THE POWER OF PROXIMITY TO COWORKERS

Training for Tomorrow or Productivity Today?[1]

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Abstract

Amidst the rise of remote work, how does proximity to colleagues affect workers? We find working near colleagues leads to a tradeoff, increasing long-run human capital development at the expense of short-term output. We study software engineers at a Fortune 500 firm, whose main campus has two buildings several blocks apart. When offices were open, engineers working in the same building as all their teammates received 22 percent more online feedback than engineers with distant teammates. After offices closed for COVID-19, this advantage largely disappears. Yet sitting together reduces engineers' programming output, particularly for senior engineers. The tradeoffs from proximity are more acute for women, who both do more mentoring and receive more mentorship when near their coworkers. Proximity impacts career trajectories, dampening short-run pay raises but boosting long-run outcomes. These results can explain national trends: those who need mentorship and those who can provide it are more likely to work from the office. However, even if most mentors and mentees go into the office, remote work may reduce interaction: pre-COVID, having just one distant teammate reduced feedback among co-located workers.

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Until recently, office work lived up to its name. Even after the advent of new communication technologies — such as Skype (in 2003) and Zoom (in 2013) — 94 percent of Americans worked in the office on most days (U.S. Census Bureau, 2019). The COVID-19 pandemic severed many workers' ties to the office, and many have yet to return (Hansen et al., 2023). But it is still unclear why the office was so central for so long and how the seismic shift in workers' relationship with the office will affect work and workers.

In the wake of COVID-19, firms were sharply divided about the value of the office. In 2020, Mark Zuckerberg, CEO of Meta, reflected that "a lot of people are actually saying that they're more productive" working from home (Newton, 2020). On the other hand, James Gorman, CEO of Morgan Stanley, found the office central: "The office is where we teach, where our interns learn. That's how we develop people" (Kelly, 2021). Could both CEOs have been right? Could working in the office facilitate investments in workers' skills for tomorrow that diminish productivity today?

We study the impact of sitting together in the office for software engineers[1] at a Fortune 500 firm. The firm gave us access to the online feedback that engineers write about each other's computer code as well as metrics of engineers' programming output. We find that sitting near coworkers increases the online feedback that engineers receive on their computer code. Proximity is particularly integral to the online feedback received by young and less tenured engineers. Yet mentorship of junior engineers is not free. Engineers — particularly those with more experience — write more programs when *not* sitting near their junior colleagues. Both of these impacts on mentors and mentees are more pronounced for female engineers. The intertemporal tradeoff from proximity is reflected in workers' pay path: sitting near coworkers leads to fewer early pay raises but increases pay raises in the long run

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

as workers build more human capital. Software engineering is quite conducive to remote collaboration, so impacts in other occupations may be more extreme.[2]

Our results suggest that working from home (WFH) has divergent effects over different time spans, as short-term gains come in part from mortgaging workers' long-run development. Consistent with this, Mark Zuckerberg became less optimistic about WFH's consequences after three years. Looking at longer-term performance data from Meta, he came to believe that the costs of WFH exceeded its benefits for junior workers (Zuckerberg, 2023).

To understand the dynamic tradeoffs from WFH, we build a simple two-period model of mentorship where each worker is first junior and then senior. Each junior engineer is paired with a senior engineer, who sits either nearby or at a distance. The junior engineer can ask their senior counterpart for mentorship, which is hard for the firm to observe and therefore reward. Mentorship takes time for both the senior engineer — who must make additional suggestions — and the junior engineer — who must figure out how to incorporate the suggested changes. As a result, mentorship comes at the cost of short-term output. Senior engineers find mentoring taxing but refusing to mentor even more costly, and so they provide mentorship when asked. Junior engineers value mentorship but find it costly to ask for it, especially when sitting apart. Thus, junior engineers ask for and receive less feedback when remote.

Our model yields a number of testable predictions. Sitting near a colleague increases mentorship but reduces output today. However, *having* sat with a colleague in a prior period increases engineers' human capital, which impacts their career outcomes. Thus, we predict that while the offices are open, junior engineers who sit

[2]Software engineering may be a 'best case' for remote work for several reasons. First, software engineers produce digital output, unlike say mechanical engineers. Second, it is industry-standard for software engineers to use the Agile meeting system, which mandates daily, real-time meetings even when remote. Third, it is also industry-standard to mandate feedback through established, online systems (like Github). Other occupations that do not have norms to give feedback online may see larger declines in mentorship when remote.

near their teammates will have lower pay. But, once the offices closed and there was no more differential investment, engineers who had sat on one building teams will see higher pay.

We test the model's predictions in the context of software engineers, whose code reviews give us data on mentorship as well as programs written. It is an industry standard worldwide for software engineers to peer review one another's code online. Reviewers aim to ensure computer code is free of bugs and other glitches before it is deployed, while also teaching engineers to write better code in the future.[3]

We identify the causal effects of proximity by leveraging variation in engineers' proximity to one another. The firm has two buildings on its main engineering campus, several blocks apart. Prior to COVID-19, some teams were assigned desks all in one building, while others spanned the buildings. Assigning desks is tricky since it makes sense to position some engineers near both teammates and other workers (e.g., sales workers) who used the tools they built. Among engineers building similar software, whether their team was in one building or not was due to desk availability when their teammates were hired. Desk positions alter team dynamics. When the offices were open, engineers on one-building teams (N=637) met in-person daily. For engineers on multi-building teams (N=418), these short, daily meetings usually occurred online.[4]

To identify the effects of proximity, we evaluate the differences between one- and multi-building teams when the offices were open and the differential changes when the offices closed. This difference-in-differences design leverages the fact that multi-building teams functioned more like remote teams even before the offices closed and thus serve as a control group.

[3]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."

[4]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."

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. Reassuringly, among those working on similar software, engineers had broadly similar characteristics regardless of their proximity to their teammates. Our results are robust to allowing for differential effects of the pandemic for engineers building different software and with different observable characteristics. We further include placebo checks and complementary designs to validate our results.

Our findings align with the predictions from the model. First, we find that proximity increases on-the-job training. While offices were open, engineers on one-building teams received 22 percent more comments on their code than engineers on multi-building teams (p-value = 0.0003). Once the offices closed and everyone was fully distributed, the gap largely disappeared.[5] Sitting near teammates primarily affects feedback *received* by junior engineers and *given* by senior engineers, who have more tenure at the firm. Analyzing online feedback likely gives us a lower bound on proximity's total effect on mentorship, since sitting together can also facilitate face-to-face conversation about code.

We find that engineers sitting near their teammates receive more feedback, partially because they ask more follow-up questions during code reviews. This greater comfort with asking for additional clarifications highlights how face-to-face interaction complements — rather solely substitutes for — online communication.

In a placebo check, we find that engineers who sit near all their teammates do not receive significantly more feedback from engineers outside their teams, suggesting that they do not simply need more feedback, which would affect comments from all sources. Furthermore, we find similar effects of proximity using two complementary designs with different identifying assumptions. First, we find that proximity to non-teammates increases feedback from non-teammates. Second, we find that en-

[5]We find similar effects for the total length of code reviews (in characters) and proxies for reviews' substantive content (e.g., whether they include code examples or links to documentation).

gineers with teammates who worked from home before the pandemic receive less feedback.[6]

We find that distant teammates impose negative externalities on the mentorship between teammates sitting together. In our baseline design, we find these externalities can explain about a third of proximity's impact. And pre-pandemic, when a new teammate's desk converts a one-building team to a multi-building team, feedback among proximate teammates (who predate the new hire) declines. By contrast, new hires in the same building have no such impact. Teams' attempts to accommodate distant teammates by, for example, moving in-person meetings online, have substantial negative externalities.[7]

Consistent with the model, we find proximity decreases output. Engineers who sit near all their teammates wrote fewer programs. Our difference-in-differences estimate suggests that proximity reduces programs written per month by 23 percent (p-value = 0.008), with similar effects on total lines of code and total files changed. The effects on output are present for both junior and senior engineers but are particularly pronounced for senior engineers, who provide most of the mentoring.

We find that the tradeoffs from proximity are more acute for women. Before the offices closed, female engineers who were in the same building as all their teammates received 38 percent more feedback than female engineers with distant teammates — twice the effect as for male engineers. When the offices shut down for COVID-19, lost proximity mattered more for women: the triple difference indicates a differential decline of 17 percentage points. These effects are largely driven by follow-up questions and clarifications, suggesting that women feel more comfortable asking for additional feedback in-person. At the same time, senior, female engineers do

[6]Our main results are limited to workers whose teammates all work on the main campus pre-pandemic, but some engineers work remotely.

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

much more mentoring when they are seated near their colleagues, leading to a larger decrease in the programs they write.

As the model predicts, proximity affects workers' career outcomes. Junior workers on one-building teams are 5 percentage points less likely to have a pay raise, consistent with their lower output. However, once the offices shut down — and mentorship equalizes — these engineers benefit from the mentorship that they have received and are 9.3 percentage points more likely to receive a pay raise. Both of these differences are suggestively larger for female engineers.

Quits also reflect the impact of proximity. Before the pandemic, quits were relatively rare. However, with the rise of remote work, it became easier to move to higher-paying tech firms in Silicon Valley without needing to relocate from this firm's east-coast city. As mobility increased, so too did quits. Notably, workers who had been trained on one-building teams saw a 1.2 percentage point greater increase in quits, about twice that of engineers who were trained on multi-building teams (p-value of difference $= 0.01$). This result is consistent with the greater training on one-building teams giving engineers the skills they need to secure higher-paying jobs elsewhere. As with pay raises, the effects are larger for women. We do not see the same impacts on firings, which while insignificant, suggest that workers on one-building teams are less likely to be fired once the offices close.

