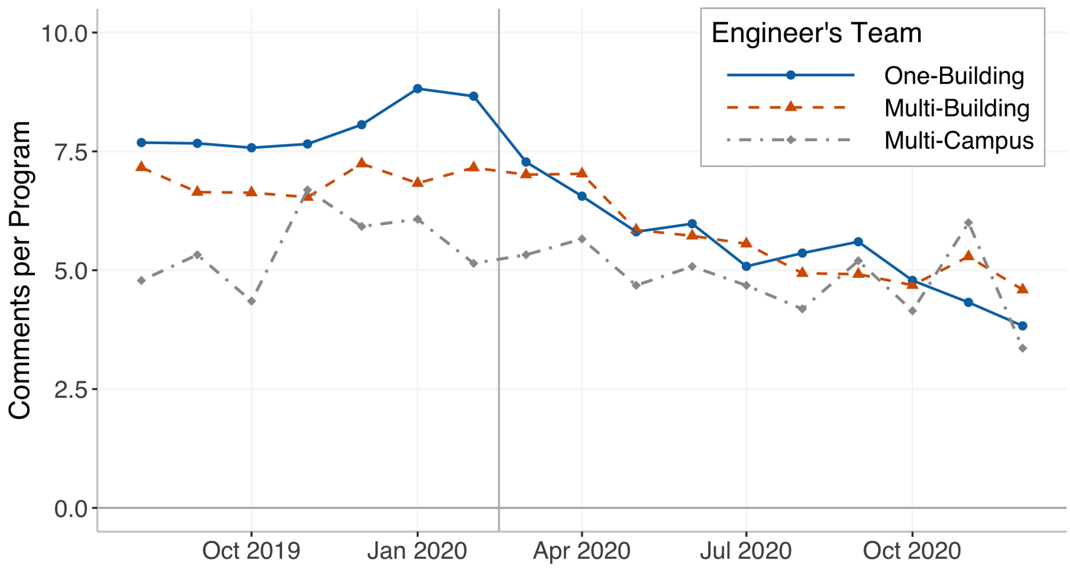
Figure 9: Impact of New Hires on Feedback from Existing, Same-Building Teammates before COVID-19



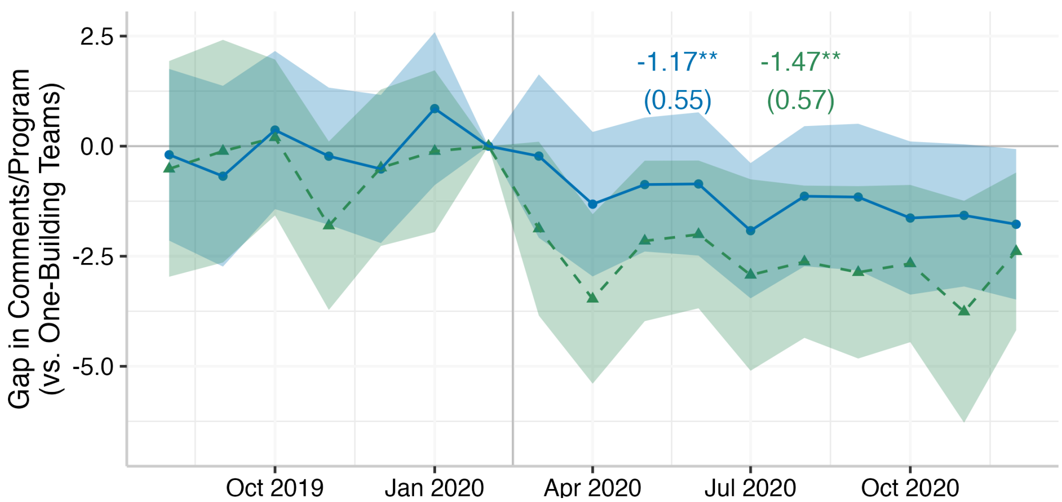
Notes: This figure compares the change in comments per program from existing teammates around the time of a new hire. It compares teams where a new hire converts the team from a one-building team to a multi-building team with teams where a new hire does not change whether the team is in one or a multiple buildings. The x-axis represents the week relative to the hire, with the grey line indicating the date of new hire. The top panel plots comments received on each program relative to the average in the coder-commenter pair. The bottom panel plots the conditional difference in feedback between these two groups, with fixed effects for engineer pairs. The sample is limited to engineers and commenters in the same building on the main campus and hired before the 6-week pre-period. *p<0.1; **p<0.05; ***p<0.01.

Figure 10: Proximity to Teammates, by Distance

Panel (a): Raw Averages of Comments per Program



Panel (b): Dynamic, Conditional Differences



Notes: This figure illustrates the online feedback received by engineers in one-building teams (N=637), multi-building, single-campus teams (N=418), and multi-campus teams (N=215) before and after the offices closed for COVID-19 (the grey vertical lines). Panel (a) plots the raw averages; Panel (b) plots the differences from Equation 2, conditional on our full set of controls listed in Subsection III.B. We use the full set of controls since multi-campus teams include engineers who chose to be in different geographies or remote. The ribbons reflect 95% confidence intervals with clustering by engineer. The annotated coefficients come from Equation 1 run separately for the two comparisons. All engineers are included, regardless of the their teammates' locations. *p<0.1; **p<0.05; ***p<0.01.

Table 1: Summary Statistics: One- and Multi-Building Teams

	Full Sample	Before Closures: One-Building	Before Closures: Multi-Building	Before Closures: Δ_0		After Closures: One-Building	After Closures: Multi-Building	After Closures: Δ_1		Diff-in-Diff: $\Delta_1 - \Delta_0$	
% Teammates in Building	39.7	100	70.1	29.9***	30.4***	0	0	0	0	-29.9***	-30.4***
				(1.51)	(1.37)			(0)	(0)	(1.51)	(1.37)
% Main Building	69.7	92.9	39.8	53.0***	51.3***	91.5	37.2	54.2***	54.1***	1.19	2.82
				(3.89)	(3.72)			(4.35)	(4.07)	(2.20)	(2.31)
Engineer Traits											
% Female	18.7	19.5	17.3	2.19	1.62	19.8	17.5	2.29	0.964	0.096	-0.653
				(2.78)	(2.79)			(2.91)	(2.96)	(1.79)	(1.97)
Age (Years)	28.9	28.5	29.1	-0.586	-0.361	28.7	29.2	-0.515	-0.264	0.070	0.097
				(0.416)	(0.439)			(0.419)	(0.437)	(0.245)	(0.264)
% Parent	16.0	17.0	16.5	0.457	-0.608	16.6	13.1	3.50	3.91	3.05	4.52*
				(4.91)	(4.59)			(4.90)	(4.67)	(2.16)	(2.48)
Firm Tenure (Years)	1.63	1.21	1.56	-0.344***	-0.063	1.76	2.01	-0.257**	-0.064	0.087	-0.001
				(0.110)	(0.072)			(0.128)	(0.070)	(0.069)	(0.053)
Job Level	1.81	1.62	1.82	-0.196***	-0.091	1.85	1.98	-0.133**	-0.053	0.063	0.038
				(0.063)	(0.061)			(0.067)	(0.065)	(0.048)	(0.044)
Hourly Pay	55.8	53.7	55.6	-1.89***	-1.12	56.2	57.8	-1.58**	-0.891	0.319	0.228
				(0.694)	(0.697)			(0.730)	(0.775)	(0.443)	(0.457)
Programming Output											
# Programs Written/Month	3.22	3.15	3.51	-0.448**	-0.510***	3.14	3.16	0.009	-0.101	0.457***	0.409***
				(0.187)	(0.184)			(0.180)	(0.187)	(0.138)	(0.140)
# Changed Lines/Program	476	483	609	-127**	-136**	357	523	-165***	-169***	-38.4	-32.9
				(56.7)	(61.2)			(45.2)	(33.5)	(65.0)	(63.1)
# Changed Files/Program	6.90	6.84	7.82	-0.982*	-1.04**	5.80	7.74	-1.94***	-1.83***	-0.955	-0.790
				(0.515)	(0.518)			(0.589)	(0.464)	(0.661)	(0.591)
Peer Reviews											
# Commenters/Program	1.27	1.37	1.25	0.112**	0.125***	1.23	1.23	0.008	0.011	-0.103***	-0.114***
				(0.045)	(0.043)			(0.035)	(0.033)	(0.039)	(0.043)
# Comments/Program	6.47	8.04	6.88	1.16**	1.03**	5.53	5.66	-0.128	-0.245	-1.29***	-1.28***
				(0.519)	(0.446)			(0.346)	(0.285)	(0.480)	(0.438)
Characters/Comment	79.6	76.6	78.6	-1.96	-3.60	78.9	85.2	-6.34*	-7.02**	-4.38	-3.42
				(2.96)	(2.71)			(3.35)	(3.26)	(3.27)	(3.31)
% With Instructive Comment	10.8	13.5	11.5	2.04	1.27	8.99	9.83	-0.838	-0.965	-2.88**	-2.23*
				(1.24)	(1.07)			(0.857)	(0.816)	(1.21)	(1.14)
% With Code	9.51	11.1	9.24	1.84*	0.824	8.72	9.06	-0.332	-0.704	-2.18*	-1.53
				(1.07)	(1.01)			(1.14)	(1.03)	(1.25)	(1.08)
Hours Until First Comment	16.7	16.0	16.6	-0.607	-0.776	17.3	16.9	0.441	0.563	1.05*	1.34**
				(0.576)	(0.519)			(0.441)	(0.434)	(0.622)	(0.628)
% Comments 8AM-6PM, M-F	95.2	95.9	95.2	0.727	0.876	94.9	94.6	0.378	0.056	-0.349	-0.820
				(0.528)	(0.541)			(0.577)	(0.704)	(0.748)	(0.906)
Team Composition Controls					✓				✓		✓
# Software Engineers	1,055	583	400			518	358				
# Months	17	7	7			10	10				
# Programs Written	29,959	7,608	6,397			9,469	6,485				
# Comments Received	174,014	50,127	38,604			50,675	34,608				

Notes: This table shows traits of the engineers, their work, and their feedback. The sample includes engineers whose teams are all in the main campus. Parenting responsibilities come from a June 2020 survey conducted by the firm. Job level refers to the engineer's position within the firm's hierarchy from zero (an intern) to six (senior staff). A review has an instructive comment if a comment shows the engineer an 'example', gives 'general' advice, or discusses best programming 'practice'. A peer review includes code if any comment includes code to illustrate the reviewer's advice. Hours until the first comment are measured from code submission. Team composition controls include indicators for the quintile of team size (2−3, 4, 5, 6−7, and 8 or more) interacted with the quintile of the average tenure on the team (<7.6 months, 7.6− 11, 11.1−15.8, 15.9−23.7, and > 23.7). Standard errors in parentheses are clustered by engineering team. *p<0.1; **p<0.05; ***p<0.01.

