The Power of Proximity

Office Interactions Affect Online Feedback and Quits, Especially for Women and Young Workers[1]

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Abstract

In an increasingly digital world, how much does sitting near coworkers matter for on-the-job training? And who is most affected by proximity? We study software engineers at a Fortune 500 firm. When offices were open, engineers working in the same building as all their teammates received 21 percent more online feedback on their computer code than engineers with distant teammates. After offices closed for COVID-19, this advantage shrank by 15 percentage points. Sitting near coworkers increases how much junior engineers can learn from their senior colleagues — not only in-person but also online. However, sitting together reduces senior engineers' programming output, suggesting a tradeoff between short-term productivity and long-run human-capital development. Proximity particularly increases feedback to female engineers from both male and female colleagues and reduces female engineers' quit-rates. 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

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Nearly two-thirds of workers' on-the-job learning and a sixth of their lifetime human capital comes from coworkers' feedback and guidance, much of which is now given online (Herkenhoff et al., 2018). How much do coworkers' interactions still depend on sitting together in the office? Do digital technologies help substitute for face-to-face interactions or are digital technologies complementary with in-person interaction — because, for example, workers are more likely to ask for and offer feedback face-to-face? Whether the office and digital communication complement one another will determine the role of physical space as an organizing force in the economy — in cities, tech hubs, and office buildings.

Firms and workers are divided about the office's value. Some firms like Netflix, Tesla, and Morgan Stanley see face-to-face interactions as essential, especially for on-the-job training. According to Morgan Stanley's CEO: "The office is where we teach, where our interns learn. That's how we develop people" (Kelly, 2021). Other firms like Deloitte, Dropbox, and Zillow are embracing remote work because they see the office as antiquated.[1]

The office may be more valuable for some workers than others. Younger workers may need office interactions more for on-the-job training. For women, leaving the office could level the playing field (Alon et al., 2022) or make it more challenging for them to enter the boys' club. If there are winners and losers from remote work, firms must ask how one worker's decisions will spillover into another worker's experiences – for example, how much will letting older workers stay at home impact the on-the-job training of younger cohorts? The answers to such questions—and firms' policy choices—will determine the intergenerational costs of remote work and its implications for workplace inequalities.

We study the impact of coworkers' physical proximity among software engineers at

[1]Even before the pandemic, Sir Richard Branson, the founder of Virgin Group, said, "In thirty years' time, as technology moves forward even further, people are going to look back and wonder why offices ever existed" (Hyken, 2020).

a Fortune 500 company — a seemingly ’best-case’ scenario for purely virtual interactions.[2] Software engineers produce purely digital output, have established online systems for giving one another required feedback, and meet routinely in real-time even when remote. Nonetheless, we find that online technologies do not substitute — but instead complement — in-person interactions. Physical proximity has an outsized effect on workers’ on-the-job training by facilitating not only in-person but also electronic guidance. Physical proximity is particularly integral to online feedback for young workers and women in this predominantly male field. The high cost of lost proximity is also borne out in these workers’ quit decisions: young workers and women are more likely to quit the firm when they lose proximity to coworkers. Finally, distance has spillovers for those who stay in the office; gaining one distant teammate reduces online feedback among coworkers sitting together.

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 check code’s functionality, efficiency, and clarity before it is deployed in a website or database. When engineers implement the requested changes, they not only improve the current program but also learn templates for writing better code in the future. Commenters often give such templates explicitly, 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 id-

[2]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).

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

iosyncrasies 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 could bump into their coworkers in the halls and during daily in-person meetings. Once a single engineer was in another building, this dynamic often changed: as one engineer noted, "[my team] would almost never book a room 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 received 21 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 commenting is causal: if causal, then we would expect the gap to shrink once the buildings closed. Empirically, we find that the gap shrank by 70 percent (15 percentage points, p-value = 0.0005) after the buildings shut down. We find similar effects when estimating the difference-in-differences in the total length of peer-reviews, the share of reviews with explicitly instructive comments, the delay until the first comment is received, and mentions of other online conversations (e.g., on Slack, Zoom, or email).

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 broadly similar baseline characteristics regardless of their proximity to their teammates. Engineers on multi-building teams tend to be on bigger teams (since many teammates are less likely to all find desks in one building), have slightly longer tenures, and write longer programs. Our results are robust to controlling for these differences and allowing differential effects of the pandemic for engineers with different observable characteristics. When testing pre-trends in feedback, we do not detect differential trends for engineers on one- and multi-building teams. Nor do we find that other measures of productivity (e.g., program length) change differentially across team types around the pandemic. 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 similar results when examining complementary forms of identification that consider other dimensions of engineers' proximity to their coworkers. Before the pandemic, engineers who sat in the firm's main building were proximate to 71 percent of the engineers on the campus and, thus, could have face-to-face contact with more engineers outside their teams. The main building also had a large cafeteria where engineers could eat lunch and talk casually. Pre-pandemic, engineers in the main building received 26 percent more feedback on their programs than engineers in the auxiliary building (p-value < 0.0001). This advantage declined by 17 percentage points once the buildings closed (p-value < 0.0001).[4]

We also consider engineers whose teammates work in a different city, either at home or in a satellite campus.[5] When the offices were open, engineers whose teammates were spread across cities received 17 percent less feedback 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.

[4]For engineers in either building, the location of their teammates affects their teammate feedback: in both the main building and the auxiliary one, engineers whose teammates were all in the same building receive more comments from teammates.

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

Distant teammates impose negative externalities on the rest of the team. Prior to COVID-19, having a teammate in a different building spilled over into the reviews 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.[6] 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 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.

Proximity to coworkers matters much more for younger workers who have more to learn on the job. Pre-pandemic, engineers who were under 30 (the firm's average age is 29) received 16 percent more comments per program than older engineers. This entire intergenerational gap in feedback hinged on proximity. When the offices were open, young engineers only received more feedback when in the same building as all their teammates. Once the offices closed, younger engineers no longer received more feedback than their older colleagues on either type of team.[7]

We also consider the gendered effects of close proximity. Does proximity perpetuate the boys' club of coders? Or does sitting near teammates help female engineers break into the club? We find that proximity matters more for female engineers' 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 (p-value < 0.0001). For male engineers, this advantage was less than half as large at 16 percent (p-value $= 0.0004$).

[6] 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.

[7] Engineers who are both young and have limited experience at the firm were most impacted, suggesting that proximity's effects were particularly concentrated among those with the most to learn.

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 (p-value = 0.030). Text analysis on the comments suggests that comments on one-building teams tend to provide more concrete feedback to their engineers than multi-building teams, a trend that shows up with comments to female engineers as well.

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 across those on one- and multi-building teams. Workers' revealed preferences show online communication cannot substitute for in-person interaction, particularly for younger workers and female engineers.

Our study provides evidence that online technologies do not substitute for but instead are complemented by face-to-face interactions between coworkers, especially for workers on the margins of the firm — young workers early in their career and women in the minority in software engineering. We contribute to the growing literature on how coworkers learn from one another: we directly observe coworkers' online feedback and then identify how these online interactions are complemented by physical proximity. This work contributes to the long-standing debate about whether digital technologies will render physical proximity irrelevant: we show that proximity matters within the bounds of the firm. We finally contribute to the literature about the pros and cons of remote work, by assessing how physical distance impacts workers' on-the-job training from their coworkers. We find that distant coworkers give each other less feedback online, suggesting that remote work will have long-run costs even in an occupation seemingly well-suited to remote work. The particularly negative consequences for women calls into question the hypothesis that an increasing prevalence of remote work will close the gender gap (Alon et al., 2022).

The rest of the paper is organized as follows. Section I situates our paper in the broader literature, while 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 interactions. Section V turns to the intergenerational consequences of proximity. Section VI investigates proximity's consequences for the minority of female engineers. Section VII considers the downstream implications for quits, particularly for younger workers and female engineers. Section VIII opens up the black box of proximity by evaluating the externalities from having a single teammate located elsewhere. Section IX 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).[8] More generally, working in a firm with cowork-

[8]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 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 contempora-

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.[9]

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).[10] Relatedly, Chen et al. (2022) show that when research teams become distributed across universities, the likelihood of pro-

neous peer effects on output depend on having a context where output is observable and the task is relatively routine.

[9]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.

[10]Similarly, funders of new creative pursuits on an online crowdsourcing platform disproportionately live close to the funded artists (Agrawal et al., 2015).

ducing 'disruptive' research falls.[11] 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.

Our paper also contributes to the remote-work literature by documenting the adverse effects of distance on on-the-job training, which can help explain the puzzling dearth of remote work before the pandemic. We extend the existing evidence that remote work reduces the breadth, depth, and creativity of coworkers' communication (Battiston et al., 2021; Yang et al., 2022; Brucks and Levav, 2022) and has negative spillovers for the well-being of workers who stay in the office (Linos, 2018).[12] Negative peer spillovers may help explain the relative rarity of remote work despite workers' high willingness to pay to work remotely (Mas and Pallais, 2017; Maestas et al., 2018; Mas and Pallais, Forthcoming; He et al., 2021) and its seemingly positive productivity effects for fairly autonomous tasks (Bloom et al., 2015; Choudhury et al., 2020). Our setting of computer programming is an especially relevant one to

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

[12] 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. DeFilippis et al. (2020) similarly leverage email and meeting meta-data and find that the COVID-19 closures were associated with a decline in long meetings with few participants, suggesting remote work reduced the depth of communication. Similarly, Battiston et al. (2021) investigates the depth of communication, using a natural experiment among 911 operators. 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.

Brucks and Levav (2022) study the creativity of in-person versus virtual communication and find that pairs of experimental participants come up with fewer and less unusual ideas when communicating on video chats rather than in-person discussions. They hypothesize that the narrower field of vision necessitated by video conferencing leads to a narrower frame of thinking, limiting out-of-the-box creativity.

Linos (2018) finds that the US Patent Office's roll-out of remote work increased absenteeism among coworkers who stayed in the office.

consider since this job is seen as highly remotable. Yet on-the-job training may be especially crucial for knowledge work like this.[13]

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.[14] 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).[15]

Engineers at the firm are predominantly male (81 percent) and highly paid ($56/hour on average), which is representative of engineers nationally (75 percent are male with an average wage of $47.40/hour).[16] Engineers at the firm tend to be 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 trajec-

[13] An adverse effect on on-the-job training may help explain the aggregate reduction in productivity among similar IT professionals around the office closures of COVID-19 studied by Gibbs et al. (2021).

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

[15] 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.

[16] 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 Analysts, 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.

tory). 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). Software engineers accounted for 8 percent of all those working remotely in 2020 (and 11 percent of all labor income accruing to remote workers).

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.[17] 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.

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.[18]

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 program-

[17] We do not have data on auxiliary code bases that, for example, produce tools for the firm's sales force.

[18] 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.

ming 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.

The text of the comments reveals that 43 percent of peer-reviews aim to make code more reliable (e.g., by adding tests).[19] A third of reviews aim to make code more readable, by, for example, organizing functions around specific aims and choosing variable names that are fitting and unambiguous. Only 16 percent of comments about readability catch typos or fix syntax (e.g., eliminate an extra white space).

Tips for writing better code are often transportable from one program to the next. Reviewers sometimes flag such generalizability by saying that their advice applies in "general" or is good "practice." Reviewers also often point to a similar "example" in the code-base that illustrates the general argument. We classify a comment as being explicitly oriented towards building the engineer's general skills if it has one of these three keywords: general, practice, or example.[20] On average, 11.8 percent of reviews have an instructive comment, with much higher rates of instructive comments for engineers who are being onboarded into the firm (Figure A.3). Reviewers took the time to illustrate their suggestions with blocks of code for 10.4 percent of programs.

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 com-

[19] The reliability of the code is more of a priority than its speed at this firm: only 3 percent of reviews discuss something explicitly related to the program's speed (e.g., pointing out that loops are slow in a given programming language).

[20] We also include the acronym "e.g." Our results are robust to other ways of categorizing instructional comments.

ments 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 his 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}.
> Coder at 4:18pm: [I added a] document in description: {link}.

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.4).[21]

Requesting Feedback. Engineers are responsible for asking coworkers to review their code. While engineers can request feedback in the code-review system, they

[21] Our results are comparable when only considering interactions that occur during standard business hours (Figure A.7).

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 half of engineers' feedback comes from teammates and the other half from non-teammates.[22]

Engineers often ask teammates for feedback before or after daily team meetings. Teams meet frequently with daily ten- to 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 practice in the industry.[23] 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).

While there are no tangible rewards for peer reviews (e.g., quotas or bonuses), there are soft incentives for engineers to give each other feedback. Programmers face social and managerial pressure to offer feedback when asked.[24] Further, engineers may feel intrinsic motivation to help out their colleagues. Face-to-face contact in the office may reinforce social incentives, by making coworkers' interactions more observable to peers and managers. Proximity may also reinforce instrinsic incentives,

[22]For example, one commenter might help ensure that the code calls an existing method in the firm's codebase rather than rewriting the same functionality, while another might point out certain features of the programming language itself that could streamline the code.

[23]At the firm, engineers' work is organized around two-week sprints (in what's called an Agile workflow in the industry). At the beginning of a sprint, the team meets to plan what work will get done. Daily "scrum" meetings give engineers opportunities to discuss their progress and what others could do to help, including offering feedback on code. Each sprint features a backlog meeting to review outstanding tasks and a retrospective to review what went well and what could be improved. There are also regular meetings to discuss the products being built, key performance indicators, and broad objectives.

[24]Managers may consider a worker's perceived helpfulness when considering promotion. Yet some engineers at the firm have told us that helpfulness is given too little weight.

by making coworkers' needs seem personal rather than anonymous. In-person interactions may also give commenters better information about what feedback that program writers need.

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 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.[25]

Proximity to Teammates. 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 costs. 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

[25]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 IV.A. We also repeat the main analyses including all engineers, regardless of their location or the level of their manager in Appendix I.C.

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.

Proximity to Other Engineers. Some engineers sit in the firm's main engineering building alongside 71 percent of the main campus engineers, while others sit in the auxiliary building. In addition to being near a broader set of engineers, the main building has a large cafeteria that doubles as a work cafe, where engineers can interact with others outside their team.

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 until a bit later. 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 the impact of coworkers' physical proximity on their electronic interactions, we compare online comments received by 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 might be due to 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 whether the greater loss of proximity for engineers on one-building teams translates into a greater decrease (or increase) in these engineers' online feedback, which would suggest that online interactions and face-to-face ones are complements (or substitutes).

Specifically, we estimate the following equation:

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

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 (Goodman-Bacon, 2021, e.g.).

We complement this design by comparing engineers in the firm's main and auxiliary buildings who have different proximity to engineers beyond their own team:

$$\begin{aligned}\text{\# Online Comments/Program}_{i,t} =& \gamma\text{Post}_t \cdot \text{Main Building}_i + \theta\text{Post}_t + \\ & \phi\text{Main Building}_i + X'_{i,t}\phi + u_{i,t}. \end{aligned} \tag{2}$$

We finally consider specifications that include both sources of variation in face-to-face interactions. With some abuse of notation:

$$\begin{aligned}\text{\# Comments/Program}_{i,t} = &\beta\text{Post}_t \cdot \text{One-Building Team}_i + \psi\text{One-Building Team}_i + \\ &\gamma\text{Post}_t \cdot \text{Main Building}_i + \phi\text{Main Building}_i + \\ &\sigma\text{Post}_t + X'_{i,t}\rho + v_{i,t}. \end{aligned} \tag{3}$$

These designs identify the causal effect of proximity on online feedback, assuming proximity to other engineers in the office was not related to engineers' idiosyncratic pandemic shocks. Particularly, Equation 1 relies on the parallel-trends assumption that engineers who were initially proximate to all of their teammates faced similar pandemic shocks as those who were distant from some teammates. Similarly, Equation 2 relies on the parallel-trends assumption that engineers who were initially in the main building faced similar pandemic shocks as those who were initially in the auxiliary building.

We probe the robustness of parallel-trends assumptions in a few ways. First, we test for imbalances in baseline characteristics and assess the robustness of our results 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 with different proximity to coworkers.

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. Table A.1 presents the same comparisons for engineers in the firm's main and auxiliary buildings.

Mechanically, engineers on smaller teams were more likely to all find desks in one building (row two). It was also easier to find desks for the whole team in the larger main building (row three). Engineers on one- and multi-building teams generally had similar demographics (rows four through six). Engineers in multi-building teams tended to have slightly longer tenures at the firm (an additional 4.1 months, row seven), higher job levels (row eight), and greater pay (an additional $2/hour in row nine). These differences, however, remain approximately constant before and after the building closures. The baseline differences can also be accounted for by engineers' buildings: when comparing engineers who are both in the main building (or both in the auxiliary one), engineers on one-building teams do not have significantly longer tenures, higher job level, or higher pay (Table A.2).

Engineers on multi-building teams tend to write longer programs (row ten) that touch more files (row eleven), both before and after the pandemic.[26] As detailed below, our preferred specification flexibly controls for program scope.

III.B Controls

Preferred controls: We include indicators for the number of teammates on the engineer's team, which mechanically tends to be lower on teams that are all in one building. We also include indicators for the number of months that the engineer has been at the firm. Finally, we control for the scope of the engineer's programs — quartics in the number of files changed, the number of lines added and the number of lines deleted — all of which might mediate the feedback that she receives. We allow all of these dimensions to have time-varying effects before versus after the COVID-19 office closures.

Full set of controls: Our full set of controls also includes age-by-gender fixed effects, the engineer's home zipcode, the engineer's job-level, and her engineering group. We allow all these coefficients to differ before and after the COVID-19 closures, allowing different types of engineers to face different pandemic shocks.

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

Engineer fixed effects: To handle any changes in the composition of engineers who submit programs to the main code-base, we include engineer fixed effects as an additional robustness check.

III.C Placebo Checks

Two Placebo Checks Using the Sources of Engineers' Feedback. First, being on a one-building team does not affect comments from non-teammates. Second, being in the main building does not affect teammate comments. These findings make us more confident that proximity to potential commenters is not related to the latent quality of engineers' code, which would affect feedback from all coworkers, not just proximate ones.

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.5).

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).[27] Indeed, in the months leading up to the office closures, peer commenting did not systematically change for either group of engineers.[28] 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).

[27] 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.

[28] 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.

IV Physical Proximity's Impact on Coworkers' Online Interactions

We find online interactions are complementary with face-to-face ones, both for teammates and non-teammates.

IV.A Proximity to Teammates

Engineers in the same building as all their teammates received more feedback than other engineers when the offices were open but not once they were closed. Figure 1(a) shows this, plotting the number of comments per program received by month without controls. Initially, there is a sizeable gap between one- and multi-building teams, which closes immediately when the offices close.[29]

Figure 1(b) illustrates the conditional differences between one- and multi-building engineers, including our preferred, time-varying controls for program scope, engineers' firm tenure, and team size (since smaller teams are mechanically more likely to be in one building). The figure shows the same pattern. Engineers on one-building teams received 1.5 additional comments, or 19.2 percent more feedback per program (p-value < 0.0001) than engineers on multi-building teams in the office. This gap narrowed to only 0.52 additional comments or 6.6 percent after the office closure. Our difference-in-differences estimate indicates that losing physical proximity decreased comments per program by 0.98 comments or 12.5 percentage points for engineers on one-building teams vs. multi-building teams (p-value $=$ 0.0018) (Column four of Table 2).

Table 2 shows the results are robust to including a variety of controls, a stability which is marked given the increase in the R^2 from 1.4 percent to 49.5 percent. Our results are also robust to including local-linear time-trends for engineers on one-

[29]When engineers were sent home, comments declined for both types of teams, which is consistent with a loss in proximity for all engineers. But this could arise from other disruptions from the pandemic, which necessitates our difference-in-differences design.

and multi-building teams on either side of the office closures (Table A.3). Moreover, we include a placebo check considering the treatment effects that would arise had the office closure occurred in another month. Our preferred specification finds no significant effect in a 2-month bandwidth for any month but the treated ones (Figure A.5). Finally, we test the parallel trends assumption by seeing whether the difference in the one- and multi-building teams' slopes changes from month to month, using a Wald test. We are unable to reject that the slope is the same throughout the entire period before the close of the offices (p-value = 0.63 in our preferred specification).

These differences are purely driven by comments given during standard work hours (8AM - 6PM, Monday through Friday), when coworkers on one-building teams would have been proximate to one another before the offices closed but not afterwards (Figure A.7).

We also find similar effects when we consider other ways of measuring online feedback and guidance: the total length of comments, whether a peer review has an explicitly instructive comment, whether the peer review includes a code block to illustrate a suggested change, and the delay to the first comment (Table 3 and Figure A.8). 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 five of Table 3 and Figure A.10).

Unsurprisingly, engineers on one-building teams received more feedback from teammates but not from engineers outside their teams. Engineers on one-building teams received 22 percent (0.83 comments) more *teammate* feedback before the pandemic even conditional on whether they sat in the main building — a difference that almost entirely disappears once the buildings closed (Figure 4(a) and columns (1) and (2) of Table 4).[30] Being on a one-building team does not affect feedback from non-teammates (Figure 4(a) and columns (3) and (4) of Table 4). The null effect for non-teammate comments is inconsistent with the alternative explanation that engineers on one-building teams need more feedback on their programs before the offices closed but not afterwards. Such a change in the need for feedback would impact reviews from both teammates and non-teammates.

We can also look directly at comments that mention problems with the code. We do not find evidence of differential changes in comments that mention 'bugs,' ask engineers to 'revert' problematic changes, or flag inputs that 'break' the logic around the office closures across engineers on one-building vs. multi-building teams (Figure A.12).

While the offices remain closed, engineers on one-building teams never regain the advantages conferred by physical proximity. Figure A.6 shows the results are similar across different post-period windows. The persistence suggests it is hard to substitute for face-to-face interactions and that our effects are not a fleeting byproduct of transitioning new technologies for engineers accustomed to in-person interactions with their teammates.[31]

While we focus on teams entirely in the firm's main campus, the results are markedly similar when we consider engineers whose teammates worked remotely or in an satellite campus, after accounting for observable differences in these engineers' char-

[30]This gap in teammate feedback was similar in the main and auxiliary buildings (Figure A.11 and Table A.4). When the offices were open, engineers in the main building received 20 percent more teammate feedback if all of their teammates were also in the main building (p-value = 0.037), while engineers in the auxiliary building received 30 percent more teammate feedback if all of their teammates were also in the auxiliary building (p-value = 0.047).

[31]When the offices closed, engineers on multi-building teams might have been more comfortable with Zoom and other ways of meeting with their team online. Yet such a difference would likely have a transitory effect not a persistent one. Further, our analysis of proximity to *non-teammates* in Section IV.B is less sensitive to this threat since engineers do not have daily meetings — either in-person or over Zoom — with engineers outside their team.

acteristics.[32] As illustrated in Figure 2(a), engineers whose teammates worked many miles away received the fewest comments on their programs before the pandemic but these differences closed with the buildings. After including our full set of controls in Figure 2(b), engineers on one-building teams received 14 percent more feedback (1.1 comments) than engineers with teammates in other cities before the pandemic and no more feedback afterwards. These gaps are similar to those using engineers whose teammates are just a few blocks away, suggesting that it may not matter much whether teammates are a few blocks or many miles away.

IV.B Proximity to Non-teammates

We next compare engineers in the main building to engineers in the auxiliary building. Before the offices closed, engineers in the main building were near 71 percent of the main campus's engineers and had more space for face-to-face interaction during lunch-time or coffee breaks. Pre-pandemic, main-building engineers received discretely more feedback. This gap narrowed considerably once the offices closed. Figure 3(a) shows the number of comments received by engineers in each building, without controls. Figure 3(b) shows the pattern is the same after including our preferred, time-varying controls for program scope, engineer tenure, and team size. Pre-pandemic, engineers in the main building averaged 2.0 additional comments per program or 24.5 percent more feedback. Once the offices closed, this gap declined by 1.3 comments per program or 15.5 percentage points (p-value < 0.0001). Adding our full set of time-varying controls for engineer characteristics and engineer fixed effects (in columns (5) and (6) of Table A.6) do not significantly change the difference-in-differences estimates, which are 19.8 and 21.5 percent, respectively.

We find similar effects when we consider other ways of measuring online feedback: the total length of all comments, whether a review has an explicitly instructive comment, whether the review includes a code block to illustrate a suggested change, and

[32]Working remotely or in a satellite campus is not random and so these engineers have different characteristics.

the delays until the first comment (Table A.7 and Figure A.13). We also find mentions of other forms of online communication — on Slack, Zoom, or email — decline more precipitously around the office closures for engineers in the main building than the auxiliary one (Figure A.15).

The feedback gap stems from non-teammates. Pre-pandemic, main-building engineers received 35.2 percent more feedback from *non-teammates*, a gap which is halved when the offices closed (Figure 4(b) and columns (3) and (4) of Table 4). Unsurprisingly, before the pandemic, main-building engineers received more feedback from non-teammates who were also in the main building and this feedback declined around the office closures (Figure A.16). By contrast, feedback from *teammates* is not related to whether or not the engineer sits in the main or auxiliary building (Figure 4(b) and columns (1) and (2) of Table 4).[33]

Our results indicate that the opportunity for face-to-face interaction is complementary with receiving more online feedback from both teammates and non-teammates. Thus, physical proximity likely has an out-sized effect on how much workers can learn from their coworkers — by facilitating not only in-person advice but also online feedback and guidance.

IV.C Conversations Between Coders and Commenters

Engineers on one-building teams receive more initial feedback from commenters and have richer digital conversations about their code.[34] When the offices were

[33] This null result suggests that main building engineers did not just receive more comments because they needed additional feedback. Consistent with this interpretation, we do not find differential changes in mentions of coding bugs or reversions for engineers in the main vs. auxiliary buildings (Figure A.17).

[34] 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 **??**), with the rest attributable to receiving feedback from more people (Table A.9). Similarly, we find that engineers who sit in the main building (as opposed to the auxiliary one) primarily receive more feedback per commenter along the intensive margin (Table **??**).

open, engineers on one-building teams received 20 percent more initial feedback, a gap which narrows when the offices close (Column (2) of Table 5). In response to initial feedback, engineers on one-building teams also replied 22 percent more and asked 25 percent more follow-up questions when the offices were open but not once they were closed (Columns (4) and (5)). In response to these questions, commenters 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 (2) of Table 5). 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.[35]

V INTERGENERATIONAL CONSEQUENCES

Younger workers who are earlier in their careers and recent hires who are less experienced in their firms are often the beneficiaries of on-the-job training. Pre-pandemic, engineers 29 and under (the firm's mean age) received 19 percent more comments per program than older engineers (p-value < 0.0001).[36] Likewise, engineers who had been at the firm for less than 16 months prior to the closures (the mean tenure) tended to receive 56 percent more comments per program than more tenured engineers prior to the office closures.[37]

Younger workers benefit more from proximity to teammates. In fact, the entire pre-

[35]Engineers in the main building also received more initial comments on their programs and richer subsequent conversations, advantages which decrease when offices close (Table A.10).

[36]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.18).

[37]We observe similar differences in other measures of feedback. Young engineers were 25 percent more likely to receive an explicitly instructive review, were marginally more likely to receive a review with an illustrative code block, and tended to receive their first comment an hour earlier (7 percent faster). Less experienced engineers were 78 percent more likely to receive an explicitly instructive review, were 48 percent more likely to receive a review with an illustrative code block, and tended to receive their first comment three hours faster (20 percent faster).

pandemic gap between online feedback received by younger and older engineers stems from one-building teams (Figure 5(a)). On multi-building teams, younger and older workers received the same amount of feedback both before and after the offices closed. Young workers on one-building teams received much more feedback than their older coworkers when working in person, but not when working remotely.

Face-to-face interactions appear to be most complementary with online interactions for young engineers who are new to the firm. Looking separately by age quintile shows the effect is driven by the youngest engineers – in their early- to mid-20s — who are relatively new to the firm (Figure 5(b)). We see similar patterns for instructive reviews (Figure A.21), illustrative blocks of code (Figure A.23, though this effect is insignificant), and delays until the first comment (Figure A.22). These patterns are consistent with face-to-face interactions mattering most for those who have the most to learn on-the-job because they have had less time to build up their general and firm-specific human capital.

Sitting in the main building also disproportionately increased the feedback received by younger engineers and those earlier in their tenure at the firm. The differences by age are smaller while the differences by tenure are more pronounced (Figure A.24). These patterns suggest that a broader network of weak ties may benefit engineers regardless of age but be especially useful for engineers getting their foothold in the company. By contrast, stronger bonds with teammates may specifically reap dividends for younger engineers.

VI Gendered Consequences

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).[38] Ex-ante it is unclear whether female engineers would benefit more or less from physical proximity. It is possible that proximity to coworkers is particularly helpful so that women do not get overlooked in this male-dominated profession. Yet it is also possible that proximity is less helpful for women since they may be excluded from the boys' club of engineer even if they are sitting nearby.

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 6(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.[39] 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 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 = 0.030). We see similar patterns for illustrative blocks of code (Figure A.27). There are no significant gendered changes in instructive reviews (Figure A.25) or delays until the first comment (Figure A.26).

The complementarity between proximity and online feedback is particularly potent for female engineers with less tenure at the firm (Figure 6(b)). This finding is consistent with women more rapidly entering the boys' network of engineers when teammates all interact face-to-face.

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

[39]Female engineers on multi-building teams received 16 percent *less* feedback relative to 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.

While female engineers tend to be younger and have less tenure at the firm than the typical male engineer, the gender differences in feedback are not driven by underlying differences in age and experience. Indeed, age, experience and gender are independently meaningful (Table 6). After controlling for the effects of age and experience, female engineers who had been working alongside all their teammates still experience a 21 percent reduction in online feedback when offices close.

Similarly, when considering engineers who work in the main building, physical proximity is particularly potent for female engineers. Female engineers in the main building received more feedback (p-value = 0.0125) than those in auxiliary buildings. This gap was present but less extreme for male engineers. When offices closed, both gaps disappeared (Figure A.28(a)). This effect is also concentrated among engineers who have a shorter tenure at the firm, with no statistical significance in the difference-in-differences estimate for more senior engineers (Figure A.28(b)).

We use text analysis of comments to further understand the nature of the comments. We use a logistic lasso to predict whether the comments were between teammates all in the same building as one another or teammates spread over multiple buildings (Figure 8(a)). We find that comments between teammates on one-building teams contain more concrete feedback (e.g., "need", "can", "should", "nit", which is language for a very detailed note) and change requests ("please"). Multi-building teams are more likely to green-light code ("good", "comment", "lgtm", which means "looks good to me").

We also predict whether the engineers who wrote the code is male or female in Panel (b) of Figure 8. Consistent with female engineers in one-building teams receiving more feedback, we find that female engineers are likely to receive comments about the content of their code (e.g., "model", "return", "array", "error") while male engineers are more likely to be deferred to ("lgtm", "maybe", "we", "nitpick"). Of the words that predict a comment going to a female engineer, 28 percent also predict a comment going to an engineer on a one-building team compared to only 22 percent of the words that predict a comment going to a male engineer.

VII QUITS

Throughout, we have seen that electronic communication does not substitute for in-person interactions. We see the same thing when we look at a measure of employees' revealed preference: quitting the firm.

In person, quit rates are low and insignificantly larger for engineers on multi-building teams.[40] After the offices closed, quit rates rose for all engineers, but they increased much more for engineers on one-building teams who lost proximity to their teammates (from 0.34 to 1.75 percent per month) than engineers on multi-building teams (from 0.5 to 1.0 percent per month).

Quits were concentrated among those engineers for whom the loss of proximity most impacted the on-the-job training they received: the increase in quits was concentrated among younger workers and among female workers. Younger engineers who had been in one-building teams were much more likely to quit than those in multi-building teams (Figure 7(a)). The difference-in-differences estimate indicates that losing teammate proximity increases quit rates among young engineers by 0.93 percentage points (p-value = 0.017, Column one of Table 7). 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 after the pandemic. Table 7 shows that these results are robust to adding time-varying engineer controls (Column two) and are driven by departures where the engineer reports quitting for a better job in the exit interview (Columns three and four).

Likewise, female engineers who lost proximity to teammates were more likely to

[40] 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. Older engineers quit even less often: 0.2 percent quit per month.

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. Difference-in-differences estimate indicates that losing teammate proximity increases quit rates among female engineers by 2.1 percentage points (p-value = 0.0056, Column one of Table 8) but had a more limited impact on male engineers' quits 0.20 percentage points (p-value = 0.31). The triple difference indicates that losing proximity increased the quit rates of female engineers by 1.8 percentage points more than that of male engineers (p-value = 0.021). As with age, these results are robust to include time-varying engineer controls in Column two of Table 8 and are driven by quits for better jobs (Columns three and four).

VIII Externalities from Distant Teammates

Distant coworkers have negative externalities on their teammates' interactions. A teammate located elsewhere decreases on-the-job training among proximate teammates, likely because teams spread across buildings substitute online for in-person meetings.

We measure the externalities from a distant teammate in two ways. First, we compare the interactions of same-building teammates on one- and multi-building teams (Figure 9). Before the office closures, engineers with distant teammates received 18 percent shorter peer reviews (with 0.76 fewer comments) from their same-building teammates than 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.11). These externalities are concentrated among engineers who are new to the firm (see Figure A.29). 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.[41] 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.11).