Finally, we examine who works in the office versus from home. Pre-pandemic, work location decisions were consistent with the firm believing that the benefits of proximity for workers' development outweighed the costs for short-term output. Junior workers — who receive the most training – and managers and quite senior workers — who provide the most training were less likely to work from home. This pattern aligns with national trends in $2022-2023$, where young workers and older workers are the most likely to have returned to the office with those in their thirties and fourties staying at home (even if they do not have children) (U.S. Census Bureau, 2023).Additionally, post-pandemic, we see that the firm is less likely to hire very junior engineers and, instead, opts to hire workers with more training. While this change could be influenced by other factors, it is consistent with the idea that when the firm faces challenges in training workers, it decides to “buy" talent instead of “building" it.

Our study makes three central contributions. First, it contributes to the remote work literature, potentially resolving a puzzle as to why remote work was rare before the pandemic despite workers' high willingness to pay for remote work (Mas and Pallais, 2017; Maestas et al., 2018; Mas and Pallais, 2020; He et al., 2021) and remote work's positive impacts on productivity in some settings (Bloom et al., 2015; Choudhury et al., 2020) and modestly negative impacts on productivity in other settings (Gibbs et al., 2023; Emanuel and Harrington, 2023). Second, the paper contributes to a robust literature on on-the-job training. It has long been known that coworkers are crucial for workers' human capital development, but the role of proximity has been hard to assess. This paper directly considers how proximity impacts on-the-job training inside firms. Finally, the paper contributes to the urban literature that has investigated whether information and communication technologies will complement or substitute for proximity. We find proximity and digital communication are complements, even among coworkers whose interactions are not purely based on serendipity.

The next section situates our paper in the broader literature. We then present a model in Section II. Section III describes our data and setting, while Section IV details our empirical strategy. We show that physical proximity leads to more training in Section V. Section VI shows that proximity decreases contemporaneous output, and Section VII show that proximity's tradeoff is more pronounced for women. We show how this tradeoff translates into career outcomes in Section VIII. Finally, we analyze the firm's work-from-home decisions pre-pandemic in Section IX. Section X concludes.

I Related Literature

A burgeoning literature on work from home finds that workers have a relatively high willingness to pay for remote work (Mas and Pallais, 2017; Maestas et al., 2018; He et al., 2021). Several papers find that remote work increases productivity (Bloom et al., 2015; Choudhury et al., 2020), while others find small negative impacts (Gibbs et al., 2023; Emanuel and Harrington, 2023). This leads to a puzzle of why more firms did not offer remote work before the pandemic (Mas and Pallais, 2020). Our paper suggests that firms may resist remote work even if increases short-run productivity if it decreases training and long-run output.

Relatively little of the remote-work research has investigated collaboration among knowledge workers. Gibbs et al. (2023) finds reductions in coding output of IT professionals around the office closures of COVID-19, but their setting lacks a natural control group. Using a difference-in-difference design similar to our own, Yang et al. (2022) show that remote work reduced the breadth of workers' communication networks at Microsoft.[8]

Others have studied the effects of remote work using lab-based experiments (Dutcher, 2012; Dutcher and Saral, 2022; Brucks and Levav, 2022) and natural experiments in more specialized settings (Battiston et al., 2021). Battiston et al. (2021) study workers who process incoming 911 calls. When the worker who answers the 911 call is in the same room as the dispatcher who sends police to the scene, the two spend more time communicating and the police arrive at the scene sooner. This poses a tradeoff from remote work between the speed and quality of calls. We analyze a different tradeoff from remote work — between mentorship and short-term output — in the highly relevant setting of software engineering.

A growing literature quantifies the importance of coworkers in on-the-job learn-

[8]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.

ing. Patenters who work in the same firm as better inventors subsequently patent more (Akcigit et al., 2018). Teachers in schools with other higher value-added teachers subsequently generate better educational outcomes (Jackson and Bruegmann, 2009). And sales workers who seek advice from their coworkers have higher sales thereafter (Sandvik et al., 2020).[9] More generally, working in a firm with coworkers 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. On the other hand, Boudreau et al. (2017); Catalini (2018) find that sitting in the same building significantly increases the likelihood of coauthorship. 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.

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;

[9] A related literature studies the impacts of contemporaneous peer effects on productivity. While grocery store clerks (Mas and Moretti, 2009), envelope stuffers (Falk and Ichino, 2006), and fruit pickers (Bandiera et al., 2010) are all significantly more productive if they work near faster peers, Cornelissen et al. (2017) estimate small contemporaneous impacts of coworkers on workers' wages in the economy overall. Cornelissen et al. (2017) argue that the micro-findings of large contemporaneous peer effects on output depend on having a context where output is observable and the task is relatively routine.

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 producing '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.

II Model

In our model of mentorship, workers live for two periods: a junior period and a senior period. There are overlapping generations of workers at any given time. Each junior worker (j) is paired with a senior worker (s); the pair can be seated together or apart. Senior workers are required to give junior workers feedback, but each period, junior workers choose whether to ask their senior partner for additional feedback, which we call mentorship. If asked, the senior worker chooses whether to provide mentorship, which is unobservable to the firm.[12]

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

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

[12]While firms can observe and require helping junior colleagues, they cannot fully observe how much time is spent mentoring. Similarly, universities may reward faculty for how many students they advise but not how much time they spend with their advisees and the quality of the feedback that they give.

Each period, workers produce output with quantity $y_{i,t}$ and quality $q_{i,t}$.[13] For simplicity, we assume that the value of their output is $y_{i,t} + q_{i,t}$. Without receiving or providing mentorship, workers produce output with quantity $y_i + \epsilon_{i,t}$ and quality $q_i + v_{i,t}$. Giving and receiving mentorship both take time that reduces current-period quantity. Providing mentorship leads seniors to produce m_s less. Receiving mentorship (e.g., responding to comments) leads juniors to produce m_j less. Receiving mentorship increases the quality of workers' future output, increasing next-period quality by $b > m_j$.

At the end of the period, $y_{i,t}$ and $q_{i,t}$ are observed. Workers are paid their marginal product $y_{i,t} + q_{i,t}$. Since there is no discounting, juniors are paid more over two periods if they receive mentoring than if they do not since $b > m_j$.

Asking for mentorship is costly for junior workers and costlier if workers are not seated together.[14] Asking for additional feedback costs $c_{j,n}$ when seated near the senior worker and $c_{j,a}$ when seated apart, where $c_{j,n} < b - m_j < c_{j,a}$.

Senior workers have no returns to providing additional feedback. But, if asked, they face a utility cost of rejecting the request: $c_s > m_s$, stemming from social desirability and office norms.

The resulting equilibrium is straightforward. Junior workers will ask for additional feedback only when seated nearby (since $c_{j,n} < b - m_j < c_{j,a}$). When asked, senior workers will agree (since $c_s > m_s$).

The model yields several testable predictions.

1. Sitting together increases mentorship that is asked for and then received.
2. Sitting together decreases the quantity of current-period programming output for junior and senior workers.

[13] For example, in the empirical setting, quality is how thoroughly the code has been tested.

[14] Asking for mentorship may be less costly in person because, for example, a junior engineer is better able to time requests so that they are convenient for the senior engineer. Alternatively, asking in person seems more natural and less demanding.

3. Sitting together decreases the wages of junior workers.
4. Senior workers who previously sat with their colleagues should have higher wages conditional on current seating location.

Gender. We extend the model to allow for gender differences. A fraction $\lambda > 0$ of men face neither a cost of asking for mentorship nor a cost of rejecting mentorship; all others face the costs defined in the last section. An individual's specific rejection cost is not observable, but λ is sufficiently small that $c_{j,n} < (1-\lambda)(b-m_j)$.

Senior men without rejection costs always reject mentorship requests, regardless of location. Senior women and men with rejection costs do more mentorship when sitting nearby because they are more likely to be asked. Junior men without asking costs always ask for mentorship, regardless of location. Junior women and men with asking costs ask for mentorship only if they are seated near their partner.

This implies that, for women, proximity leads to larger

5. Increases in receiving and asking for advice.
6. Increases in providing feedback.
7. Decreases in output.

Quits. We next extend the model by giving workers a choice to quit between their junior and senior periods. There is a group of superstar tech firms (e.g., Google) at which productivity is more sensitive to skill and training. Specifically, worker i's marginal product at a superstar firm is $(1+\sigma)(y_{i,t}+q_{i,t}-\bar{f})$ where $\sigma > 0$. This assumes that mentorship provides general skills training.[15]

We assume that superstar firms can observe the worker's skill through technical interviews. They then decide whether to make offers to workers and, if so, at what

[15] While, in practice, some of the training is likely to be firm-specific, much of it offers general lessons about coding technique that would be valuable across firms. As long as σ is sufficiently large, our predictions about quits hold even if some of the training is firm-specific.

wage. Workers compare their expected inside wage to their outside wage offer and decide whether to quit. They face mobility cost v, which depends on the period. Before COVID-19, the cost of switching firms (v_0) was high because it often involved a cross-country move. After tech offices closed for COVID-19, the cost of switching firms plummeted to ($v_1 < v_0$) since a physical move was no longer necessary in the short- to medium-term. We assume $v_0 > \sigma(y_i + q_i + b - \bar{f})$ for all i, but v_1 is sufficiently low that $v_1 < \sigma(y_i + q_i + b - \bar{f})$ for some workers i.[16]

Because there are several superstar firms, they will offer workers their marginal product.[17] Given the high moving cost before COVID (v_0), no one quits for a better job at a superstar firm. But workers for whom the wage gain of moving to a better firm exceeds the moving cost – $\sigma(y_i + q_i + t - \bar{f}) > v_1$ – will move after the pandemic. Since the benefit of moving is increasing in productivity, workers who have received mentorship are more likely to move. This implies that

8. Once the pandemic starts, junior workers who previously sat near their teammate are more likely to quit.
9. This difference in quits will be more pronounced for women than men.