Table 2: Proximity to Teammates and Online Feedback

	Comments per Program							
							Teammates Comments	Non-Teammate Comments (Placebo)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post x One-Building Team	-1.29^{***}	-1.28^{***}	-1.35^{***}	-1.37^{***}	-1.41^{***}	-1.17^{**}	-1.20^{***}	-0.02
	(0.48)	(0.44)	(0.40)	(0.46)	(0.45)	(0.55)	(0.45)	(0.39)
One-Building Team	1.16^{**}	1.03^{**}	1.84^{***}	1.74^{***}				
	(0.52)	(0.45)	(0.39)	(0.43)				
Post	-1.22^{***}							
	(0.36)							
Pre-Mean, One-Building Team	8.04	8.04	8.04	8.04	8.04	8.04	4.28	3.73
Percentage Effects								
Post x One-Building Team	-16.1%	-15.9%	-16.8%	-17%	-17.5%	-14.5%	-28%	-0.59%
One-Building	14.5%	12.8%	22.9%	21.6%				
% One-Building Team	58.3	58.3	58.3	58.3	58.3	58.3	58.3	58.3
Team Composition x Post FE		✓	✓	✓	✓	✓	✓	✓
Program Scope Quartics			✓	✓	✓	✓	✓	✓
Engineer Traits x Post FE				✓	✓	✓	✓	✓
Engineer FE					✓	✓	✓	✓
Main Building x Post FE						✓	✓	✓
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304	9,304	9,304
R^2	0.02	0.05	0.29	0.37	0.47	0.48	0.41	0.44

Notes: This table investigates the relationship between physical proximity and the online feedback engineers receive from coworkers. Each observation is an engineer-month pair. The dependent variable is the average number of comments that the engineer receives on each program in the month from all other engineers (1-6), from teammates (7), and from non-teammates (8). Each column estimates Equation 1, which compares engineers who were in the same building as all of their teammates before the pandemic to those on teams already distributed across multiple buildings. Column 1 presents the raw estimates, corresponding to Figure 1. Column 2 includes time-varying controls for team composition, indicators for quintiles team size interacted with indicators for quintiles of average team tenure, since these help determine whether the team is in one building or spread over the two buildings. Column 3 adds controls for program scope (quartics for the number of lines added, number of lines deleted, and number of files changed). Column 4 allows for differential changes in feedback for engineers with different observable characteristics: tenure (in months), age (in years), gender, home zipcode, and job level. Column 5 includes engineer fixed effects. Columns 6-8 include building-by-post fixed effects to allow programmers who sat in the main and auxiliary buildings to experience different changes in feedback around the office closures. The sample includes engineers who submit programs to the firm's main code-base in the month and whose teams are all in the firm's main campus. Table A.2 shows robustness of the results to the inclusion of controls for the engineer's sub-department within engineering (e.g., front-end, website design versus back-end, database maintenance). Standard errors are clustered by engineering team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 3: Proximity and Dimensions of Online Feedback

Panel (a): Feedback Length, Delay, and Mentions of Other Online Conversations

	Comments per Program (1)	Total Characters (2)	Hours to Comment (3)	% Other Online Convo (4)
Post x One-Building Team	-1.35^{***}	-157.30^{***}	1.43^{**}	-1.00^{*}
	(0.40)	(52.99)	(0.60)	(0.59)
One-Building Team	1.84^{***}	189.00^{***}	-1.50^{***}	1.45^{**}
	(0.39)	(49.45)	(0.49)	(0.56)
Pre-Mean, One-Building Team	8.04	833.24	16.02	4.06
Percentage Effects				
Post x One-Building Team	-16.8%	-18.9%	8.9%	-24.7%
One-Building	22.9%	22.7%	-9.4%	35.7%
# Engineer-Months	9,304	9,304	9,304	9,304

Panel (b): Back-and-Forth Conversations

	Commenter's	Program Writer		Commenter's
	Initial Comments	Replies	Questions	Follow-up Comments
	(1)	(2)	(3)	(4)
Post x One-Building Team	-0.85^{***}	-0.41^{**}	-0.06^{**}	-0.50
	(0.23)	(0.20)	(0.02)	(0.31)
One-Building Team	1.13^{***}	0.42^{**}	0.04^{*}	0.71^{**}
	(0.23)	(0.21)	(0.02)	(0.29)
Pre-Mean, One-Building Team	4.91	2.14	0.19	3.13
Post x One-Building Team	-17.3%	-19.2%	-33.6%	-16.1%
One-Building Team	23%	19.7%	23.7%	22.7%
# Engineer-Months	9,304	9,304	9,304	9,304

Notes: This table replicates considers alternative metrics of (a) the extent and timeliness of feedback and (b) the back-and-forth conversation between the commenter and program writer. Each specification replicates Column 3 of Table 2, reported in Column 1 of Panel (a) for reference. In Panel (a), Column 2 considers the total number of characters in the comments on a program; Column 3, the hours of delay between program submission and the first comment; Column 4, the percentage of reviews that reference another online conversation between the commenter and program writer (on Slack, email, or Zoom). In Panel (b), Column 1 considers the number of comments that the commenter writes before the program writer responds; Column 2, the program writer's replies; Column 3, the program writer's questions to the commenter; and Column 4, the commenter's follow-up comments after the program writer has replied. Standard errors are clustered by engineering team. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Tradeoffs Between Feedback and Programming Output

	Comments per Program				Programs per Month			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Junior (< 16mo) x Post x One-Building Team	-1.40^{**}	-2.02^{***}	-1.78^{***}	-1.61^{**}	0.36^{**}	0.32^{*}	0.22	0.17
	(0.65)	(0.54)	(0.59)	(0.62)	(0.16)	(0.17)	(0.18)	(0.19)
Junior (< 16mo) x One-Building Team	1.27^{*}	2.67^{***}			-0.31	-0.39^{*}		
	(0.68)	(0.53)			(0.21)	(0.20)		
Senior (≥ 16mo) x Post x One-Building Team	-0.41	-0.30	0.59	0.70	0.57^{***}	0.52^{***}	0.75^{***}	0.68^{***}
	(0.45)	(0.44)	(0.56)	(0.61)	(0.19)	(0.19)	(0.21)	(0.22)
Senior (≥ 16mo) x One-Building Team	0.13	0.56			-0.66^{***}	-0.67^{***}		
	(0.39)	(0.34)			(0.25)	(0.25)		
Junior Pre-Mean, One-Building Team	9.56	9.56	9.56	9.56	1.84	1.84	1.84	1.84
Senior Pre-Mean, One-Building Team	4.99	4.99	4.99	4.99	1.69	1.69	1.69	1.69
Percentage Effects								
Junior x Post x One-Building Team	-14.7%	-21.1%	-18.6%	-16.8%	19.6%	17.4%	12%	9.28%
Junior x One-Building Team	13.2%	27.9%			-16.8%	-21.5%		
Senior x Post x One-Building Team	-8.2%	-5.9%	11.9%	14.1%	34%	30.8%	44.6%	40.37%
Senior x One-Building Team	2.5%	11.1%			-39.1%	-39.5%		
Team Composition x Post FE		✓	✓	✓		✓	✓	✓
Program Scope Quartics		✓	✓	✓				
Engineer Traits x Post FE			✓	✓			✓	✓
Engineer FE			✓	✓			✓	✓
Main Building x Post FE			✓	✓			✓	✓
Sub-Org. x Post FE				✓				✓
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304	9,304	9,304
R^2	0.04	0.30	0.49	0.49	0.01	0.03	0.56	0.56

Notes: This table investigates the relationship between physical proximity and engineers' online feedback and engineering output. Each observation is an engineer-month pair. In Columns 1-4, the dependent variable is the average number of comments that the engineer receives on each program in the month. In Columns 5-8, the dependent variable is the number of programs submitted in the month. Each column estimates a version of Equation 1, which compares engineers who were in the same building as all of their teammates before the pandemic to those on teams already distributed across multiple buildings, where the effects of proximity are allowed to vary by seniority at the firm. Team composition include indicators for the quintile of team size interacted with the quintile of the average tenure on the team. Program-scope controls include quartics in average files changes, lines deleted, and lines added by the engineer's programs. Engineer characteristics include fixed effects for tenure (in months), age (in years), gender, home zipcode, and job level. Sub-organization uses the hierarchy of managers to identify engineers who are under the same sub-head of engineering that manage a particular sub-department (e.g., front-end, website design versus back-end, database maintenance). The sample include engineers whose teammates are all in the firm's main campus. Standard errors are clustered by engineering team. Tables A.5 and A.6 show robustness to a fuller set of specifications. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 5: Effect of Proximity on Quits by Age and Gender

	% Quit Per Month					
	By Age		By Gender		Both, In Gaps	
	(1)	(2)	(3)	(4)	(5)	(6)
<30: Post x One-Building Team	0.927**	0.892**				
	(0.401)	(0.357)				
<30: One-Building Team	−0.166	−0.137				
	(0.241)	(0.197)				
≥30: Post x One-Building Team	−0.031	0.100				
	(0.382)	(0.357)				
≥30: One-Building Team	0.223	0.115				
	(0.267)	(0.249)				
Female: Post x One-Building Team			2.056***	1.449**		
			(0.745)	(0.599)		
Female: One-Building Team			−0.186	0.088		
			(0.486)	(0.299)		
Male: Post x One-Building Team			0.201	0.379		
			(0.311)	(0.310)		
Male: One-Building Team			0.014	−0.075		
			(0.193)	(0.199)		
Age Gap: Post x One-Building Team					0.566	0.698**
					(0.445)	(0.324)
Age Gap: One-Building Team					−0.166	−0.252
					(0.280)	(0.233)
Gender Gap: Post x One-Building Team					1.602*	0.974*
					(0.824)	(0.585)
Gender Gap: One-Building Team					−0.024	0.219
					(0.552)	(0.289)
Pre-Mean One-Building Teams	>30: 0.4 ≥30: 0.47	>30: 0.4 ≥30: 0.47	Female: 0.6 Male: 0.38	Female: 0.6 Male: 0.38		
Team Composition Controls X Post		✓		✓		✓
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17	17
# Engineer-Months	16,100	16,100	16,100	16,100	16,100	16,100
R^2	0.003	0.008	0.003	0.008	0.003	0.008

Notes: This table considers quits, for young engineers at or below the mean age of 29 and older engineers at least thirty, as well as for female and male engineers. The dataset is at the engineer by month level. The odd columns present the raw triple difference design while the even columns add time-varying, team composition controls. The sample is limited to engineers whose teams are all in the main campus. Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.