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

$$\begin{aligned}\text{\# Comments/Program}_{i,j,t} =& \gamma \text{Post Hire}_t \cdot \text{One- to Multi-building Team}_i + \\ &+ \sigma \text{Post Hire}_t + \mu_{i,j} + v_{i,j,t} \qquad (4)\end{aligned}$$

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 10(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 to other teams with a new hire (p-value=0.05), with similar estimates controlling for

[41] 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.

program scope (Table A.12). 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.[42]

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.

IX Conclusion

Face-to-face interactions increase the feedback and guidance coworkers give each other online. Digital technologies and in-person interactions are complements: online tools cannot fully substitute for face-to-face interactions. This is true even in an occupation where workers are very comfortable with digital technology and remote work was relatively common even before the pandemic and in a setting where coworkers already know each other, meet routinely online even when remote, and have managers overseeing their interactions.

One worker's choice to work remotely impacts her peers. Older workers not coming back to the office may depress younger workers' skill accumulation. This may be particularly important as young workers learn the most on the job, benefit the most from proximity, and are much more likely to quit when proximity is lost. Moreover, having even one remote worker on a team depresses interactions 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

[42]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).

fully in-person meetings. This raises the question of whether a few days in the office are enough to spur online interactions. Similarly, given that one remote teammate has an outsized impact on team interactions, 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. If will be interesting to see whether as workers return to the office, we see segregation of in-person and remote workers across firms.

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.

References

Agrawal, Ajay and Avi Goldfarb, "Restructuring Research: Communication Costs and the Democratization of University Innovation," *American Economic Review*, 2008, *98* (4), 1578–90.

—, **Christian Catalini, and Avi Goldfarb**, "Crowdfunding: Geography, Social Networks, and the Timing of Investment Decisions," *Journal of Economics & Management Strategy*, 2015, *24* (2), 253–274.

Akcigit, Ufuk, Santiago Caicedo, Ernest Miguelez, Stefanie Stantcheva, and Valerio Sterzi, "Dancing with the stars: Innovation through interactions," Technical Report, National Bureau of Economic Research 2018.

Alon, Titan, Sena Coskun, Matthias Doepke, David Koll, and Michèle Tertilt, "From Mancession to Shecession: Women's Employment in Regular and Pandemic Recessions," *NBER Macroeconomics Annual*, 2022, *36* (1), 83–151.

Atkin, David, Keith Chen, and Anton Popov, "The Returns to Face-to-face Interactions: Knowledge Spillovers in Silicon Valley," 2019.

Azoulay, Pierre, Joshua S Graff Zivin, and Jialan Wang, "Superstar Extinction," *The Quarterly Journal of Economics*, 2010, *125* (2), 549–589.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul, "Social Incentives in the Workplace," *The Review of Economic Studies*, 2010, *77* (2), 417–458.

Battiston, Diego, Jordi Blanes i Vidal, and Tom Kirchmaier, "Face-to-face Communication in Organizations," *The Review of Economic Studies*, 2021, *88* (2), 574–609.

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying, "Does working from Home Work? Evidence from a Chinese Experiment," *The Quarterly Journal of Economics*, 2015, *130* (1), 165–218.

Brucks, Melanie S and Jonathan Levav, "Virtual Communication Curbs Creative Idea Generation," *Nature*, 2022, pp. 1–5.

Cairncross, Frances, *The Death of Distance: How the Communications Revolution is Changing our Lives* number 303.4833 C3 2001. 2001.

Chen, Chinchih, Carl Benedikt Frey, and Giorgio Presidente, "Disrupting Science," 2022.

Choudhury, Prithwiraj, Cirrus Foroughi, and Barbara Zepp Larson, "Work-from-Anywhere: The Productivity Effects of Geographic Flexibility," in "Academy of Management Proceedings" number 1. In '2020.' Academy of Management Briarcliff Manor, NY 10510 2020, p. 21199.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg, "Peer Effects in the Workplace," *American Economic Review*, 2017, *107* (2), 425–56.

DeFilippis, Evan, Stephen Michael Impink, Madison Singell, Jeffrey T Polzer, and Raffaella Sadun, "Collaborating During Coronavirus: The Impact of COVID-19 on the Nature of Work," *NBER Working Paper*, 2020, (w27612).

Eckert, Fabian, Mads Hejlesen, and Conor Walsh, "The Return to Big-City Experience: Evidence from Refugees in Denmark," *Journal of Urban Economics*, 2022, p. 103454.

Falk, Armin and Andrea Ichino, "Clean Evidence on Peer Effects," *Journal of Labor Economics*, 2006, *24* (1), 39–57.

Friedman, Thomas L, *The World is Flat: A Brief History of the Twenty-first Century*, Macmillan, 2005.

Gaspar, Jess and Edward L Glaeser, "Information Technology and the Future of Cities," *Journal of Urban Economics*, 1998, *43* (1), 136–156.

Gibbs, Michael, Friederike Mengel, and Christoph Siemroth, "Work from Home & Productivity: Evidence from Personnel & Analytics Data on IT Professionals," *Chicago Booth Research Paper*, 2021, (21-13).

Glaeser, Edward L and David C Mare, "Cities and Skills," *Journal of Labor Economics*, 2001, *19* (2), 316–342.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

He, Haoran, David Neumark, and Qian Weng, "Do Workers Value Flexible Jobs? A Field Experiment," *Journal of Labor Economics*, 2021, *39* (3), 709–738.

Herkenhoff, Kyle, Jeremy Lise, Guido Menzio, and Gordon M Phillips, "Production and Learning in Teams," Technical Report, National Bureau of Economic Research 2018.

Hyken, Shep, "Going Remote: When The Office Is Optional—Or Even Obsolete," *Forbes*, September 2020.

Jackson, C Kirabo and Elias Bruegmann, "Teaching students and teaching each other: The importance of peer learning for teachers," *American Economic Journal: Applied Economics*, 2009, *1* (4), 85–108.

Jaffe, Adam B, Manuel Trajtenberg, and Rebecca Henderson, "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *the Quarterly journal of Economics*, 1993, *108* (3), 577–598.

Jarosch, Gregor, Ezra Oberfield, and Esteban Rossi-Hansberg, "Learning from Coworkers," *Econometrica*, 2021, *89* (2), 647–676.

Kelly, Jack, "Morgan Stanley CEO James Gorman On His Return-To-Work Plan: 'If You Can Go To A Restaurant In New York City, You Can Come Into The Office'," *Forbes*, June 2021.

Linos, Elizabeth, "Does Teleworking Work for Organizations?," Technical Report, Harvard University Working Paper 2018.

Maestas, Nicole, Kathleen J Mullen, David Powell, Till Von Wachter, and Jeffrey B Wenger, "The Value of Working Conditions in the United States and Implications for the Structure of Wages," Technical Report, National Bureau of Economic Research 2018.

Mas, Alexandre and Amanda Pallais, "Valuing alternative work arrangements," *American Economic Review*, 2017, *107* (12), 3722–59.

_ **and** _ , "Alternative Work Arrangements," Technical Report Forthcoming.

_ **and Enrico Moretti**, "Peers at Work," *American Economic Review*, 2009, *99* (1), 112–45.

Nix, Emily, "Learning Spillovers in the Firm," Technical Report, Working Paper 2020.

Roca, Jorge De La and Diego Puga, "Learning by working in big cities," *The Review of Economic Studies*, 2017, *84* (1), 106–142.

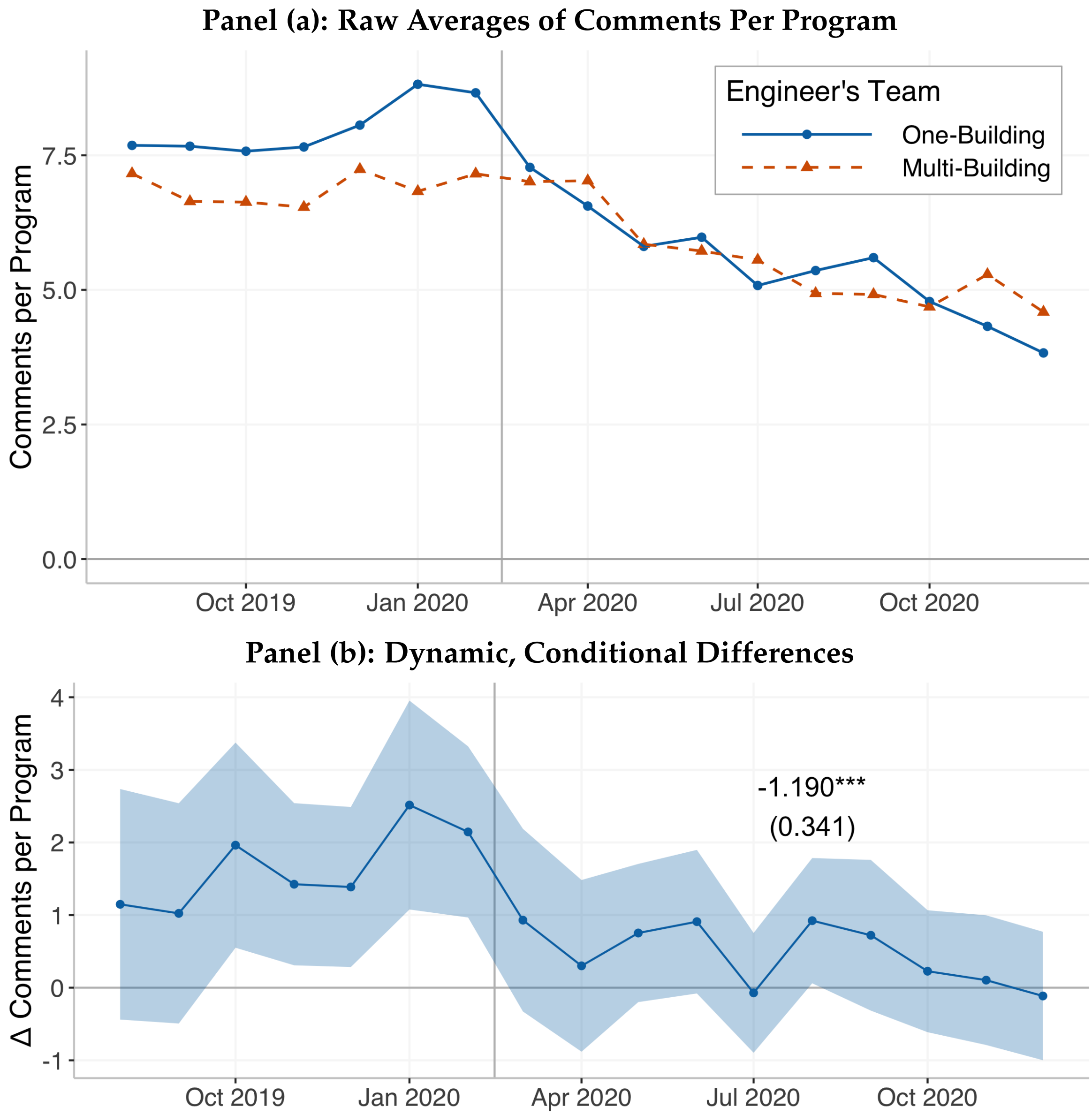
Sandvik, Jason J, Richard E Saouma, Nathan T Seegert, and Christopher T Stanton, "Workplace Knowledge Flows," *The Quarterly Journal of Economics*, 2020.

Waldinger, Fabian, "Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany," *The Review of Economic Studies*, 2012, *79* (2), 838–861.

Yang, Longqi, David Holtz, Sonia Jaffe, Siddharth Suri, Shilpi Sinha, Jeffrey Weston, Connor Joyce, Neha Shah, Kevin Sherman, Brent Hecht et al., "The Effects of Remote Work on Collaboration Among Information Workers," *Nature: Human Behaviour*, 2022, *6* (1), 43–54.

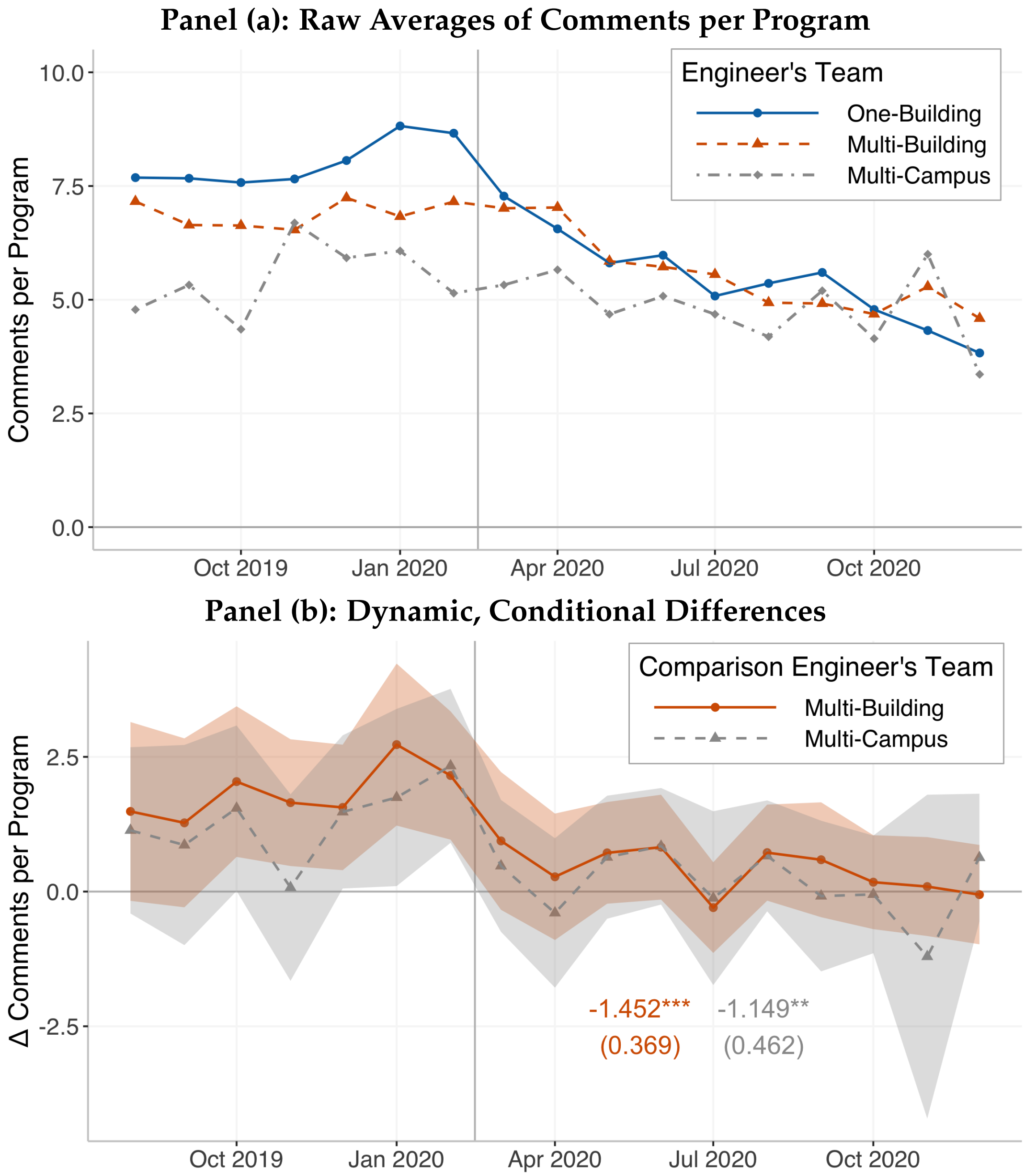
X Figures and Tables

Figure 1: Proximity to Teammates and Online Feedback



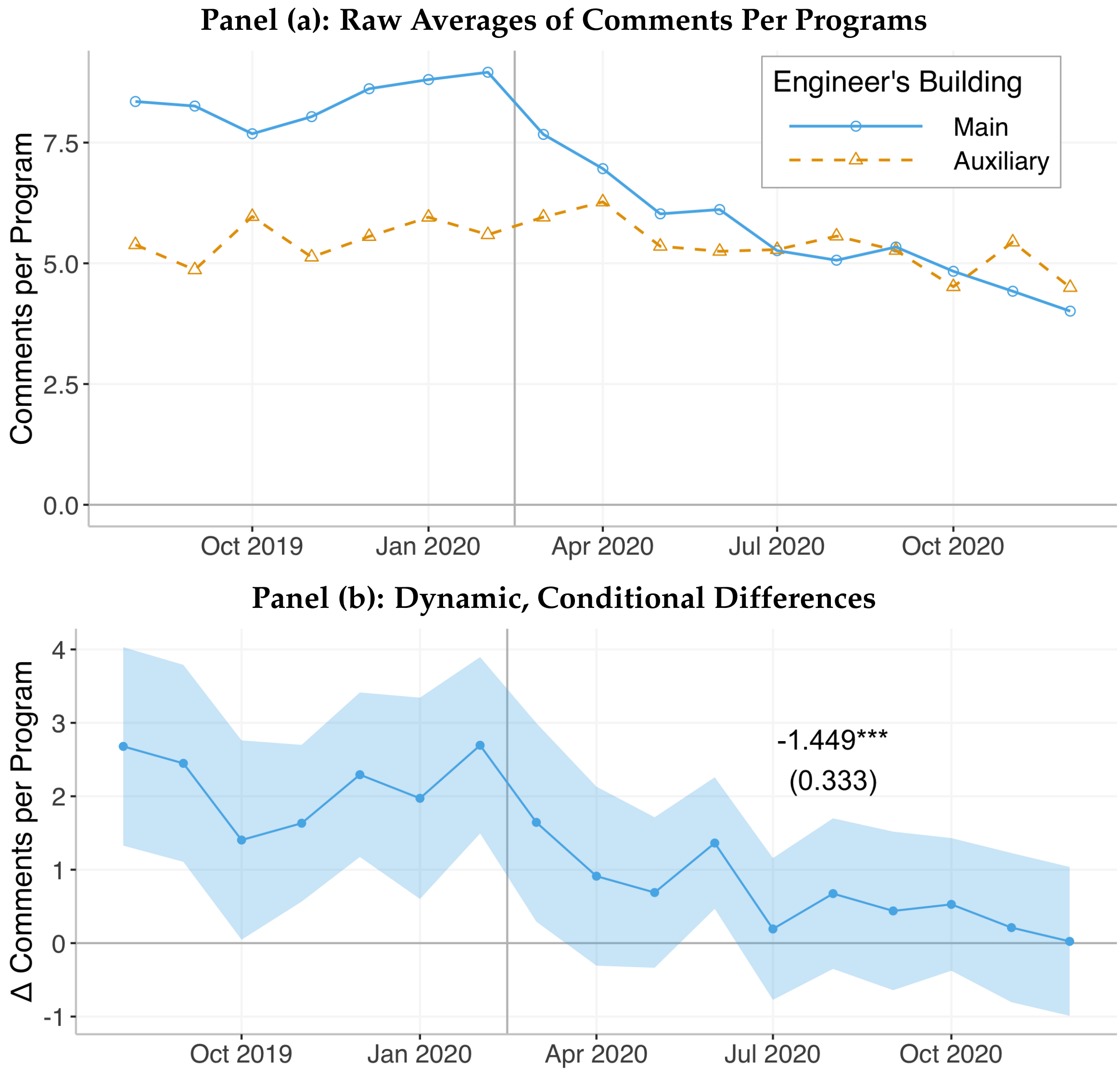
Notes: This figure illustrates the online feedback received by engineers in one-building teams (N=637) and engineers on multi-building teams (N=418) before and after the offices closed for COVID-19 (the grey vertical lines). Panel (a) plots the raw averages, while Panel (b) plots the differences, conditional on our preferred controls for program scope, team size, and tenure as in column four of Table 2. 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 2: Proximity to Teammates, by Distance



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, 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.

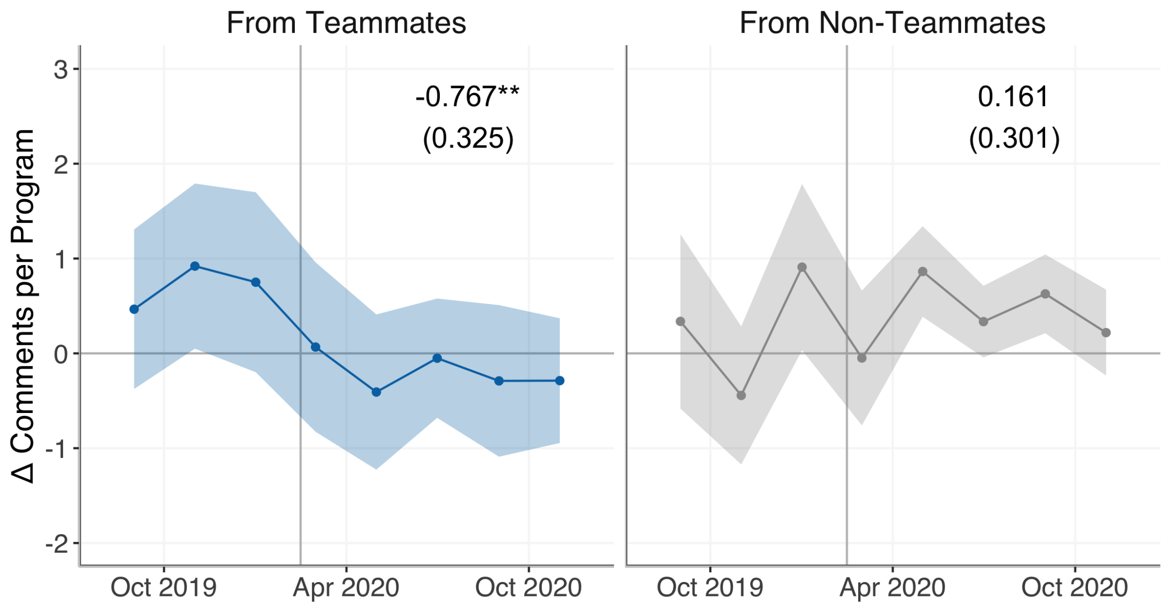
Figure 3: Proximity to Non-Teammates and Online Feedback



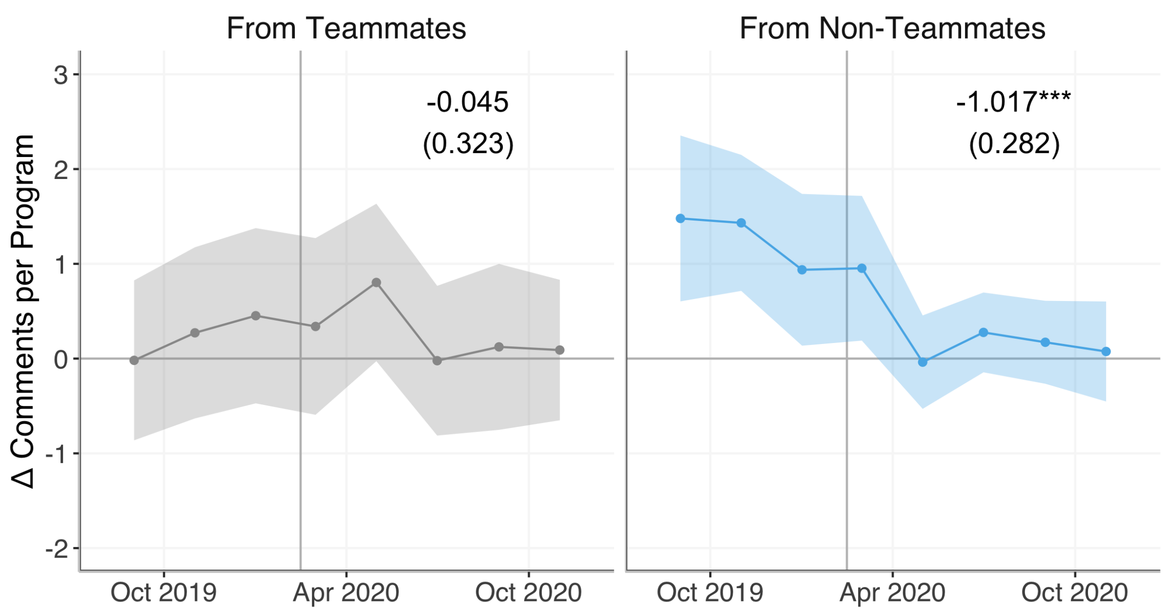
Notes: This figure illustrates the differences in comments received by engineers who were in the firm's main building (N=778) and auxiliary building (N=277) pre-COVID around the COVID-19 office closures (grey vertical lines). Panel (a) plots the raw averages, while Panel (b) plots the differences, conditional on our preferred controls for program scope, team size, and tenure (see Subsection III.B). The ribbon reflects 95% confidence intervals with clustering by engineer. The annotated coefficient is the difference-in-difference estimate from Equation 2. Only engineers whose teammates all worked in the main campus are included. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Figure 4: Proximity and Source of Comments

Panel (a): One- vs. Multi-Building Teams



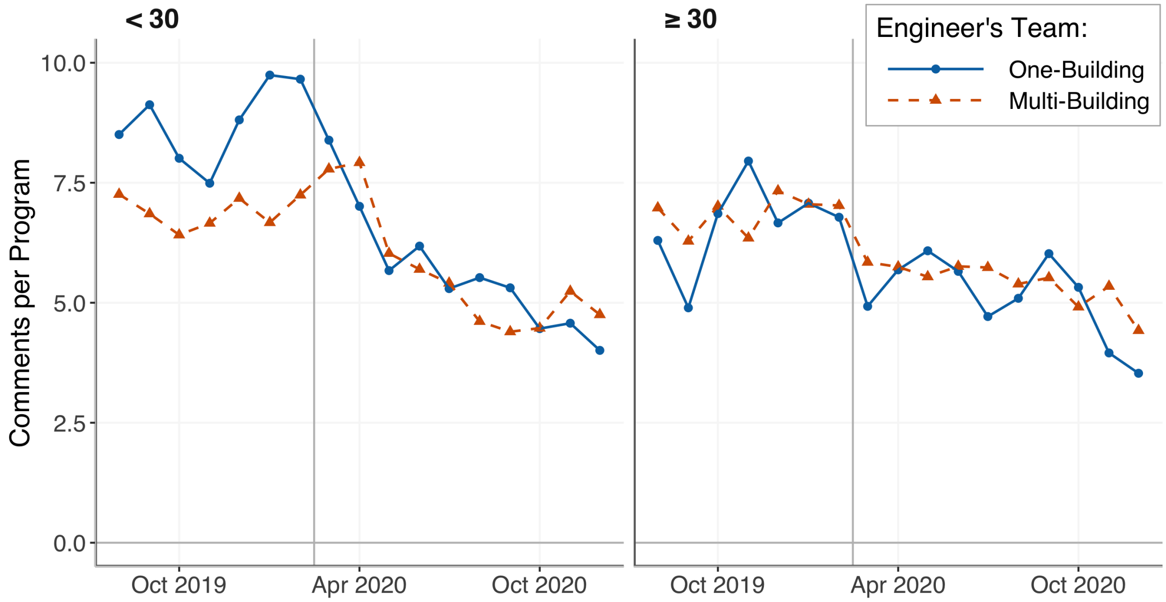
Panel (b): Main vs. Auxiliary Building



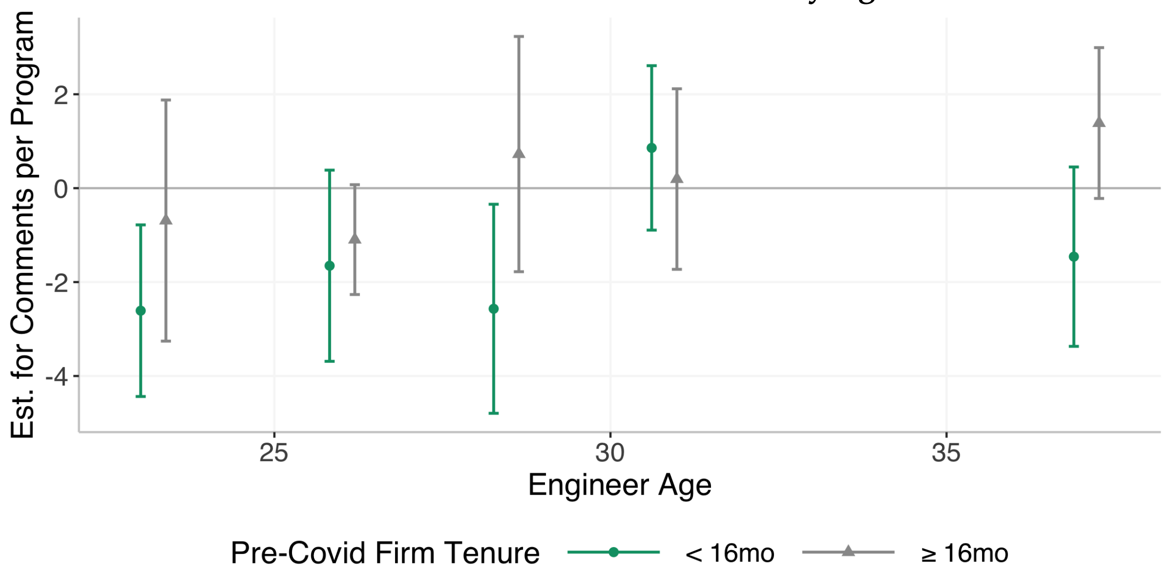
Notes: This figure differentiates between feedback from teammates (left plots) and non-teammates (right plots). Panel (a) presents the differences between engineers on one- and multi-building teams, conditional on their buildings. Panel (b) presents the differences between engineers in the main and auxiliary buildings, conditional on their proximity to their teammates. The annotated coefficients come from Equation 3, conditional on our preferred controls for program scope, team size, and tenure (see Subsection III.B). The points come from a dynamic version of this equation with bimonthly rather than monthly differences to reduce noise in these specific subsets of comments. Ribbons are 95% confidence intervals with clustering by engineer. 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 5: Intergenerational Impacts of Teammate Proximity

Panel (a): Raw Averages of Comments Per Programs by Age



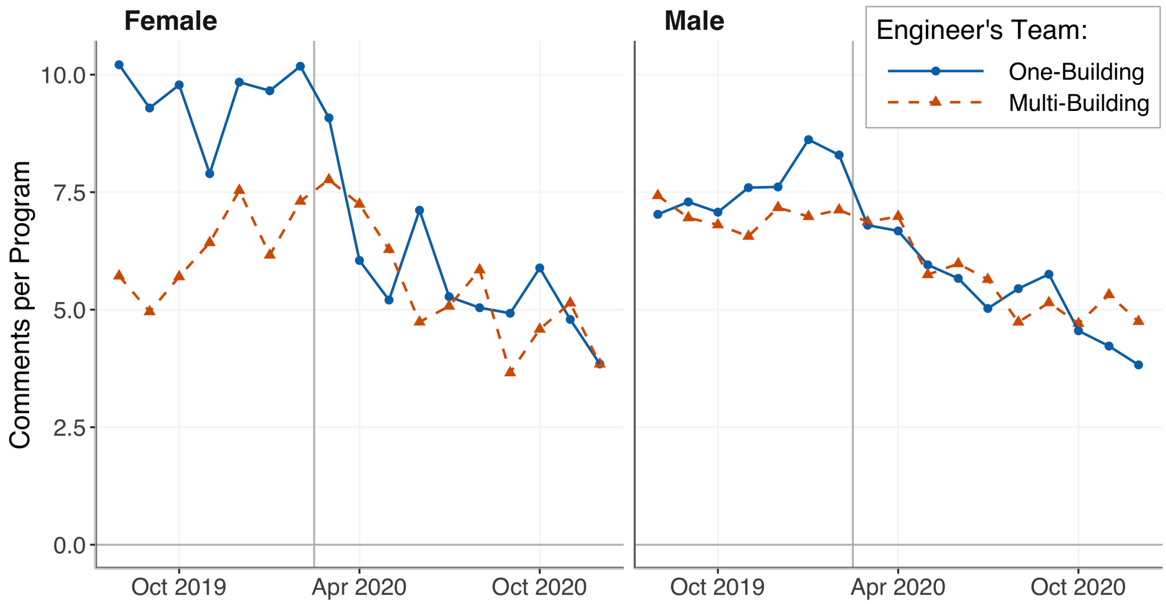
Panel (b): Difference-in-Differences Estimates by Age and Tenure



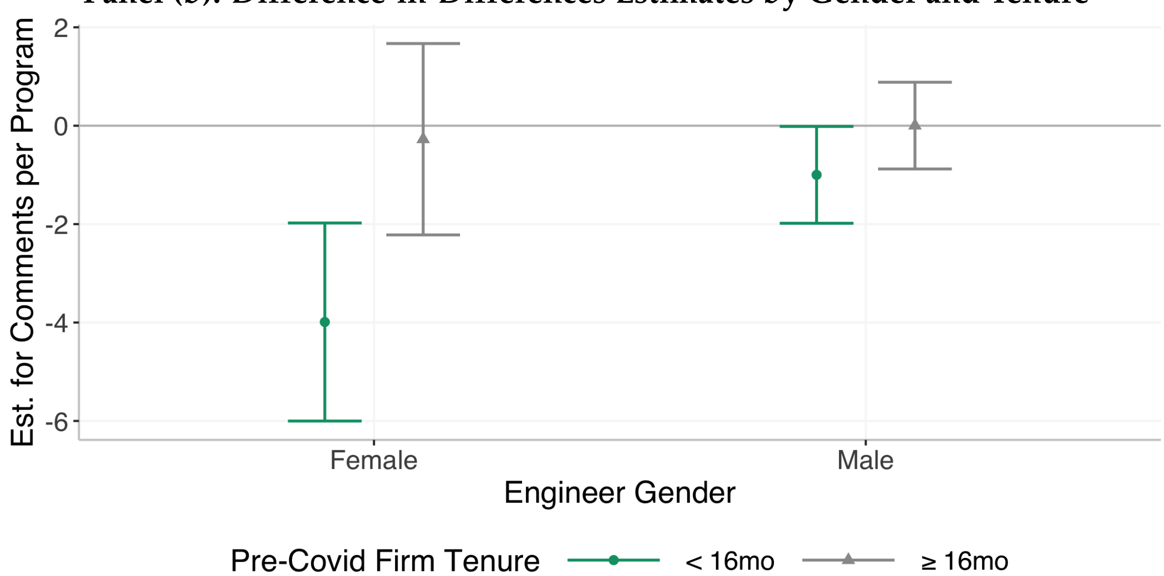
Notes: This figure illustrates the heterogeneous impacts of proximity by engineer's age. Panel (a) shows monthly averages of the number of comments received per program before and after the COVID-19 office closures (grey vertical lines). The left plot includes engineers younger than 30 years old; the right plot includes engineers 30 years or older. Panel (b) displays difference-in-differences estimates for quintiles of engineer age ([19-24], (24-27], (27,29], (29,32], (32, 68]) separately for engineers with more and less than average tenure (16 months) before the office closures. Estimates come from Equation 1, with our preferred controls for program scope, team size, and tenure (see Subsection III.B). The whiskers show 95% confidence intervals with clustering by engineer. Only engineers whose teammates all worked in the main campus are included.