III 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.[18] 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.

[16] For simplicity, we assume that workers' expectations about how much mentoring they will have to do are the same across firms. Before COVID-19, workers believe they will mentor with some probability but do not know exactly where they will sit. Afterwards, workers know they will not provide mentoring.

[17] They are indifferent to making wage offers to workers who will not take them.

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

III.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).[19]

Software engineering is a predominantly male occupation, both at this firm and more broadly: 81 percent of the engineers in our sample (and 75 percent of programmers nationally) are male.[20] Engineers at the firm are highly paid ($56/hour on average), which is representative of software engineers nationally ($47.40/hour on average). 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 of the firm's engineers are parents.

The engineers that we study handle typical tasks for software engineers at online retail firms. Some teams maintain the front-end interface for the website, while others maintain the website's back-end database that determines the products displayed in search results. Finally, a third group develops internal tools for the firm's supply chain and sales/service teams. The supply-chain tools help ensure that products can be efficiently located in warehouses and shipped to customers' homes. The sales/service tools help call-center agents track purchases and resolve issues like damaged or delayed deliveries.

III.B Programming and Code-Review Data

Our data includes reviews of code that runs the firm's front-end website and back-end databases. To maintain code quality, every piece of code is reviewed by at least

[19] 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.

[20] Our gender information come from HR data for firm statistics and US Census data for national statistics (U.S. Census Bureau, 2019). Both sources uses respondents' self-reported gender. In the Census, we define software engineers as either (1) Computer Scientists and Systems Analysts, Network systems Analysts, and Web Developers (Occupation 1000 in the 2010 Census), (2) Computer Programmers (1010), or (3) Software Developers, Applications and Systems Software (1020). We use Census sampling weights for these averages.

one other engineer before it is committed to the code-base. This is standard practice in software engineering, often as part of the Github code management system.

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.

Programming Output. We can use this dataset to measure an engineer's monthly contributions to the main code-base. 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., applications for the firm's retail stores), which are outside the scope of our data.[21]

Our preferred measure of programming output is the monthly number of programs submitted to the main code-base: writing longer and more complicated programs often conflicts with best programming practice to write concise, self-contained programs that are easier to test and review. To reduce the influence of outliers, we winsorize programming-output outcomes at the 95th percentiles.[22]

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

Reviewers' comments often aim to improve a program's reliability or readability and give engineers general advice that can improve their subsequent coding. Re-

[21] 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.

[22] This is useful because, for example, changing a commonly-used variable's name can lead to many lines and files being changed without representing a substantive change in the code-base.

viewers average six comments per program, each of which averages eighty characters long. Often the commenter is a more experienced engineer than the program writer, either in terms of age or tenure at the firm (Figure A.3).

We use the text of the comments to draw out common themes. Specifically, we use principal component analysis to identify grouping of words that frequently appear together in comments (Appendix Section I.A details the approach). Two of the top components are about verifying that programs are working as expected (see Figure A.1(a) for word clouds of the top components and Table A.1 for illustrative examples). One component identifies comments that are about *function* output, which often concern edge cases such as *empty* values. Another identifies comments about how to *test* code, which often use the testing suite of the firm's primary programming language, PHP, called *PHPUnit* tests. Making code testable often requires that the programmer rewrite it to have separable components and clearly-articulate the expected behaviors of their program.

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

> *Commenter at 3:14pm:* Can you please add testing details to this program?
>
> *Coder at 3:32pm:* What do you mean by testing details? I added more information on the description if that helps. Let me know if you need

further information.

Commenter at 3:40pm: [I meant] what you did to validate that your changes are working as expected. Here is an example testing doc I made for a ticket in the past: {link to example}.

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

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 percent of comments were given during standard work hours, which only marginally declined by 0.8 percentage points when the offices closed (Figure A.2).[23]

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

Engineers often ask teammates for feedback before or after daily team meetings. Teams have daily fifteen-minute "stand-up" meetings and longer one- to two-hour meetings each week. The nature and frequency of meetings both follow a set routine

[23]Our results are comparable when limiting to interactions in standard business hours (Figure A.7).

under Agile management, which is common in the industry.[24] 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).

III.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] We exclude the small number of engineers hired after the offices closed in March 2020.

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

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

[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 V.

easily discuss their work face-to-face than engineers on multi-building teams before, during, and after meetings.

All teams face desk constraints that can make it difficult to place everyone together. This constraint is more likely to bind for teams who work on developing internal tools since it can be advantageous for these teams to sit near the stakeholders who use their tools. Co-locating an internal-tools team alongside the team that it serves is numerically more challenging and thus results in more multi-building teams among engineers working on internal tools than the other types of teams. When analyzing the effects of sitting near teammates, we account for differences across these types of engineering.

Before the pandemic, 637 engineers were on teams where all of the members worked together in one building, while the remaining 419 engineers were on teams that spanned the two office buildings. For engineers on multi-building teams, 30 percent of their team — or one to two teammates — were in the other building. We define engineers as being in one-building teams if we always observe them in the same building as all of their teammates during the pre-period from August 2019 through February 2020. During the pre-period, only 14 percent of engineers switched teams, and only 2 percent of engineers switched buildings.[26]

COVID-19 Closures. The office closures of COVID-19 eliminated differences in coworkers' proximity. On Friday March 6th, most engineers went home from the office expecting to return the following Monday. Almost no engineers came into the office come Monday, though the firm did not officially close the campus immediately. Engineers had an opportunity to collect any belongings that they may have left in the

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

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.

IV Empirical Design

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

Specifically, we estimate the following equation:

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

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

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

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

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

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

IV.A Balance in Engineer Characteristics

Table 1 describes the sample, comparing engineers whose teams are all in one building with those whose teams span the two buildings. Engineers' baseline characteristics are largely well-balanced after accounting for engineering type (Column 5). Engineers on one- and multi-building teams have similar demographics (Rows 3−6), similar job level and pay (Rows 8−9), and managers with similar tenure, level, and pay (Rows 10−12). The one notable difference is firm tenure (Row 7): engineers who had been at the company longer were more likely to end up physically separated from at least one teammate so averaged an additional 5.0 months at the firm.

IV.B Controls

Preferred controls: Our preferred controls account for the type of engineering that the team does (front-end website, back-end databases, or internal tools). We allow the controls for engineering groups to have time-varying effects before versus after the COVID-19 office closures to account for any differential shocks to the demand for these tasks. We further include indicators for the number of months that the engineer has been at the firm and allow the effects of firm experience to differ before and after the offices closed. For online feedback, we also control for program scope — 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 an engineer receives.

Full set of controls: Our full set of controls also includes indicators for the engineer's age (in years), gender, home zipcode, job-level, and initial building.[27] We allow all these coefficients to differ before and after the COVID-19 closures to allow different types of engineers to face different pandemic shocks. We further include engineer fixed effects to handle any changes in the composition of engineers who submit programs to the main code-base.

IV.C 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 = 0.37 for the raw and p-value = 0.61 for our full set of controls).[28] Indeed, in the months leading up to the office closures, peer commenting did not systematically change for either group of engineers.[29] Further, a Wald test considering whether the difference between one- and

[27]For home zipcode, we include the thirty-two zipcodes with at least ten engineers. For the engineers in less populous zipcodes, we include an indicator for being in the firm's primary state or in an adjoining state.

[28]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.

[29]Peer comments insignificantly increased by 2.7 percent per month (or 0.20 comments) for engineers in one-building teams and by 0.51 percent for engineers in multi-building teams.

multi-building teams is the same in each month before office closures also finds no significant differences (p-value = 0.92 for the raw and p-value = 0.98 for our full set of controls).

We see similar parallelism in programs written in the pre-period: there is no significant differential trend across engineers in one- and multi-building teams (p-value = 0.96 for the raw and p-value = 0.51 for our full set of controls), and indeed, programs written per month did not substantially change for either group of engineers in the pre-period.[30] A Wald test that investigates whether the difference between one- and multi-building teams is the same in each month before office closures also finds no significant differences (p-value = 0.93 for the raw and p-value = 0.79 for our full set of controls).

V PROXIMITY'S IMPACT ON ONLINE MENTORSHIP

Consistent with the model's first prediction, we find that engineers who are seated near their teammates ask for and receive more (online) feedback than those seated farther away from their teammates. Since physical proximity can lead to in-person advice too, our estimates of proximity's impact on online mentorship are likely to be lower bounds of proximity's total effect on mentorship.

Engineers on one-building teams received more feedback than engineers on multi-building teams only when the offices were open. Figure 1(a) shows this, plotting the average number of comments received per program without controls. Initially, engineers on one-building teams received more feedback on their code than engineers on multi-building teams. But this gap disappears when the offices close, suggesting that physical proximity to teammates explained the initial gap. Using our preferred specification, we find that when the offices were open, engineers on one-building teams received 22.4 percent more comments per program (p-value = 0.0002, Column 4 of Table 2) than engineers on multi-building teams, when compar-

[30] Programs written insignificantly decreased by about 1.5 percent per month for both groups.

ing engineers who were hired in the same month, write similar programs, and work on similar engineering tasks. This gap narrowed to only 7.9 percent after the offices closed. Thus, the difference-in-differences design indicates that the greater loss of proximity for engineers on one-building teams reduced feedback by 14.4 percent (p-value = 0.007).