A APPENDIX

I.A Principal Component Analysis

To identify common themes in the data, we use principal components analysis (PCA). We first transform each comment into a vector of words. We then strip the comments of "stop words," such as "the", "a", "we", and "she" and use stemming to join together words like "test," "tests," and "testing." We then limit to words that appear in at least one hundred distinct comments. We then count the number of times each of these words appears in each comment. Even this more parsimonious representation of the code-review data is high-dimensional, with over a thousand variables. To interpret the data, we reduce its dimensionality by using principal component analysis (PCA). PCA transforms the data into a new coordinate system, in which most of the variation can be described in fewer dimensions.

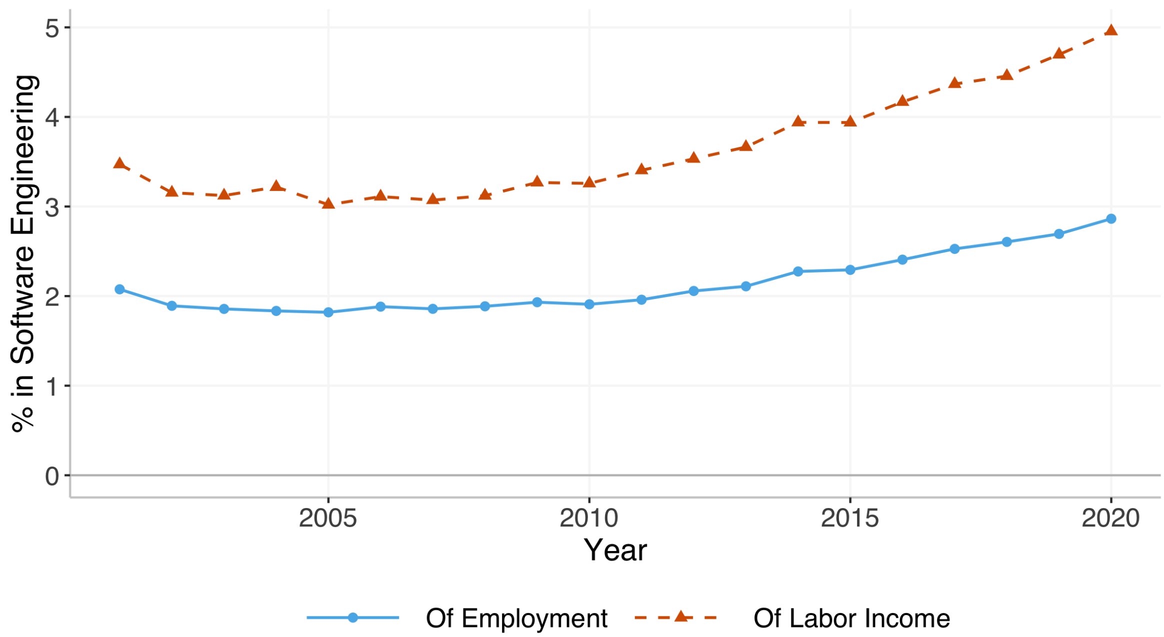
Table A.1: Example Emblematic Comments of Principal Components

PCA	Total Load	Text of Comment
1	1.25	This **logic** is very confusing to **read** for the first **time**. Please add a paragraph in the comment section to clearly explain the **logic**.
1	0.98	So, you are still **reading** all jobs and then **counting** in PHP. I would think you want to make a **count** query to **SQL server**.
1	0.90	If you change it to **SELECT COUNT**(*) AS **COUNT** without a GROUP BY, would that work for you? GROUP BY is an expensive operation on our **server**
1	0.87	Do we want to add the price range **logic** in there then? I'm confused why that **logic** hasn't changed but this **logic** here has.
1	0.85	Do you think it's getting close to time to separate the filtering **logic** and the transfor ming **logic** here?
2	1.29	We agree and approve the **ownership** transfer from Jane Doe's **team** to our **team**.
2	1.08	Can you please get **approval** from John Doe's **team** first? We have a pr in review which makes John Doe's **team codeowners** of this file.
2	0.95	Instead of giving static **team** id, can we give random **team** id. Get **team** id from tabl e and do ORDER BY `ORDER BY newid()` to get random **teams**
2	0.92	If this **team** is yours, it would be great if you could migrate the – **owners** in this change to the appropriate **owner team** and **reviewer** group
2	0.85	LGTM note: should we move this file **ownership** in **codeowners** to your **team**?
2	−0.48	This if **return**, else if **return** else **return** statement can be turned into if **return**, if **re turn**, **return**
2	−0.41	Type hint **return** int, if it is **nullable** you can use ?int. ``` **public function** id_supplier(): int { **return** $this->id_supplier; } ```
2	−0.39	Can we just **return** this **bool** check? Rather than if () {**return false**} else {**return true**}
2	−0.38	Stick this in the **return** below so we have `**return** a || b || c;` instead of `if(a) {**retur n** true}; **return** b || c;`
2	−0.38	Should update this **return** type to match the actual **return** type. Especially since you added a **return** type hint.
2	−0.38	Could we add the **return** type hint? Also in the doc string above, the **return** is listed as **string** but this **function** returns a **function**.
3	1.06	Why do we want to do this? If a **class** has a **test class** and non-**test class**, it should be able to run the **test** file, no?
3	0.99	Could we create a **function** in conversation model and put the **DAO** function there? Then here, we'll call the **model function**.
3	0.91	Any reason to make this as a static **function** and moving it to **DAO**? Looks more like an helper **function** instead of a **DAO function**?
3	0.88	If this **method** and the **method** below are only used in **test**, could we add them in th e **test DAO class**?
3	0.86	Make this into a wrapper around the real **method**, and pass the request into the real **method**. Then you can create a unit **test** for that **method**.

Notes: This table shows five emblematic examples with high loadings on each principal component. The second principal component has identified two clusters of comments: where each cluster includes words that often appear together but rarely appear with words in the other cluster. These comments were selected because they have the maximum loadings of all comments less than 150 characters long. See Section I.A for details on principal component analysis.

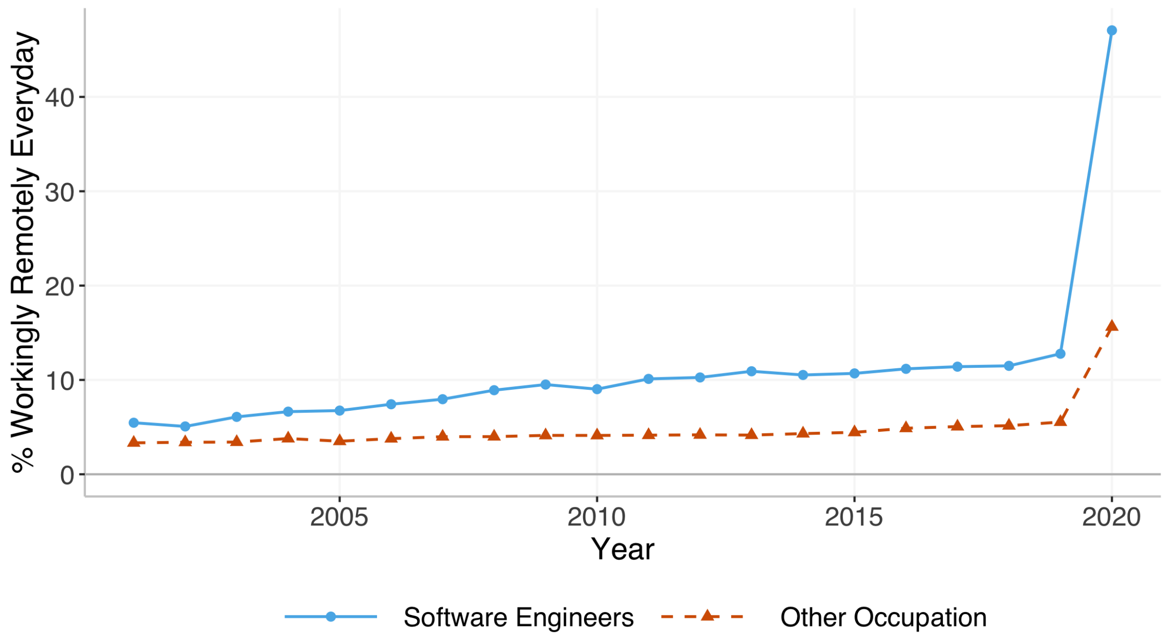
I.B Figures & Tables

Figure A.1: Trends in Remote Work for Software Engineers and Other Occupations in the Census