Figure 6: Gendered Impacts of Teammate Proximity

Panel (a): Raw Averages of Comments Per Programs by Gender

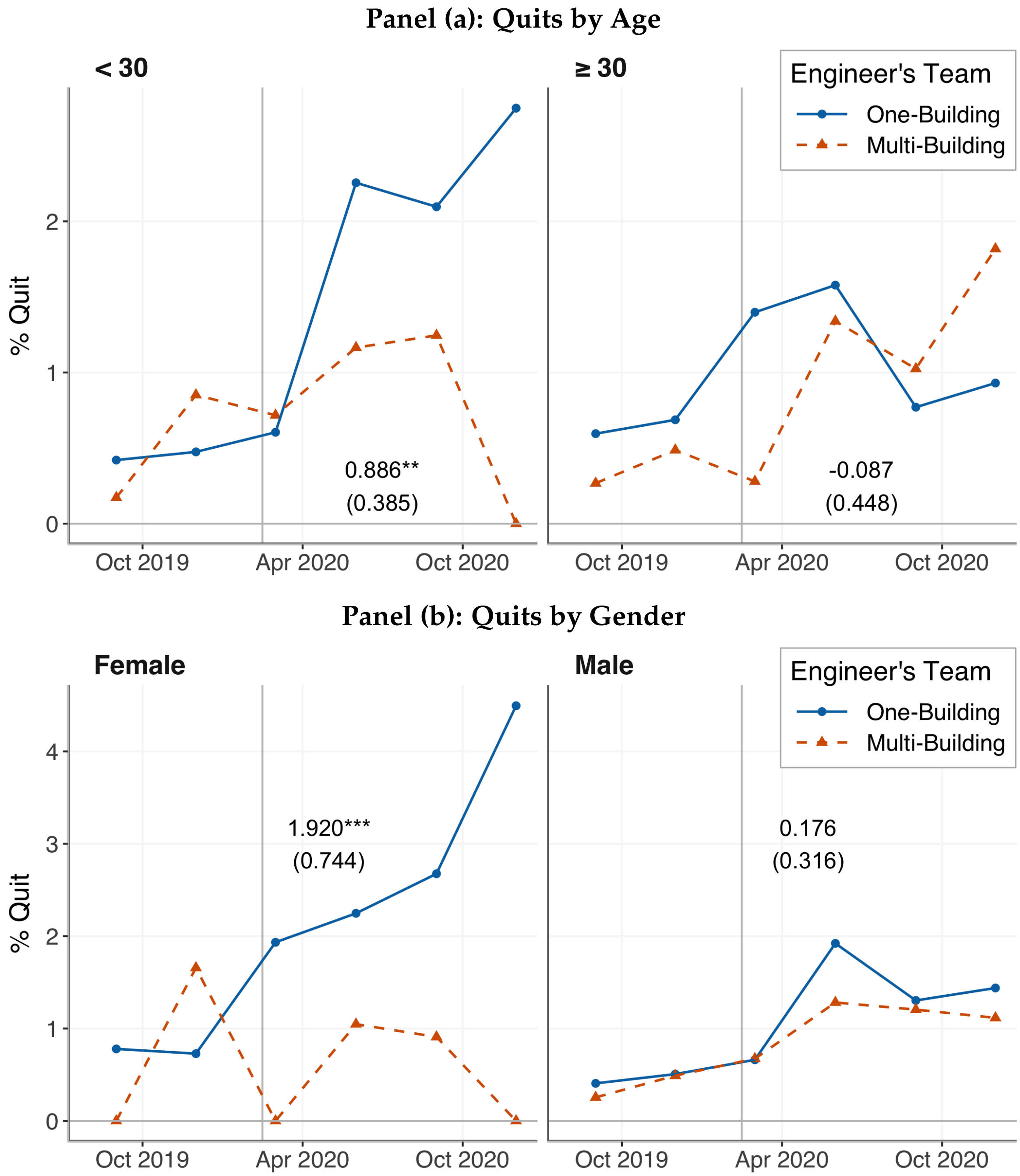


Panel (b): Difference-in-Differences Estimates by Gender and Tenure



Notes: This figure illustrates the heterogeneous impacts of proximity on female and male engineers. Panel (a) shows monthly averages of the number of comments received per program over time. The left panel includes engineers who identify as women; the right panel includes those who identify as men. We drop engineers who did not disclose their gender identity (within this binary) from the analysis. Panel (b) shows difference-in-differences estimates by gender and tenure at the firm (above and below the firm's median of 16 months). Estimates come from Equation 1 with our preferred controls for program scope, team size, and tenure (see Subsection III.B). The whiskers show 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.

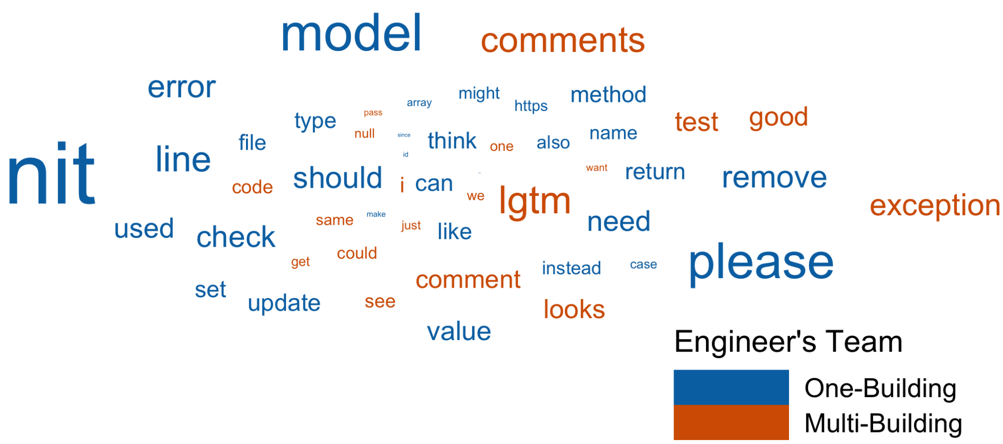
Figure 7: Impacts of Proximity on Turnover



Notes: Both panels show monthly quits rates over time. In Panel (a), the left panel shows quit rates for engineers under 30; the right panel shows these rates for engineers 30 or older. In Panel (b), the left panel shows quit rates for female engineers and the right panel shows quit rates for male engineers. The annotated coefficients come 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 8: Comment Words Usage

Panel (a): Words Predicting Engineer Team Structure

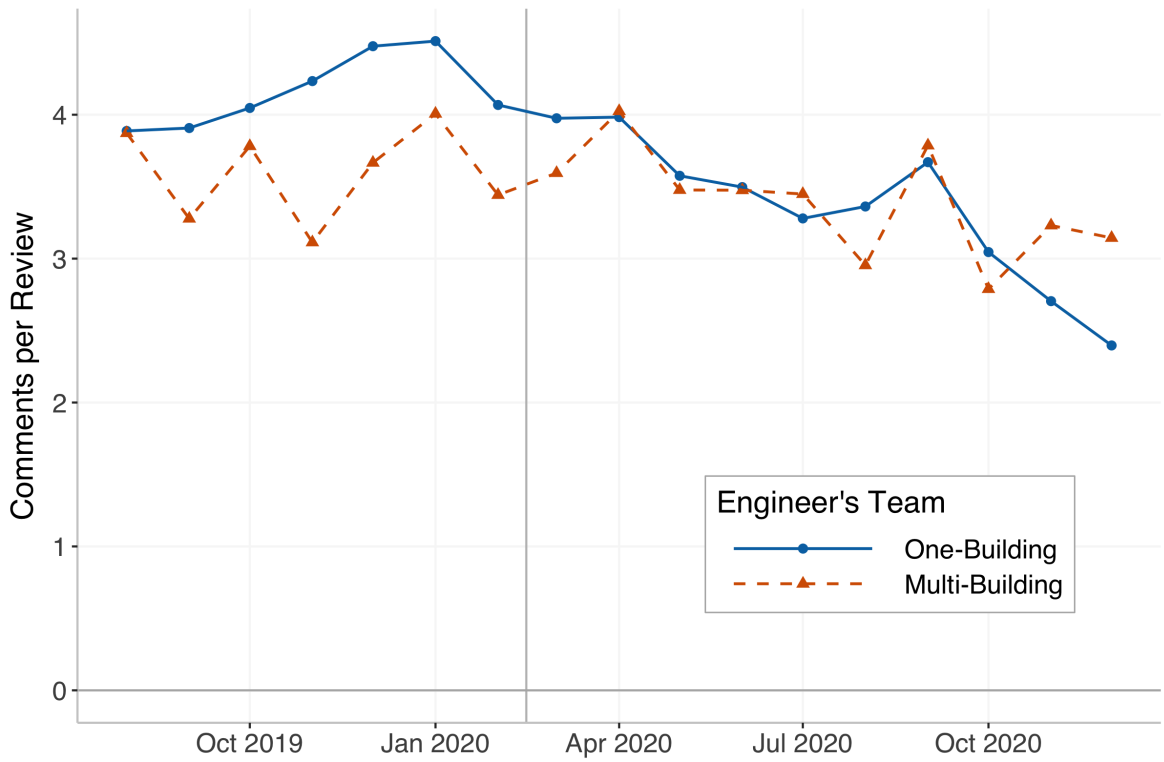


Panel (b): Words Predicting Engineer Gender

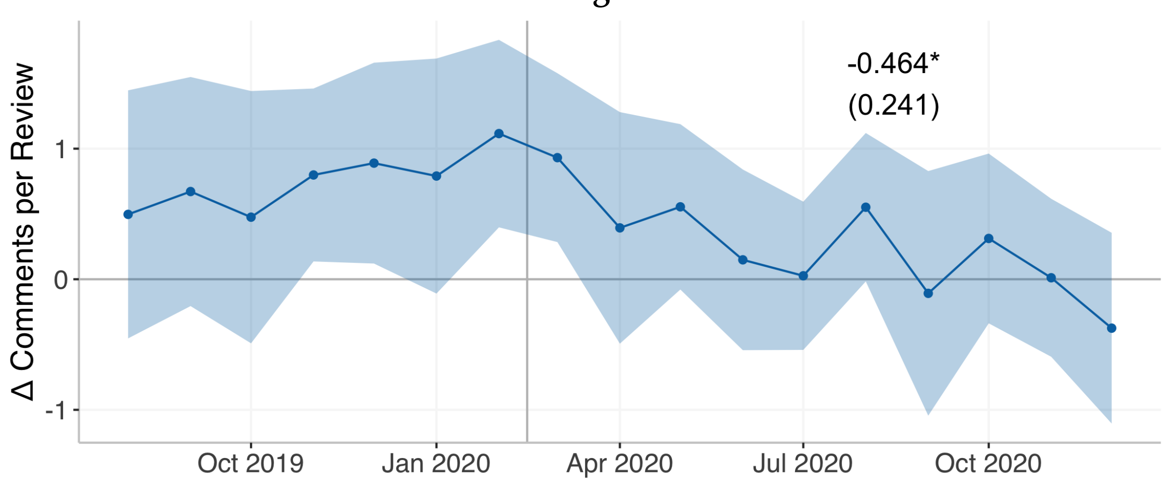
Notes: Both panels show the result of logistic lasso regressions that predict the engineer's team structure and the engineer's gender, respectively. The figures show the top 50 most frequently used words, where the size shows the predictive value of the word and the color shows if the word predicts whether the engineer who wrote the code is on a one- or multi-building team or is a male or female engineer, respectively.

Figure 9: Externalities from Distant Teammates

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

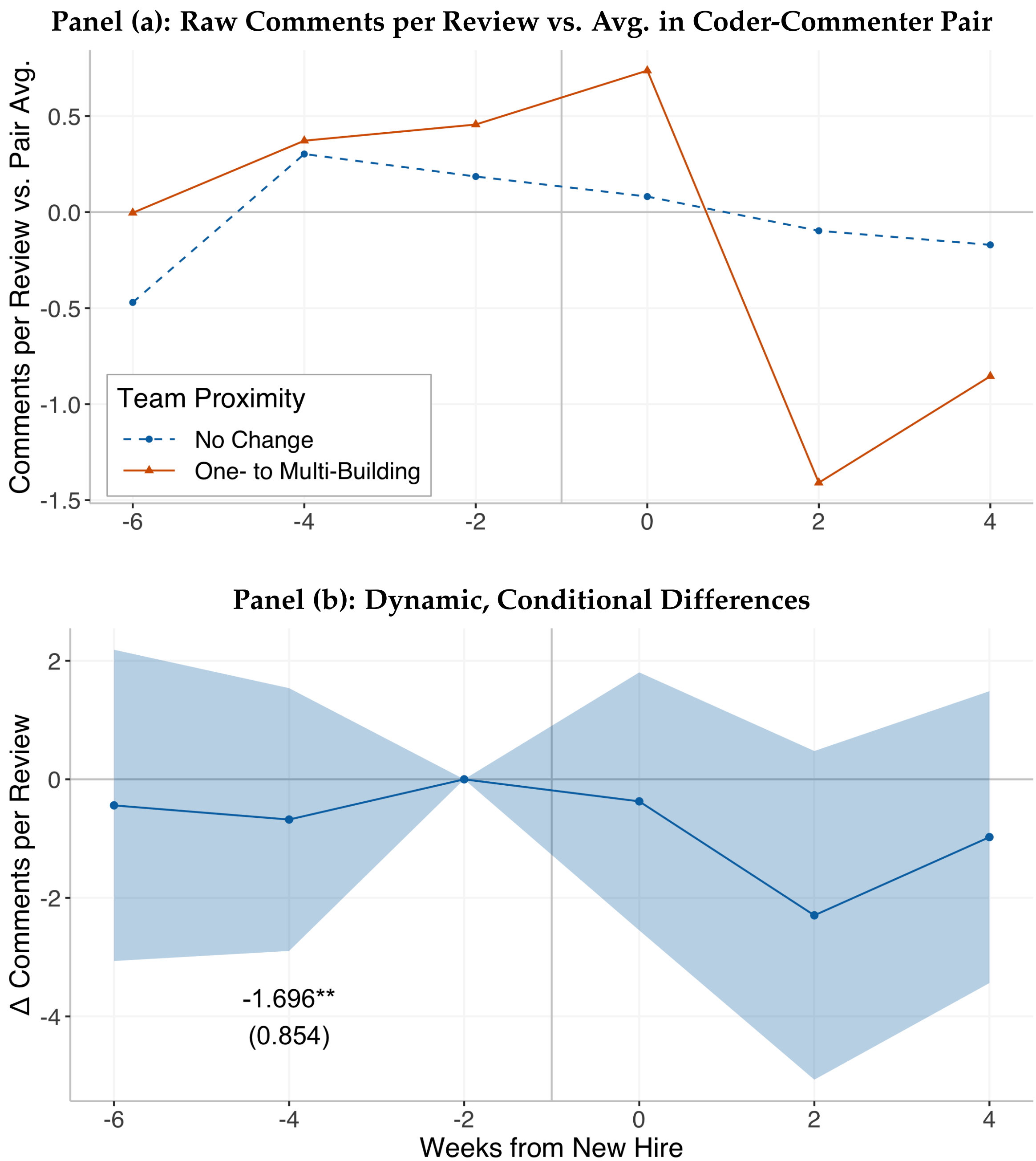


Panel (b): Dynamic, Conditional Differences in Comments per Reviews from Same-Building Teammates



Notes: This figure investigates the externalities from having a distant teammate on the feedback an engineer receives from teammates in the same building. The top panel plots the monthly averages of comments received per peer-review from same-building teammates, separately for engineers in one- and multi-building teams. The bottom panel plots the differences conditional on team size, program scope, and engineer tenure as in column four of Table A.11. 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 10: 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.

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

		Before Closures			After Closures			
	Full Sample	One-Building	Multi-Building	Δ_0	One-Building	Multi-Building	Δ_1	**Diff-in-Diff** $\Delta_1 - \Delta_0$
% Teammates in Building	39.7	100	70.1	29.9	0	0	0	-29.9
				(1.21)			(0.000)	(1.21)
# Teammates	5.61	5.32	6.22	-0.898	5.21	6.00	-0.785	0.113
				(0.181)			(0.199)	(0.114)
% Main Building	69.7	92.9	39.8	53.0	91.5	37.2	54.2	1.19
				(2.86)			(3.22)	(1.97)
Engineer Traits								
% Female	18.7	19.5	17.3	2.19	19.8	17.5	2.29	0.096
				(2.69)			(2.97)	(1.73)
Age (Years)	28.9	28.5	29.1	-0.586	28.7	29.2	-0.515	0.070
				(0.389)			(0.367)	(0.251)
% Parent	16.0	17.0	16.5	0.457	16.6	13.1	3.50	3.05
				(4.63)			(4.45)	(2.20)
Firm Tenure (Years)	1.63	1.21	1.56	-0.344	1.76	2.01	-0.257	0.087
				(0.097)			(0.104)	(0.064)
Job Level	1.81	1.62	1.82	-0.196	1.85	1.98	-0.133	0.063
				(0.052)			(0.057)	(0.044)
Hourly Pay	55.8	53.7	55.6	-1.89	56.2	57.8	-1.58	0.319
				(0.557)			(0.606)	(0.427)
Program Scope								
# Changed Lines/Program	475	482	609	-127	357	522	-165	-38.1
				(53.9)			(39.0)	(61.1)
# Changed Files/Program	6.90	6.84	7.82	-0.982	5.80	7.74	-1.94	-0.955
				(0.466)			(0.474)	(0.600)
Peer Reviews								
# Commenters/Program	1.27	1.37	1.25	0.112	1.23	1.23	0.008	-0.103
				(0.032)			(0.028)	(0.036)
# Comments/Program	6.49	8.04	6.88	1.16	5.57	5.67	-0.104	-1.26
				(0.395)			(0.257)	(0.389)
Characters/Comment	79.9	76.9	78.7	-1.82	79.2	85.5	-6.32	-4.51
				(2.31)			(2.64)	(2.89)
% With Instructive Comment	11.8	14.6	12.5	2.17	9.89	10.8	-0.877	-3.05
				(1.09)			(0.790)	(1.18)
% With Code	10.4	12.1	10.2	1.97	9.59	9.87	-0.280	-2.25
				(0.936)			(0.897)	(1.14)
Hours Delay Until First Comment	15.7	14.9	15.5	-0.559	16.3	15.9	0.400	0.959
				(0.447)			(0.397)	(0.538)
# 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	174,424	50,128	38,630		50,988	34,678		

Notes: This table shows traits of the engineers, their work, and their feedback. Standard errors in parentheses are clustered by engineer. Only engineers whose teams are all in the main campus are included. 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 review has code if a comment includes code to illustrate the advice. Hours until the first comment are measured from code submission.

Table 2: Proximity to Teammates and Online Feedback

	Comments per Program					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x One-Building Team	-1.26^{***}	-0.91^{**}	-1.28^{***}	-1.19^{***}	-1.45^{***}	-1.36^{***}
	(0.39)	(0.38)	(0.34)	(0.34)	(0.37)	(0.39)
One-Building Team	1.16^{***}	0.71^{*}	1.85^{***}	1.69^{***}	1.87^{***}	
	(0.39)	(0.38)	(0.33)	(0.32)	(0.35)	
Post	-1.21^{***}					
	(0.27)					
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	-15.71%	-11.36%	-15.97%	-14.8%	-18.06%	-16.96%
One-Building	14.42%	8.89%	22.97%	21.02%	23.31%	
% One-Building Team	58.33	58.33	58.33	58.33	58.33	58.33
Team Size x Post FE		✓	✓	✓	✓	✓
Program Scope x Post FE			✓	✓	✓	✓
Tenure Months x Post FE				✓	✓	✓
Other Engineer Controls X Post					✓	✓
Engineer 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	0.01	0.03	0.29	0.34	0.38	0.49

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. 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. The first column presents the raw estimates, corresponding to Figure 1. The second column includes fixed effects for team size, which is useful to account for because mechanically smaller teams will be more likely to be in one building. The third column adds controls for program scope (quartics for the number of lines added, number of lines deleted, and number of files changed). The four column allows for differential changes in feedback for more and less experienced engineers around the office closures to account for the lower tenure of one-building teams. The fifth column includes controls for other engineer characteristics — age (in years) and gender, home zipcode, job-level, and job-type — where we allow the effects to vary before and after the pandemic. The last column includes engineer fixed effects to handle any changes in the composition of engineers who submit programs to the main code-base. Regressions include engineers who submit programs to the firm's main code-base in the month and are limited to engineers whose teams are all in the firm's main campus. *p<0.1; **p<0.05; ***p<0.01.

Table 3: Proximity to Teammates and Online Feedback: Alternative Measures

	(1) Total Characters	(2) With Instruction	(3) With Code	(4) Hours to First Comment	(5) Mention Other Online Convo
Post x One-Building Team	-139.100^{***}	-0.023^{**}	-0.017	0.914^{*}	-0.014^{**}
	(46.950)	(0.010)	(0.011)	(0.527)	(0.006)
One-Building Team	178.500^{***}	0.025^{***}	0.023^{***}	-1.083^{***}	0.017^{***}
	(42.880)	(0.009)	(0.008)	(0.409)	(0.006)
Pre-Mean in One-Building	687.52	0.11	0.1	16.73	0.03
Percentage Effect					
Post x One-Building Team	-20.23%	-21.35%	-17.18%	5.46%	-41.61%
One-Building Team	25.97%	22.87%	23.29%	-6.48%	49.55%
% One-Building Team	58.33	58.33	58.33	58.33	58.33
Preferred Controls	✓	✓	✓	✓	✓
# Engineers	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304
R^2	0.294	0.183	0.096	0.140	0.062

Notes: This table considers alternative measures of coworkers' online feedback other than the number of comments on each program in the peer review system. Each column estimates Equation 1, with the preferred set of controls (see Subsection III.B). Column one considers the total number of characters in comments on a program. Columns two considers the share of reviews that have a specifically instructive comment that shows the engineer an 'example', gives 'general' advice, or discusses best programming 'practice'. Columns three considers the share of programs where reviewers write code to illustrate the desired changes. Columns four consider the number of hours between program submission and when the first comment is received. Column five considers the share of reviews that mention another online conversation (e.g., on Slack, Zoom, or email). Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Type of Proximity and Source of Comments

	Comments per Program			
	Total		From Teammates	
	(1)	(2)	(3)	(4)
Post x One-Building Team	-0.77^{**}	-0.73^{**}	0.17	0.11
	(0.33)	(0.35)	(0.30)	(0.34)
One-Building Team	0.59^{*}		0.24	
	(0.31)		(0.27)	
Post x Main Building	-0.04	-0.36	-1.02^{***}	-1.16^{***}
	(0.32)	(0.38)	(0.28)	(0.35)
Main Building	0.32		1.32^{***}	
	(0.29)		(0.26)	
Pre-Mean, One-Building Team	4.28	4.28	3.73	3.73
Pre-Mean, Main Building	4.31	4.31	4.06	4.06
Percentage Effects				
Post x One-Building Team	-17.93%	-17%	4.45%	2.94%
One-Building Team	13.89%		6.46%	
Post x Main Building	-1.04%	-8.32%	-25.08%	-28.53%
Main Building	7.39%		32.51%	
Controls	Preferred	All	Preferred	All
# 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	0.19	0.42	0.39	0.52

Notes: This table investigates the relationship between physical proximity and specific sources of online feedback on an engineer's programs. In the first two columns, the dependent variable is the average number of comments per program an engineer receives from her teammates in the month. In the next two columns, the dependent variable is the average number of comments per program an engineer receives from non-teammates. Each column estimates Equation 3. The odd columns present the preferred set of time-varying controls for team-size, program scope, and engineer tenure (see Subsection III.B). The even columns also include other time-varying engineer controls and engineer fixed effects. Of the engineers studied, 58.3 percent are on one-building teams and 71.1 percent are located in the main building. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 5: Proximity and Coworker Conversations about Code

	From Commenter			From Program Writer	
	Initial	Follow-up	Questions	Replies	Questions
	(1)	(2)	(3)	(4)	(5)
Post x One-Building Team	-0.669^{***}	-0.521^{*}	-0.132	-0.566^{**}	-0.070^{**}
	(0.219)	(0.300)	(0.150)	(0.223)	(0.028)
One-Building Team	0.962^{***}	0.727^{**}	0.143	0.464^{*}	0.046^{*}
	(0.211)	(0.300)	(0.163)	(0.245)	(0.027)
Pre-Mean, One-Building Team	4.91	3.13	1.94	2.14	0.19
Percentage Effects					
Post x One-Building Team	-13.6%	-16.6%	-6.8%	-26.5%	-37.6%
One-Building Team	19.6%	23.2%	7.4%	21.7%	24.8%
% One-Building Team	58.3	58.3	58.3	58.3	58.3
Preferred Controls	✓	✓	✓	✓	✓
# Engineers	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304
R^2	0.364	0.175	0.229	0.165	0.072

Notes: This table explores the relationship between proximity and the conversations between commenters and program writers about code. The first three columns focus on the commenters' comments. Column one considers only initial comments — comments written before the program writer replies — while column two considers only replies written after the program writer responds. The third column considers only comments that include a question to the program writer. The final two columns focus on program writers. Column four includes all replies to the commenters' comments. Column five only considers authors' replies that include a question. Each column estimates Equation 1, including the preferred set of controls for team-size, program scope, and engineer tenure (see Subsection III.B). Results including other time-varying engineer controls and engineer fixed effects are in Table A.8. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 6: Effect of Proximity by Age, Tenure and Gender

	Comments per Program			
	(1)	(2)	(3)	(4)
Post x One-Building Team x <30	-1.78^{***}			-1.48^{**}
	(0.64)			(0.66)
One-Building Team x <30	1.41^{**}			1.24^{**}
	(0.61)			(0.62)
Post x One-Building Team x Low Tenure		-1.54^{**}		-1.21^{*}
		(0.61)		(0.63)
One-Building Team x Low Tenure		1.96^{***}		1.70^{***}
		(0.54)		(0.54)
Post x One-Building Team x Female			-1.98^{**}	-1.87^{**}
			(0.86)	(0.86)
One-Building Team x Female			2.50^{***}	2.32^{***}
			(0.82)	(0.84)
Post x One-Building Team	-0.09	-0.02	-0.63^{*}	0.83
	(0.50)	(0.41)	(0.36)	(0.58)
One-Building Team	0.81	0.34	1.13^{***}	-0.62
	(0.49)	(0.31)	(0.34)	(0.51)
Pre-Mean <30 Years Old	8.78	8.78	8.78	8.78
Pre-Mean Low Tenure	9.56	9.56	9.56	9.56
Pre-Mean Female	9.56	9.56	9.56	9.56
% One-Building Team	58.3	58.3	58.3	58.3
# 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	0.34	0.34	0.34	0.33

Notes: This table explores the relationship between physical proximity and coworker feedback by age, tenure, and gender. "Low tenure" indicates that the worker has been at the firm less than 16 months, the median tenure, before the COVID-19 office closures. Each column estimates Equation 3, using our preferred set of controls: team-size, program scope, and engineer tenure, where the effects of the controls are allowed to vary before and after the pandemic (see Subsection III.B). *p<0.1; **p<0.05; ***p<0.01.

Table 7: Effect of Proximity on Quits by Age

	% Quit Per Month			
	All		For Better Job	
	(1)	(2)	(3)	(4)
<30: Post x One-Building Team	0.927**	0.828**	0.571**	0.484*
	(0.384)	(0.393)	(0.279)	(0.288)
<30: One-Building Team	−0.166	−0.076	−0.013	0.054
	(0.226)	(0.232)	(0.180)	(0.192)
<30: Post	0.424		0.069	
	(0.296)		(0.203)	
≥30: Post x One-Building Team	−0.031	−0.355	−0.297	−0.449
	(0.448)	(0.474)	(0.315)	(0.335)
≥30: One-Building Team	0.223	0.445	0.201	0.340*
	(0.273)	(0.274)	(0.181)	(0.189)
≥30: Post	0.697**		0.510**	
	(0.332)		(0.237)	
<30: Pre-Mean One-Building Teams	0.4	0.4	0.28	0.28
≥30: Pre-Mean One-Building Teams	0.47	0.47	0.24	0.24
Engineer Controls X Post		✓		✓
# Engineers	1,055	1,055	1,055	1,055
# Months	17	17	17	17
# Engineer-Months	16,100	16,100	16,100	16,100
R^2	0.003	0.029	0.001	0.023

Notes: This table considers quits, for young engineers at or below the mean age of 29 and older engineers at least thirty. The dataset is at the engineer by month level. In the first two columns, the dependent variable is quits; in the next two columns, the dependent variable is quitting with the explicit reason of a better job elsewhere. The odd column present the raw triple difference design while the even columns add time-varying, engineer controls for engineer age by gender, job-level, job-type, and tenure (in months). The sample is limited to engineers whose teams are all in the main campus. Standard errors are clustered by engineer. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 8: Effect of Proximity on Quits by Gender

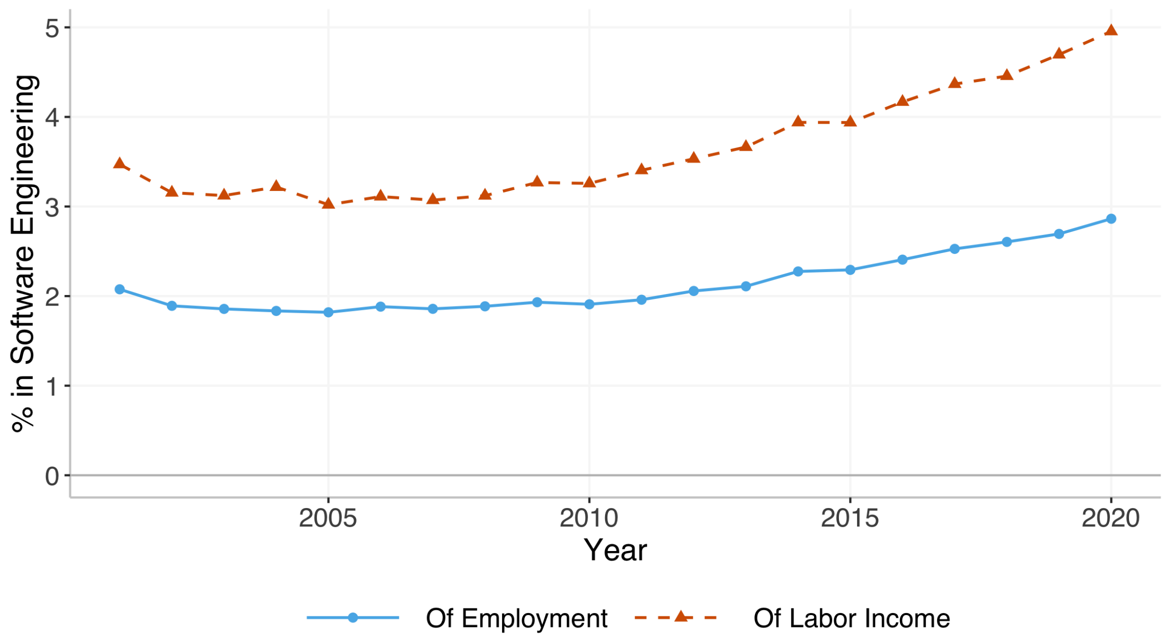
	All Quits		For Better Job	
Female: Post x One-Building Team	2.056***	1.912***	1.339***	1.227**
	(0.742)	(0.726)	(0.503)	(0.487)
Female: One-Building Team	−0.186	−0.077	−0.389	−0.372
	(0.495)	(0.460)	(0.367)	(0.356)
Female: Post	−0.145		−0.350	
	(0.519)		(0.379)	
Male: Post x One-Building Team	0.201	0.227	−0.046	−0.047
	(0.316)	(0.326)	(0.233)	(0.243)
Male: One-Building Team	0.014	−0.008	0.178	0.193
	(0.180)	(0.191)	(0.138)	(0.147)
Male: Post	0.694***		0.393**	
	(0.247)		(0.173)	

Notes: This table considers quits, separately for male and female engineers. The dataset is at the engineer by month level. In the first two columns, the dependent variable is quits; in the next two columns, the dependent variable is quitting with the explicit reason of a better job elsewhere. The odd column present the raw triple difference design while the even columns add time-varying, engineer controls for engineer age by gender, job-level, job-type, and tenure (in months). Standard errors are clustered by engineer. *p<0.1; **p<0.05; ***p<0.01.