The differential decline in feedback for engineers on one-building teams versus multi-building teams is closely tied to the timing of the office closures.[31] The event study in Figure 1(b) illustrates this, plotting the coefficients from Equation 2 conditional on our preferred set of controls. As we can see visually, other untreated months do not feature similar changes in the feedback received by one- versus multi-building teams (also shown in the placebo check in Figure A.4).

While the offices remain closed, engineers on one-building teams never regain the advantages conferred by physical proximity. The persistence suggests our effects are not a fleeting byproduct of transitioning to new technologies for engineers accustomed to in-person interactions with their teammates.[32]

Our results are robust to adding a variety of controls (Table 2), a stability that is notable given the increase in the R^2 from 2 percent to 50 percent. Our results are also robust to including local-linear time-trends for engineers on one- and multi-building teams (Table A.2) and to limiting to alternative bandwidths around the office closures (Figure A.5).We also find similar results when limiting to engineering teams who work on internal tools for others in the firm and so are more likely to end up spread across buildings (Figure A.6 and Table A.3).[33]

[31]One might have expected that those who sat together in the office and had a habit of increased online collaboration might have collaborated more after the offices closed at least in the short-term. But we do see little evidence for a lasting effect of proximity.

[32]This is less surprising when we note that all engineers were familiar with Github, the online software used for giving comments on code. However, engineers on one-building teams might have been less comfortable with Zoom and other online tools. Our persistent effects suggests that the transitory costs of learning to use these tools likely did not drive our effects.

[33]Since engineers who worked on internal tools found it useful to sit near those who used their tools, their teams were more likely to face desk constraints and end up in multiple building. The fact

We find that the differential declines in feedback are driven by comments given during standard work hours (8AM − 6PM, Monday through Friday), when teammates on one-building teams would have been proximate to one another before the offices closed but not afterwards (Figure A.7).

We find similar results using different measures of feedback. Proximity enhances not only the number of comments (Table 3(a), Column 1) but also the total number of characters (Column 2). It leads to timelier feedback, with shorter delays between program submission and the receipt of the first comment (Column 3). Proximity also appears to *increase* references to other online conversations, such as email, Slack, or Zoom (Column 4), suggesting that collaboration did not simply migrate to another means of digital communication when offices closed. Using a principal component analysis, we also see that various different types of comments are impacted by proximity, including those about testing code and verifying that functions are producing the right outputs (Figure A.1(b)). Both of these themes capture substantive feedback that may be time-consuming to give, would often be broadly applicable to other programs, and would likely impact the reliability of the code in the long run.

As a placebo check, Figure 1(c) shows that losing proximity to teammates only affects feedback from teammates not feedback from other engineers. The null effect for non-teammate comments is inconsistent with an alternative explanation based on engineers' need for feedback: if engineers on one-building teams simply needed more help before the offices closed but not afterwards, this change would impact reviews from both teammates and non-teammates.

A similar design shows that proximity to *non*-teammates only impacts feedback from non-teammates. Engineers who sat in the main building — near 71 percent of the main campus's engineers and near the main campus's lunch room — saw larger declines in feedback from non-teammates (Figure A.8(a)) than engineers who sat in

that we find similar results when limiting to these groups suggests that our results are not driven by differential shocks to those working on internal tools versus the website.

the auxiliary building.[34] Engineers in the main building did not see larger declines in teammate feedback, conditional on their type of team (Figure A.8(b)). This finding suggests that serendipitous watercooler chats facilitate online interaction across teams.

We also find similar impacts when we compare one-building teams to teams that are spread across campuses (Figure A.11). Engineers whose teammates worked many miles away received the fewest comments on their programs before the pandemic, but these gaps also closed when the offices closed. Engineers on multi-campus teams do not receive substantially fewer comments than engineers whose teammates are just a few blocks away. The comparable results for multi-building and multi-campus teams suggest that small frictions to face-to-face contact can have outsized effects on feedback. Further, this similarity suggests that our main results do not simply reflect some managers agitating for their teams to be unified on the main campus.

Asking for Feedback. Our results indicate that engineers ask for more feedback when seated near their colleagues, consistent with the model's prediction.

While we do not directly observe initial requests for feedback (which are typically made in person or over Slack), we do observe the number of commenters per program. Since commenters have to be asked to review, we view this as a proxy for the number of people asked. Engineers on one-building teams have 11.5 percent more commenters before the closures and this gap is more than halved when the offices close (Column 2 of Table 3(b)).

Through the code-review system, we can also directly see the number of follow-up questions that the program writer asks the commenter. We find that engineers on one-building teams ask 47.5 percent more follow-up questions than engineers on

[34] This change was particularly driven by feedback from non-teammates who were also in the main building A.9). The declines in teammate feedback were similar in the main and auxiliary buildings (Figure A.10).

multi-building teams when the offices are open, and this gap disappears once the offices close (Column 3 of Table 3(c)). More follow-up questions lead to more clarification and additional feedback: indeed, commenters' additional follow-up comments explain more than half of the effect of proximity on total feedback received (comparing Column 4 of Table 3(c) to Column 1 of Table 3(a)).

These patterns are consistent with engineers feeling more comfortable asking for feedback and advice when sitting with their colleagues in-person. As a result, sitting together increases even online feedback.

V.A Mentorship of Juniors by Seniors

Our results are driven by feedback received by less-experienced engineers and feedback given by more-experienced engineers. Figure 2 shows these patterns. Junior engineers (with less than the median tenure of 16 months) receive more feedback generally, and the feedback that they receive is also more sensitive to teammate proximity. Comments are disproportionately written by senior engineers (with at least the median tenure of 16 months), and the feedback that these senior engineers give is also more sensitive to teammate proximity.

When the offices were open, junior engineers on one-building teams received 27 percent more feedback than those on distributed teams (Column 2 of Table A.4(a)), but this gap quickly narrowed when the offices closed. On the other hand, proximity did not impact feedback for more-experienced engineers either before or after the offices closed (Column 5 of Table A.4(a)).

When we consider the seniority of the comment writers in Figure 2(b), we see the opposite pattern. When the offices were open, engineers on one-building teams received 39 percent more feedback from senior engineers than those on multi-building teams (Column 5 of Table A.4(b)). Once the offices closed, this gap largely disappeared. By contrast, proximity did not impact feedback that was given by junior engineers (Column 2 of Table A.4).

These findings are consistent with the model in which the firm requires feedback on all code, but juniors receive extra mentoring from senior colleagues when sitting together in the office.

Mentorship is particularly important for junior engineers who are also early in their careers. Young, junior engineers received the most feedback before the offices closed, and the feedback that they received was most sensitive to their proximity to their teammates (Figure A.12(a)). Even among young engineers who had considerable experience at the firm, they received significantly more feedback when sitting near their teammates (Figure A.12(b)). These patterns are consistent with young engineers having more to learn from their more experienced colleagues and proximity facilitating these knowledge flows.

V.B Externalities from Distant Teammates

In the model, engineers are paired with one mentor, but, at this firm, engineers work in teams. Distant teammates have externalities on their teammates' interactions, decreasing the feedback workers get from teammates sitting in their same building. These externalities likely arise because once one worker is distant, teams hold online meetings instead of in-person ones.[35]

We measure the impact of a distant teammate in two ways. First, we compare the interactions of *same-building* teammates on one- and multi-building teams around the office closures in Figure 3(a). Before the office closures, engineers with distant teammates received 17 percent fewer comments per review from a *proximate* teammate than did engineers whose teammates were all in their building. This gap largely closed once the offices shut down for the pandemic (Column 2 of Table A.5). These externalities explain about 30 percent of both the initial feedback gap between one- and multi-building teams and the differential decline in feedback around the closures (Table A.5).

[35]The small-talk before in-person meetings, which is often hard to replicate on Zoom, may help ease requests for additional help.

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. We estimate

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

where i indexes the coder and j indexes the commenter. We only consider coders and commenters who are in the same building and were hired before the 6-week window.

Figure 3(b) 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, with similar estimates controlling for program scope (Table A.6).

For both of these designs, the 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 (Figure A.15).

These estimates suggest that having even one teammate in another location diminishes feedback from same-building colleagues. These results suggest that even as workers come back to the office after the pandemic, their interactions will be affected by coworkers who continue to work remotely.

VI PROXIMITY'S IMPACT ON PROGRAMMER OUTPUT

When junior engineers sit near their coworkers, they receive more on-the-job training, but this has an opportunity cost. In keeping with the model's second prediction, both junior and senior engineers write fewer programs when seated near their teammates. The effects are particularly large for senior engineers. Thus, proximity creates a trade-off between long-run human capital development and short-run output.

Figure 4(a) illustrates the consequences of proximity for workers' programming output. When the offices were open, engineers who sat near all their teammates submitted 19 percent fewer programs per month (or 0.32 fewer programs) than similar engineers whose teammates were distributed across the main campus's two buildings (p-value = 0.04, Column 3 of Table 4(a)). When the offices closed for COVID-19, this gap narrowed. The programming output of all engineers fell — likely due to the pandemic's many stressors — but the decline was less precipitous for engineers who had been proximate to all of their colleagues in the office. Thus, in relative terms, engineers who had sat near all their teammates in the office caught up to the programming output of engineers on already-distributed teams once they too were distributed (shown in Figure 4(b)).