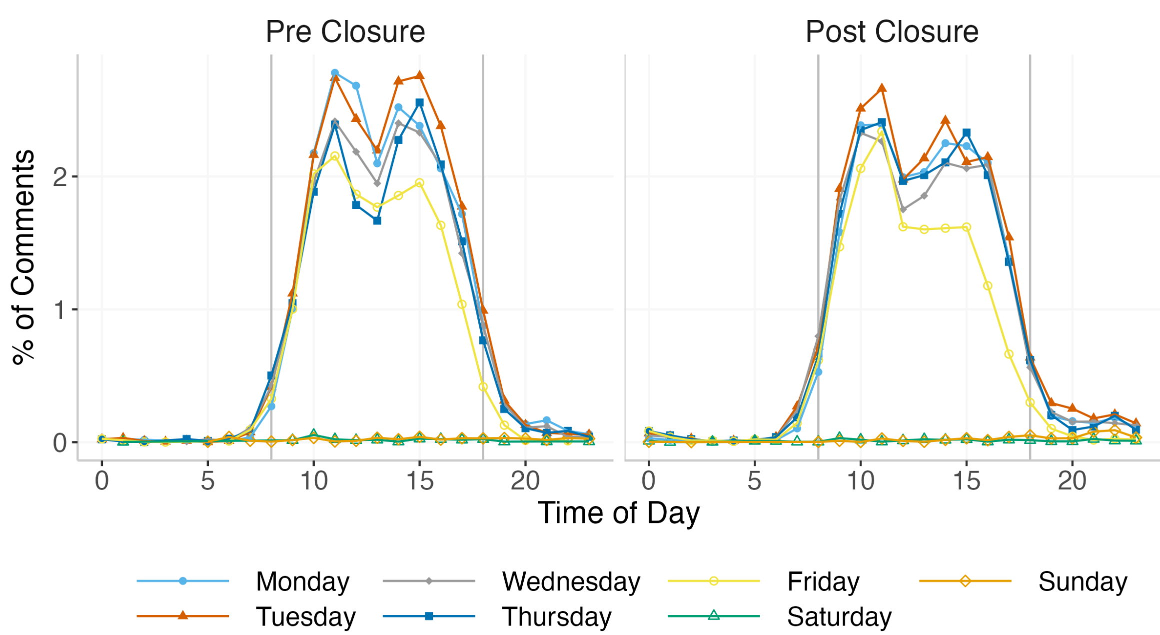
*Notes:*This figure illustrates the trends in the share of the workforce in software engineering in terms of employment (in blue circles) and labor earnings (in orange triangles) based on data from the American Community Survey. Software engineers are defined as the three Census occupational codes: Computer Scientists and Systems Analysts, Network systems Analysts, and Web Developers (Occupation 1000 in the 2010 Census), Computer Programmers (1010), and Software Developers, Applications and Systems Software (1020). The sample is limited to employed workers between the ages of 22 and 64. Observations are weighted with Census survey weights but the unweighted means yield similar patterns.

Figure A.2: Trends in Remote Work for Software Engineers and Other Occupations in the Census



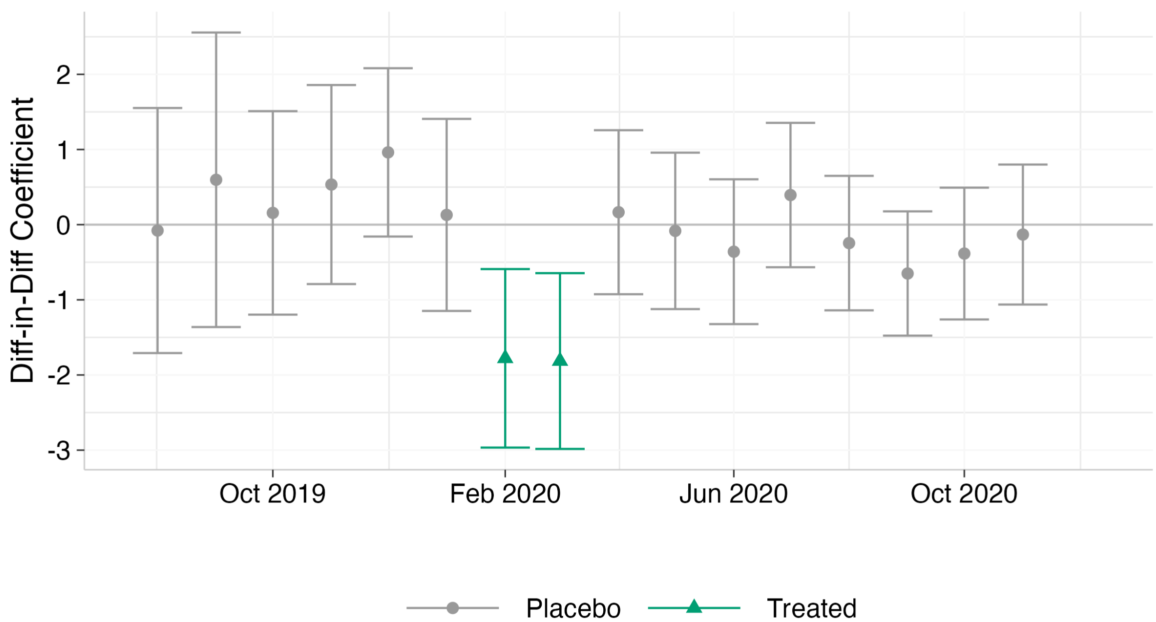
*Notes:*This figure illustrates the trends in remote work for workers in software engineering (in blue circles) and other occupations (in orange triangles) based on data from the American Community Survey. Each point reflects the percent of workers in the occupational group who reported working at home everyday. Workers who work remotely everyday can be identified from their reported means of transportation to work in the previous week. Workers who report that they did not need to travel to work are classified as working remotely everyday. Software engineers are defined as the three Census occupational codes: Computer Scientists and Systems Analysts, Network systems Analysts, and Web Developers (Occupation 1000 in the 2010 Census), Computer Programmers (1010), and Software Developers, Applications and Systems Software (1020). The sample is limited to employed workers between the ages of 22 and 64. Observations are weighted with Census survey weights but the unweighted means yield similar patterns.

Figure A.3: Timing of Comments Over the Course of the Day



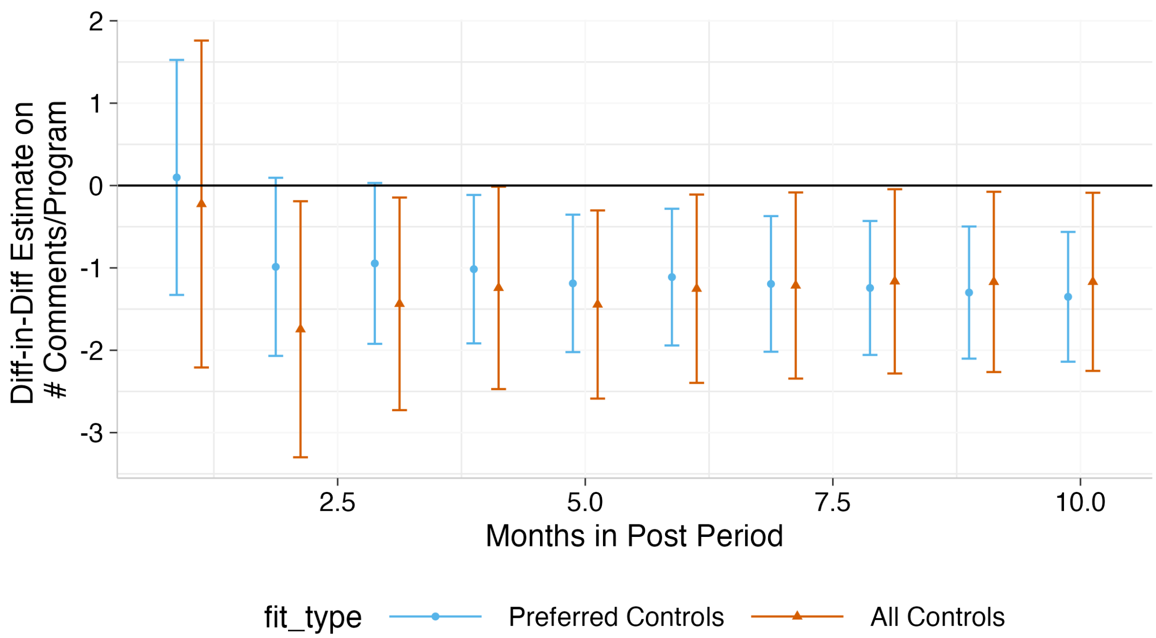
Notes: This figure plots the timing of comments over the course of the day. The x-axis plots the time of day in military time. The y-axis is the percent of comments that occur in that particular time of day on that particular day of week. The left plot is the period before the office closures of COVID-19. The right plot is the period after the office closures of COVID-19. The vertical lines highlight typical office hours from 8am to 6pm.

Figure A.4: Placebo Treatment Dates' Effects of Proximity on On-the-Job Training from Coworkers



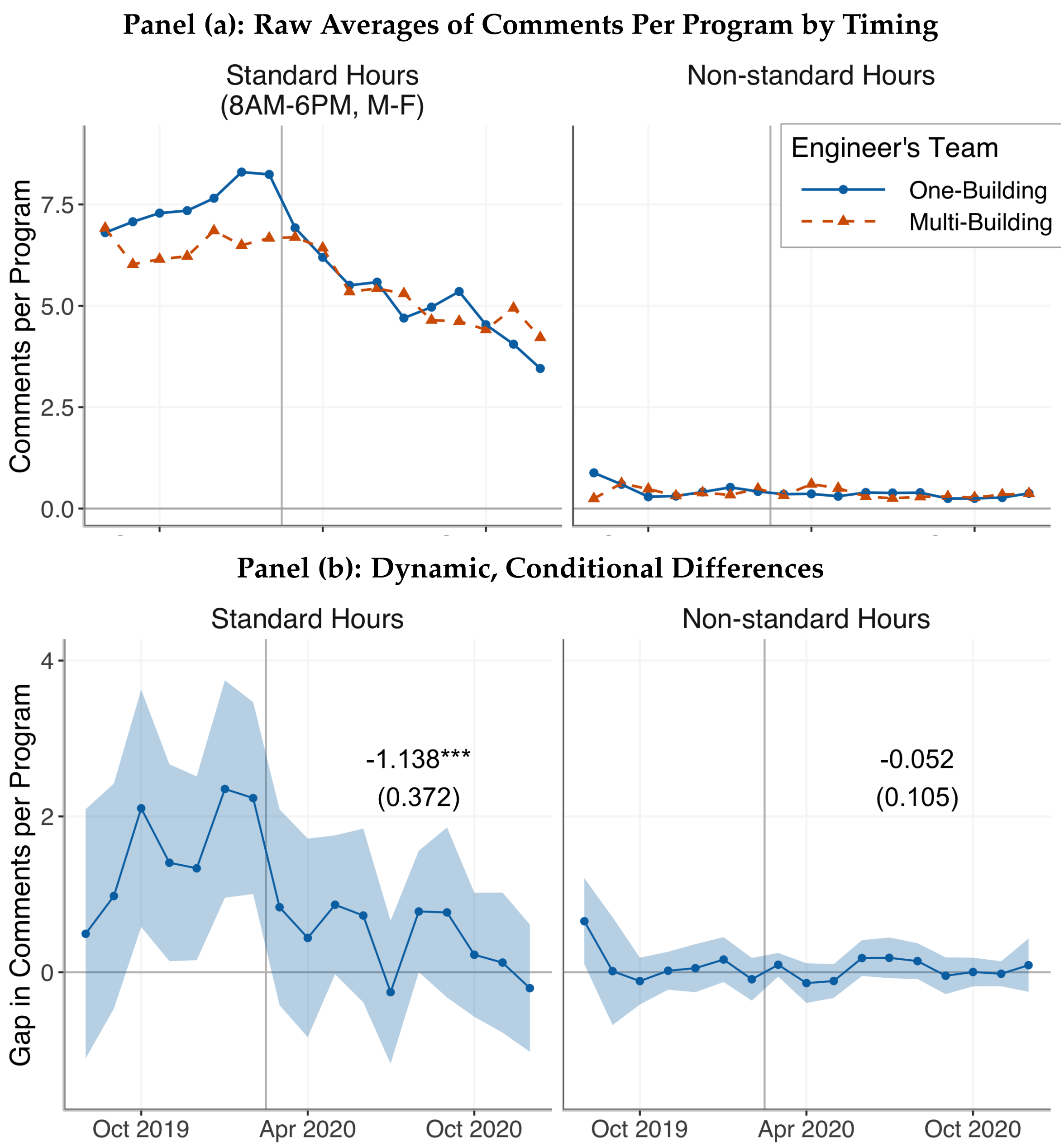
Notes: This figure illustrates difference-in-differences estimates that compare the change in comments for engineers on one- and multi-building teams in two-month bandwidths. The grey circles show periods that do not include the treated window; the green triangles include the treated window. All regressions include our preferred controls for team-size, tenure, and program scope (in column four of Table 2). The error bars are 95% confidence intervals with standard errors clustered by engineer.