A Appendix

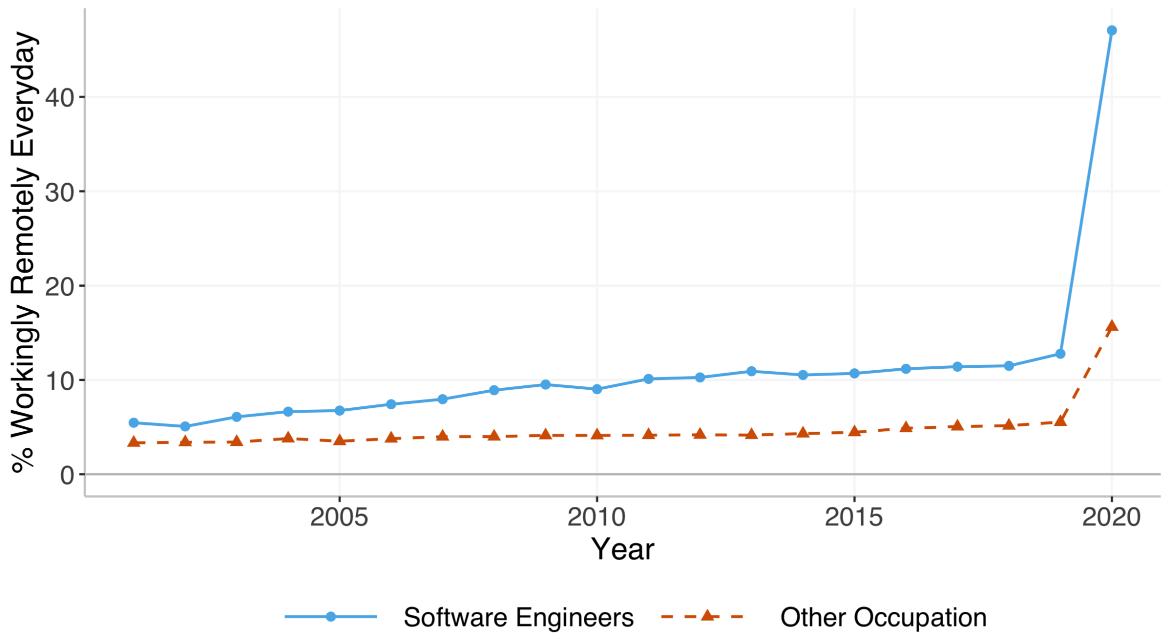
I.A Figures

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.

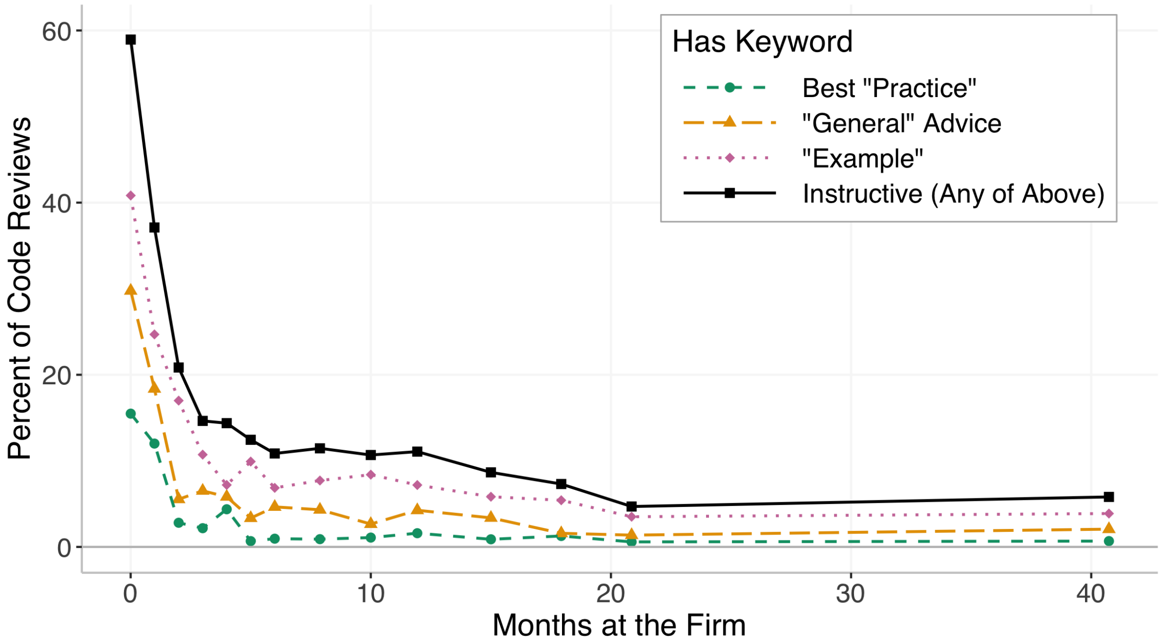
Figure A.2: Trends in Remote Work for Software Engineers and Other Occupations in the Census



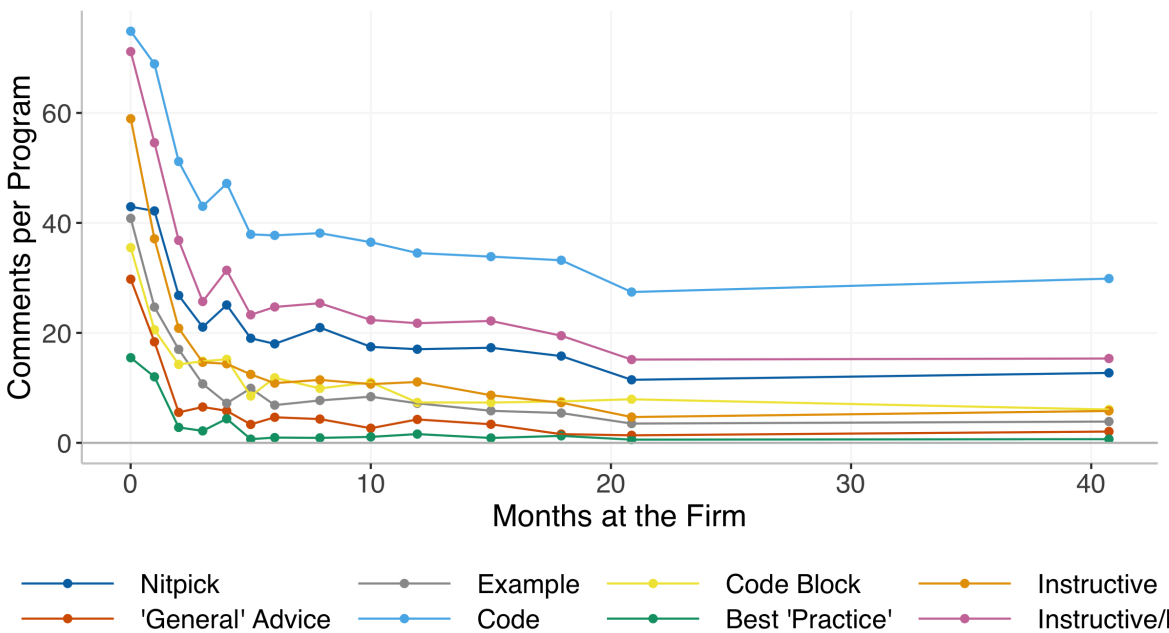
*Notes:*This figure illustrates the trends in remote work for workers in software engineering (in blue circles) and other occupations (in orange triangles) based on data from the American Community Survey. Each point reflects the percent of workers in the occupational group who reported working at home 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: Code Reviews and Onboarding

Panel (a): Code reviews with Instructive Keywords by Firm Tenure

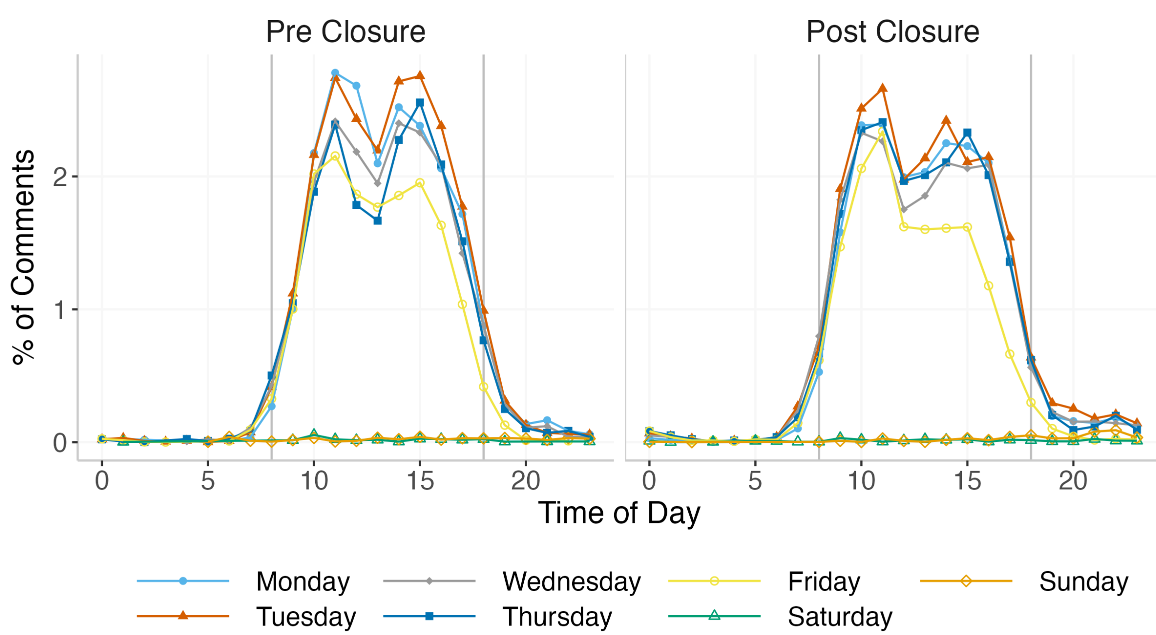


Panel (b): Comments per Program by Firm Tenure



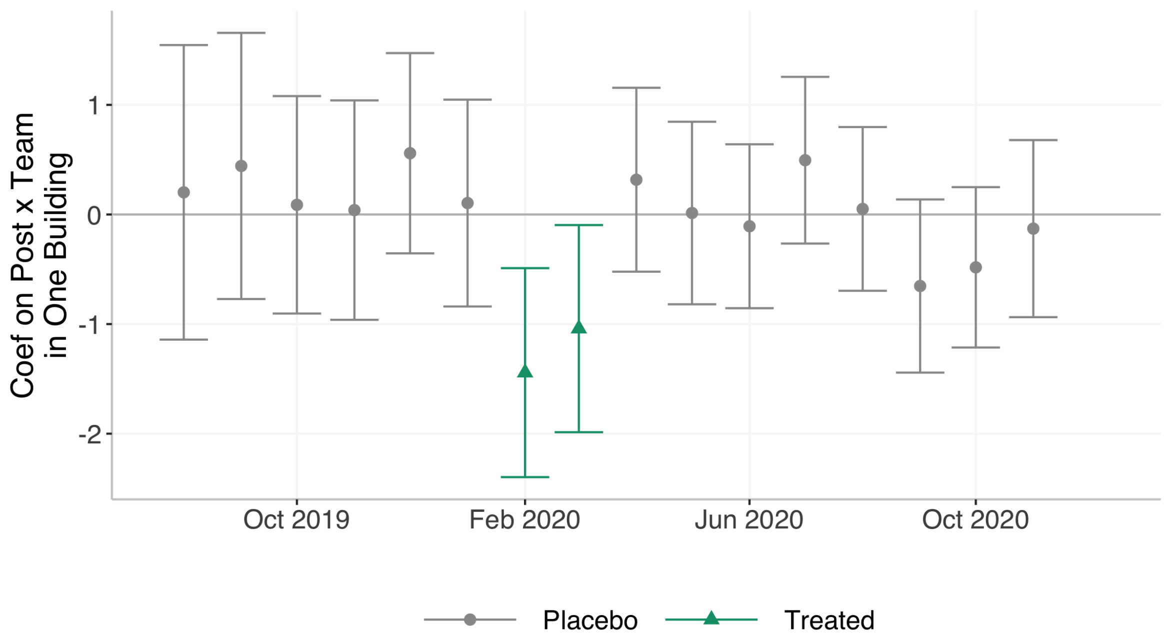
Notes: These figures illustrates how code reviews change as engineers gain experience at the firm. Panel (a) considers the percent of code reviews that have a specifically instructive comment that shows the engineer an "example", gives "general" advice, or discusses best programming "practice". Panel (b) considers the total number of comments on each program. Each point is a mean for engineers of the given tenure at the firm. For the first six months, each month is shown separately; for the next six months, every two months are pooled; for the next year, every three months are pooled; and engineers with at least two years of experience are pooled in the final point. The sample is limited to the pre-pandemic period and includes engineers whose teams are entirely in the firm's main engineering campus.

Figure A.4: Timing of Comments Over the Course of the Day



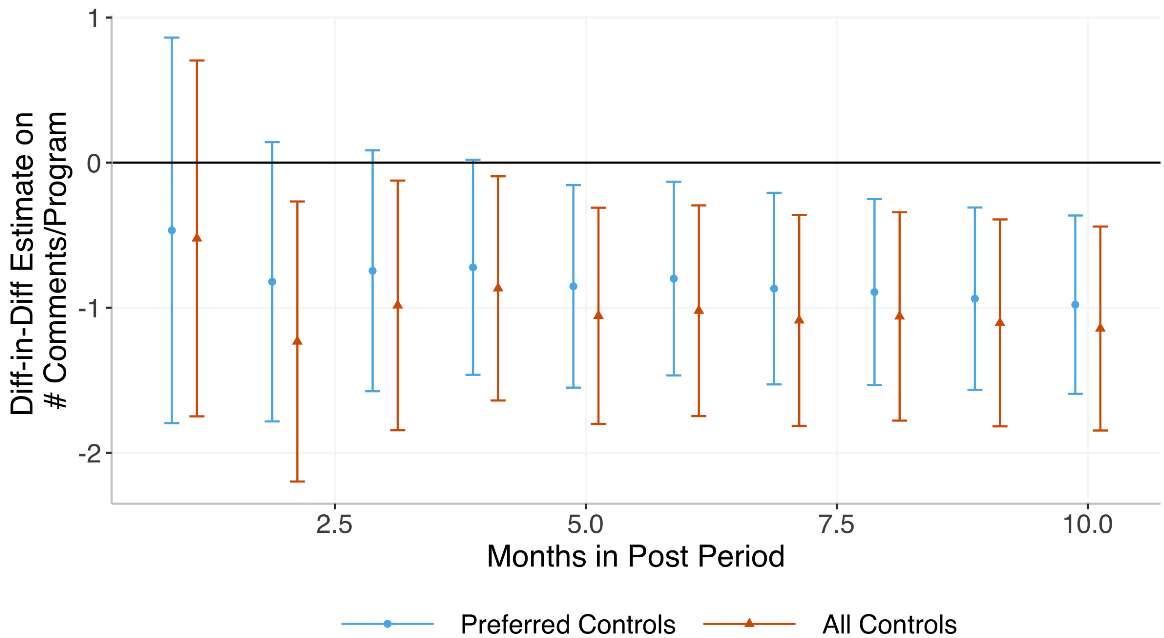
Notes: This figure plots the timing of comments over the course of the day. The x-axis plots the time of day in military time. The y-axis is the percent of comments that occur in that particular time of day on that particular day of week. The left plot is the period before the office closures of COVID-19. 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.5: 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.

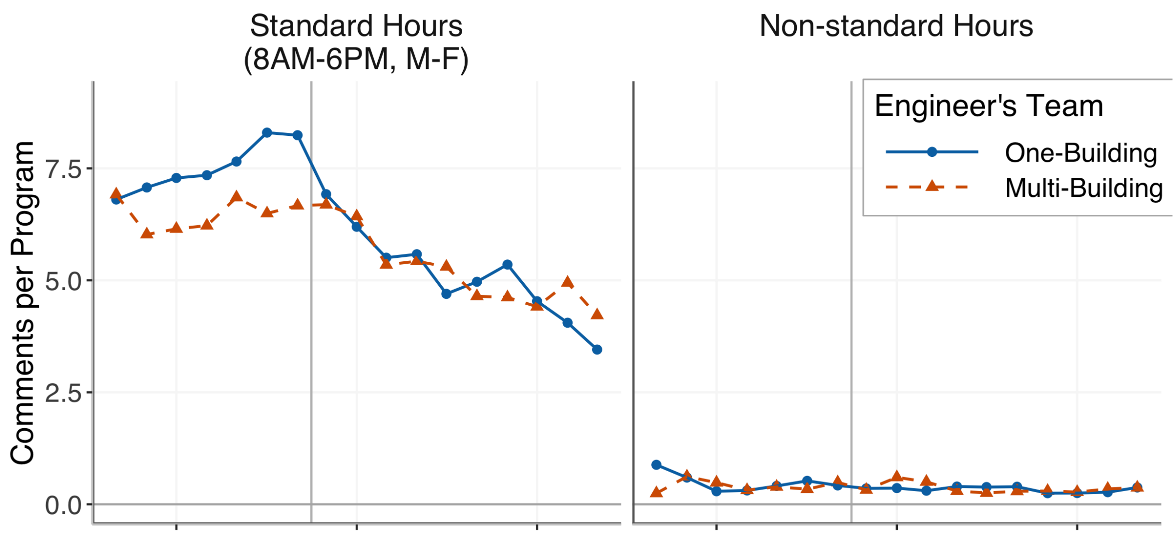
Figure A.6: Robustness of Effect of Proximity on On-the-Job Training from Coworkers to Alternative Post-Periods



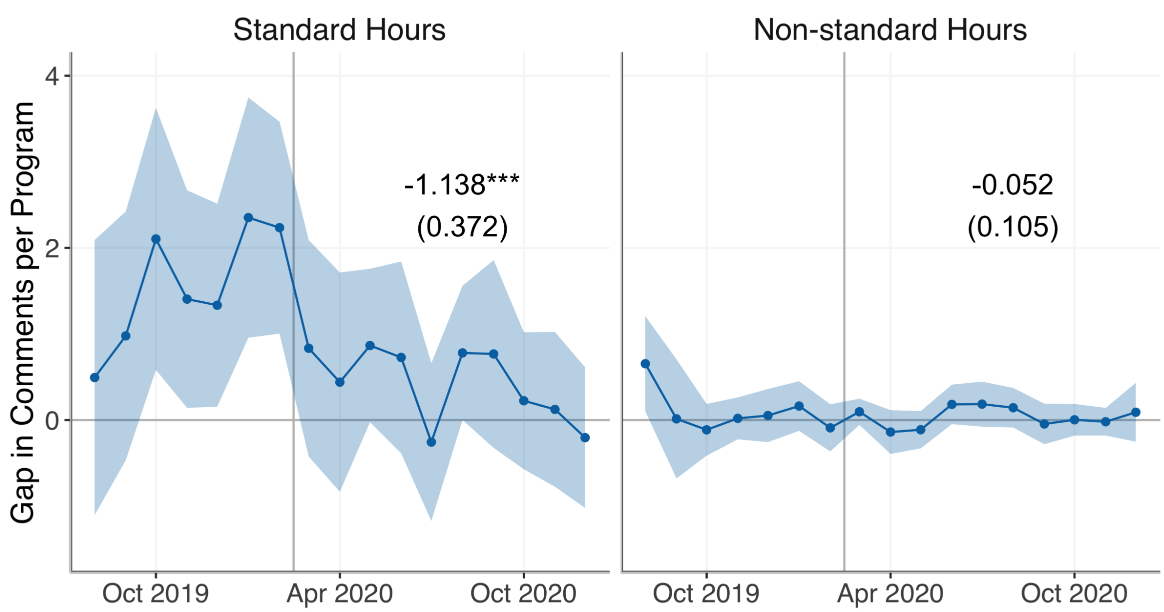
Notes: This figure illustrates how the difference-in-differences estimate from Equation 1 — that compares engineers on one- and multi-building teams, before and after the office closures — varies with the number of months in the post period. The blue circles are the coefficients using our preferred controls 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.7: Proximity to Teammates and Online Feedback Inside and Outside of Standard Work Hours

Panel (a): Raw Averages of Comments Per Program by Timing

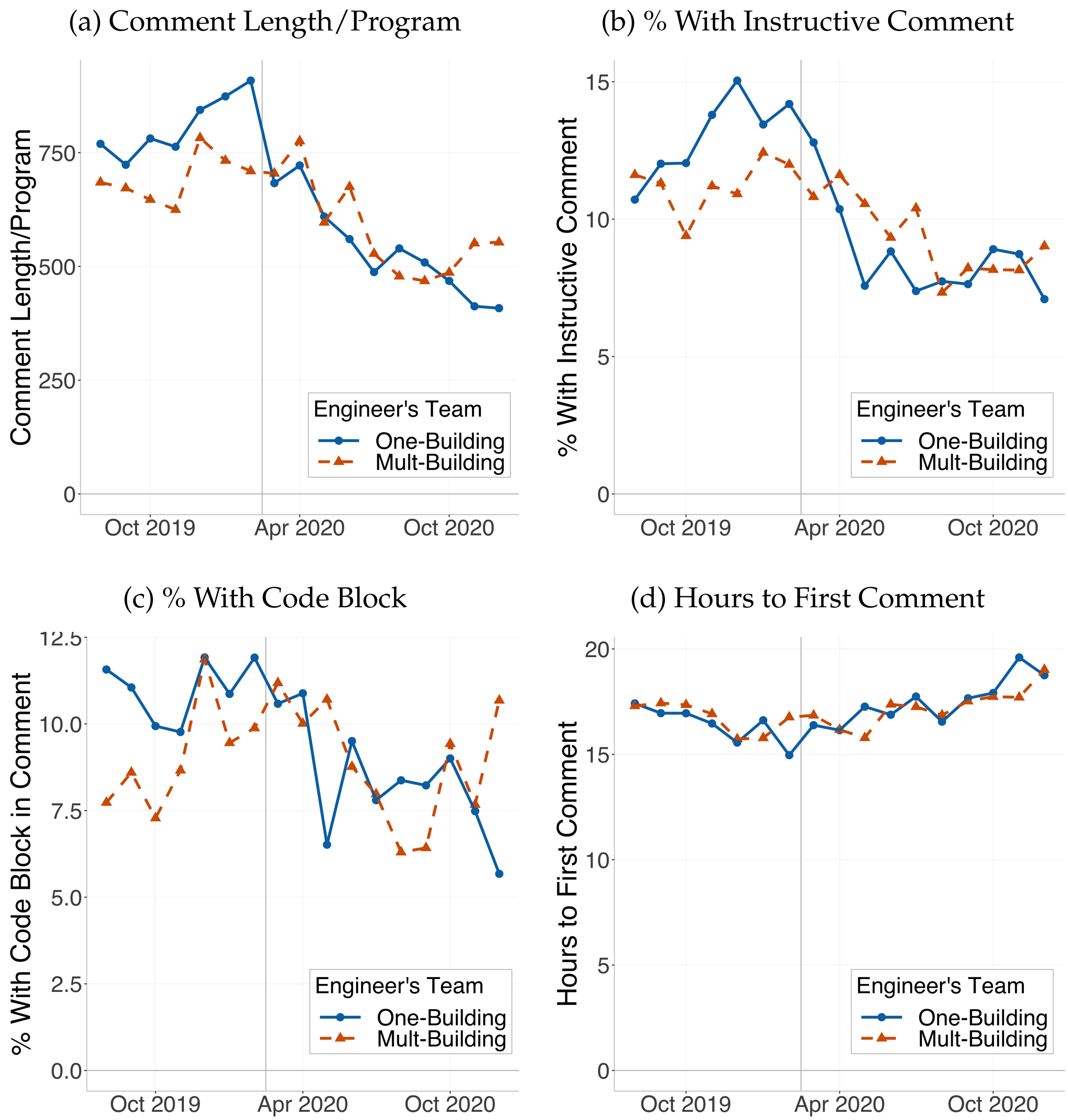


Panel (b): Dynamic, Conditional Differences



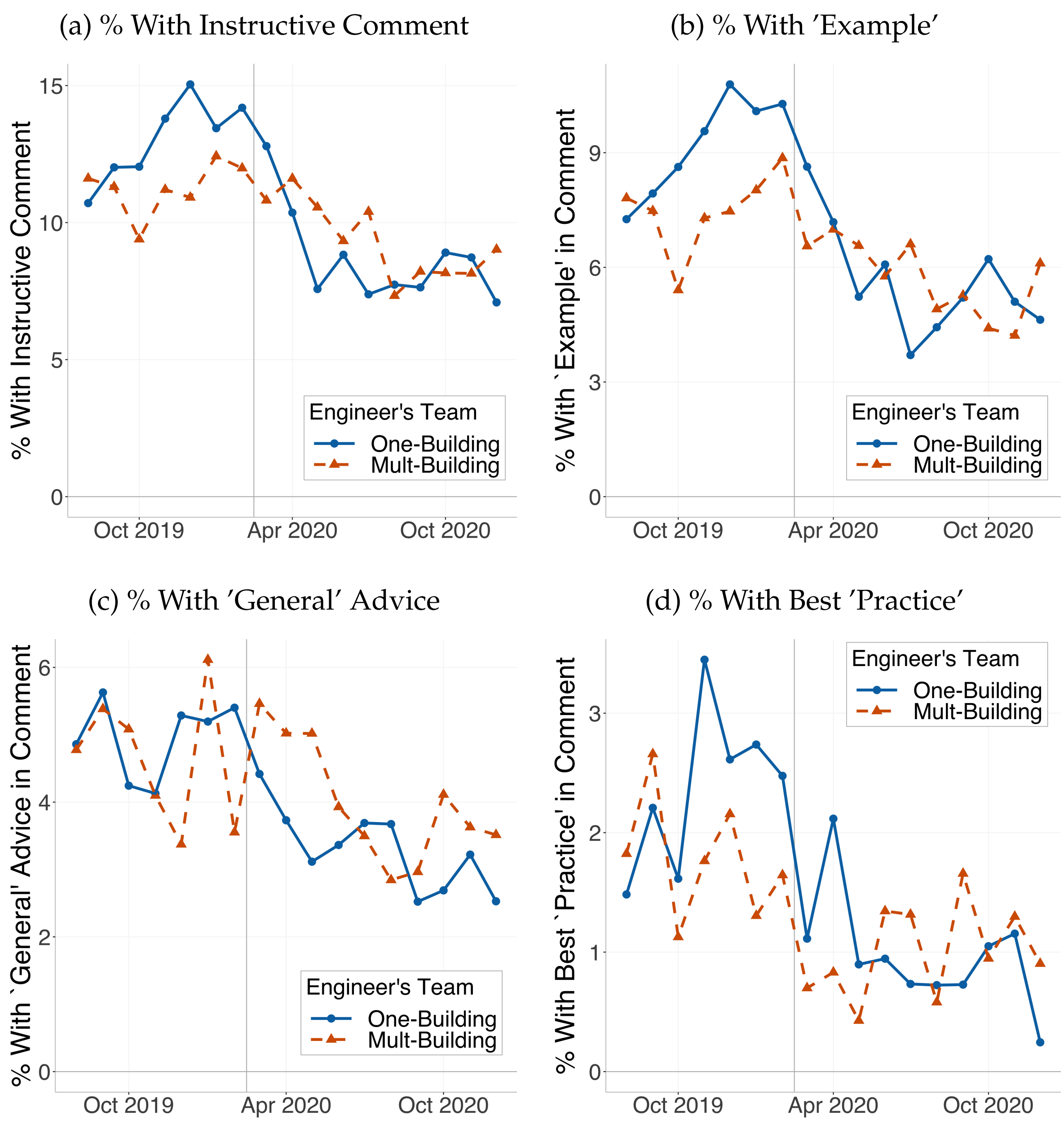
Notes: This figure illustrates the online feedback received by engineers in one-building teams (N=637) and engineers on multi-building teams (N=418) before and after the offices closed for COVID-19 (the grey vertical lines). The left plots consider comments given in standard work hours (8AM to 6PM, Monday 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.8: Proximity to Teammates and On-the-Job Training: Alternative Measures



Notes: This figure replicates Figure 1 with alternative measures of on-the-job training from coworkers. Panel (a) plots the total number of characters in comments on a program. Panel (b) plots the percent of reviews that have a specifically instructive comment that shows the engineer an 'example', gives 'general' advice, or discusses best programming 'practice'. The trends for each of these three keywords are shown separately in Figure A.9. Panel (c) plots the share of programs where reviewers write code to illustrate the desired changes. Panel (d) plots the delay until the first comment is received. In each plot, the x-axis represents the month, with the grey line highlighting the COVID-19 office closures. The monthly averages for engineers on one-building teams are in navy circles and those for engineers on multi-building teams are in red triangles. Table 3 presents these difference-in-differences analyses with controls.

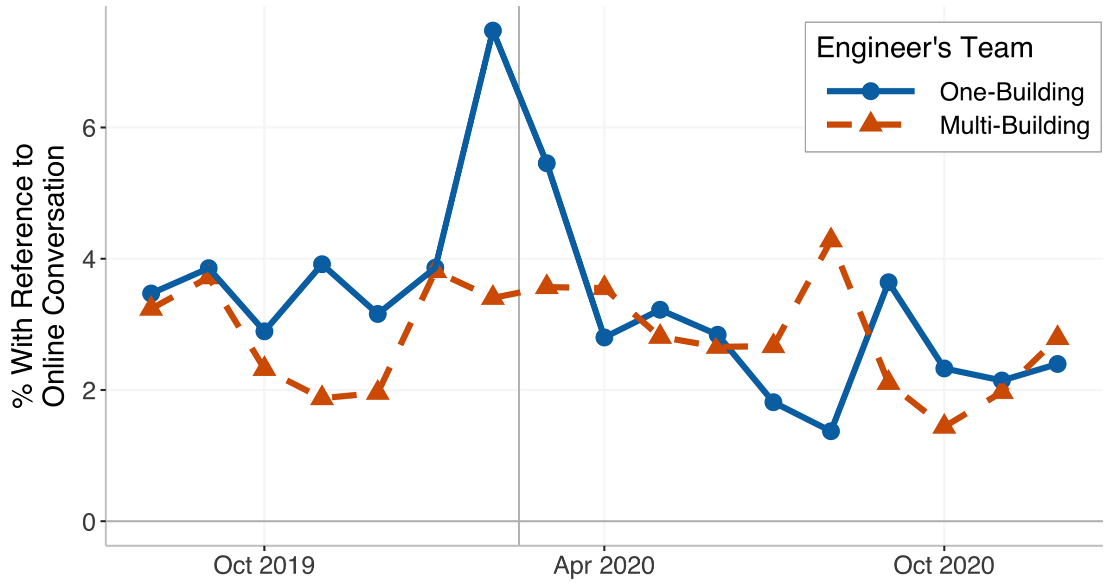
Figure A.9: Proximity to Teammates and On-the-Job Training: Instructive Comments



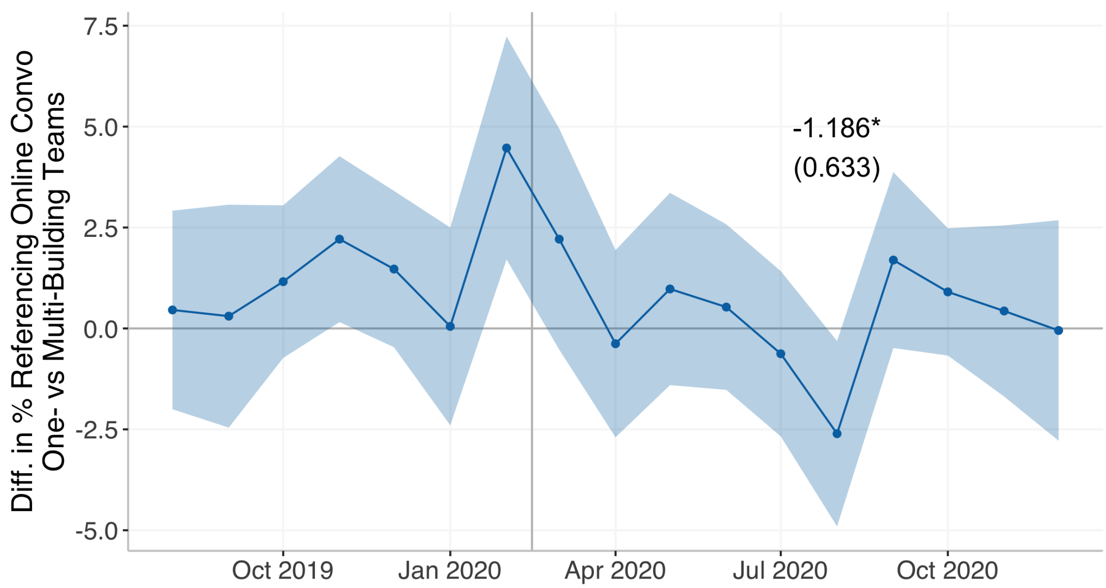
Notes: This figure replicates Figure 1 but considers three keywords used to identify reviews that invest in the engineer's skill. Panel (a) plots the percent of reviews with any instructive comment for reference. Panel (b) plots the percent of reviews where a comment gives the engineer a specific 'example' to illustrate the advice. Panel (c) plots the percent of reviews with 'general' advice. Panel (d) plots the percent with tips about best programming 'practice'. In each plot, the x-axis represents the month, with the grey line highlighting the COVID-19 office closures. The monthly averages for engineers on one-building teams are in navy circles and those for engineers on multi-building teams are in red triangles.