Our difference-in-differences estimate indicates that proximity to teammates reduces programming output by 24 percent (0.41 programs per month) (p-value = 0.0001, Column 3 of Table 4(a)). Table 4 shows similar results for different specifications. This table also shows similar patterns for lines of code written, ruling out the explanation that engineers on one-building teams simply submitted more frequent, smaller chunks of code once they were no longer sitting near their colleagues. We also see similar patterns when we replicate this analysis for the subset of engineering teams who build internal tools for others in the firm and so are more likely to end up spread across the buildings (Figure A.13 and Table A.10).

The effect of proximity on programming output is more pronounced for senior engineers, as illustrated in Figure 4(c). While the offices were open, senior engineers on one-building teams wrote 39 percent fewer programs than senior engineers on distributed teams (Column 1 of Table A.11). After the offices closed, this gap quickly closed. The difference-in-differences indicates that proximity reduces senior engineers' output by 30 percent. These differences are even more pronounced for lines of code and files changed (Column 3−6 of Table A.11).

Junior engineers on one-building teams also submit slightly fewer programs than junior engineers on distributed teams before the offices closed but not afterwards (Figure 4(c)). This negative effect of proximity on junior engineers' programming output is driven by the most junior engineers who also see the largest declines in feedback when proximity is lost (Figure A.14). This pattern is consistent with the most inexperienced engineers being able to submit more programs when they spend less time responding to feedback.

Together, the results on programming output are consistent with the model's third prediction that mentorship has opportunity costs for both mentors and mentees. The results suggest that additional mentoring has larger opportunity costs for the mentors than the mentees.

VII GENDER

In our model, male engineers are more comfortable asking for feedback when remote. As a result, we predict that proximity will have a larger impact on the feedback female engineers ask for and receive (Prediction 7). Consistent with this prediction, we find that female engineers' feedback is more sensitive to their proximity to their teammates. Figure 5(a) shows this, plotting the raw average of the comments received per program on one-and multi-building teams around the office closures, separately for female and male program writers.

Focusing first on the pre-period patterns (to the left of the grey line in Figure 5(a)), female programmers on multi-building teams (the orange line in the left plot) received fewer comments than their male counterparts (the orange line in the right plot). With our preferred controls, this gap represents an 18 percent deficit in feedback for female engineers on distributed teams while the offices were open (p-value

= 0.01). What's more, female engineers saw a much bigger impact of being on a one-building team. Female engineers on one-building teams received fully 48 percent more comments than their multi-building counterparts, relative to a gap of only 17 percent for male engineers (Column 1 of Table A.7(a)).[36]

After offices closed, the advantage in feedback for engineers on one-building teams shrank by much more for female engineers (35 percent, p-value = 0.0005) than for male engineers (10 percentage points, p-value = 0.067). The triple difference indicates that losing proximity decreased feedback by 25 percent more for female engineers than male engineers (p-value = 0.01, Column 1 of Table A.7(b)). Differences in tenure and age do not explain the differential impact of proximity. While female engineers do tend to be about two years younger and have one fewer months at the firm, we still find similar gender differences after also allowing for the effects of proximity to vary by engineers' age and tenure (Table A.8).

The data suggest that these gendered effects on feedback stem from differences in engineers' willingness to ask for feedback when remote. We first consider the number of commenters per program, which proxies for the number of people whom the engineer asked to review the code (Figure 5(b)). When the buildings were open, female engineers had more commenters on their code on one-building teams than on multi-building teams — a differential which was larger than that for male programmers. When the buildings closed, female engineers also experienced more of a drop off in commenters on one-building teams. On average, female engineers saw a 14 percent larger relative decline in commenters on one- versus multi-building teams compared to male engineers (p-value = 0.003, Column 2 of Table A.7(b)).

Within the code-review process, we find that proximity matters more for female engineers' willingness to ask follow-up questions. Figure 5(c) illustrates this result.

[36]The fact that female engineers receive less feedback when distant from their teammates and more feedback when nearby suggests that underlying differences in the quality of code produced by female and male engineers are unlikely to account for these differences.

When the offices were open, female engineers were more likely to ask follow-up questions on one-building teams than multi-building teams — a differential which was largely absent for male engineers. Female engineers also see a suggestively larger decline in follow-up questions when the offices closed. This differential in follow-up questions is reflected in commenters' engagement in the review. The gendered effect of proximity on comments received is almost entirely driven by follow-up responses from commenters, not in their initial feedback on the code (Figure A.16 and Columns 3−5 of Table A.7).

The gendered effect of proximity on the feedback that engineers receive is present for comments from both male and female commenters (Figure A.17). This pattern suggests that the gender match between the programmer and commenter is not the primary moderator of the effect of proximity on mentorship.

Our model also predicts that proximity has larger impacts on the feedback women give (Prediction 8), because they have larger rejection costs on average. We see this borne out in Figure 5(d): female commenters give much more feedback on one-building teams before the pandemic and see a much bigger decrease in the feedback they give on one-building teams when the offices close. Using our preferred controls, the difference-in-differences design indicates that losing proximity reduces the extensiveness of female engineers' code reviews by 28 percent more than those of male engineers (p-value = 0.07, Column 1 of Table A.9(b)).

These gaps translate into output (Prediction 9). Women face a larger output cost of sitting near their teammates than do men (Figure 5(e)). As with the other outcomes, this is true both when looking at the difference between one- and multi-building teams before the pandemic and the differential change once the offices close. With our preferred controls, the estimated cost of proximity for programming output is suggestively 15 percent larger for women but not significant at traditional levels (p-value = 0.29, Column 2 of Table A.9(b)). As expected, the output cost of proximity is particularly large for senior women, who are doing a lot of the mentoring (Figure

A.18).

VIII Career Outcomes

Our analysis of wage changes and quits suggest that the additional training junior workers get from sitting near their coworkers improves their future job outcomes but has an opportunity cost. Throughout this section, we consider workers who were hired before our data starts, so they have spent enough time at the firm to gain skills from their coworkers before the offices close. This restriction does not affect our analysis of the contemporaneous costs of proximity, but it does allow us to more cleanly estimate the long-run returns to having sat with coworkers.

VIII.A Wages

Engineers write fewer programs when seated near their coworkers. The model suggests that this leads junior engineers working near their coworkers to earn lower wages, and this is exactly what happens empirically (Column 2 of Table 5). Pay raises happen three times during the year, when the firm reviews workers' performance and decides whether to increase a worker's pay. While the offices were open, junior workers on one-building teams were substantially less likely to get a raise than those on distributed teams.

The model's prediction about wages for senior workers on one-building teams is less clear. On the one hand, we see they write less code, which would translate into lower wages. On the other hand, although team type can vary over workers' careers, they were likely trained on one-building teams and so accumulated more human capital. Empirically, senior engineers on one-building teams earn insignificantly less than seniors on multi-building teams (Column 3). Overall, (insignificant) point estimates indicate that female engineers on one-building teams take a particularly large wage hit, reflective of the fact that they both do more mentoring and spend more time getting mentored.

Once the offices close, there is no difference in mentoring between team types. Thus, the model predicts that workers who were trained on one-building teams should have more human capital and earn more than their counterparts. This is borne out in the data (Columns 4−6 of Table 5). Workers who had been on one-building teams were 17 percent more likely to receive a raise after the offices closed (Column 4). This is particularly pronounced for junior engineers (whom we know were trained on one-building teams), who were 23 percent more likely to receive a raise after the closures (Column 5). This differential is also more pronounced among female engineers, for whom mentorship was particularly sensitive to proximity (Column 6).[37] These patterns are similar when we limit the sample to engineers who work on internal tools (Table A.12).[38]

Consistent with junior engineers who were trained on one-building teams being more productive once the offices closed, they were also suggestively although insignificantly less likely to be fired (Table A.13).

VIII.B Quits

Consistent with the model, workers trained on one-building teams are more likely to quit once tech jobs go remote. Figure 6(a) shows that before the pandemic, quit rates are low for workers on both one- and multi-building teams. After the start of the pandemic, quit rates increase for both groups, and workers trained on one-building teams are more likely to quit.[39]

Figure 6(b)-(c) show that the increase in quits is concentrated in the groups that likely gained the most human capital from being nearby. Panel (b) shows that the effect is particularly large for junior engineers (who we know were trained on

[37] Figure A.19 illustrates these reversals in relative raises graphically.

[38] We see the same reversal in rates of pay raises overall (Columns 1 vs. 4), with more pronounced effects for female engineers. The patterns look more similar for junior and senior engineers, however, rather than looking more pronounced for junior engineers.

[39] When asked why they quit, most workers say they quit for a better job. While we take workers' responses to this with a grain of salt, results are similar if our dependent variable is quits that workers report are to better jobs.

one-building teams). Indeed, junior engineers who had sat with their coworkers in the office saw a 1.2 percentage point greater increase in quits, about twice that of engineers who were trained on multi-building teams (p-value of difference = 0.01). Panel (c) show that the impact is larger for women, who we have seen gain much more in terms of mentorship from proximity. We also see higher quit rates for younger engineers (Figure A.21), who also have bigger boosts in feedback from sitting near their teammates.

We see broadly similar patterns when limiting to engineers who work on internal tools. Engineers on one-building teams are significantly more likely to quit after the offices closed, which is especially true among women (Figure A.20). However, we do not see the same pattern of heterogeneity by engineers' tenure, which may be due to the more limited sample.

IX WHO WORKS IN THE OFFICE?

We assume that the firm cannot incentivize mentorship directly, but the firm can affect mentorship through choosing where workers sit. Junior and senior workers pay for the training through lower wages, but if the firm has to compete over workers with other firms, it has an incentive to provide the efficient level of training. If mentorship's benefits exceed its costs, we expect to see that:

1. When proximity is possible, both mentees and mentors will be on-site.
2. When proximity is difficult, the firm will shift away from requiring mentorship. They will "buy" talent rather than "building" talent by hiring more experienced workers.