Figure A.5: Robustness of Effect of Proximity on On-the-Job Training from Coworkers to Alternative Post-Periods



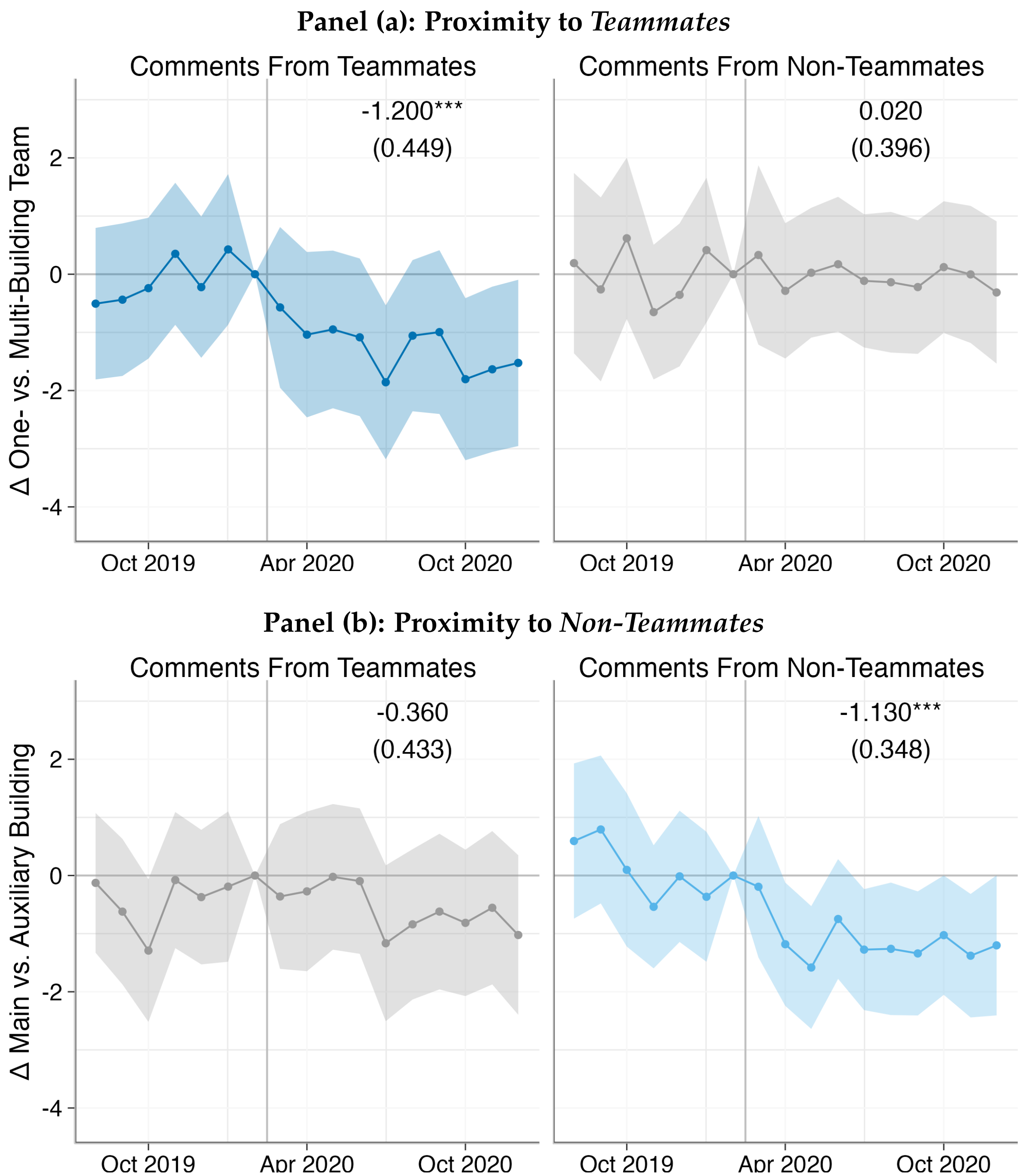
Notes: This figure illustrates how the difference-in-differences estimate from Equation 1 — that compares engineers on one- and multi-building teams, before and after the office closures — varies with the number of months in the post period. The blue circles are the coefficients using our preferred controls for team-size, tenure, and program scope (in column four of Table 2); the red triangles are the coefficients using the full set of controls (in column six of Table 2). The error bars are 95% confidence intervals with standard errors clustered by engineer.

Figure A.6: Proximity to Teammates and Online Feedback Inside and Outside of Standard Work Hours



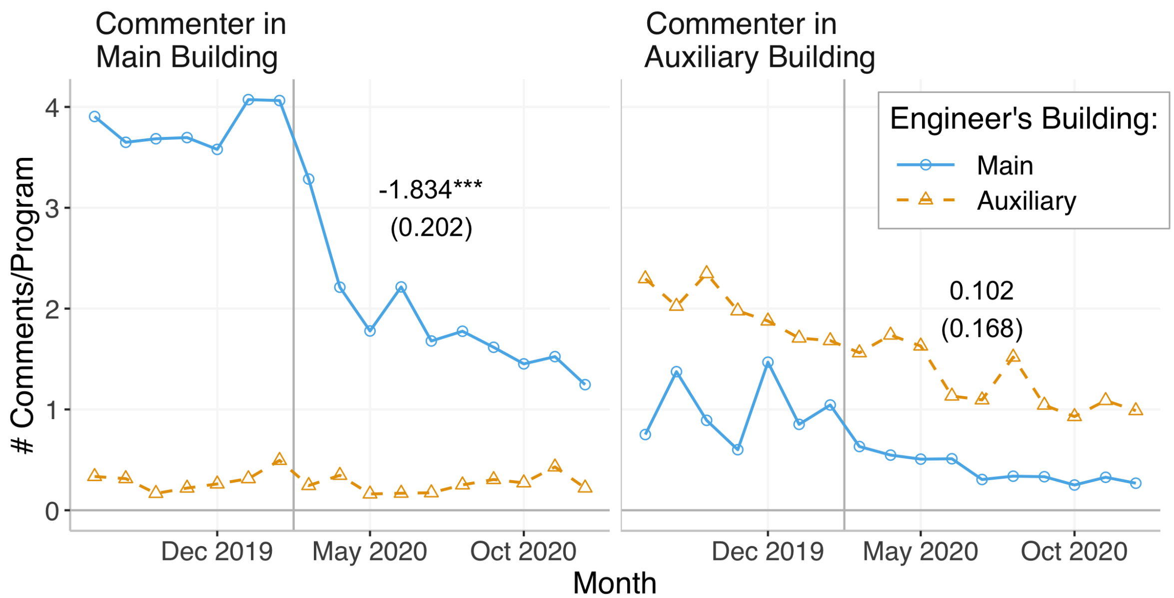
Notes: This figure illustrates the online feedback received by engineers in one-building teams (N=637) and engineers on multi-building teams (N=418) before and after the offices closed for COVID-19 (the grey vertical lines). The left plots consider comments given in standard work hours (8AM to 6PM, Monday through Friday); the right plots consider comments given in other times. Panel (a) plots the raw averages, while Panel (b) plots the differences, conditional on our preferred controls for program scope, team size, and tenure. The ribbon is a 95% confidence interval with clustering by engineer. The annotated coefficient is the difference-in-differences estimate from Equation 1. Only engineers whose teammates all worked in in the main campus are included. *p<0.1; **p<0.05; ***p<0.01.