Figure A.10: Proximity to Teammates and References to Other Online Conversations about the Code

Panel (a): Raw Averages of References to Other Online Conversations

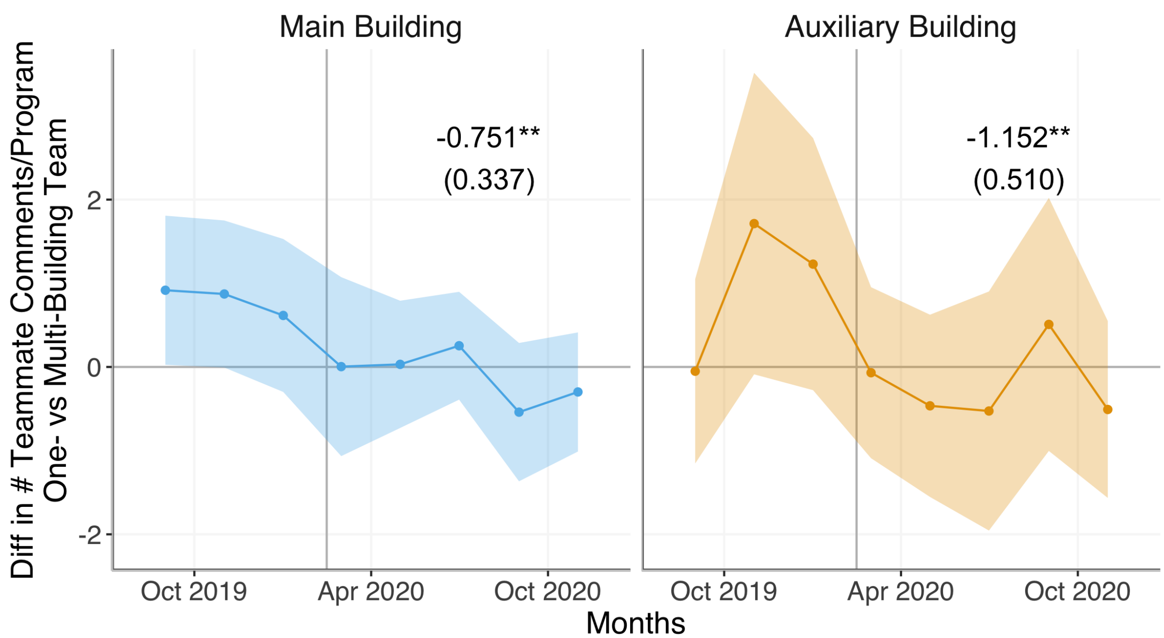


Panel (b): Dynamic, Conditional Differences



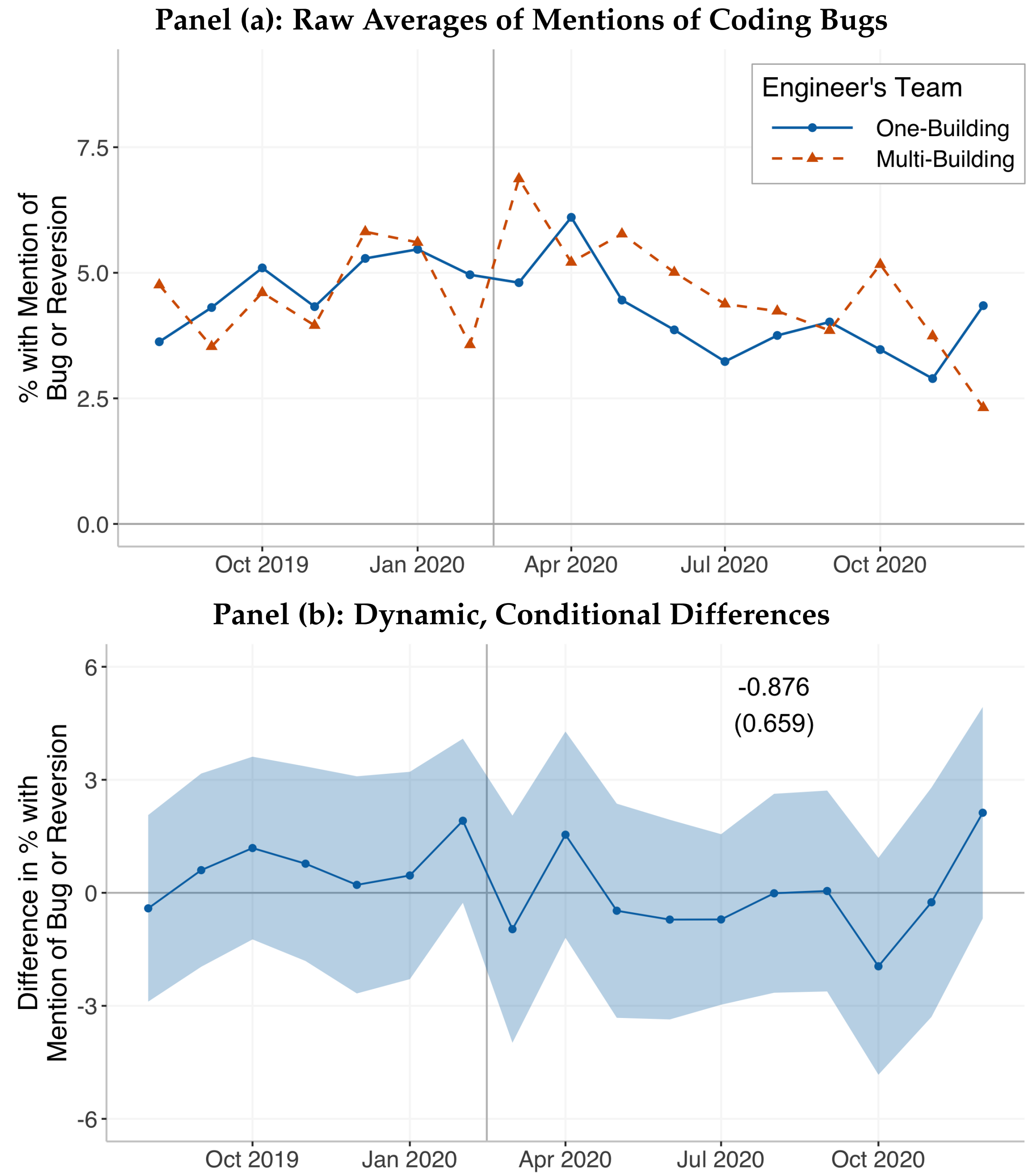
Notes: This figure investigates the relationship between physical proximity to coworkers and references to other online conversations (on Slack, Zoom, or email) about the code in peer reviews, which commenters flag to document the source of changes. The x-axis represents the month, with the grey line highlighting the COVID-19 office closures. In the top panel, the points reflect the monthly percent of reviews that mention another online conversation: the navy circles represent engineers on one-building teams; the red triangles, engineers on multi-building teams. The bottom panel plots the conditional difference, controlling for program scope and time-varying controls for team size and tenure. The annotated coefficient presents the corresponding difference-in-differences estimate. The ribbon is a 95% confidence interval with clustering by engineer. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Figure A.11: Proximity to Teammates and their Feedback: In the Main and Auxiliary Buildings



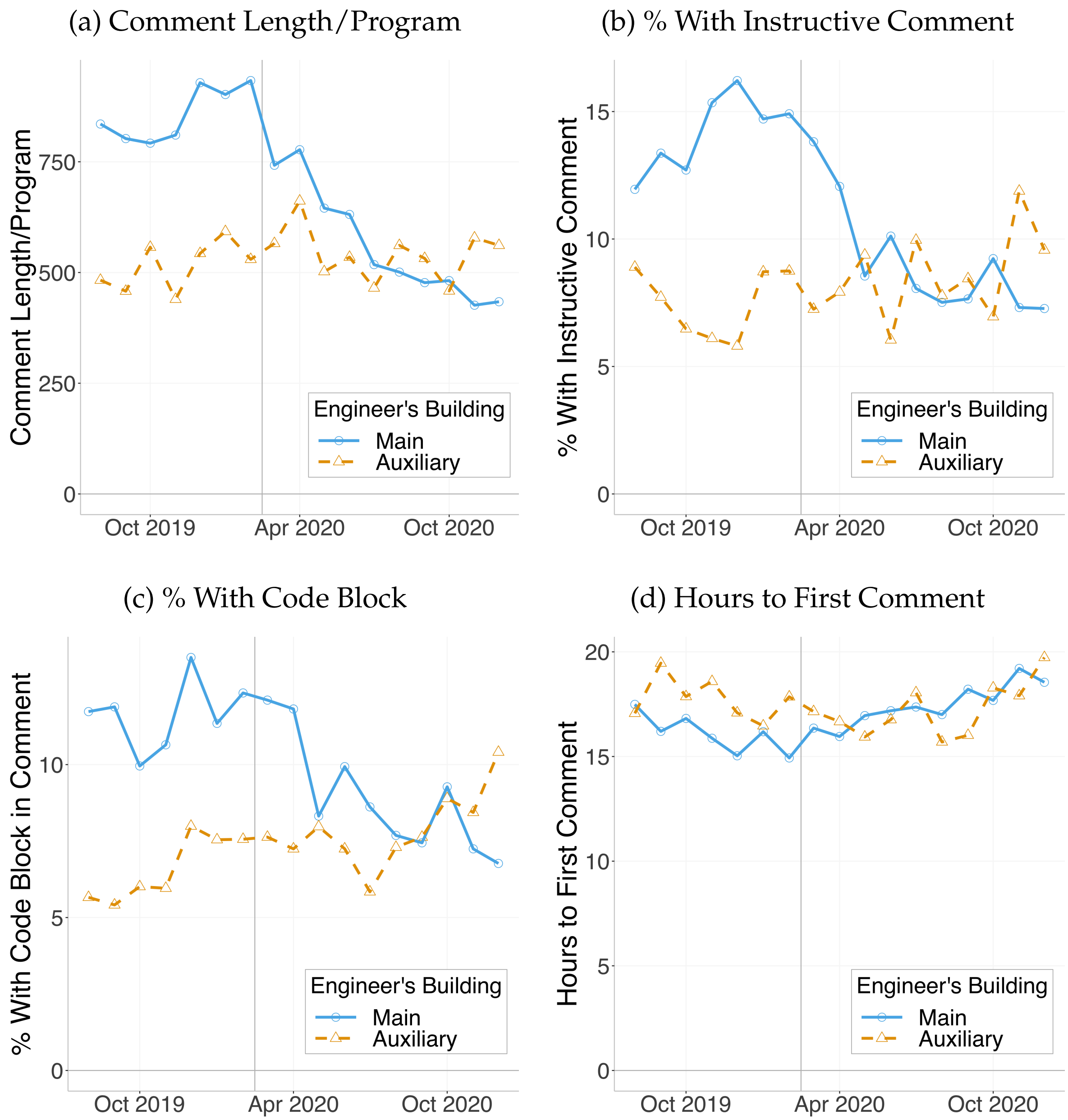
Notes: This figure compares the change in peer feedback from teammates around the COVID-19 office closures for engineers in one-building teams versus those on multi-building teams. The left panel focuses on engineers in the main building. The right panel focuses on engineers in the auxiliary building. 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. The points come from a dynamic version of this regression. Ribbons reflect 95% confidence intervals. Standard errors are clustered by engineer. *p<0.1; **p<0.05; ***p<0.01.

Figure A.12: Proximity to Teammates and Mentions of Coding Bugs



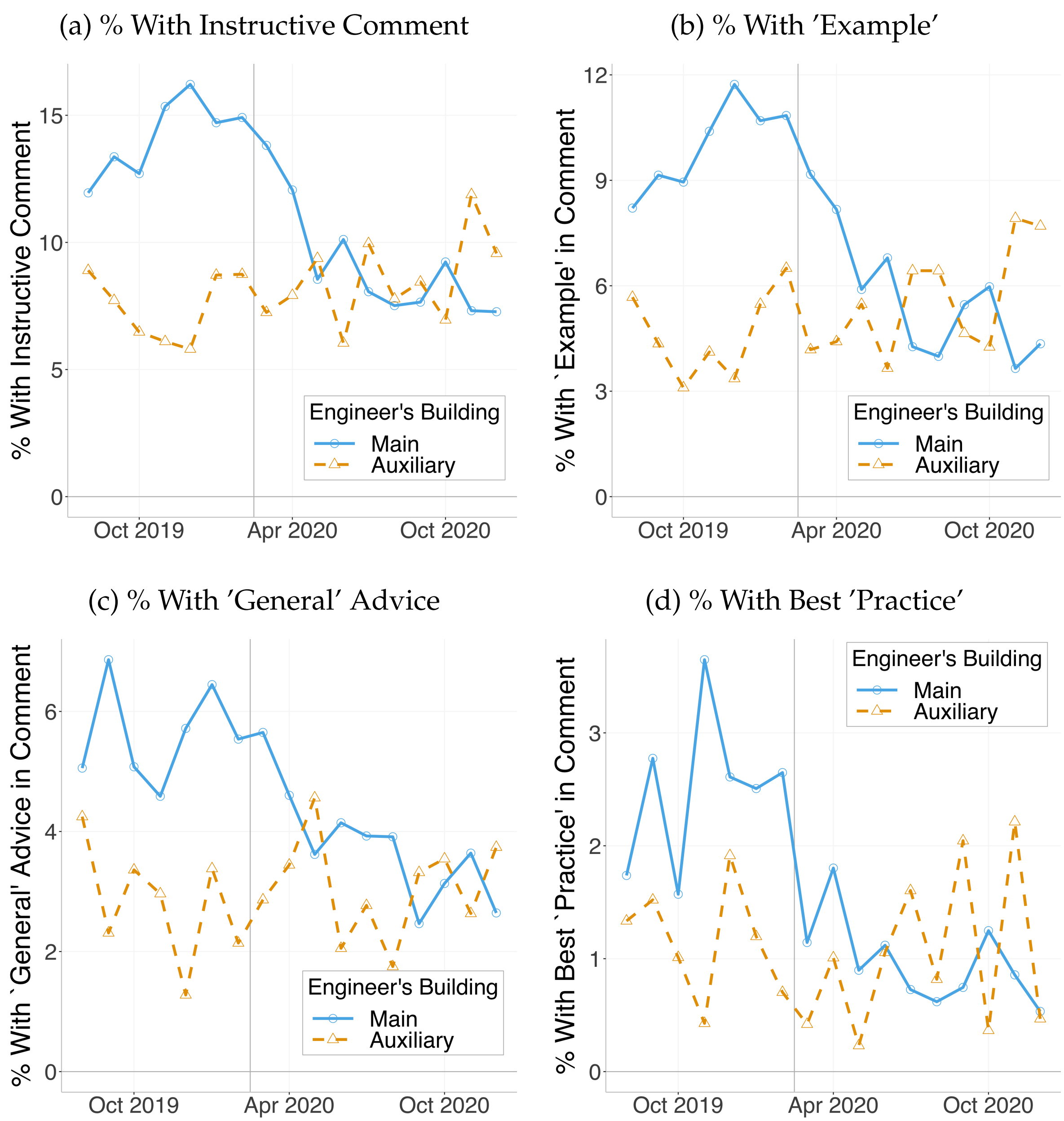
Notes: This figure compares the change in mentions of coding bugs around the COVID-19 office closures for engineers in one- and multi-building teams. Coding bugs are identified because a 'bug' is mentioned, an error needed to be 'reverted', or an edge case 'breaks' the program's logic. Since changes in the frequency of coding bugs could change the required comments without reflecting a change in on-the-job training, it is useful to test the parallelism in their evolution. The x-axis represents the month, with the grey line highlighting the COVID-19 office closures. The top panel plots the monthly averages of the percent of reviews that mention a coding bug. Engineers on one-building teams are in navy circles and engineers on multi-building teams are in red triangles. The bottom panel plots the difference between these two groups of engineers, conditional on team size, program scope, and engineer tenure. The ribbon reflects 95% confidence intervals with standard errors clustered by engineer. The annotated coefficient is the difference-in-difference estimate from Equation 1. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Figure A.13: Proximity to Non-Teammates and On-the-Job Training: Alternative Measures



Notes: This figure replicates Figure 3 with alternative measures of on-the-job training from coworkers. Panel (a) plots the total number of characters in comments on a program. Panel (b) plots the percent of reviews that have a specifically instructive comment with an 'example', 'general' advice, or tip about best programming 'practice' (Figure A.14 plots each keyword separately). Panel (c) plots the percent of programs where reviewers include code to illustrate the desired changes. Panel (d) plots the delay until the first comment is received. In each plot, the x-axis represents the month: the grey line highlights the COVID-19 office closures. The monthly averages for engineers in the main building are in building circles and those for engineers in the auxiliary building are in orange triangles. Table A.7 presents these difference-in-differences analyses with controls.

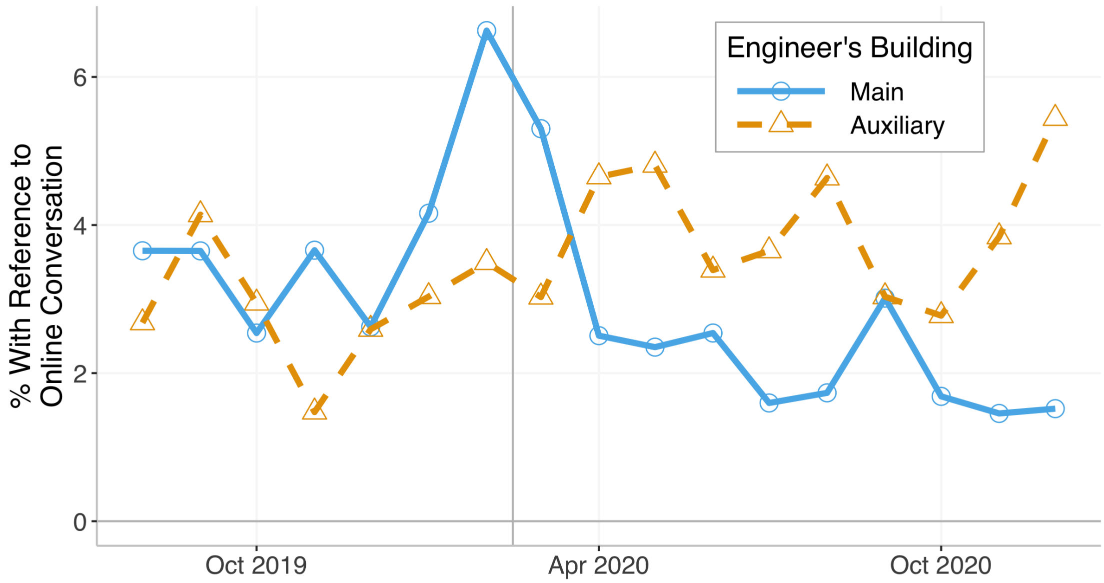
Figure A.14: Proximity to Non-Teammates and On-the-Job Training: Instructive Comments



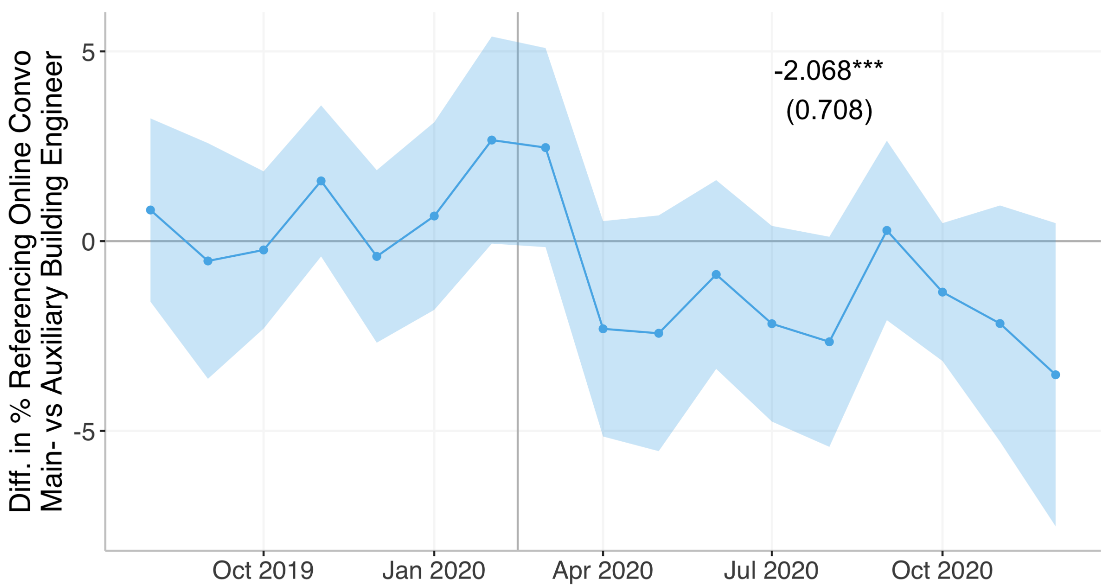
Notes: This figure replicates Figure 3 but considers three keywords used to identify reviews that invest in the engineer's skill. Panel (a) plots the percent of reviews with any instructive comment for reference. Panel (b) plots the percent of reviews where a comment gives the engineer a specific 'example' to illustrate the advice. Panel (c) plots the percent of reviews with 'general' advice. Panel (d) plots the percent with tips about best programming 'practice'. In each plot, the x-axis represents the month, with the grey line highlighting the COVID-19 office closures. The monthly averages for engineers in the main building are in building circles and those for engineers in the auxiliary building are in orange triangles.

Figure A.15: Proximity to Non-Teammates and References to Other Online Conversations about the Code

Panel (a): Raw Averages of References to Other Online Conversations

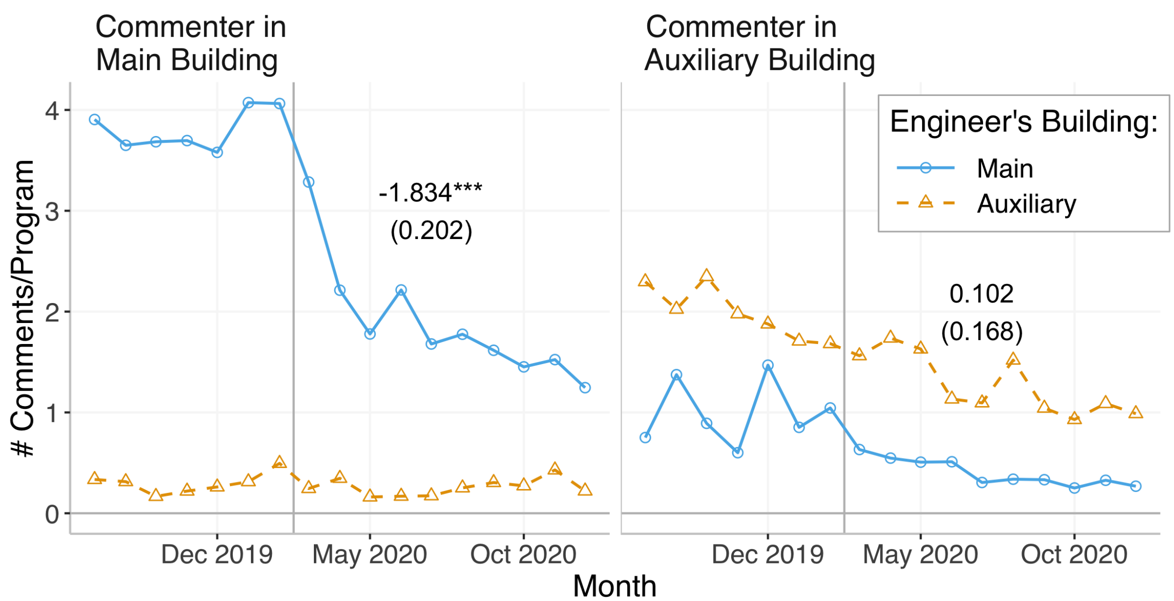


Panel (b): Dynamic, Conditional Differences



Notes: This figure compares the change in references to online conversations — over email, Slack, or Zoom — in peer reviews around the COVID-19 office closures for engineers who were initially in the firm's main building versus the auxiliary building. The x-axis represents the month, with the grey line highlighting the COVID-19 office closures. The top panel plots the monthly averages of reviews that mention an online conversation about the code: engineers in the main building are in blue circles and engineers in the auxiliary building are in orange triangles. The bottom panel plots the conditional difference, controlling for team-size, engineer tenure, and program scope. The annotated coefficient reports the difference-in-differences estimate. The ribbon reflects 95% confidence intervals with standard errors clustered by engineer. *p<0.1; **p<0.05; ***p<0.01.

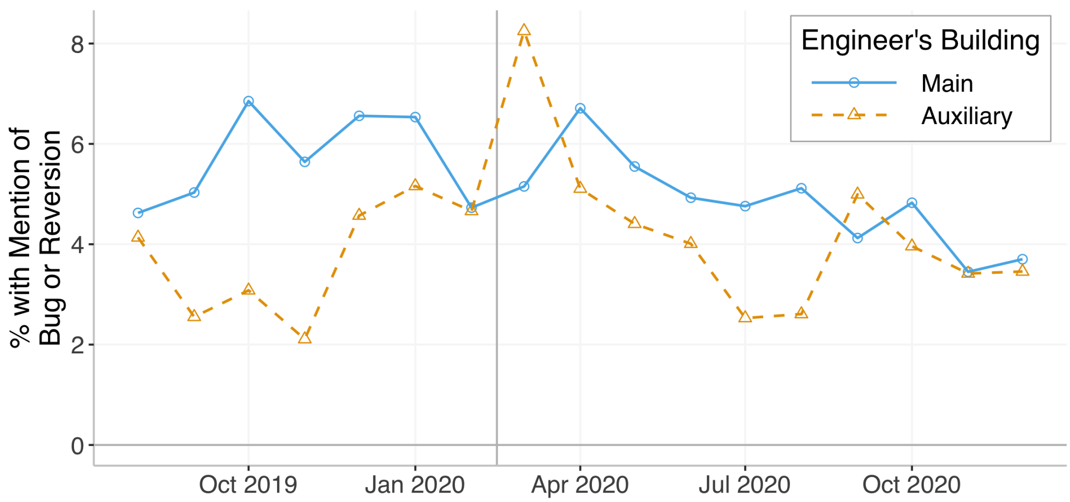
Figure A.16: Proximity to Non-Teammates and On-the-Job Training from Coworkers Outside an Engineer's Team



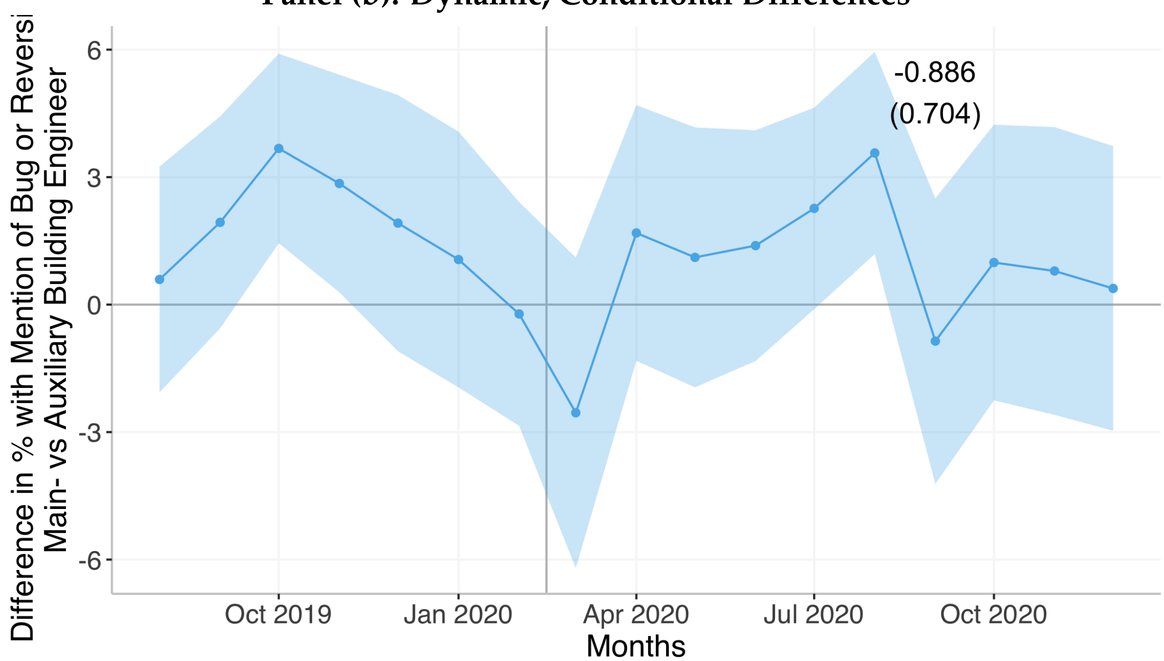
Notes: This figure compares the change in peer feedback from non-teammates around the COVID-19 office closures for engineers in the firm's main building (in blue circles) to engineers in an auxiliary building (in orange triangles) based on the commenter's location. In both plots, the x-axis represents 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 as in Equation 2. Standard errors are clustered by engineer. *p<0.1; **p<0.05; ***p<0.01.

Figure A.17: Proximity to Non-Teammates and Mentions of Coding Bugs

Panel (a): Raw Averages of Mentions of Coding Bugs

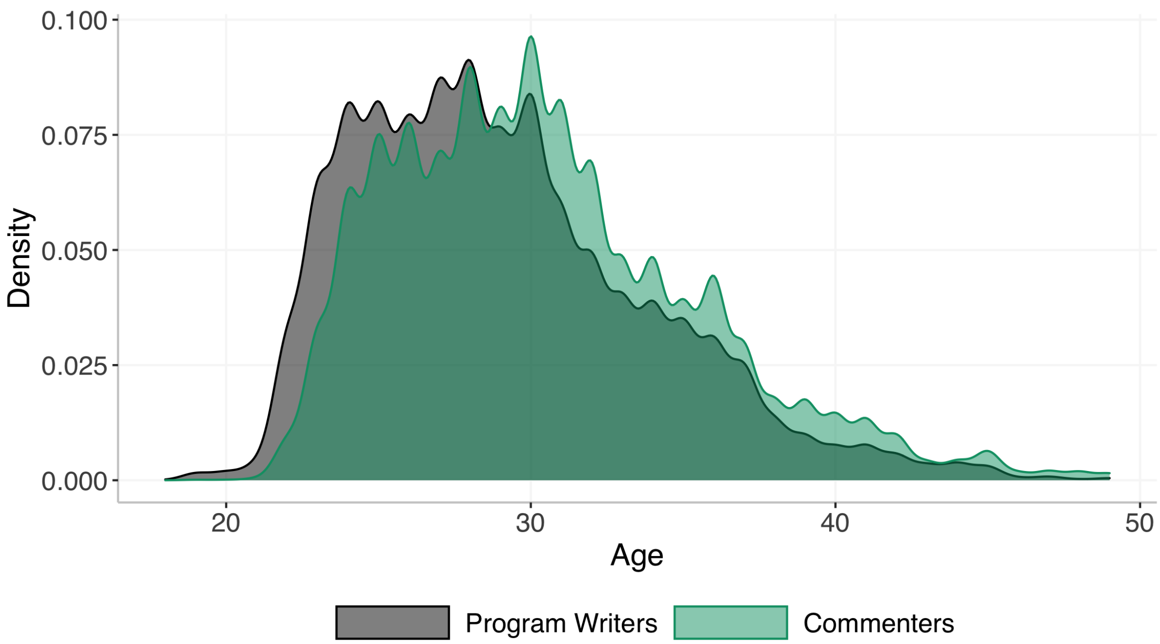


Panel (b): Dynamic, Conditional Differences



Notes: This figure compares the change in mentions of coding bugs around the COVID-19 office closures for engineers in the main building and the auxiliary one. Coding bugs are identified because a 'bug' is mentioned, an error needed to be 'reverted', or an edge case 'breaks' the program's logic. The x-axis represents the month, with the grey line highlighting the COVID-19 office closures. The top panel plots the monthly averages of the percent of reviews that mention a coding bug. Engineers in the main building are in blue circles and engineers in the auxiliary building are in orange triangles. The bottom panel plots the difference between these two groups of engineers, conditional on team size, program scope, and engineer tenure. The ribbon reflects 95% confidence intervals with standard errors clustered by engineer. The annotated coefficient is the difference-in-difference estimate from Equation 2. *p<0.1; **p<0.05; ***p<0.01.