Both predictions are borne out in our firm's remote work and hiring decisions.

Before the pandemic, when proximity was possible, mentees — with the most junior job levels — and mentors — with the most senior job levels or management roles — were required to be in the office (Figure 7(a)). These policies created a U-shaped pattern in office work across worker age: the youngest and oldest engineers were more likely to be in the office (Figure A.22). These patterns of on-site work are reflected in national trends from the Household Pulse Survey in which the youngest workers and relatively older college-graduates are more likely to return to the office in 2022−2023 (Figure 7(b)). In 2023, 74 percent of workers aged 21−23 were working on-site, relative to just 60 percent of 30−32 year old workers.[40]

Consistent with the second prediction, our firm shifted its hiring practices from before the pandemic to after remote work's implementation. Before the offices closed, 55 percent of engineers hired were the lowest level of engineer; afterward, that number sank to 37 percent (p-value of change = 0.0073), leading to a marked decline in the share of workers who need mentoring. By contrast, the share of engineers hired who are unlikely to need as much training (levels 3 and above) went from 23 percent to 41 percent (p-value = 0.0018).

To the extent that mentorship increases junior workers' skills, barriers to mentorship may have scarring effects on less experienced workers. First, even if junior workers go to the office, all the potential mentors may not. Further, if firms are more likely to "buy" talent rather than "build" it when in-person work is challenging, then even having an opportunity to be in the office may be harder to come by for junior workers.

X CONCLUSION

Remote work leads to a tradeoff. It increases output today, particularly from more senior workers. But it decreases training of more junior workers, which has future costs. We find this tradeoff is particularly pronounced for women. When not sitting near their colleagues, junior women ask for and receive less mentorship. Yet senior women are asked to provide less guidance and can therefore focus more on their own productivity. Work arrangements seem to respond to this tradeoff with junior

[40] Levels of on-site work are lower post-pandemic nationally than they are in the share of workers at our firm who were onsite pre-pandemic. This may reflect shifts to remote work from the pandemic.

workers and potential mentors less likely to work remotely.

A key finding is that one worker's choice to work remotely impacts her peers. Older workers are much more likely to work remotely than young workers. If they do not come back to the office, this can depress younger workers' skill accumulation. And even one remote worker can have an outsized impact, depressing collaboration between co-located coworkers.

This suggests policies coordinating workers' locational choices may yield benefits. For example, 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. Moreover, coordinating which days teams spend in the office may lead to more fully in-person meetings and more mentorship. This raises the question of how much of the mentorship benefits of in-person work can be achieved by only a few days per week in the office.

Finally, if there is a permanent increase in remote work post-pandemic, can alternative management practices encourage more training of junior workers? While mentorship is hard to fully observe, it will be interesting to see whether firms start collecting more mentorship metrics, putting more weight on training in worker evaluations, and formalizing training that was previously based on informal interaction.

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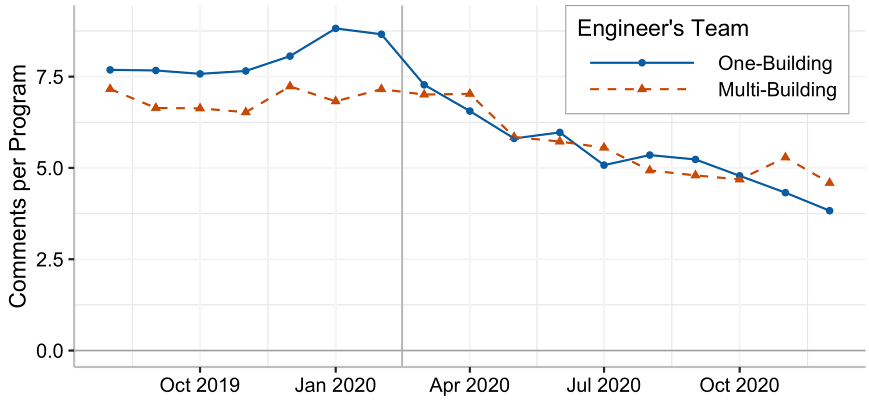
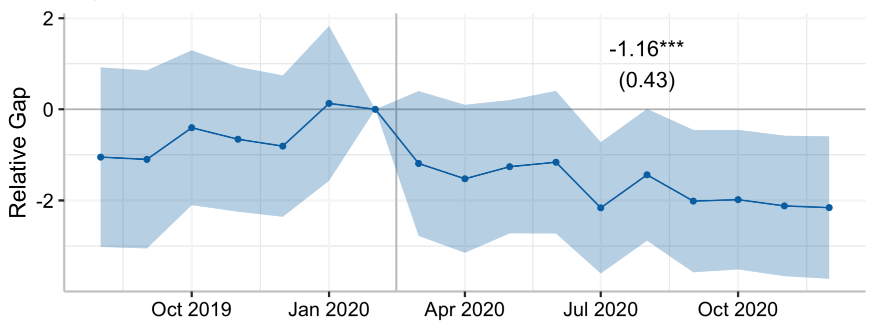
Figure 1: Proximity to Teammates and Online Feedback

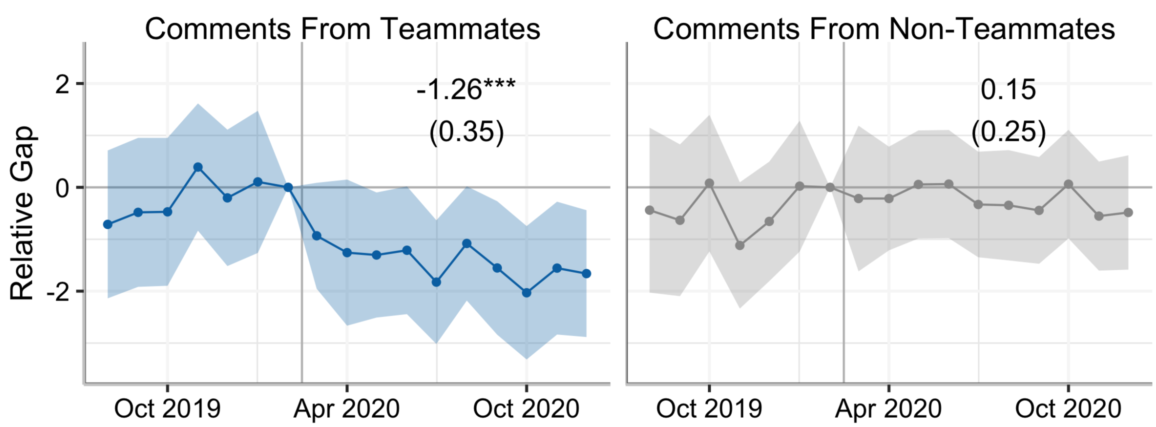
Panel (a): Raw Averages of Comments Per Program