Figure A.7: Proximity and Source of Comments: Placebo Checks



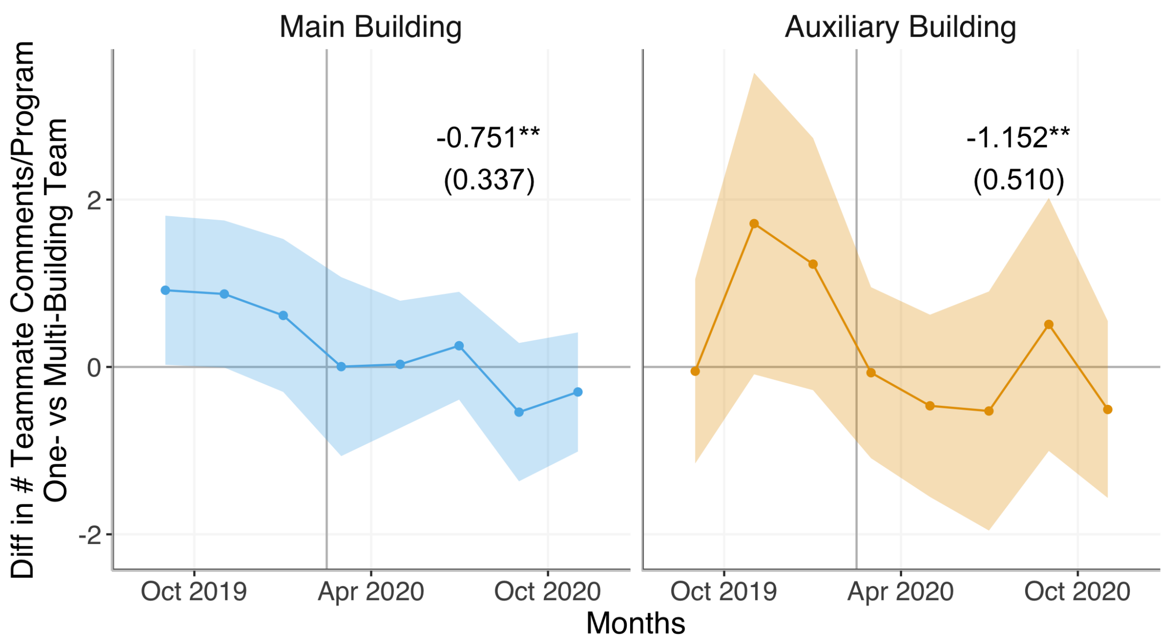
Notes: This figure differentiates between feedback from teammates (left plots) and non-teammates (right plots). Panel (a) presents the differences between engineers on one- and multi-building teams, conditional on their buildings. Panel (b) presents the differences between engineers in the main and auxiliary buildings, conditional on their proximity to their teammates. The annotated coefficients come from Equation 1 with additional controls for being in the main building or an auxiliary building interacted with post, and conditional on our full set of controls (as in Columns 7–9 in Table 2). The points come from a dynamic version of this equation with monthly differences. Ribbons are 95% confidence intervals with clustering by engineering team. Only engineers whose teammates all worked in the main campus are included. The grey vertical lines mark the COVID-19 office closures. *p<0.1; **p<0.05; ***p<0.01.

Figure A.8: Proximity and Online Feedback from Non-Teammates



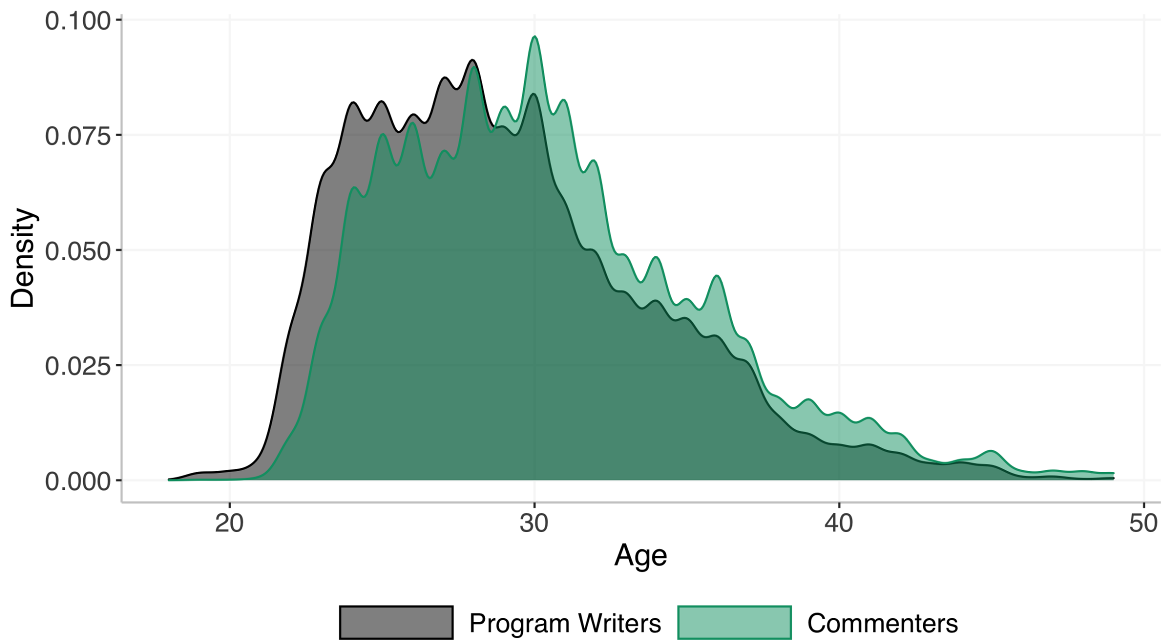
Notes: This figure compares the change in peer feedback from non-teammates around the COVID-19 office closures for engineers in the firm's main building (in blue circles) to engineers in an auxiliary building (in orange triangles) based on the commenter's location. In both plots, the x-axis represents the month, with the grey line highlighting the COVID-19 office closures. In the left plot, the y-axis represents the quantity of comments from non-teammates in the main building. In the right plot, the y-axis represents the quantity of comments from non-teammates in an auxiliary building. The annotated coefficients compare the difference between engineers in the main versus auxiliary buildings after the closure to the same difference before the closure. Standard errors are clustered by engineering team. *p<0.1; **p<0.05; ***p<0.01.

Figure A.9: Proximity to Teammates and their Feedback: In the Main and Auxiliary Buildings



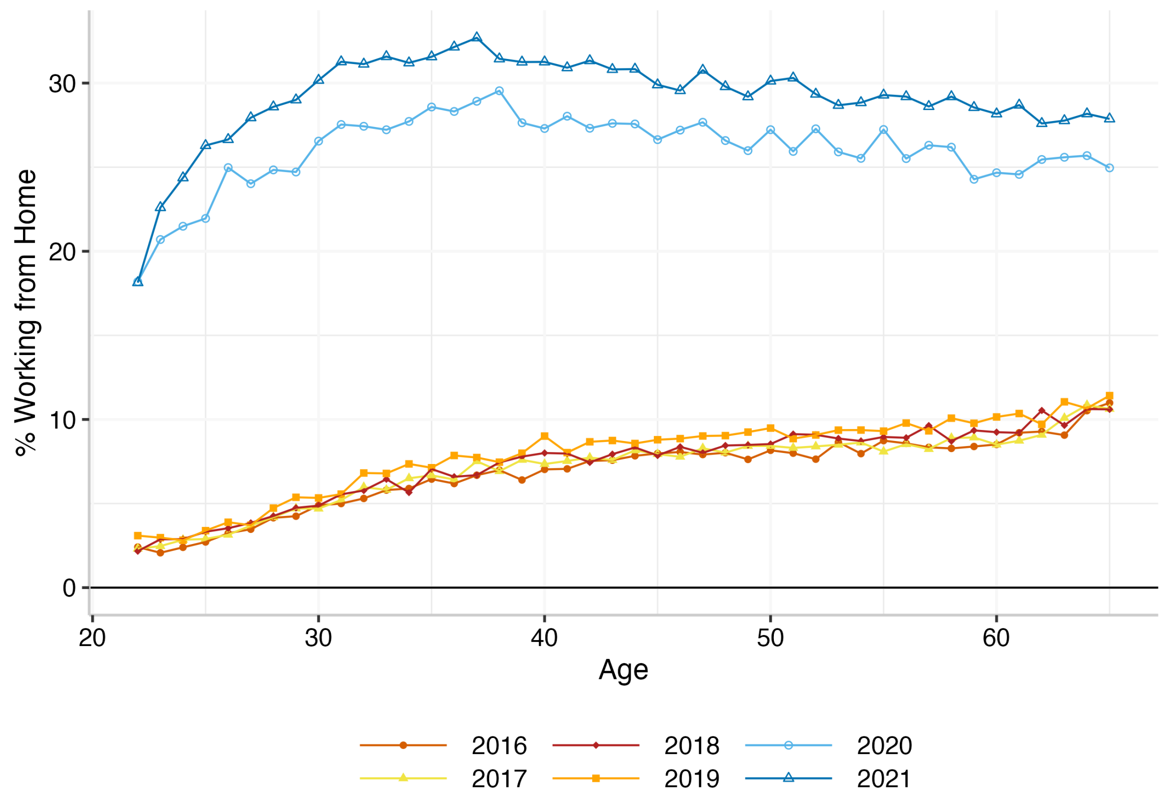
Notes: This figure compares the change in peer feedback from teammates around the COVID-19 office closures for engineers in one-building teams versus those on multi-building teams. The left panel focuses on engineers in the main building. The right panel focuses on engineers in the auxiliary building. The annotated coefficients compare the difference between engineers in one- and multi-building teams after the closure to the same difference before the closure as in Equation 1 with the full set of controls (as in Columns 6−8 of Table 2). The points come from a dynamic version of this regression. Ribbons reflect 95% confidence intervals. Standard errors are clustered by engineering team. *p<0.1; **p<0.05; ***p<0.01.

Figure A.10: Distribution of Program Writer and Commenter Ages



Notes: The grey histogram shows the density of ages of the software engineers who write programs, weighted by the number of programs that they write. The green distribution shows the ages of the engineers who write comments on code, again weighted by the number of programs they comment upon. The average age of a program writer is 29.8 and of a commenter is 31.2.