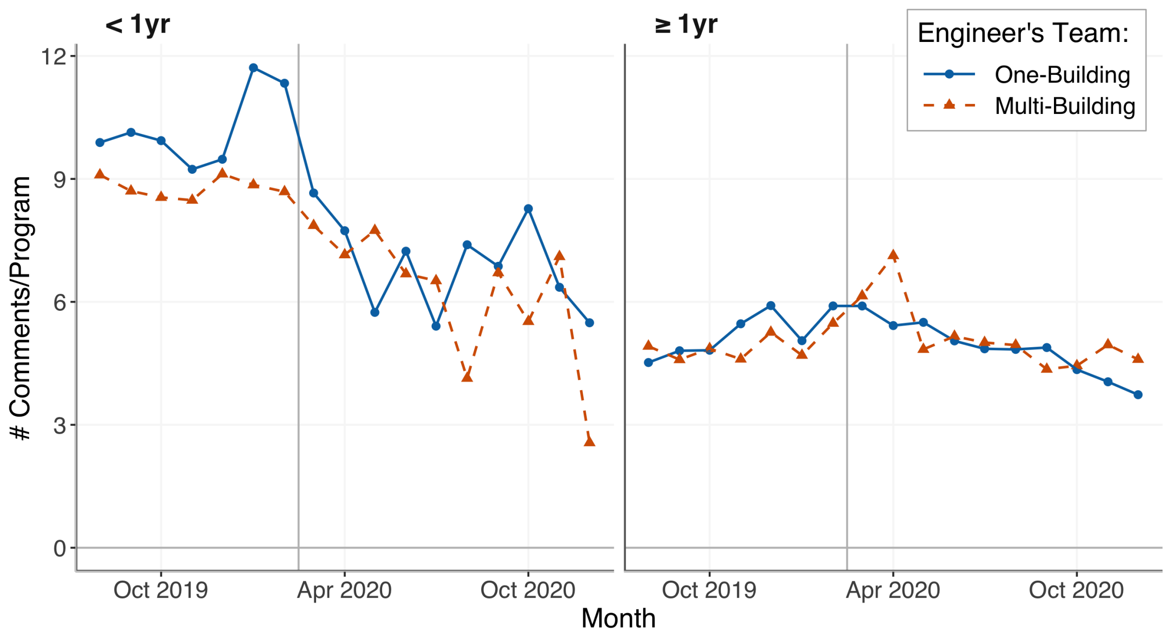
Figure A.18: Distribution of Program Writer and Commenter Ages



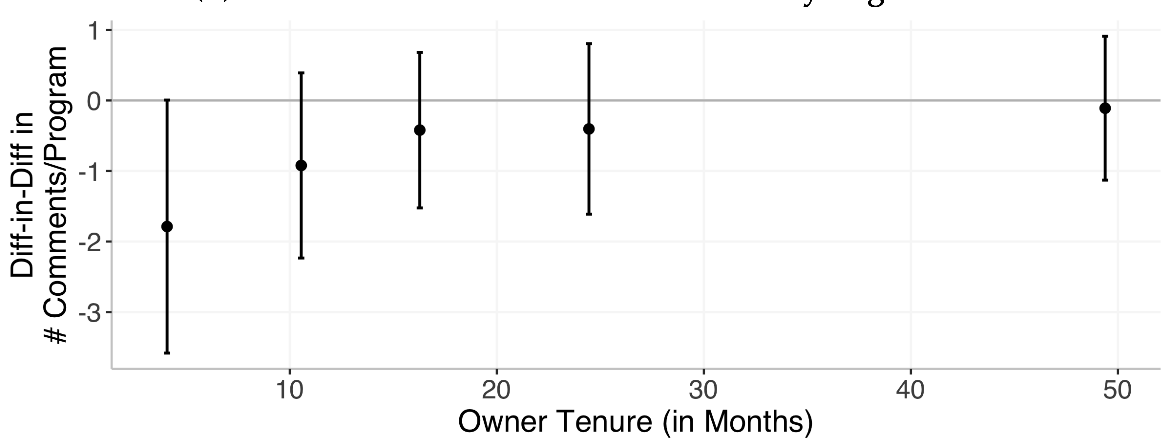
Notes: The grey histogram shows the density of ages of the software engineers who write programs, weighted by the number of programs that they write. The green distribution shows the ages of the engineers who write comments on code, again weighted by the number of programs they comment upon. The average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

Figure A.19: Impacts of Proximity on Coworker Feedback by Engineer Tenure

Panel (a): Difference-in-Differences for More and Less Tenured Engineers



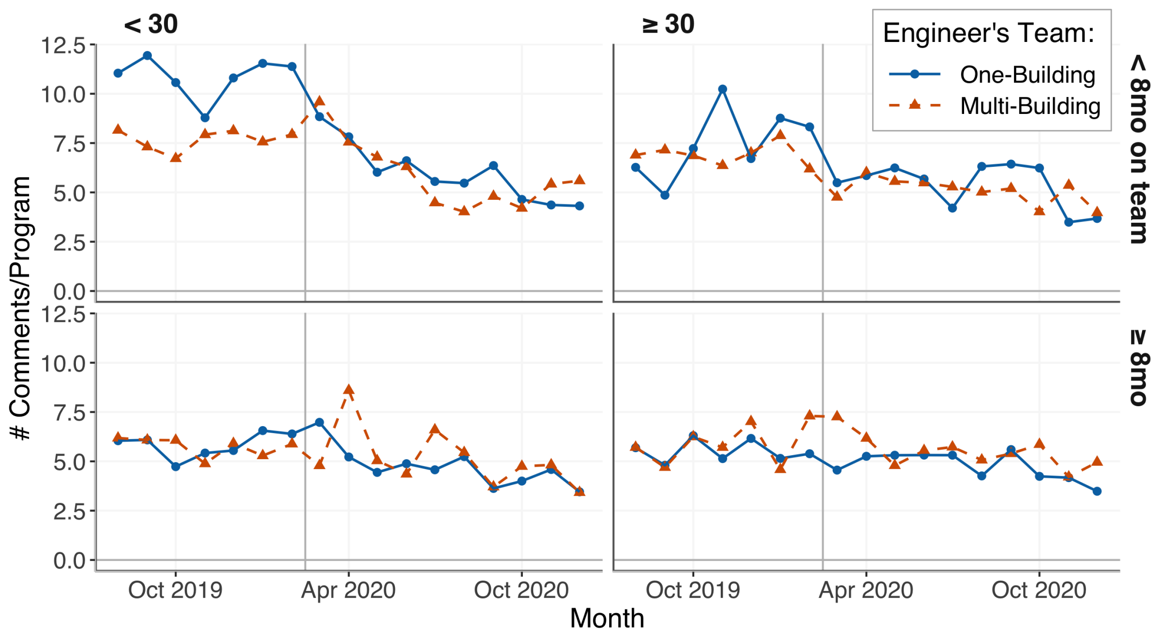
Panel (b): Difference-in-Differences Estimates by Engineer Tenure



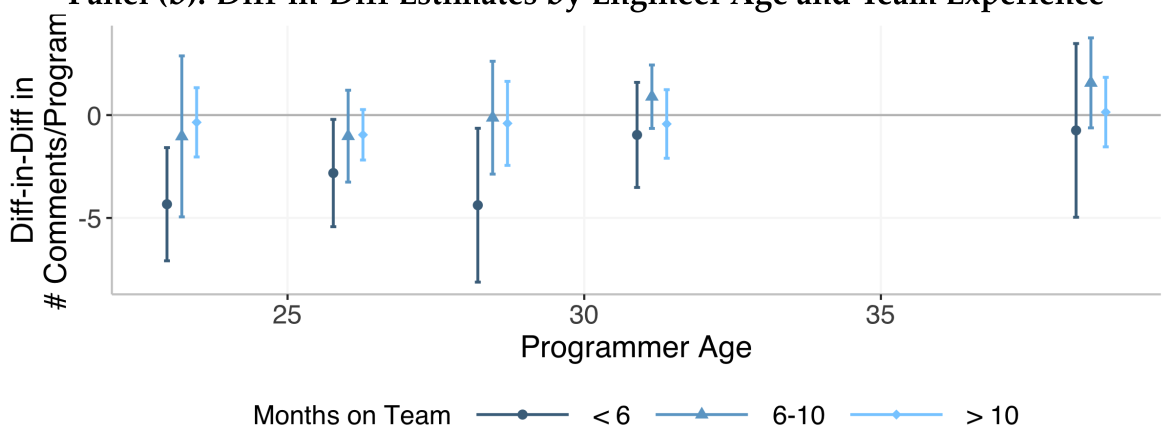
Notes: This figure compares the online feedback received by more and less tenured engineers around the COVID-19 office closures based on whether the engineer was in a one-building or multi-building team. Panel (a) shows monthly averages of the average delay until the first comment on a program in hours over time, with the grey line indicating office closures due to COVID-19. The left panel shows engineers with less than a year of experience at the firm, the right panel shows engineers with at least a year of firm experience. Panel (b) displays difference-in-differences estimates for quintiles of engineer tenure, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.20: Intergenerational Impacts of Proximity on Coworker Feedback by Engineer's Pre-pandemic Team Experience

Panel (a): Raw Averages of Comments per Program



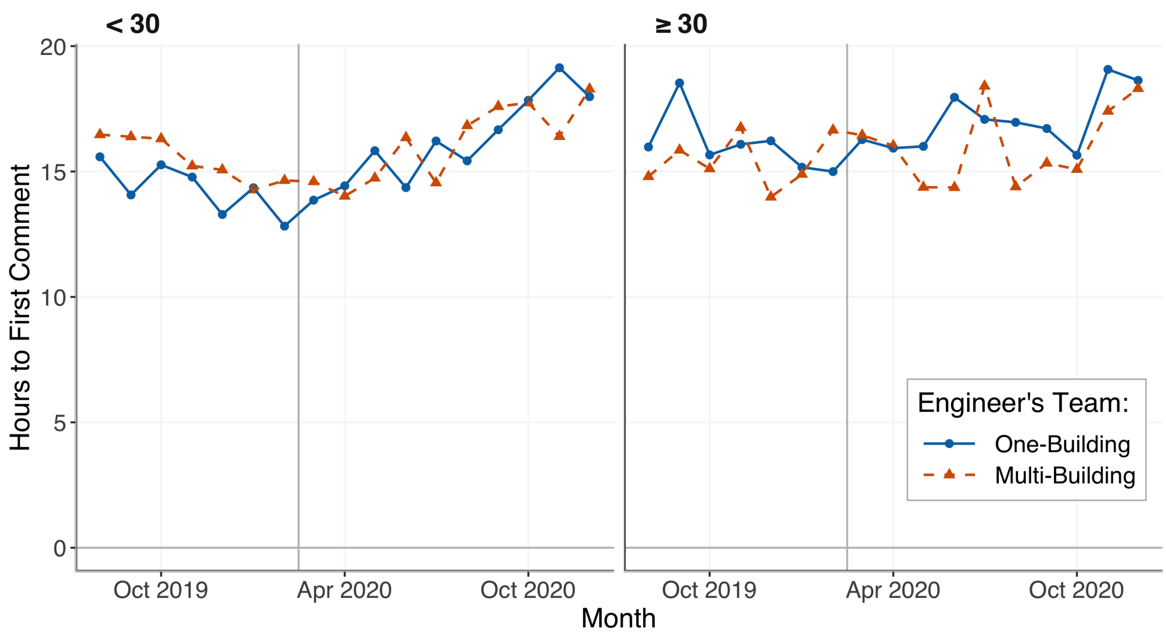
Panel (b): Diff-in-Diff Estimates by Engineer Age and Team Experience



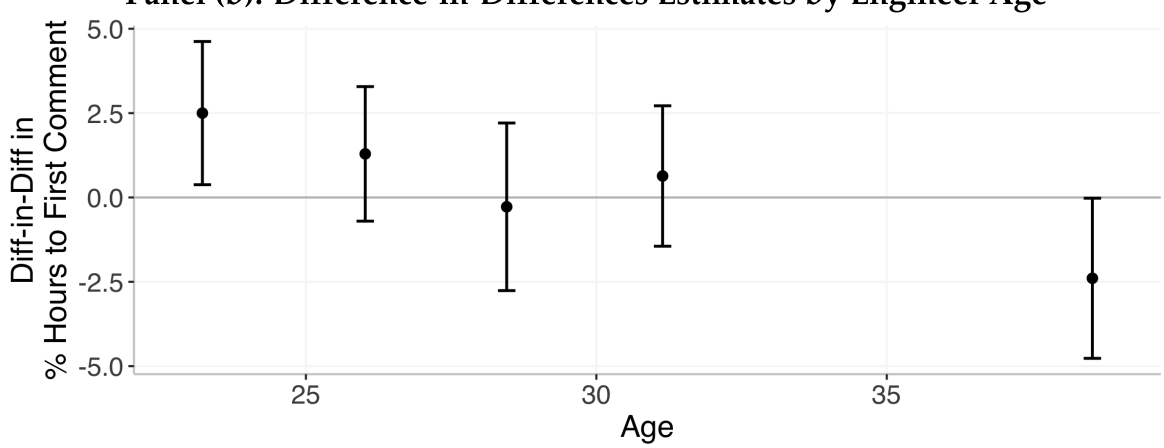
Notes: This figure compares online feedback from coworkers for younger and older workers with more and less experience on their teams around the COVID-19 office closures based on whether they were on one-building or multi-building teams. Panel (a) shows monthly averages of the number of comments received per program over time, with the grey line indicating office closures due to COVID-19. The left panel shows engineers younger than 30 years old; the right panel shows engineers 30 years or older. The top panel shows engineers who averaged less than 8 months of experience with their team before the pandemic; the bottom panel shows engineers with more team experience. Panel (b) displays difference-in-differences estimates for quintiles of engineer age separately for terciles of pre-pandemic team experience, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.21: Intergenerational Impacts of Proximity on Delays to Coworker Feedback

Panel (a): Raw Averages of Delays to Feedback



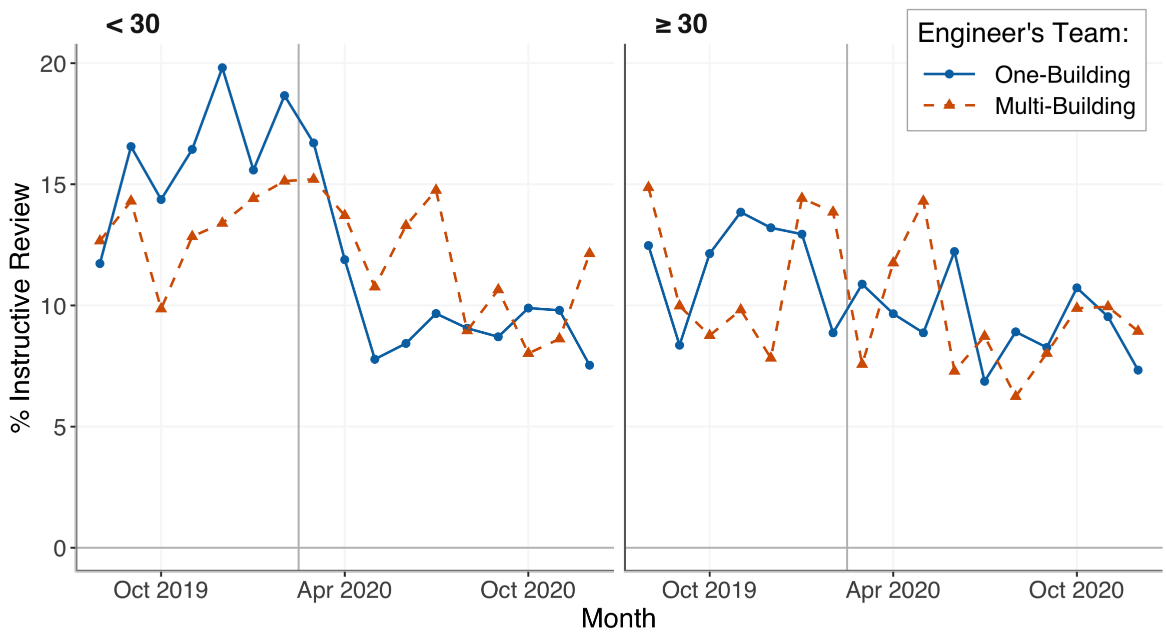
Panel (b): Difference-in-Differences Estimates by Engineer Age



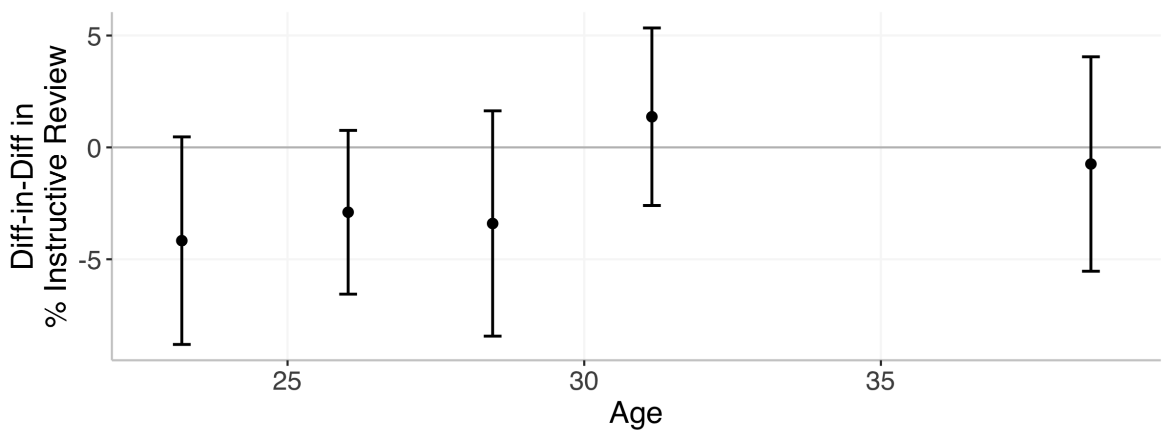
Notes: This figure compares the delays in receiving feedback for younger and older engineers around the COVID-19 office closures based on whether the engineer was on a one-building or multi-building team. Panel (a) shows monthly averages of the number of comments received per program over time, with the grey line indicating office closures due to COVID-19. Explicitly instructive reviews include advice that applies in "general", points to good "practice", or references an illustrative "example" in the code-base. Panel (b) displays difference-in-differences estimates for quintiles of engineer age, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.22: Intergenerational Impacts of Proximity on Instructive Reviews from Coworkers

Panel (a): Raw Averages of Instructive Reviews



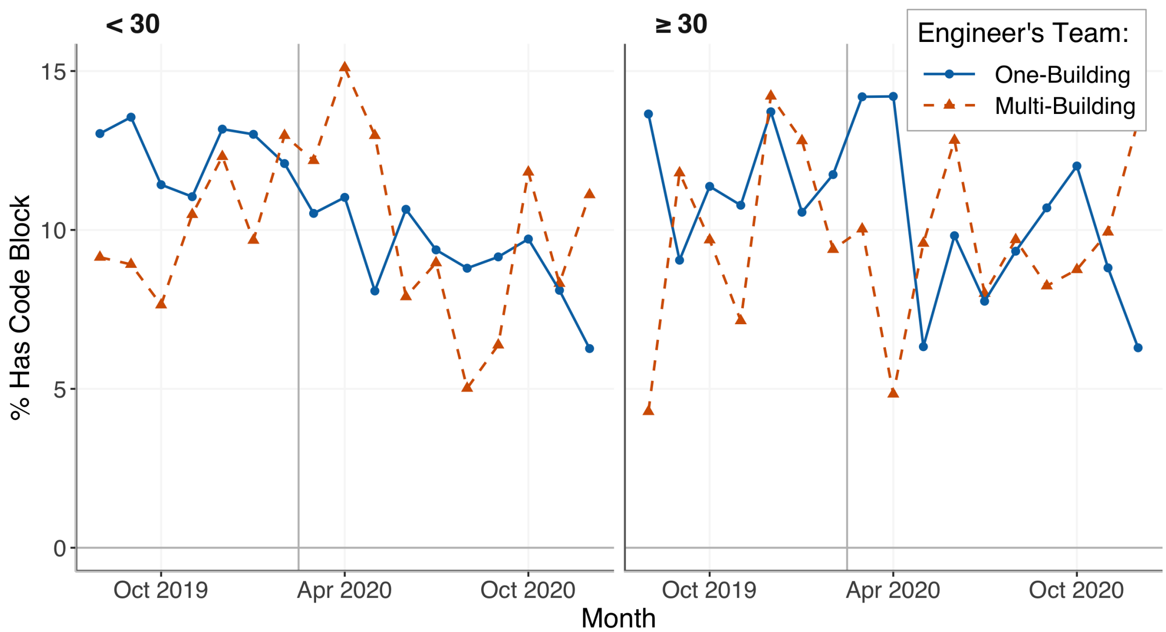
Panel (b): Difference-in-Differences Estimates by Engineer Age



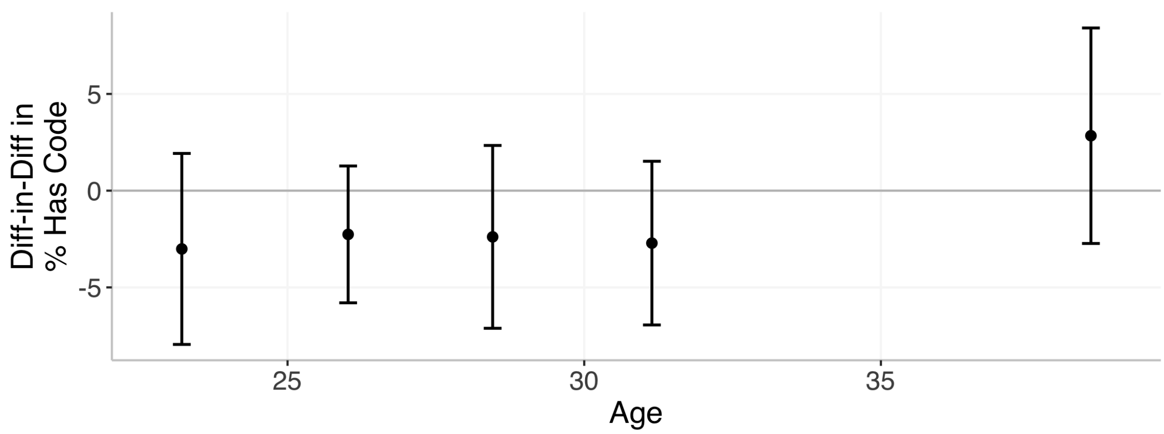
Notes: This figure compares the incidence of explicitly instructive reviews for younger and older engineers around the COVID-19 office closures based on whether the engineer was on a one-building or multi-building team. Panel (a) shows monthly averages of the percent of reviews with an explicitly instructive comment, with the grey line indicating office closures due to COVID-19. The left panel shows engineers younger than 30 years old; the right panel shows engineers 30 years or older. Panel (b) displays difference-in-differences estimates for quintiles of engineer age, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.23: Intergenerational Impacts of Proximity on Reviews with Illustrative Code Blocks from Coworkers

Panel (a): Raw Averages of Reviews with Code Blocks

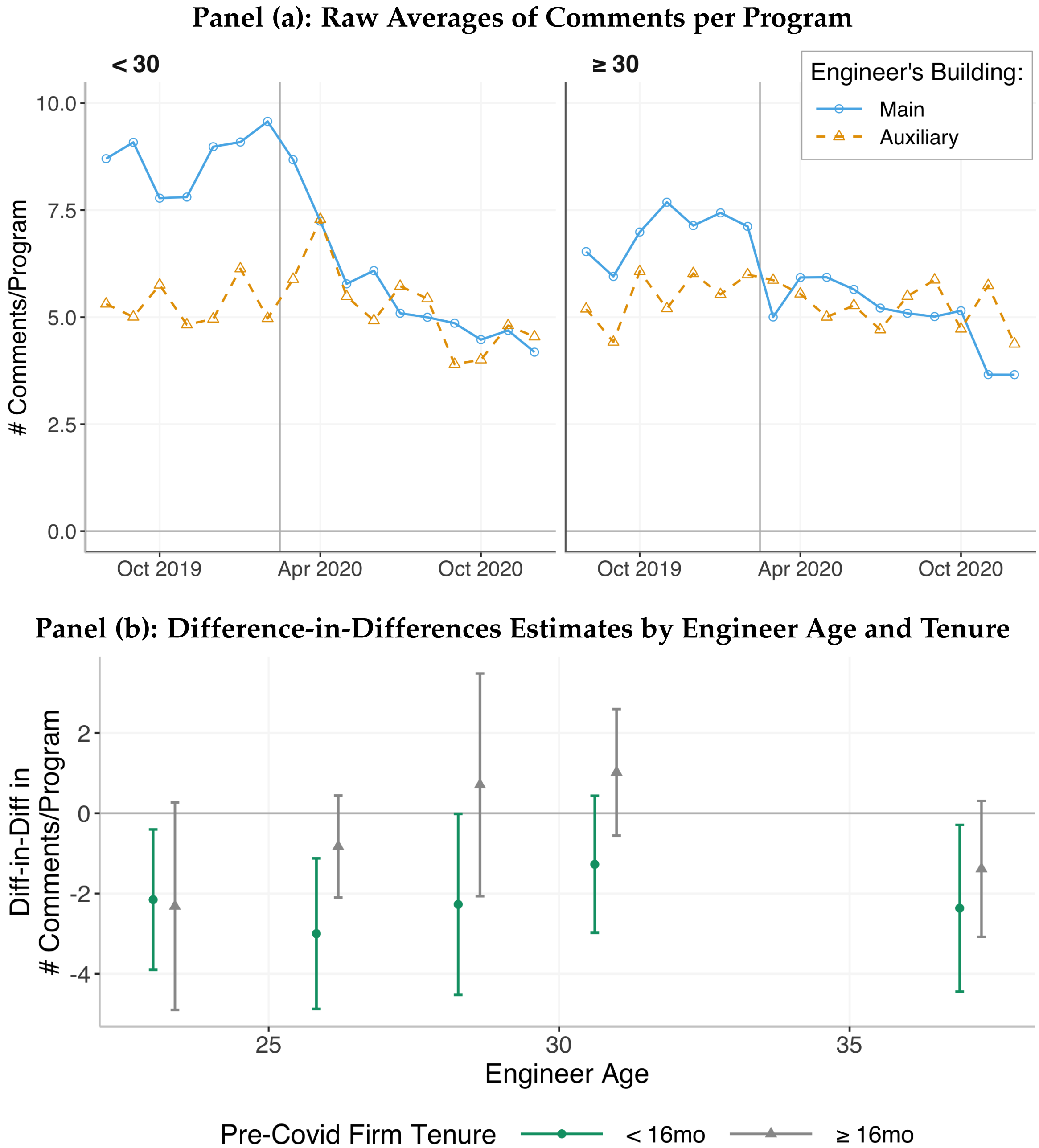


Panel (b): Difference-in-Differences Estimates by Engineer Age



Notes: This figure compares the incidence of reviews with illustrative blocks of code for younger and older engineers around the COVID-19 office closures based on whether the engineer was on a one-building or multi-building team. Panel (a) shows monthly averages of the percent of reviews with an block of code, with the grey line indicating office closures due to COVID-19. The left panel shows engineers younger than 30 years old; the right panel shows engineers 30 years or older. Panel (b) displays difference-in-differences estimates for quintiles of engineer age, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

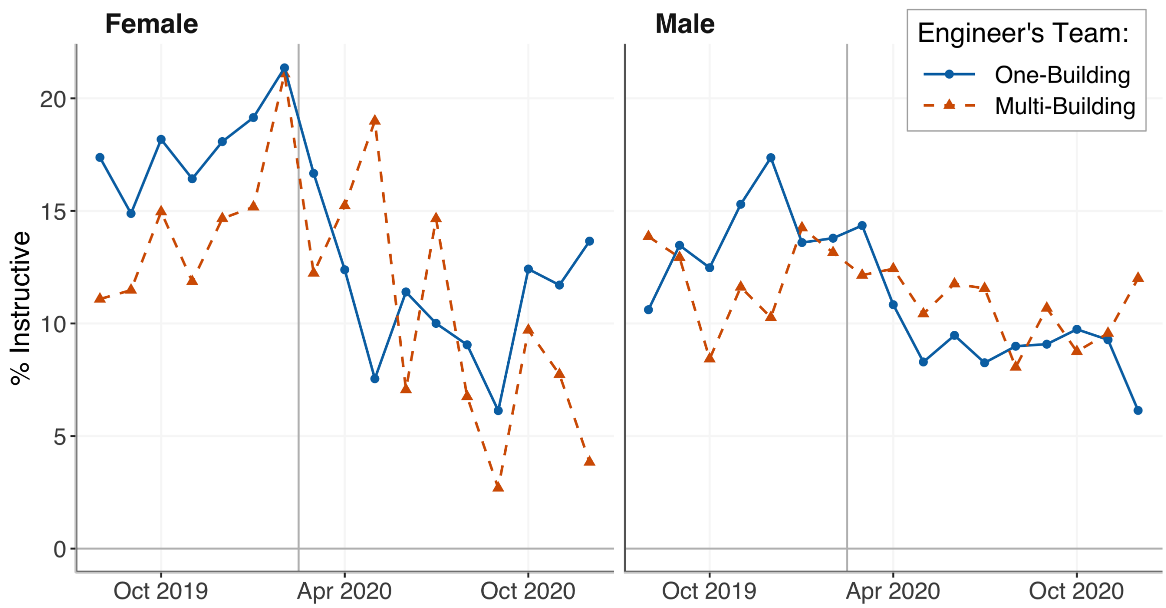
Figure A.24: Intergenerational Impacts of Proximity on Coworker Feedback by Main vs Auxiliary Building



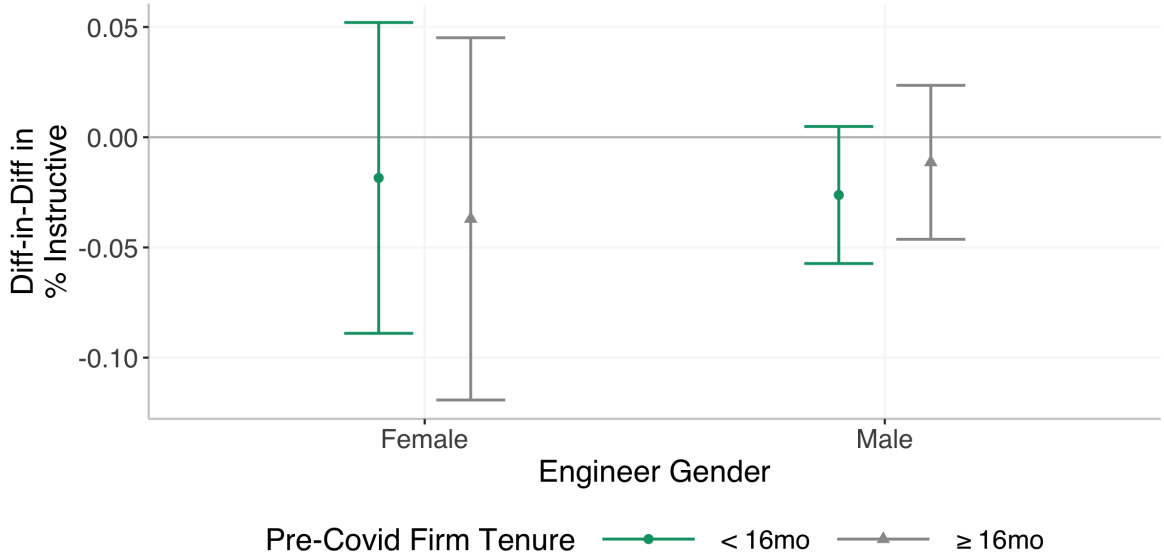
Notes: This figure compares the change coworker feedback around the COVID-19 office closures for engineers in the main or auxiliary building, separately for younger and older workers. Panel (a) shows monthly averages of the number of comments received per program over time, with the grey line indicating office closures due to COVID-19. The left panel shows engineers younger than 30 years old, the right panel shows engineers 30 years or older. Panel (b) displays difference-in-differences estimates for quintiles of engineer age for engineers with above and below mean pre-pandemic tenure at the firm, where each estimate comes from Equation 2 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.25: Gendered Impacts of Proximity on Coworker Feedback with Instructive Content