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

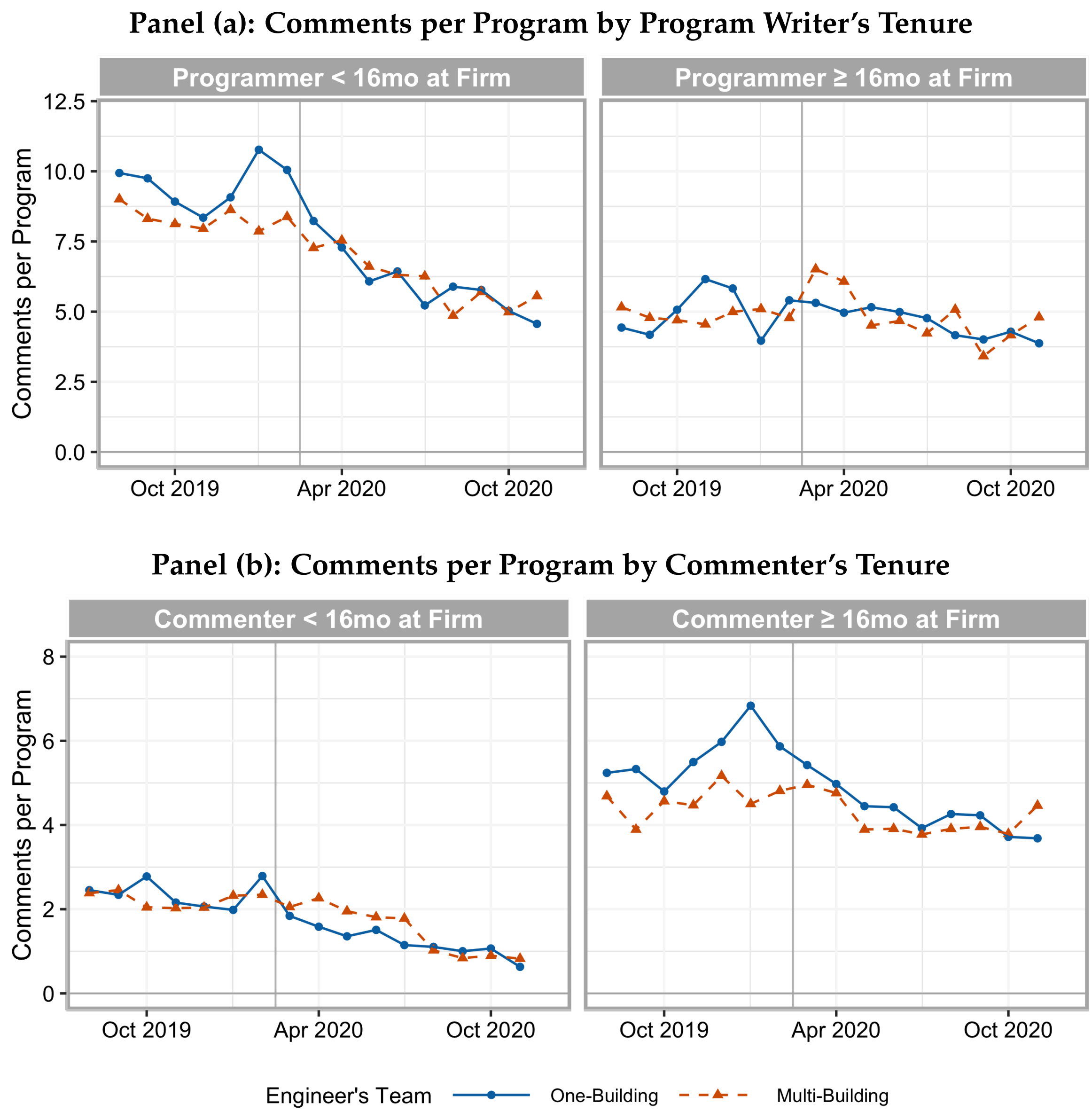


Panel (c): Placebo Check with Comments from Teammates or Non-Teammates



Notes: This figure illustrates the online feedback received by engineers on one-building teams (N=637) and on multi-building teams (N=418) around the COVID-19 office closures (the grey vertical lines). Panel (a) plots the raw averages, while Panel (b) plots the differences from Equation 2, conditional on our preferred controls (as in Column 4 of Table 2). Panel (c) uses the same specification as in (b) to illustrate a placebo check: the left panel show comments from teammates which should be affected, and the right panel shows comments from non-teammates which should not be. The ribbons in Panels (b) and (c) show 95% confidence intervals with clustering by team. The annotated coefficients are the difference-in-differences estimate from Equation 1. The sample limits to engineers whose teammates all worked in the main campus. *p<0.1; **p<0.05; ***p<0.01.

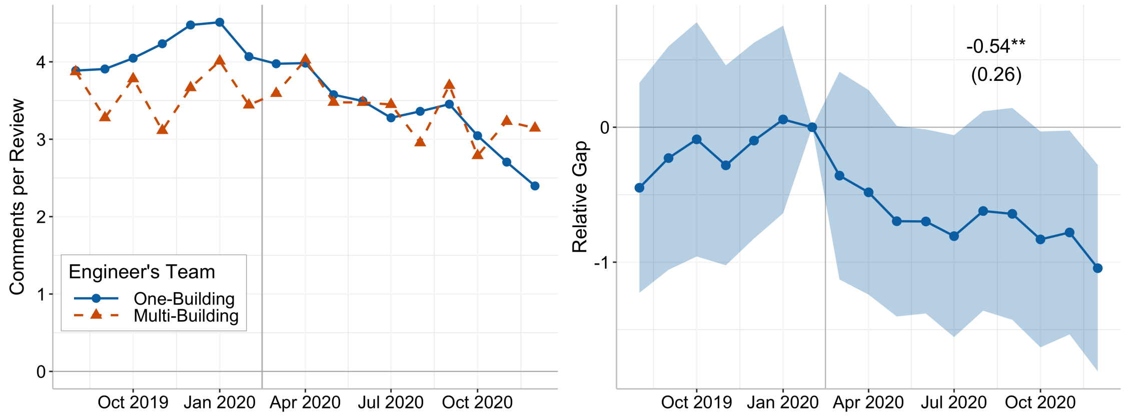
Figure 2: Proximity and Mentorship



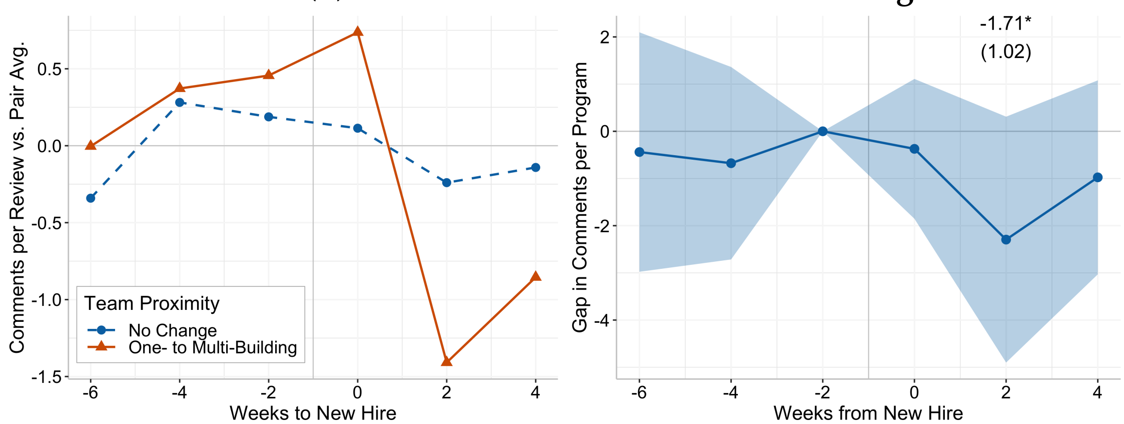
Notes: Panel (a) shows the effects of proximity on online feedback received by engineers of different tenures. It shows the raw monthly averages of comments received per program for engineers on one- and multi-building teams, separately by those below the median tenure of 16 months. Panel (b) shows a comparable plot of raw averages of comments per program broken down by the seniority of the commenter rather than the program writer.