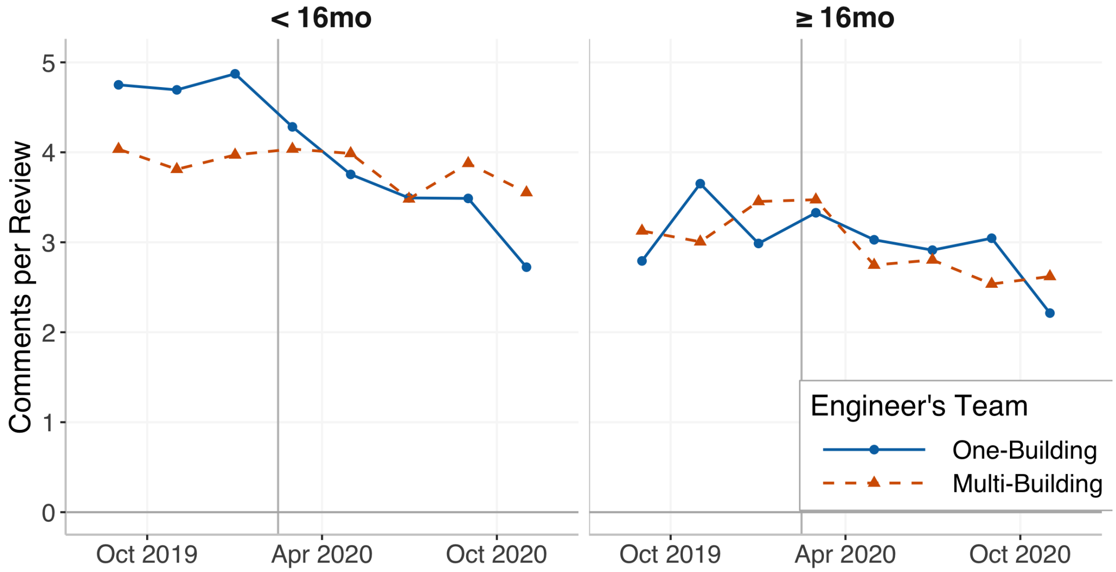
Figure A.11: Work from Home by Worker Age among College Grads



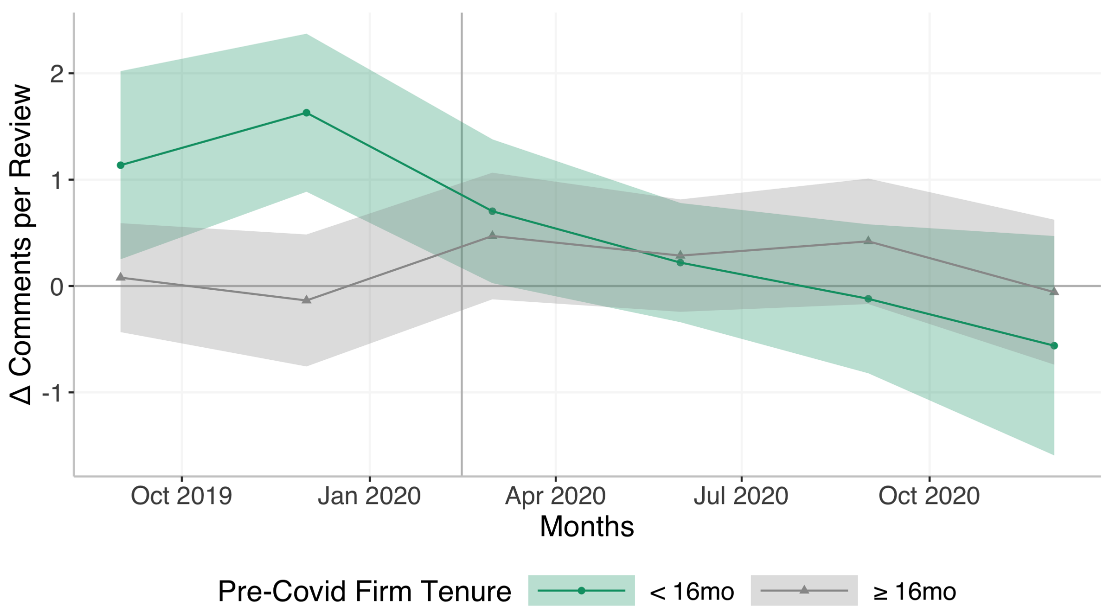
Notes: This figure plots the share of college-educated Americans working from home as a function of the respondent's age and the survey year. Data comes from the American Community Survey. Work-from-home status comes from the Census question about the mode of transportation to work, where one of the possible responses is work from home. Survey weights are used to reweight respondents.

Figure A.12: Externalities from Distant Teammates By Tenure

Panel (a): Raw Comments from Same-Building Teammates

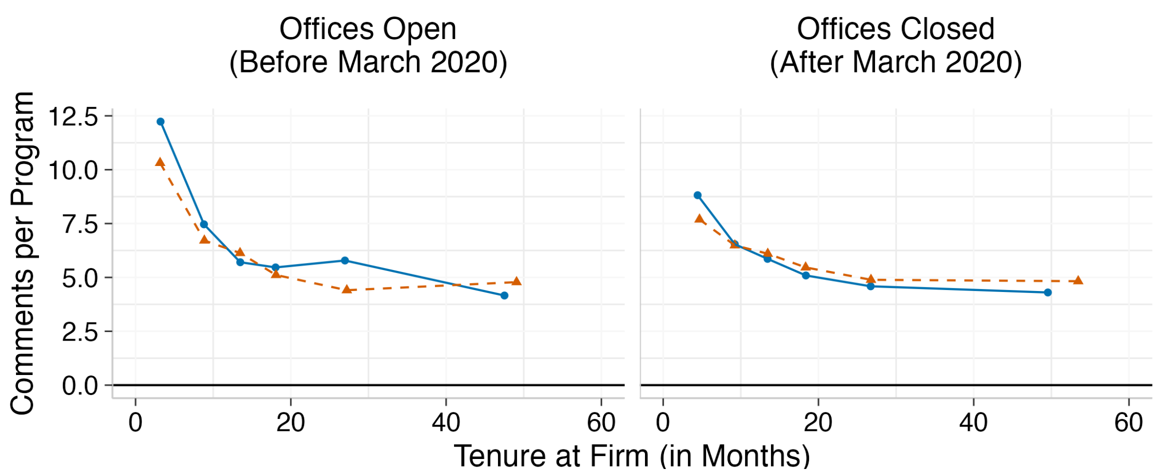


Panel (b): Dynamic, Conditional Differences in Same-Building Teammate Comments



Notes: This figure investigates the externalities from having a distant teammate on the feedback engineers with shorter and longer tenures receive from their same-building teammates. The top panel plots the bimonthly averages of comments received per peer-review from teammates in the same building. The left panel plots comments received by engineers with below-median tenure (under 16 months); the right plots comments received by those with above-median tenures. The bottom panel plots the differences conditional on team size, program scope, and engineer tenure. The ribbon reflects 95% confidence intervals with standard errors clustered by engineer. Only engineers whose teammates all worked in the main campus are included. The grey vertical lines mark the COVID-19 office closures.

Figure A.13: Feedback by Worker Tenure



Notes: This figure illustrates the path of feedback for engineers on one- and multi-building teams before and after the pandemic. Each plot shows the raw monthly averages of comments received per program for engineers on one-building and multi-building teams as a function of their tenure at the firm, separately for before and after the offices closed. Each point represents a sextile of tenure.

Table A.2: Proximity to Teammates and Online Feedback: Robustness to Sub-Organization Controls

	Comments per Program							
							Teammates Comments	Non-Teammate Comments (Placebo)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post x One-Building Team	-1.19^{**}	-1.04^{**}	-0.87^{*}	-1.03^{**}	-1.05^{**}	-1.01^{*}	-1.31^{***}	0.25
	(0.50)	(0.50)	(0.47)	(0.51)	(0.53)	(0.57)	(0.44)	(0.39)
One-Building Team	0.60	0.27	0.81^{*}	0.90^{*}				
	(0.52)	(0.55)	(0.46)	(0.49)				
Post								
	(0.00)							
Pre-Mean, One-Building Team	8.04	8.04	8.04	8.04	8.04	8.04	4.28	3.73
Percentage Effects								
Post x One-Building Team	-14.9%	-12.9%	-10.8%	-12.8%	-13.1%	-12.6%	-30.6%	6.64%
One-Building	7.5%	3.3%	10%	11.2%				
% One-Building Team	58.3	58.3	58.3	58.3	58.3	58.3	58.3	58.3
Sub-Organization x Post FE	✓	✓	✓	✓	✓	✓	✓	✓
Team Composition x Post FE		✓	✓	✓	✓	✓	✓	✓
Program Scope Quartics			✓	✓	✓	✓	✓	✓
Engineer Traits x Post FE				✓	✓	✓	✓	✓
Engineer FE					✓	✓	✓	✓
Main Building x Post FE						✓	✓	✓
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304	9,304	9,304
R^2	0.05	0.08	0.31	0.37	0.47	0.48	0.41	0.44

Notes: This table shows robustness of the results in Table 2 to the inclusion of controls for the engineer's sub-organization within engineering (e.g., front-end, website design versus back-end, database maintenance). The engineer's sub-organization is found using the management hierarchy and identifying the engineer's "grandparent" starting from the head of all of engineering at the firm. See the Table 2's note for specification details. Standard errors are clustered by engineering team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.3: Testing Robustness of Results to Local-Linear Time-Trends

	# Comments/Program					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x In One-Building Team	-1.29^{***}	-1.72^{**}	-1.35^{***}	-1.36^{**}	-1.17^{**}	-1.39^{**}
	(0.48)	(0.86)	(0.40)	(0.67)	(0.55)	(0.65)
One-Building Team	1.16^{**}	1.82^{**}	1.84^{***}	2.49^{***}		
	(0.52)	(0.93)	(0.39)	(0.63)		
Post	-1.22^{***}	-0.24				
	(0.36)	(0.63)				
Pre-Mean in One-Building Teams	8.04	8.04	8.04	8.04	8.04	8.04
Percentage Effects						
Post x One-Building Team	-16.06%	-21.35%	-16.81%	-16.95%	-14.54%	-17.24%
One-Building	14.46%	22.63%	22.87%	30.96%		
% One-Building Team	58.33	58.33	58.33	58.33	58.33	58.33
Local-Linear Time-Trends		✓		✓		✓
Team Composition x Post FE			✓	✓	✓	✓
Program Scope Quartics			✓	✓	✓	✓
Engineer Traits x Post FE					✓	✓
Engineer FE					✓	
Main Building x Post FE					✓	
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304
R^2	0.02	0.02	0.29	0.29	0.48	0.49

Notes: This table tests the robustness of the results in Table 2 to the inclusion of local-linear time-trends on each side of the office closures for engineers on one- and multi-building teams. The odd columns repeat the results from Table 2 for reference. The even columns include local-linear time-trends that allow comments on each program to evolve deferentially over time for engineers on one- and multi-building teams both before and after the offices closed for the pandemic. See Table 2's note for details on controls. Standard errors are clustered by engineering team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.4: Proximity's Impacts on Feedback by Program Writer and Commenter Gender