Panel (a): Raw Averages in Instructive Reviews



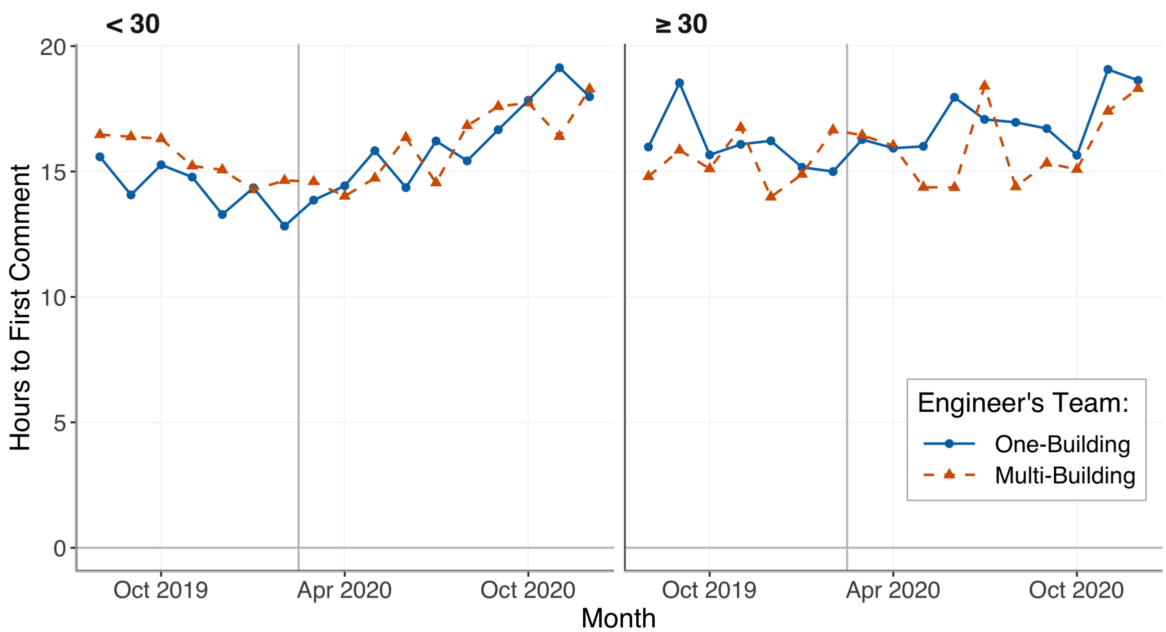
Panel (b): Difference-in-Differences Estimates by Engineer Gender and Tenure



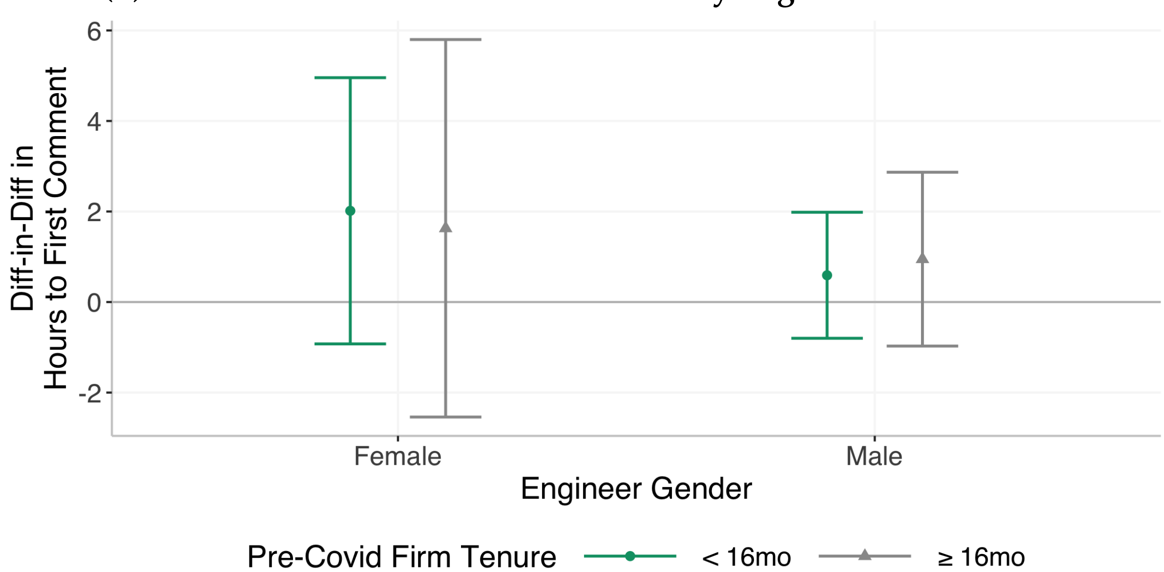
Notes: This figure compares the percent of instructive comments per program for female and male engineers around the COVID-19 office closures based on whether the engineer was on a one-building or multi-building team. Panel (a) shows monthly averages of the number of explicitly instructive comments received per program over time, with the grey line indicating office closures due to COVID-19. Explicitly instructive reviews include advice that applies in "general", points to good "practice", or references an illustrative "example" in the code-base. Panel (b) displays difference-in-differences estimates by gender and tenure, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.26: Gendered Impacts of Proximity on Delay Until Reviews from Coworkers

Panel (a): Raw Averages in Delays Until First Comment



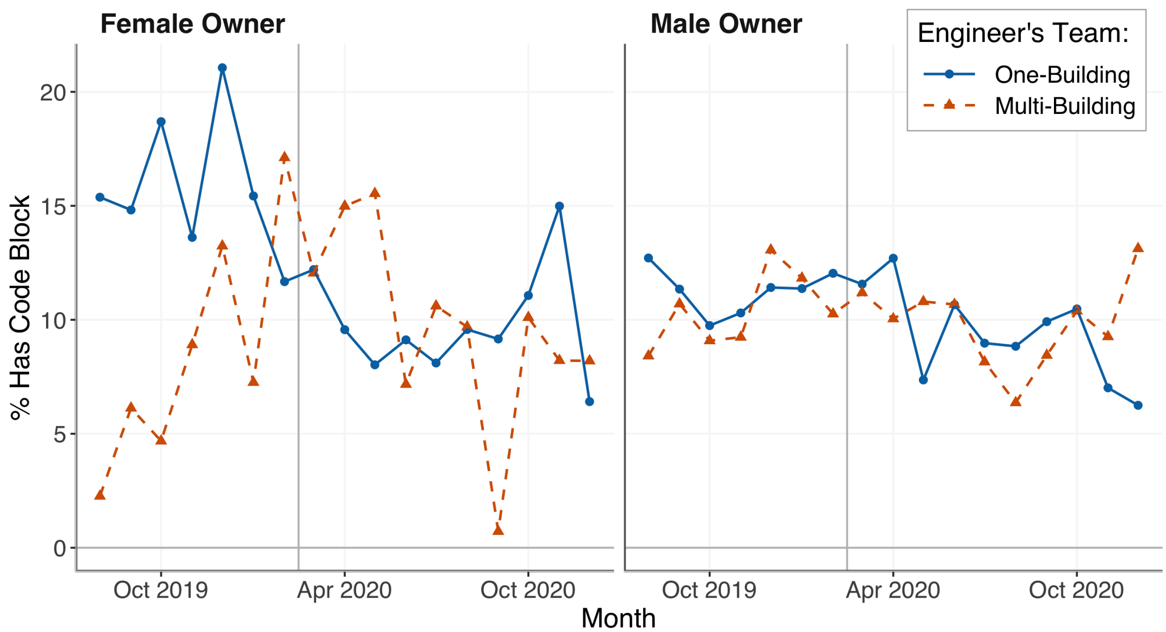
Panel (b): Difference-in-Differences Estimates by Engineer Gender and Tenure



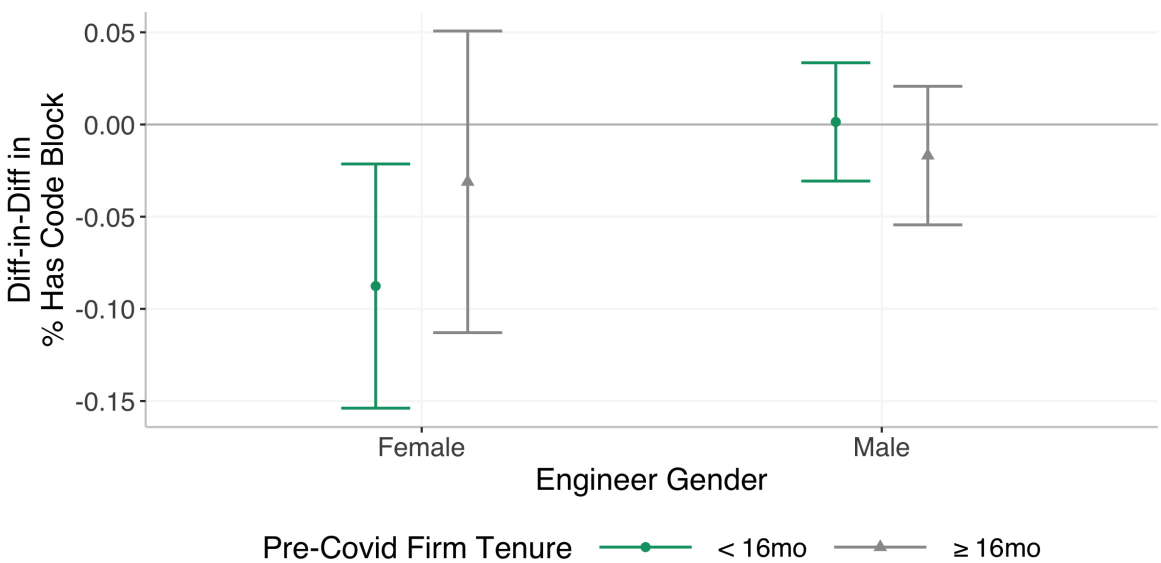
Notes: This figure compares the delay in receiving reviews for female and male engineers around the COVID-19 office closures based on whether the engineer was on a one-building or multi-building team. Panel (a) shows monthly averages of hours until a comment is given, with the grey line indicating office closures due to COVID-19. The left panel shows female engineers; the right male. Panel (b) displays difference-in-differences estimates by gender and tenure, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.27: Gendered Impacts of Proximity on Reviews with Illustrative Code Blocks from Coworkers

Panel (a): Raw Averages in Reviews with Code Blocks

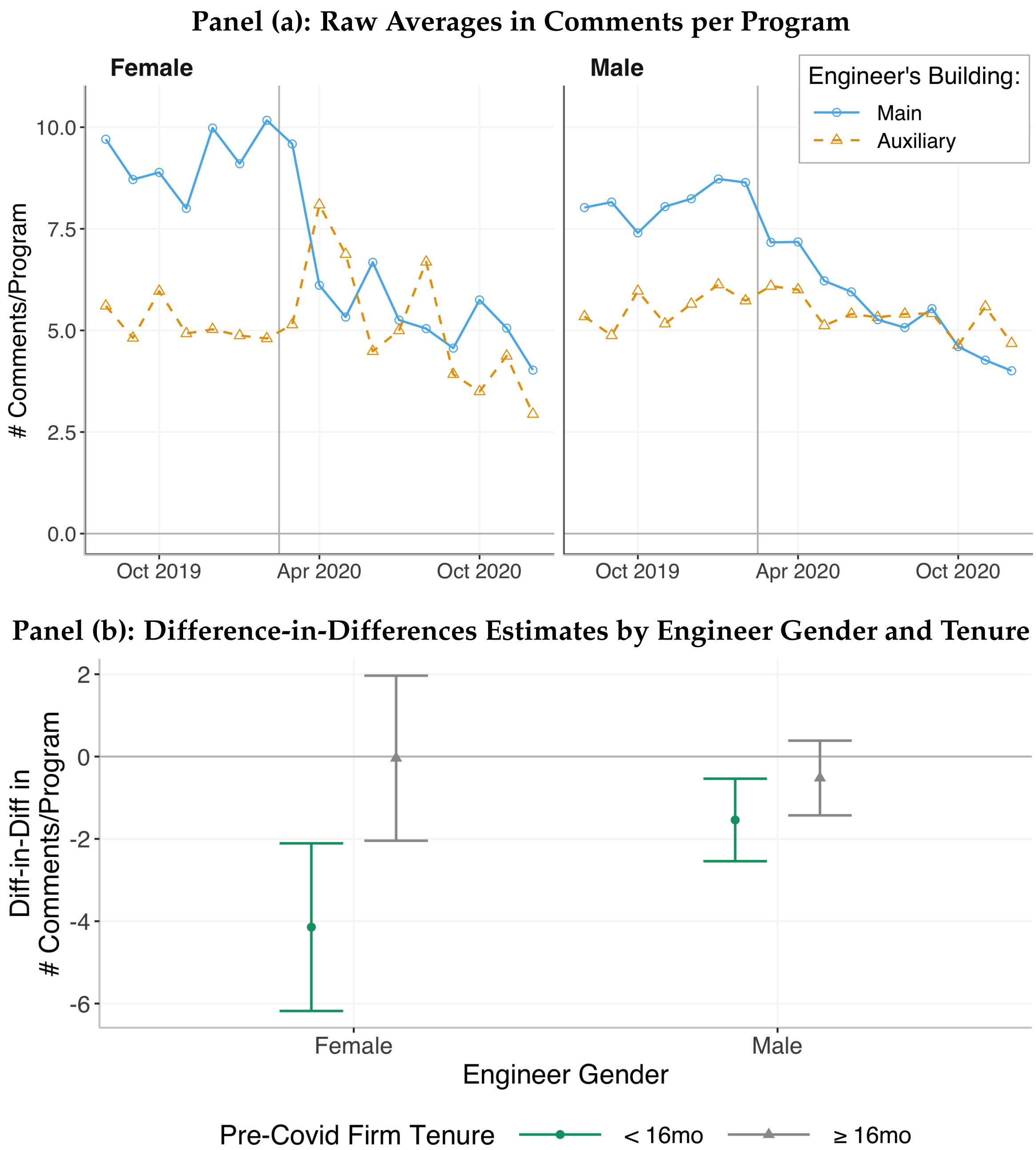


Panel (b): Difference-in-Differences Estimates by Engineer Gender and Tenure



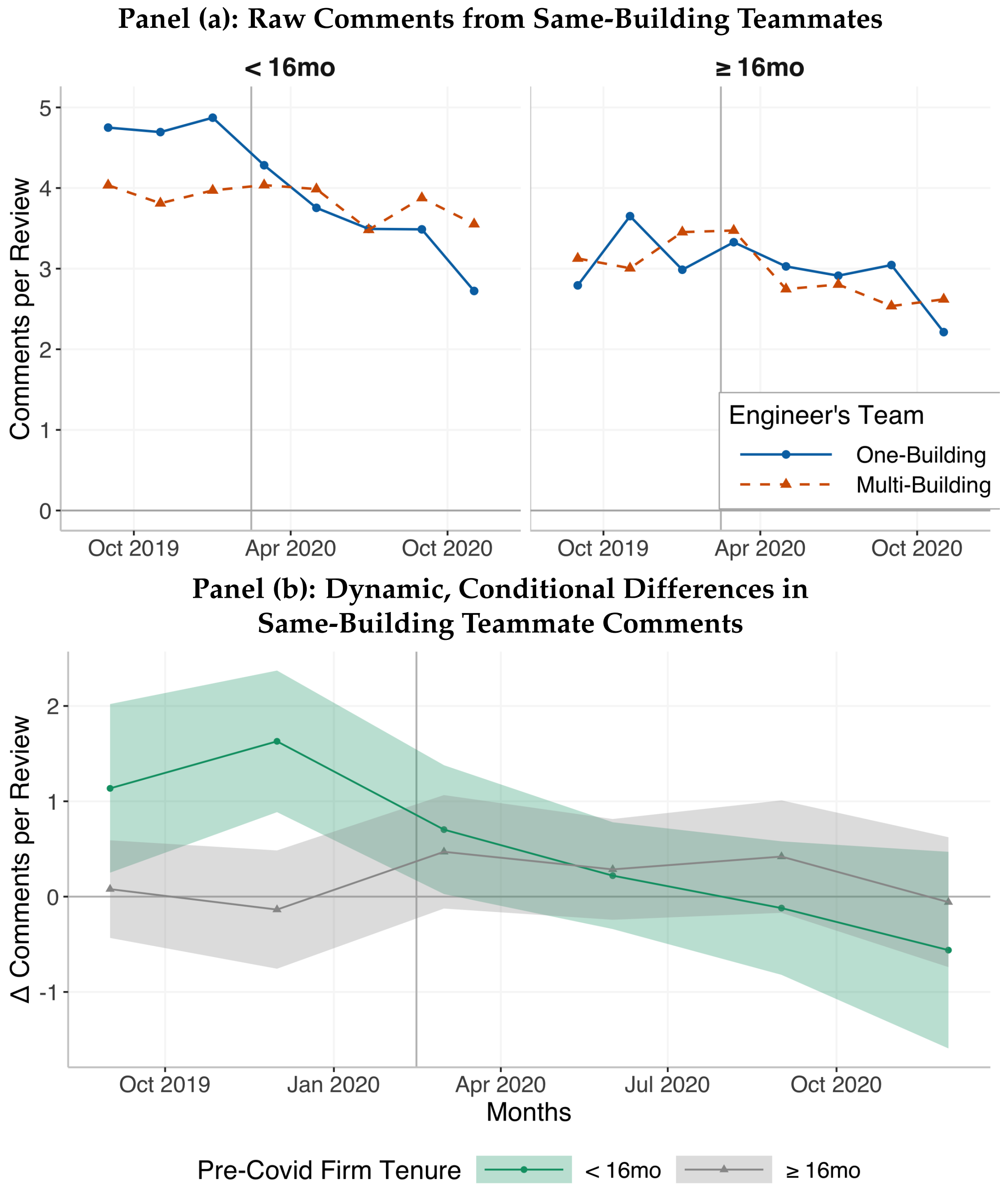
Notes: This figure compares the incidence of reviews with illustrative blocks of code for female and male engineers around the COVID-19 office closures based on whether the engineer was on a one-building or multi-building team. Panel (a) shows monthly averages of the percent of reviews with an block of code, with the grey line indicating office closures due to COVID-19. The left panel shows female engineers; the right panel male engineers. Panel (b) displays difference-in-differences estimates by gender and tenure, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.28: Gendered Impacts of Proximity on Coworker Feedback by Main vs Auxiliary Building



Notes: This figure compares the change coworker feedback around the COVID-19 office closures for engineers in the main or auxiliary building, separately for female and male engineers. Panel (a) shows monthly averages of the number of comments received per program over time, with the grey line indicating office closures due to COVID-19. The left panel shows female engineers; the right panel male engineers. Panel (b) displays difference-in-differences estimates by engingeer gender and tenure, where each estimate comes from Equation 2 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.29: Externalities from Distant Teammates By Tenure



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.

I.B Tables

Table A.1: Summary Statistics

Characterizing Engineers in the Main and Auxiliary Buildings Before and After the COVID-19 Closures

		Before Closures			**After Closures**			
	Full Sample	One-Building	Multi-Building	Δ_0	One-Building	Multi-Building	Δ_1	**Diff-in-Diff** $\Delta_1 - \Delta_0$
% Teammates in Building	39.66	89.77	80.81	8.954	0.00	0.00	0.000	-8.954
				(1.409)			(0.000)	(1.409)
# Teammates	5.61	5.51	6.17	-0.656	5.36	5.96	-0.603	0.052
				(0.203)			(0.219)	(0.119)
% Female	18.72	20.13	14.88	5.254	21.31	12.56	8.754	3.500
				(2.883)			(2.950)	(1.715)
Engineer Traits								
Age (Years)	28.86	28.42	29.70	-1.287	28.47	30.05	-1.578	-0.292
				(0.417)			(0.379)	(0.264)
% Parent	15.97	14.91	21.24	-6.334	14.13	18.75	-4.619	1.715
				(5.246)			(5.343)	(2.610)
Firm Tenure (Yrs)	1.63	1.18	1.79	-0.607	1.68	2.31	-0.632	-0.025
				(0.113)			(0.123)	(0.069)
Job Level	1.81	1.56	2.05	-0.490	1.74	2.31	-0.574	-0.083
				(0.055)			(0.056)	(0.044)
Hourly Pay	55.79	53.14	57.86	-4.723	55.18	61.04	-5.869	-1.145
				(0.606)			(0.624)	(0.448)
# Changed Lines/Program	475.43	523.65	568.47	-44.817	377.90	541.26	-163.359	-118.542
				(57.754)			(44.600)	(65.833)
Program Scope								
# Changed Files/Program	6.90	7.15	7.54	-0.393	6.06	7.93	-1.866	-1.473
				(0.516)			(0.500)	(0.640)
# Commenters/Program	1.27	1.35	1.24	0.108	1.25	1.19	0.053	-0.054
				(0.033)			(0.030)	(0.037)
Peer Reviews								
# Comments/Program	6.49	8.39	5.50	2.891	5.69	5.40	0.293	-2.598
				(0.350)			(0.279)	(0.369)
Characters/Comment	79.88	79.29	73.72	5.568	81.97	81.18	0.788	-4.780
				(2.434)			(2.723)	(3.101)
% From Older Engineer	58.42	61.48	53.10	8.381	59.95	52.82	7.126	-1.255
				(2.743)			(2.947)	(2.346)
% With Instructive Comment	11.81	15.89	8.45	7.439	10.58	9.39	1.188	-6.251
				(0.993)			(0.842)	(1.173)
% With Code	10.42	12.80	7.64	5.166	10.18	8.50	1.678	-3.488
				(0.921)			(0.945)	(1.197)
Hours Delay Until First Comment	15.70	14.61	16.40	-1.795	16.25	15.97	0.280	2.075
				(0.466)			(0.432)	(0.582)
# Software Engineers	1,055	723	260		634	242		
# Months	17	7	7		10	10		
# Programs Written	29,959	9,436	4,569		11,327	4,627		
# Comments Received	174,424	64,071	24,687		61,521	24,145		

Notes: Standard errors are clustered by engineer.

Table A.2: Engineers' Baseline Characteristics by their Proximity to Teammates and Non-Teammates

	Tenure	Job Level	Pay	Changed Lines	Changed Files
		Engineer Traits		Program Traits	
	(1)	(2)	(3)	(4)	(5)
One-Building Team	-0.504	0.087	0.824	-152.100^{**}	-1.142^{*}
	(1.424)	(0.066)	(0.746)	(71.700)	(0.619)
Main Building	-6.973^{***}	-0.544^{***}	-5.228^{***}	48.370	0.307
	(1.648)	(0.067)	(0.753)	(78.370)	(0.657)
Dependent Mean	16.32	1.71	55.79	536.88	7.26
Percentage Difference					
One-Building Team	-3.09%	5.08%	1.51%	-28.32%	-15.73%
Main Building	-42.72%	-31.83%	-9.59%	9.01%	4.23%
# Engineers	983	983	983	983	983
# Months	7	7	7	7	7
# Engineer-Months	4,235	4,235	4,235	4,235	4,235
R^2	0.042	0.092	0.072	0.002	0.002

Notes: This table compares the differences in baseline characteristics based on engineers' proximity to their teammates (in one- versus multi-building teams) and their proximity to non-teammates (in the main versus auxiliary building). Job level refers to the engineer's position within the firm's hierarchy from zero (an intern) to six (senior staff). Engineers' annual salary is converted to hourly pay. The sample limits to the period before the office closures and considers engineers whose teams are entirely in the firm's main campus. Standard errors are clustered by 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	-1.26^{***}	-1.71^{**}	-1.19^{***}	-1.64^{**}	-1.36^{***}	-1.67^{***}
	(0.39)	(0.79)	(0.34)	(0.65)	(0.39)	(0.63)
One-Building Team	1.16^{***}	1.81^{**}	1.69^{***}	2.44^{***}		
	(0.39)	(0.76)	(0.32)	(0.58)		
Post	-1.21^{***}	-0.24				
	(0.27)	(0.56)				
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	-15.71%	-21.26%	-14.8%	-20.41%	-16.96%	-20.78%
One-Building	14.42%	22.56%	21.02%	30.34%		
% One-Building Team	58.33	58.33	58.33	58.33	58.33	58.33
Local-Linear Time-Trends		✓		✓		✓
Team Size x Post FE		✓	✓	✓	✓	✓
Program Scope x Post			✓	✓	✓	✓
Tenure Months x Post FE				✓	✓	✓
Other Engineer Controls X Post					✓	✓
Engineer 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	0.01	0.02	0.34	0.34	0.49	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. The first two columns do not include any additional controls. The second two columns include our preferred controls for team size, program scope (quartics for the number of lines added, number of lines deleted, and number of files changed), and engineer experience, where the coefficients on team size and engineer experience are allowed to differ before and after the pandemic. The last two columns include controls for other engineer characteristics — age (in years) and gender, home zipcode, job-level, and job-type — where we allow the effects to vary before and after the pandemic — and engineer fixed effects. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.4: Proximity to Teammates and their Feedback: In the Main and Auxiliary Buildings

	# Teammate Comments/Program		
	(1)	(2)	(3)
Main Building: Post x On One-Building Team	-0.616^{*}	-0.751^{**}	-0.911^{***}
	(0.325)	(0.337)	(0.258)
Main Building: On One-Building Team	-0.041	0.661^{**}	
	(0.323)	(0.316)	
Auxiliary Building: Post x On One-Building Team	-1.042^{**}	-1.152^{**}	-1.402^{**}
	(0.500)	(0.510)	(0.613)
Auxiliary Building: On One-Building Team	0.484	0.970^{**}	
	(0.591)	(0.488)	
Pre-Mean, One-Building Team			
Main Building	3.26	3.26	3.26
Auxiliary Building	1.97	1.97	1.97
Percentage Effects			
Main Building: Post x On One-Building Team	-18.86%	-23.01%	-27.9%
Main Building: On One-Building Team	-1.24%	20.24%	
Auxiliary Building: Post x On One-Building Team	-52.84%	-58.43%	-71.07%
Auxiliary Building: On One-Building Team	24.55%	49.16%	
Controls	Raw	Preferred	All
# Engineers	1,153	1,153	1,153
# Months	17	17	17
# Engineer-Months	9,986	9,986	9,986
R^2	0.003	0.170	0.421

Notes: This table 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 in the main and auxiliary buildings. Each specification estimates Equation 1, where the effects of being in a one-building team are allowed to differ for engineers in the main building and the auxiliary one. The first column does not include any controls (as in Figure A.11(a)). The second column includes our preferred controls (as in Figure A.11(b)). The third column includes the full set of controls. Standard errors are clustered by engineer. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.5: Comparing Feedback for Engineers on One-Building vs. Multi-Campus Teams

	# Comments/Program					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x In One-Building Team	-1.749^{***}	-1.047^{**}	-0.696^{*}	-0.393	-1.072^{**}	-1.222^{**}
	(0.447)	(0.461)	(0.385)	(0.407)	(0.443)	(0.475)
One-Building Team	2.477^{***}	1.634^{***}	1.097^{***}	0.540	1.089^{***}	
	(0.397)	(0.429)	(0.371)	(0.380)	(0.388)	
Post	-0.616^{*}					
	(0.361)					
Pre-Mean in One-Building Teams	7.81	7.81	7.81	7.81	7.81	7.81
Percentage Effects						
Post x In One-Building Team	-22.39%	-13.4%	-8.91%	-5.03%	-13.72%	-15.64%
In One-Building	31.7%	20.91%	14.04%	6.91%	13.93%	
% One-Building Team	73.069	73.069	73.069	73.069	73.069	73.069
Team Size x Post FE		✓	✓	✓	✓	✓
Program Content			✓	✓	✓	✓
Tenure Months x Post FE				✓	✓	✓
Other Engineer Controls X Post					✓	✓
Engineer FE						✓
# Engineers in One-Building Team	699	699	699	699	699	699
# Engineers in Multi-Campus Team	254	254	254	254	254	254
# Engineers	953	953	953	953	953	953
# Engineer-Months	8,028	8,028	8,028	8,028	8,028	8,028
R^2	0.020	0.035	0.270	0.324	0.378	0.492

Notes: This table compares the change in peer feedback around the COVID-19 office closures for engineers in the same building as all their teammates in the office versus engineers who had at least one teammate who worked remotely or in a satellite campus. Each column estimates Equation 1. The first column presents the raw estimates, corresponding to the comparison between the navy and grey lines in Figure 2. The second column includes fixed effects for team size. The third column adds controls for program scope (quartics for the number of lines added, number of lines deleted, and number of files changed). The fourth column allows for differential changes in feedback for more and less experienced engineers around the office closures. The fifth column includes controls for other engineer characteristics — age (in years) and gender, home zipcode, job-level, and job-type — where we allow the effects to vary before and after the pandemic. The last column includes engineer fixed effects to handle any changes in the composition of engineers who submit programs to the main code-base. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.6: Proximity to Non-Teammates and On-the-Job Training

	# Comments/Program					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x In Main Building	-2.505^{***}	-2.299^{***}	-1.641^{***}	-1.258^{***}	-1.604^{***}	-1.744^{***}
	(0.351)	(0.355)	(0.300)	(0.307)	(0.354)	(0.371)
In Main Building	2.717^{***}	2.435^{***}	2.695^{***}	1.990^{***}	1.975^{***}	
	(0.335)	(0.340)	(0.288)	(0.290)	(0.327)	
Post	-0.086					
	(0.261)					
Pre-Mean in Main Building	8.11	8.11	8.11	8.11	8.11	8.11
Percentage Effects						
Post x In Main Building	-30.88%	-28.33%	-20.23%	-15.5%	-19.77%	-21.49%
In Main Building	33.49%	30.01%	33.21%	24.53%	24.34%	
% In Main Building	72.201	72.201	72.201	72.201	72.201	72.201
Team Size x Post FE		✓	✓	✓	✓	✓
Program Content			✓	✓	✓	✓
Tenure Months x Post FE				✓	✓	✓
Other Engineer Controls X Post					✓	✓
Engineer FE						✓
# Engineers	1,153	1,153	1,153	1,153	1,153	1,153
# Months	17	17	17	17	17	17
# Engineer-Months	9,986	9,986	9,986	9,986	9,986	9,986
R^2	0.022	0.039	0.282	0.339	0.378	0.495

Notes: This table investigates the relationship between on-the-job training and physical proximity based on an engineer's building. Each observation is an engineer-month pair and includes all engineers who submit programs to the firm's main code-base in the month. The dependent variable is the average number of comments that the engineer receives on each program in the month. Each column estimates Equation 2, which compares engineers in the firm's main building (with 72% of the engineers in the main campus) to those in the auxiliary building (with the remaining 28% of engineers). The first column presents the raw estimates, corresponding to Figure 3. The second column includes fixed effects for team size. The third column adds controls for program scope (quartics for the number of lines added, number of lines deleted, and number of files changed). The four column allows for differential changes in feedback for more and less experienced engineers around the office closures. The fifth column includes controls for other engineer characteristics — age (in years) and gender, home zipcode, job-level, and job-type — where we allow the effects to vary before and after the pandemic. The last column includes engineer fixed effects to handle any changes in the composition of engineers who submit programs to the main code-base. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.7: Proximity to Non-Teammates and On-the-Job Training: Alternative Measures

	Peer Review Characteristics							
	Total # Characters		With Instructive Comment		With Code		Hours to First Comment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post x On Main Building	-156.100^{***}	-193.100^{***}	-0.027^{***}	-0.029^{**}	-0.014	-0.016	1.187^{**}	1.379^{**}
	(44.280)	(50.280)	(0.010)	(0.012)	(0.011)	(0.012)	(0.567)	(0.679)
On Main Building	249.400^{***}		0.045^{***}		0.036^{***}		-1.230^{***}	
	(40.150)		(0.008)		(0.008)		(0.426)	
Pre-Mean in One-Building	704.46	704.46	0.12	0.12	0.1	0.1	16.75	16.75
Percentage Effect								
Post x On Main Building	-22.15%	-27.41%	-23.74%	-25.39%	-13.51%	-15.79%	7.08%	8.23%
On Main Building	35.4%		38.87%		34.94%		-7.34%	
% On Main Building	72.201	72.201	72.201	72.201	72.201	72.201	72.201	72.201
Controls	Pref	All	Pref	All	Pref	All	Pref	All
# Engineers	1,153	1,153	1,153	1,153	1,153	1,153	1,153	1,153
# Months	17	17	17	17	17	17	17	17
# Engineer-Months	9,986	9,986	9,986	9,986	9,986	9,986	9,986	9,986
R^2	0.295	0.468	0.181	0.345	0.098	0.301	0.137	0.302

Notes: This table considers four alternative measures of peer investment other than comment quantity. Each column estimates Equation 2. The odd columns use the preferred set of controls, while the even columns use the full set of controls. Columns one and two consider the total number of characters in comments on a program. Columns three and four consider the percent of reviews that have a specifically instructive comment that shows the engineer an 'example', gives 'general' advice, or discusses best programming 'practice'. Columns five and six consider the percent of programs where reviewers write code to illustrate the desired changes. Columns eight and nine consider the delay until the first comment is received. Standard errors are clustered by engineer. *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Proximity and Coworker Conversations about Code (All Controls)

	From Commenter			From Program Writer	
	Initial	Follow-up	Questions	Replies	Questions
	(1)	(2)	(3)	(4)	(5)
Post x One-Building Team	-0.726^{***}	-0.638^{*}	-0.058	-0.725^{***}	-0.083^{**}
	(0.251)	(0.327)	(0.166)	(0.265)	(0.036)
Pre-Mean, One-Building Team	4.91	3.13	1.94	2.14	0.19
Percentage Effects					
Post x One-Building Team	-14.8%	-20.4%	-3%	-33.9%	-44.5%
% One-Building Team	58.3	58.3	58.3	58.3	58.3
# Engineers	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304
R^2	0.504	0.363	0.407	0.427	0.281

Notes: This table explores the relationship between proximity and the conversations between commenters and program writers about code with our full set of controls (see Subsection III.B). The first three columns focus on the commenters' comments. Column one considers only initial comments — comments written before the program writer replies — while column two considers only replies written after the program writer responds. The third column considers only comments that include a question to the program writer. The final two columns focus on program writers. Column four includes all replies to the commenters' comments. Column five only considers authors' replies that include a question. Each column estimates Equation 1, including the full controls. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.9: Proximity to Teammates and the Extensive Margin of Coworker's Feedback

	# Commenters		# New Commenters	
	(1)	(2)	(3)	(4)
Post x On One-Building Team	-0.071^{*}	0.005	-0.099^{**}	-0.023
	(0.042)	(0.045)	(0.045)	(0.048)
On One-Building Team	0.068^{*}		0.065	
	(0.038)		(0.040)	
Post x In Main Building	0.079^{*}	0.031	0.047	0.006
	(0.044)	(0.052)	(0.047)	(0.055)
In Main Building	0.014		0.036	
	(0.041)		(0.043)	
Pre-Mean, One-Building Team	1.76	1.76	1.29	1.29
Pre-Mean, Main Building	1.75	1.75	1.28	1.28
Percentage Effects				
Post x On One-Building Team	-4.02	0.27	-7.66	-1.77
On One-Building Team	3.85		5.04	
Post x In Main Building	4.52	1.78	3.62	0.49
In Main Building	0.81		2.79	
% On One-Building Team	58.74	58.74	58.74	58.74
% In Main Building	72.2	72.2	72.2	72.2
Controls	Preferred	All	Preferred	All
# Engineers	1,153	1,153	1,153	1,153
# Months	17	17	17	17
# Engineer-Months	9,986	9,986	9,986	9,986
R^2	0.096	0.347	0.052	0.321

Notes: This table explores the extensive margin of the relationship between proximity and feedback among engineers. The first two columns measure the total number of commenters who provide feedback on all programs in a month. The next two columns measure the number of new commenters relative to the prior month in which the engineer wrote a program for review. Each column estimates Equation 2. The odd columns present the preferred set of controls for team-size, program scope, and engineer tenure, where the effects of team-size and tenure are allowed to vary before and after the pandemic. The even columns also include other time-varying engineer controls and engineer fixed effects. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.10: Proximity and Coworker Conversations in the Main vs. Auxiliary Building

	From Commenter			From Program Writer	
	Initial	Follow-up	Questions	Replies	Questions
	(1)	(2)	(3)	(4)	(5)
Post x Main Building	-0.999^{***}	-0.450^{*}	-0.250^{**}	-0.483^{***}	-0.044^{**}
	(0.184)	(0.239)	(0.124)	(0.187)	(0.021)
Main Building	1.375^{***}	0.781^{***}	0.320^{**}	0.330	0.057^{***}
	(0.178)	(0.265)	(0.146)	(0.204)	(0.019)
Pre-Mean, Main Building	5.18	3.21	2.08	2.18	0.2
Percentage Effects					
Post x Main Building	-19.3%	-14%	-12%	-22.2%	-22.4%
Main Building	26.5%	24.3%	15.4%	15.2%	29.2%
% Main Building	71.2	71.2	71.2	71.2	71.2
Preferred Controls	✓	✓	✓	✓	✓
# Engineers	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304
R^2	0.366	0.175	0.230	0.165	0.072

Notes: This table explores the conversations that engineers have about code in the main building relative to engineers in the auxiliary building in the main campus. The first three columns focus on the commenters' comments. Column one considers only initial comments — comments written before the program writer replies — while column two considers only replies written after the program writer responds. The third column considers only comments that include a question to the program writer. The final two columns focus on program writers. Column four includes all replies to the commenters' comments. Column five only considers authors' replies that include a question. Each column estimates Equation 2, including the preferred set of controls, including team-size, program scope, and engineer tenure (see Subsection III.B). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.11: 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	-1.190^{***}	-0.464^{*}	-1.364^{***}	-0.671^{***}
	(0.341)	(0.241)	(0.387)	(0.253)
On One-Building Team	1.690^{***}	0.752^{***}		
	(0.323)	(0.217)		
Pre-Mean, One-Building Team	8.04	4.17	8.04	4.17
Percentage Effects				
Post x On One-Building Team	-14.8%	-11.14%	-16.96%	-16.1%
On One-Building Team	21.02%	18.03%		
Avg. on Multi-Building Teams				
# Teammate Commenters	1.71	1.71	1.71	1.71
% From Proximate Teammates	39.4	39.4	39.4	39.4
# Proximate Teammate Commenters	0.67	0.67	0.67	0.67
Back-of-the-envelope Calculations				
% Initial Gap Explained		29.92%		
% Differential Change Explained		26.24%		33.1%
Controls	Preferred	Preferred	All	All
# Engineers	1,055	934	1,055	934
# Engineer-Months	9,304	7,174	9,304	7,174
R^2	0.343	0.226	0.494	0.460

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.12: 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 4. Standard errors are clustered by the commenter-coder pair. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.13: Engineers' Traits by Tenure at the Firm and On Their Teams

	$<$ 1 yr at Firm	$<$ 1 yr on Team	$\geq$ 1yr
% Teammates in Building	34.08	43.04	44.97
	(44.27)	(45.75)	(47.09)
# Teammates	4.97	6.39	5.86
	(2.82)	(2.36)	(2.38)
% In Main Building	79.2	63.75	67.47
	(40.6)	(48.08)	(46.86)
Engineer Traits			
% Female	21.24	16.51	15.25
	(40.9)	(37.13)	(35.95)
Age (Years)	28.1	30.06	29.49
	(4.94)	(5.78)	(6.39)
Firm Tenure (Yrs)	0.67	2.77	1.94
	(0.4)	(1.75)	(0.94)
Job Level	1.57	2.18	1.94
	(0.75)	(0.88)	(0.79)
Hourly Pay	54.99	58.37	55.87
	(9.15)	(8.22)	(8.54)
Program Content			
# Changed Lines/Program	507.82	461.4	445.9
	(1471.98)	(1240.98)	(1290.68)
# Changed Files/Program	7.15	7.11	6.69
	(12.62)	(11.88)	(11.43)
Peer Reviews			
# Commenters/Program	1.31	1.24	1.23
	(0.78)	(0.75)	(0.73)
# Comments/Program	8.16	5.29	4.97
	(10.61)	(7.03)	(5.49)
Characters/Comment	88.15	73.67	72.94
	(61.1)	(60.73)	(56.93)
% With Instructive Comment	15.96	8.77	8.36
	(30.5)	(22.4)	(21.78)
% With Code	13.07	8.58	8.22
	(27.56)	(22.51)	(21.41)
Hours Delay Until First Comment	14.21	17.09	16.97
	(11.87)	(12.81)	(12.43)
# Software Engineers	452	373	328
# Months	17	17	17
# Programs Written	12350	10363	9572
# Comments Received	84523	52551	46604

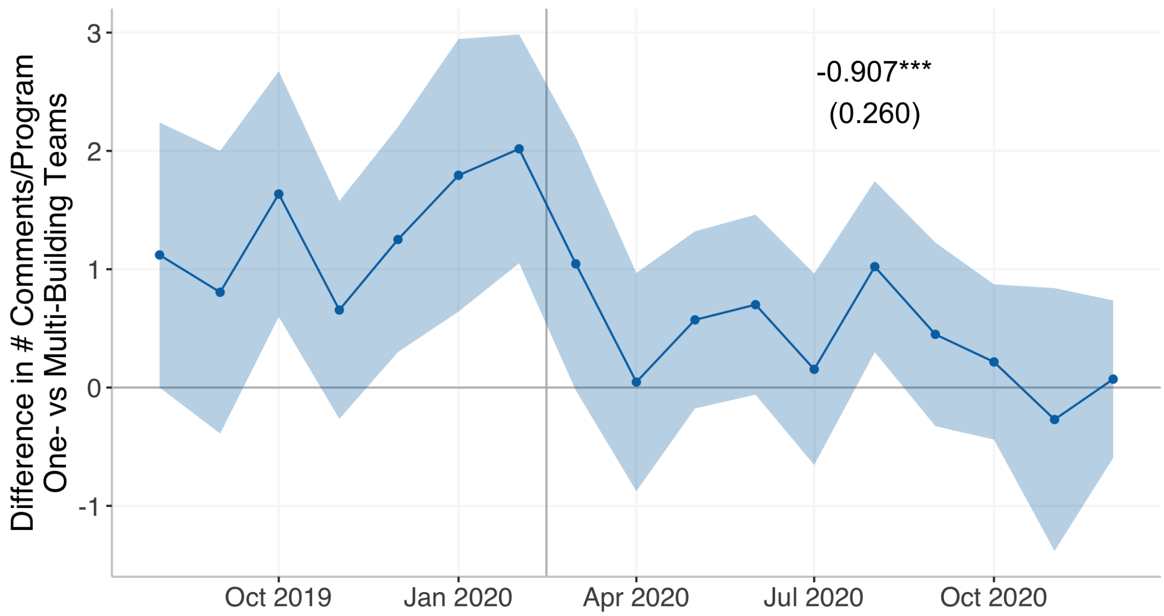
Notes: This table displays characteristics for engineers based on how long they have been at the firm and on their team. Engineers who have been at the firm for less than a year are shown in the first column; engineers who have been at the firm for a year or more, but on their particular team for less than a year are shown in the second column; engineers who have been on their teams and at the firm for a year or more are in the third column. Standard deviations are shown in parentheses.

I.C Main Results for the Full Sample

Figure A.30: Proximity to Teammates and On-the-Job Training

Panel (a): Raw Averages of Comments Per Programs

Panel (b): Dynamic, Conditional Differences



top_legend.png

Notes: This figure compares the change in peer feedback around the COVID-19 office closures for engineers who were initially proximate to all their teammates in the office versus those who were initially distant from at least one teammate. The x-axis represents the month, with the grey line highlighting the COVID-19 office closures. The top panel plots the monthly averages of comments received on each program for engineers on one-building teams in navy circles and engineers on multi-building teams in red triangles. The bottom panel plots the difference in feedback between these two groups of engineers, conditional on team size, program scope, and engineer tenure as in column four of Table 2. The ribbon reflects 95% confidence intervals with standard errors clustered by engineer. The annotated coefficient is the difference-in-difference estimate from Equation 1. *p<0.1; **p<0.05; ***p<0.01.

Table A.14: Summary Statistics

Characterizing All Engineers and those in One- and Multi-Building Teams Before and After the COVID-19 Closures

		Before Closures			After Closures			
	Full Sample	One-Building	Multi-Building	Δ_0	One-Building	Multi-Building	Δ_1	**Diff-in-Diff** $\Delta_1 - \Delta_0$
% Teammates in Building	40.11	100.00	73.73	26.270	0.00	0.00	0.000	-26.270
				(0.910)			(0.000)	(0.910)
# Teammates	6.05	5.38	6.80	-1.416	5.27	6.68	-1.411	0.006
				(0.147)			(0.170)	(0.092)
Building Traits								
% In Main Campus	87.50	86.25	87.60	-1.354	87.96	87.98	-0.022	1.332
				(2.041)			(2.066)	(1.113)
% In Primary Building	64.16	80.55	48.84	31.716	81.37	47.71	33.662	1.946
				(2.625)			(2.857)	(1.599)
Engineer Traits								
% Female	18.36	19.05	17.44	1.615	19.09	17.91	1.176	-0.439
				(2.197)			(2.436)	(1.401)
Age (Years)	29.48	29.17	29.54	-0.376	29.42	29.72	-0.302	0.074
				(0.322)			(0.343)	(0.199)
Firm Tenure (Years)	1.87	1.33	1.86	-0.525	1.85	2.33	-0.479	0.046
				(0.081)			(0.088)	(0.055)
Job Level	1.94	1.71	2.01	-0.298	1.88	2.14	-0.256	0.042
				(0.045)			(0.051)	(0.038)
Hourly Pay	54.67	51.37	55.04	-3.675	54.38	57.31	-2.933	0.742
				(0.611)			(0.641)	(0.415)
Programs								
# Programs Written/Month	3.40	3.37	3.63	-0.261	3.26	3.35	-0.082	0.179
				(0.123)			(0.141)	(0.150)
# Changed Lines/Program	476.34	516.69	539.11	-22.421	394.41	466.96	-72.550	-50.129
				(41.438)			(30.740)	(45.783)
# Changed Files/Program	7.21	7.50	7.47	0.029	6.50	7.43	-0.925	-0.954
				(0.390)			(0.371)	(0.462)
Peer Reviews								
# Commenters/Program	1.24	1.33	1.22	0.113	1.21	1.20	0.006	-0.107
				(0.026)			(0.024)	(0.030)
# Comments/Program	5.96	7.62	6.09	1.530	5.31	5.12	0.190	-1.340
				(0.305)			(0.206)	(0.303)
Characters/Comment	78.40	76.39	74.90	1.489	78.73	82.90	-4.172	-5.661
				(1.910)			(2.126)	(2.405)
% From Older Engineer	56.32	59.25	55.35	3.903	57.19	53.96	3.225	-0.679
				(2.051)			(2.237)	(1.763)
% With Instructive Comment	9.64	12.39	9.49	2.893	8.67	8.50	0.174	-2.720
				(0.762)			(0.575)	(0.847)
% With Code	9.42	11.27	9.17	2.093	9.00	8.56	0.448	-1.645
				(0.708)			(0.657)	(0.866)
Hours Delay Until First Comment	17.27	16.40	17.31	-0.904	17.51	17.69	-0.186	0.718
				(0.360)			(0.330)	(0.438)
# Software Engineers	1,572	709	759		629	654		
# Months	17	7	7		10	10		
# Programs Written	46,960	10,232	12,317		11,988	12,423		
# Comments Received	250,444	64,491	65,773		60,958	59,222		

Notes: This table shows traits of the engineers, their work, and the feedback they receive. Unlike Table 1, this table includes engineers who are not located on the main campus. Standard errors are displayed in parentheses and are clustered by engineer.

Table A.15: Proximity to Teammates and On-the-Job Training

	# Comments/Program					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x In One-Building Team	-1.340^{***}	-0.951^{***}	-0.907^{***}	-0.901^{***}	-0.895^{***}	-0.900^{***}
	(0.303)	(0.300)	(0.260)	(0.261)	(0.270)	(0.291)
One-Building Team	1.530^{***}	1.008^{***}	1.333^{***}	1.261^{***}	1.194^{***}	
	(0.305)	(0.302)	(0.260)	(0.251)	(0.258)	
Post	-0.969^{***}					
	(0.191)					
Pre-Mean in One-Building Teams	7.62	7.62	7.62	7.62	7.62	7.62
Post x One-Building as Percent	-17.58	-12.48	-11.89	-11.81	-11.74	-11.81
% One-Building Team	48.567	48.567	48.567	48.567	48.567	48.567
Team Size x Post FE		✓	✓	✓	✓	✓
Program Content			✓	✓	✓	✓
Tenure Months x Post FE				✓	✓	✓
Other Engineer Controls X Post					✓	✓
Engineer FE						✓
# Engineers	1,572	1,572	1,572	1,572	1,572	1,572
# Months	17	17	17	17	17	17
# Engineer-Months	13,818	13,818	13,818	13,818	13,818	13,818
R^2	0.014	0.028	0.247	0.303	0.326	0.463

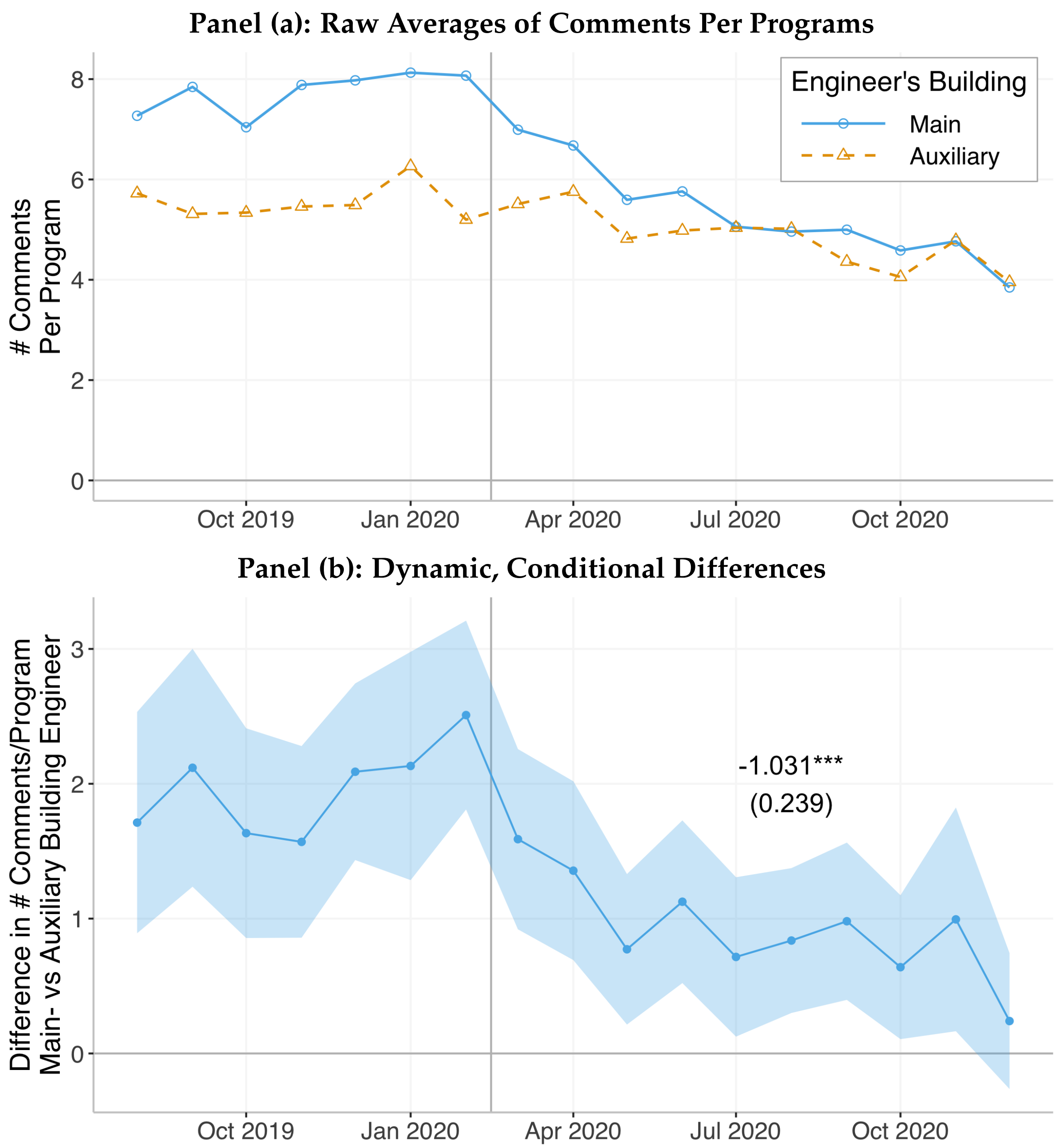
Notes: This table investigates the relationship between physical proximity and coworkers' investments in each other's on-the-job training. Each observation is an engineer-month pair and includes all engineers who submit programs to the firm's main code-base in the month. The dependent variable is the average number of comments that the engineer receives on each program in the month. 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. The first column presents the raw estimates, corresponding to Figure 1. The second column includes fixed effects for team size, which is useful to account for because mechanically smaller teams will be more likely to be in one building. The third column adds controls for program scope (quartics for the number of lines added, number of lines deleted, and number of files changed). The four column allows for differential changes in feedback for more and less experienced engineers around the office closures to account for the lower tenure of one-building teams. The fifth column includes controls for other engineer characteristics — age (in years) and gender, job-level, and job-type — where we allow the effects to vary before and after the pandemic. The last column includes engineer fixed effects to handle any changes in the composition of engineers who submit programs to the main code-base. *p<0.1; **p<0.05; ***p<0.01.

Table A.16: Coherence Checks of Proximity: Type of Proximity and Source of Additional Comments (Full Sample)

	# Comments/Program					
	Total		From Teammates		From Non-Teammates	
	(1)	(2)	(3)	(4)	(5)	(6)
Post x On One-Building Team	-0.520^{*}	-0.559^{*}	-0.630^{***}	-0.515^{**}	0.116	-0.028
	(0.288)	(0.324)	(0.227)	(0.245)	(0.220)	(0.243)
On One-Building Team	0.717^{***}		0.645^{***}		0.071	
	(0.264)		(0.210)		(0.202)	
Post x In Main Building	-0.982^{***}	-0.947^{***}	-0.300	-0.375	-0.669^{***}	-0.549^{**}
	(0.299)	(0.336)	(0.245)	(0.259)	(0.221)	(0.255)
In Main Building	1.489^{***}		0.038		1.438^{***}	
	(0.262)		(0.215)		(0.209)	
Pre-Mean, One-Building Team	7.62	7.62	3.36	3.36	4.24	4.24
Pre-Mean, Main Building	7.58	7.58	3.14	3.14	4.42	4.42
Post x One-Building as Percent	-6.82	-7.33	-18.75	-15.33	2.74	-0.65
Post x Main Building as Percent	-12.95	-12.49	-9.54	-11.94	-15.16	-12.44
% In Main Building	65.3	65.3	65.3	65.3	65.3	65.3
% On One-Building Team	48.57	48.57	48.57	48.57	48.57	48.57
Preferred Controls	✓		✓		✓	
All Controls		✓		✓		✓
# Engineers	1,572	1,572	1,572	1,572	1,572	1,572
# Months	17	17	17	17	17	17
# Engineer-Months	13,818	13,818	13,818	13,818	13,818	13,818
R^2	0.313	0.464	0.158	0.386	0.318	0.472

Notes: This table investigates the relationship between physical proximity with coworkers and the feedback that engineers receive on their programs. Each observation is an engineer-month pair and includes all engineers who submit programs to the firm's main code-base in the month. In the first two columns, the dependent variable is the average number of comments that an engineer receives on each program in the month. In the next two columns, the dependent variable is the average number of comments that an engineer receives from her teammates on each program in the month. In the last two columns, the dependent variable is the average number of comments that an engineer receives from non-teammates on each program in the month. Each column estimates Equation 3. The odd columns present the preferred set of controls for team-size, program scope, and engineer tenure, where the effects of team-size and tenure are allowed to vary before and after the pandemic. The even columns also include other time-varying engineer controls and engineer fixed effects to handle any changes in the composition of engineers who submit programs to the main code-base. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

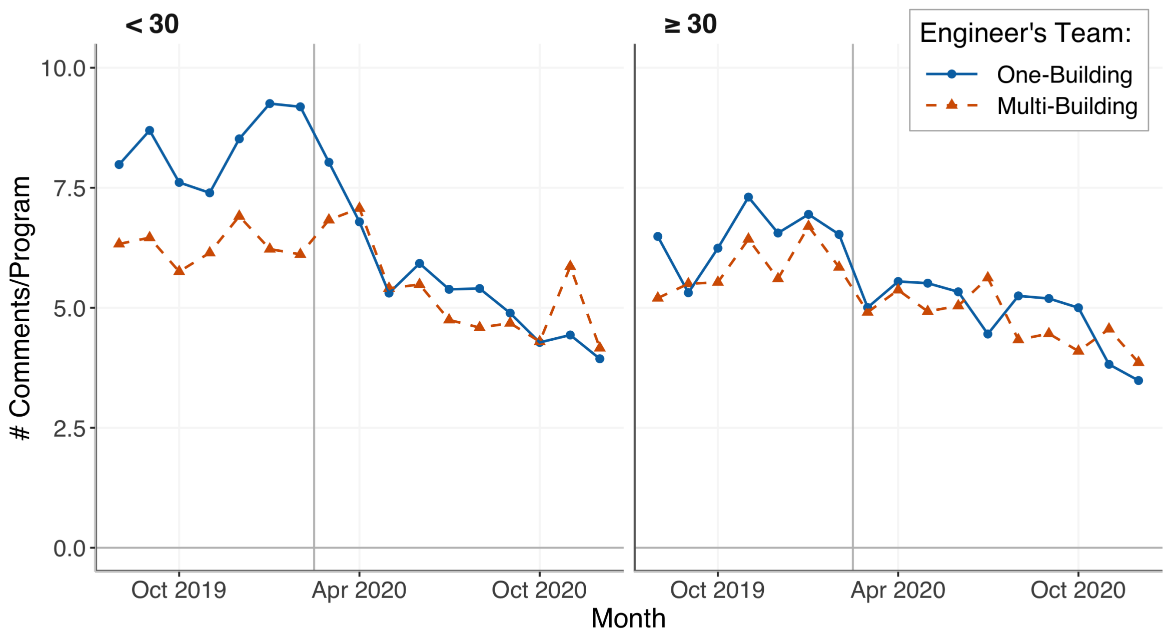
Figure A.31: Proximity to Non-Teammates and On-the-Job Training



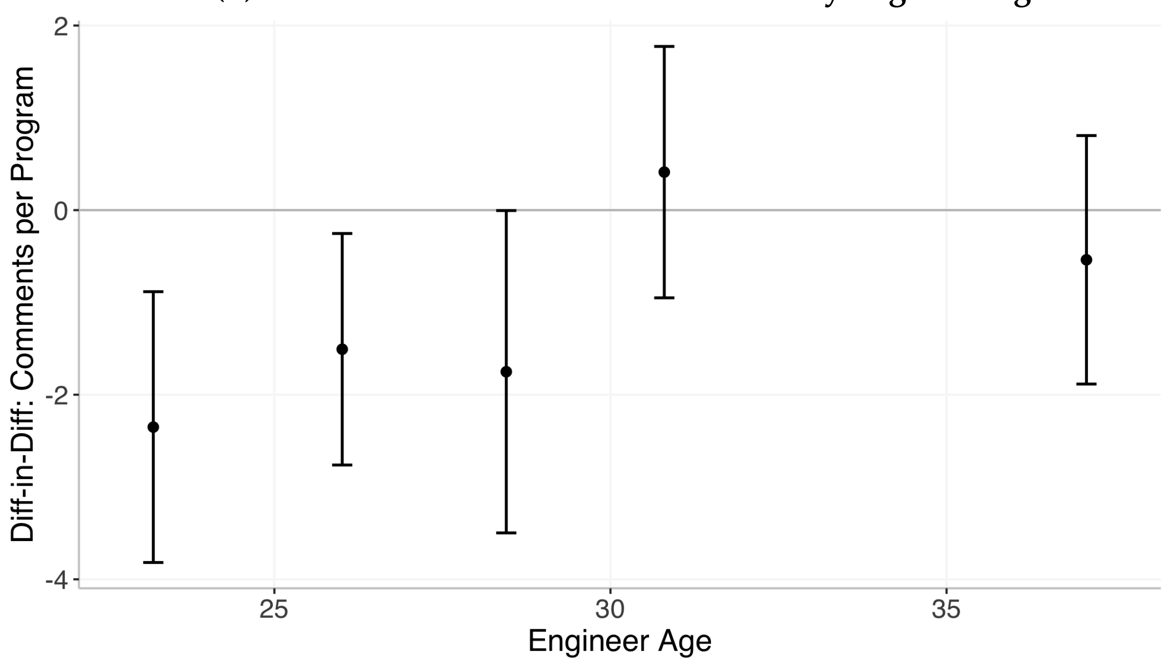
Notes: This figure compares the change in feedback around the COVID-19 office closures for engineers who were initially in the firm's main building (with 65% of the engineers) versus an auxiliary building (with the remaining 35% of engineers), who differed in their face-to-face contact with potential reviewers in the office. The x-axis represents the month, with the grey line highlighting the COVID-19 office closures. The top panel plots the monthly averages of comments received on each program for engineers in the main building in blue circles and engineers in an auxiliary building in orange triangles. The bottom panel plots the conditional difference in feedback between these two groups of engineers, controlling for team-size, engineer tenure, and program scope. The ribbon reflects 95% confidence intervals with standard errors clustered by engineer. The annotated coefficient is the difference-in-difference estimate from Equation 2. *p<0.1; **p<0.05; ***p<0.01.

Figure A.32: Intergenerational Impacts of Proximity on Coworker Feedback

Panel (a): Difference-in-Differences for Younger and Older Engineers



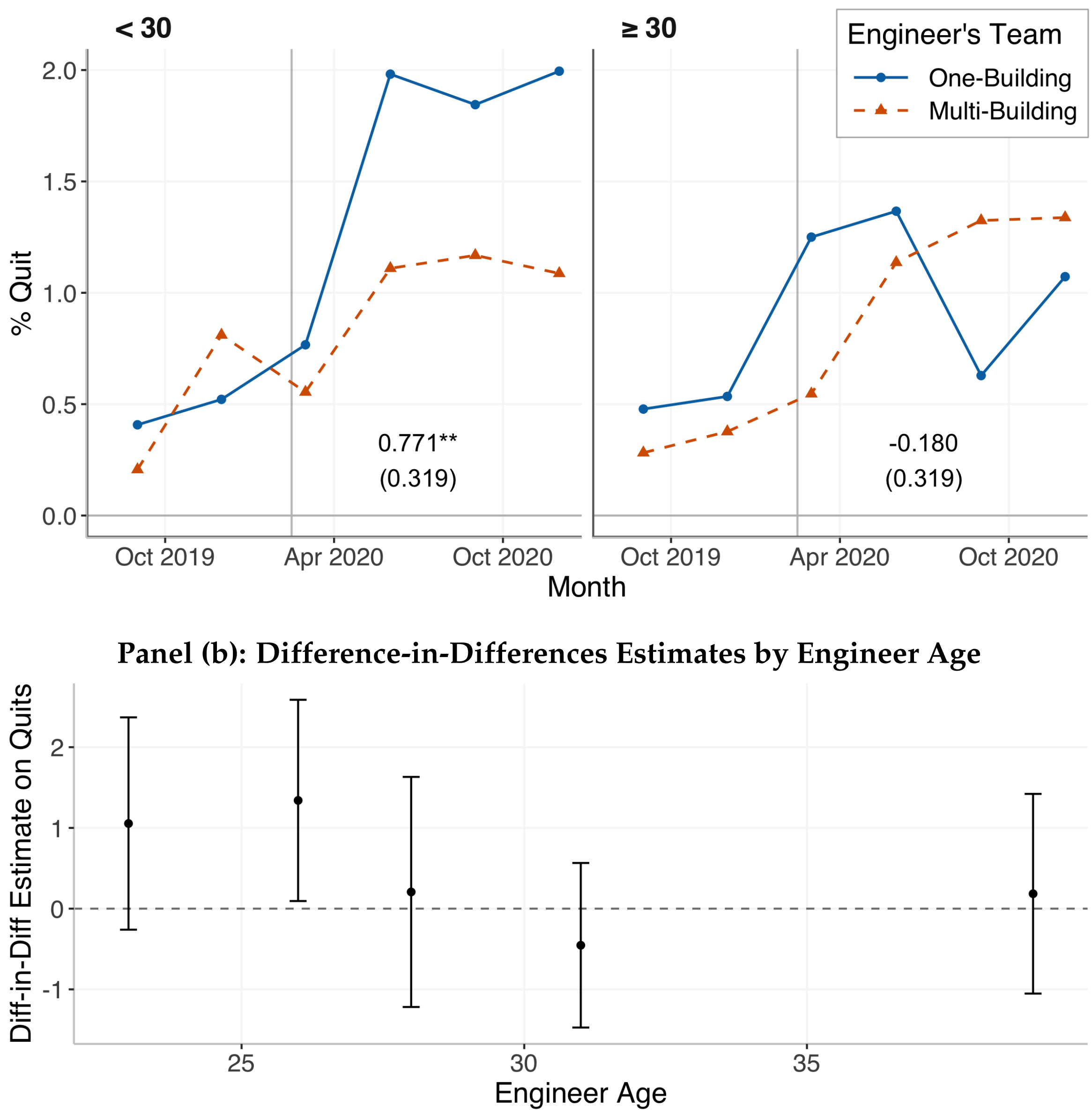
Panel (b): Difference-in-Differences Estimates by Engineer Age



Notes: This figure compares coworker investments for younger and older workers around the COVID-19 office closures based on whether they were one-building or multi-building teams. Panel (a) shows monthly averages of the number of comments received per program over time, with the grey line indicating office closures due to COVID-19. The left panel shows engineers younger than 30 years old, the right panel shows engineers 30 years or older. Panel (b) displays difference-in-differences estimates for quintiles of engineer age, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.

Figure A.33: Intergenerational Impacts of Proximity on Turnover

Panel (a): Difference-in-Differences in Quits for Younger and Older Engineers



Notes: This figure compares coworker investments for younger and older workers around the COVID-19 office closures based on whether they were one-building or multi-building teams. Panel (a) shows monthly quits rates over time, with the grey line indicating office closures due to COVID-19. The left panel shows engineers younger than 30 years old, the right panel shows engineers 30 years or older. Panel (b) displays difference-in-differences estimates for six quantiles of engineer age, where each estimates Equation 1 with our preferred set of controls. The whiskers show 95% confidence intervals with standard errors clustered by engineer.