	Comments per Program		Commenters per Program	
	From Male	From Female	From Male	From Female
	(1)	(2)	(3)	(4)
Female x Post x One-Building Team	-1.78^{**}	-0.80^{**}	-0.23^{**}	-0.08
	(0.71)	(0.40)	(0.10)	(0.05)
Female x One-Building Team	2.11^{***}	1.00^{***}	0.19^{**}	0.12^{***}
	(0.70)	(0.34)	(0.09)	(0.03)
Male x Post x One-Building Team	-0.69^{*}	-0.50^{***}	-0.01	-0.07^{***}
	(0.39)	(0.19)	(0.04)	(0.02)
Male x One-Building Team	0.93^{**}	0.73^{***}	0.02	0.09^{***}
	(0.38)	(0.19)	(0.05)	(0.02)
Pre-Mean, One-Building Team for Male	6.09	1.58	1.09	0.24
Pre-Mean, One-Building Team for Female	7.68	1.88	1.24	0.27
# Engineer-Months	9,304	9,304	9,304	9,304

Notes: This table investigates the relationship between physical proximity and the online feedback engineers receive from coworkers, separately for male and female engineers according to the gender of the commenter. See Table 2's note for specification details. Standard errors are clustered by engineering team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.5: Proximity to Teammates and Online Feedback by Engineer Tenure at the Firm

	Comments per Program						Teammates Comments	Non-Teammate Comments (Placebo)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Junior (< 16mo) x Post x One-Building Team	-1.40^{**}	-1.72^{***}	-2.02^{***}	-1.79^{***}	-1.83^{***}	-1.78^{***}	-1.47^{***}	-0.37
	(0.65)	(0.62)	(0.54)	(0.58)	(0.55)	(0.59)	(0.46)	(0.43)
Junior (< 16mo) x One-Building Team	1.27^{*}	1.52^{**}	2.67^{***}	2.29^{***}				
	(0.68)	(0.62)	(0.53)	(0.57)				
Senior (≥ 16mo) x Post x One-Building Team	-0.41	-0.53	-0.30	-0.56	-0.44	0.59	-0.23	0.70^{*}
	(0.45)	(0.47)	(0.44)	(0.50)	(0.50)	(0.56)	(0.49)	(0.36)
Senior (≥ 16mo) x One-Building Team	0.13	0.26	0.56	0.51				
	(0.39)	(0.39)	(0.34)	(0.40)				
Junior Pre-Mean, One-Building Team	9.56	9.56	9.56	9.56	9.56	9.56	4.82	4.7
Senior Pre-Mean, One-Building Team	4.99	4.99	4.99	4.99	4.99	4.99	3.19	1.77
Percentage Effects								
Junior x Post x One-Building Team	-14.7%	-18%	-21.1%	-18.7%	-19.2%	-18.6%	-30.4%	-7.8%
Junior x One-Building Team	13.2%	15.9%	27.9%	23.9%				
Senior x Post x One-Building Team	-8.2%	-10.7%	-5.9%	-11.2%	-8.9%	11.9%	-7.2%	39.29%
Senior x One-Building Team	2.5%	5.3%	11.1%	10.3%				
Team Composition x Post FE		✓	✓	✓	✓	✓	✓	✓
Program Scope Quartics			✓	✓	✓	✓	✓	✓
Engineer Traits x Post FE				✓	✓	✓	✓	✓
Engineer FE					✓	✓	✓	✓
Main Building x Post FE						✓	✓	✓
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304	9,304	9,304
R^2	0.04	0.06	0.30	0.36	0.47	0.49	0.42	0.51

Notes: This table investigates the relationship between physical proximity and the online feedback engineers receive from coworkers, separately for junior and senior engineers. Junior engineers are defined as those with less than 16 months of experience at the firm before the office closures and senior engineers as those with at least 16 months at the firm (the average tenure). See Table 2's note for specification details. Standard errors are clustered by engineering team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.6: Proximity to Teammates and Programming Output by Engineer Tenure at the Firm

	Programs per Month			
	(1)	(2)	(3)	(4)
Junior (< 16mo) x Post x One-Building Team	0.36^{**}	0.32^{*}	0.36^{**}	0.24
	(0.16)	(0.17)	(0.16)	(0.16)
Junior (< 16mo) x One-Building Team	-0.31	-0.39^{*}	-0.58^{***}	
	(0.21)	(0.20)	(0.20)	
Senior ($\geq$ 16mo) x Post x One-Building Team	0.57^{***}	0.52^{***}	0.64^{***}	0.71^{***}
	(0.19)	(0.19)	(0.20)	(0.20)
Senior ($\geq$ 16mo) x One-Building Team	-0.66^{***}	-0.67^{***}	-0.82^{***}	
	(0.25)	(0.25)	(0.24)	
Junior Pre-Mean, One-Building Team	1.81	1.81	1.81	1.81
Senior Pre-Mean, One-Building Team	1.61	1.61	1.61	1.61
Percentage Effects				
Junior x Post x One-Building Team	19.9%	17.6%	19.7%	13%
Junior x One-Building Team	-17%	-21.7%	-32%	
Senior x Post x One-Building Team	35.7%	32.3%	39.9%	44.2%
Senior x One-Building Team	-41.1%	-41.5%	-51%	
Team Composition x Post FE		✓	✓	✓
Engineer Traits x Post FE			✓	✓
Engineer FE				✓
Main Building x Post FE				
# Engineers	1,055	1,055	1,055	1,055
# Months	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304
R^2	0.01	0.03	0.18	0.47

Notes: This table investigates the relationship between physical proximity and engineers' programming output, separately for junior and senior engineers. Junior engineers are defined as those with less than 16 months of experience at the firm before the office closures and senior engineers as those with at least 16 months at the firm (the average tenure). See Table 2's note for specification details. Standard errors are clustered by engineering team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.7: Proximity to Teammates and Promotions

	Promotion Rate		Has Been Promoted	
	(1)	(2)	(3)	(4)
One-Building Team x Tenure <16mo	-0.49^{**}	-0.64^{***}	-1.27^{**}	-1.56^{**}
	(0.20)	(0.23)	(0.63)	(0.71)
One-Building Team x Tenure ≥16mo	1.71^{***}	1.08^{*}	4.57^{**}	3.13
	(0.40)	(0.62)	(2.30)	(3.15)
Dependent Mean	2.91	2.91	13.23	13.23
Tenure <16mo	✓	✓	✓	✓
Team-Size x Tenure <16mo		✓		✓
Building x Tenure <16mo		✓		✓
# Engineers	1,055	1,055	1,055	1,055
# Months	17	17	17	17
# Engineer-Months	17,935	17,935	17,935	17,935
R^2	0.02	0.02	0.11	0.11

Notes: This table investigates the relationship between physical proximity and the timing and likelihood of promotion. Each observation is an engineer-month pair. The sample is limited to engineers whose teams are all in the firm's main campus and to promotions that occur before June 2020 and so are primarily based on pre-pandemic performance. In the first two columns, the dependent variable is one if the worker got promoted in the month. In the next two columns, the dependent variable reflects the cumulative stock of promotions so is one if we ever observe the worker getting promoted. The even columns control for the the engineer's building and the size of their team, both interacted with the engineer's tenure. Standard errors are clustered by engineering team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.8: Externalities from a Distant Teammate on an Engineer's On-the-Job Training from Proximate Teammates

	# Comments			
	All Per Program	From Proximate Teammates Per Review	All Per Program	From Proximate Teammates Per Review
	(1)	(2)	(3)	(4)
Post x On One-Building Team	-1.474^{***}	-0.622^{*}	-1.805^{***}	-0.858^{***}
	(0.411)	(0.344)	(0.420)	(0.298)
On One-Building Team	1.747^{***}	0.771^{**}		
	(0.383)	(0.322)		
Pre-Mean, One-Building Team	8.04	4.17	8.04	4.17
Percentage Effects				
Post x On One-Building Team	-18.33%	-14.91%	-22.44%	-20.58%
On One-Building Team	21.73%	18.48%		
Avg. on Multi-Building Teams				
# Teammate Commenters	1.71	1.71	1.71	1.71
% From Proximate Teammates	39.39	39.39	39.39	39.39
# Proximate Teammate Commenters	0.67	0.67	0.67	0.67
Back-of-the-envelope Calculations				
% Initial Gap Explained		29.66%		
% Differential Change Explained		28.36%		31.97%
Controls	Preferred	Preferred	All	All
# Engineers	1,055	934	1,055	934
# Engineer-Months	9,304	7,174	9,304	7,174
R^2	0.352	0.238	0.498	0.465

Notes: This table investigates whether having a teammate in a different building impacts the on-the-job training than an engineer receives from her proximate teammates. The odd columns consider all comments on each program. The even columns consider the average length of reviews from proximate teammates, conditional on them leaving reviews. The first two columns include the preferred controls. The next two columns include all controls. The back-of-the-envelope calculations consider how much feedback from proximate teammates can explain overall effects on comments in the preceding column, based on the share of comments that come from proximate teammates. Each column estimates Equation 1. Standard errors are clustered by engineer. *p<0.1; **p<0.05; ***p<0.01.

Table A.9: Difference-in-Differences Around New Hires in a Different Building From Teammates vs. Other Hires Before COVID-19

	Comments per Review from Same-Building Teammate		
Post Hire x One- to Multi-Building Team	-1.500^{*}	-1.696^{**}	-1.715^{**}
	(0.770)	(0.854)	(0.771)
Post Hire	0.004	-0.102	0.061
	(0.280)	(0.335)	(0.304)
Bandwidth = 6 weeks	✓	✓	✓
Pre-Period Mean for Treated	4.329	4.329	4.329
Engineer x Event FE	✓	✓	✓
Engineer x Commenter x Event FE		✓	✓
Program Content			✓
# Teams	126	126	126
# Treated Teams	16	16	16
# Engineers	400	400	400
# Treated Engineers	46	46	46
# Engineer-Commenter Pairs	1159	1159	1159
# Treated Engineer-Commenter Pairs	142	142	142
Observations	4,017	4,017	4,017
R^2	0.231	0.401	0.517

Notes: This table compares the change in comments per program in teams where a new hire converts the team from a one-building team to a multi-building team relative to teams where a new hire does not change whether they are a one- or a multi-building team. Each observation is the comments that a particular commenter left on a coder's program. The analysis compares the change in the length of the peer-reviews in the commenter-coder pair around the two types of new hires as in Equation 3. Standard errors are clustered by the commenter-coder pair. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.