Figure 3: Externalities from Distant Teammates

Panel (a): Diff-in-Diff Design for Reviews from Same-Building Teammates

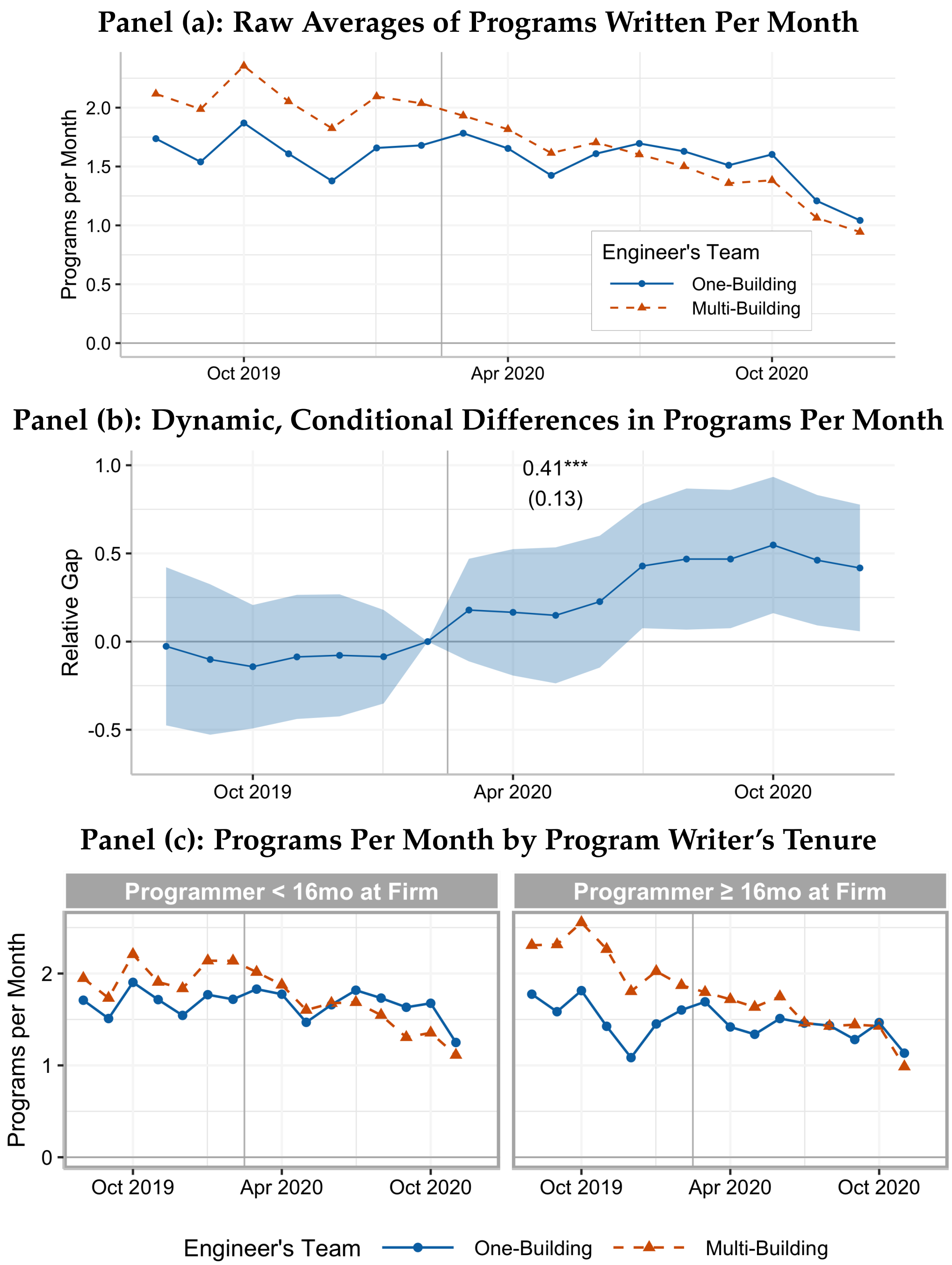


Panel (b): Pre-COVID Hire in Another Building



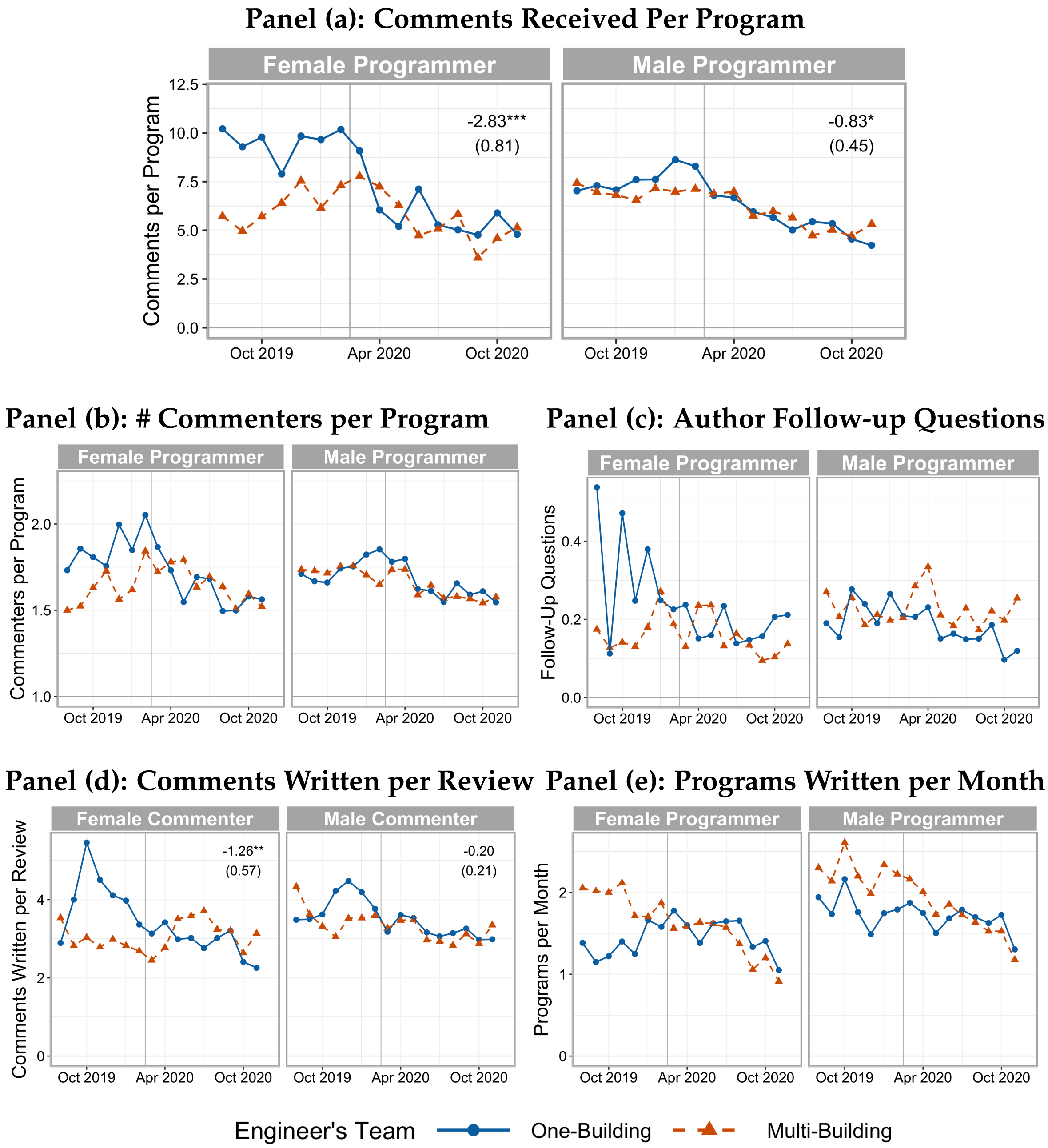
Notes: This figure investigates the externalities from having a distant teammate on the feedback exchanged between teammates who sit in the same building. Panel (a) replicates Figure 1 but focuses on comments received per review from a same-building teammate. Panel (b) considers the impact of a new hire that converts the team from a one-building team to a multi-building team versus a new hire that does not change the distribution of the team. The plots focus on pre-existing relationships between teammates in the same building. The left plot shows comments received on each program relative to the average in the coder-commenter pair. The right plot shows 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. Ribbons reflect 95% confidence intervals with standard errors clustered by team. *p<0.1; **p<0.05; ***p<0.01.

Figure 4: Proximity to Teammates and Engineer Output



Notes: This figure illustrates the impact of proximity on short-term output. Panels (a) and (c) show the raw monthly averages of the number of programs submitted per month for engineers on one-building and multi-building teams. In Panel (c) the averages are plotted separately by those who have been at the firm for more or fewer months than the median tenure (16 months) before the offices closed and those who were more experienced. Panel (c) shows the difference-in-differences estimates in percentage terms with our preferred set of controls. Standard errors are clustered by engineering team. *p<0.1; **p<0.05; ***p<0.01.

Figure 5: Gendered Impacts of Proximity to Teammates



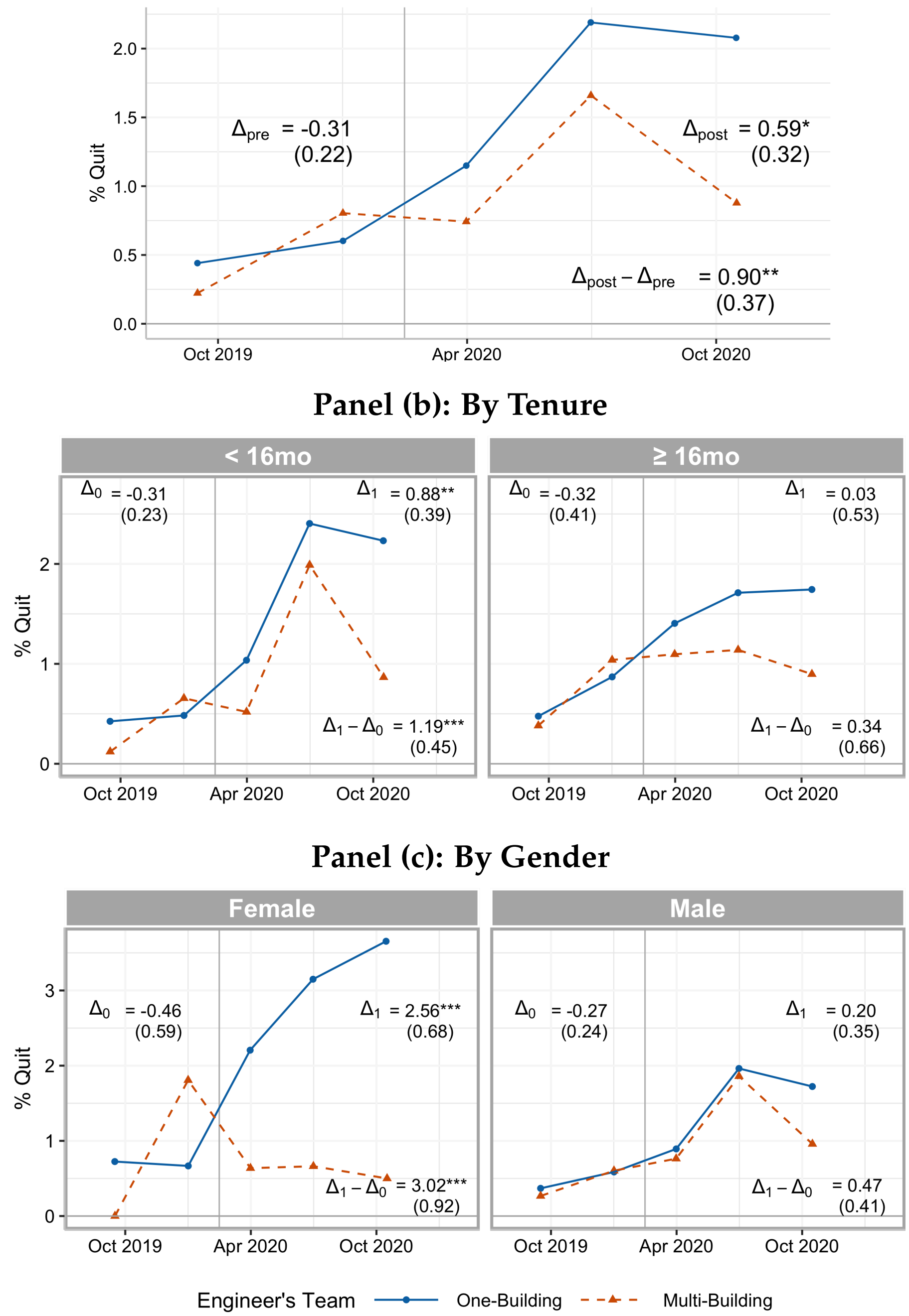
Notes: This figure illustrates the gendered impact of proximity on mentorship given and received. Each plot shows the raw monthly averages of comments received per program for engineers on one- and multi-building teams, separately by female and male engineers. Panel (a) shows the average comments that engineers receive on their programs. Panel (b) shows the average number of commenters that comment on the engineer's program, which is a proxy for how many programmers the engineer asked to look at their code. Panel (c) shows the average number of follow-up questions that authors ask commenters in the code-review process. Panel (d) turns to giving rather than receiving mentorship, plotting the average number of comments writter per code review. Panel (e) shows the average number of programs that engineers submit to the main code-base each month. The sample limits to engineers whose teammates all worked in the main campus.

Figure 6: Impacts of Proximity on Quits

Panel (a): Quit rates for all engineers

Panel (b): By Tenure

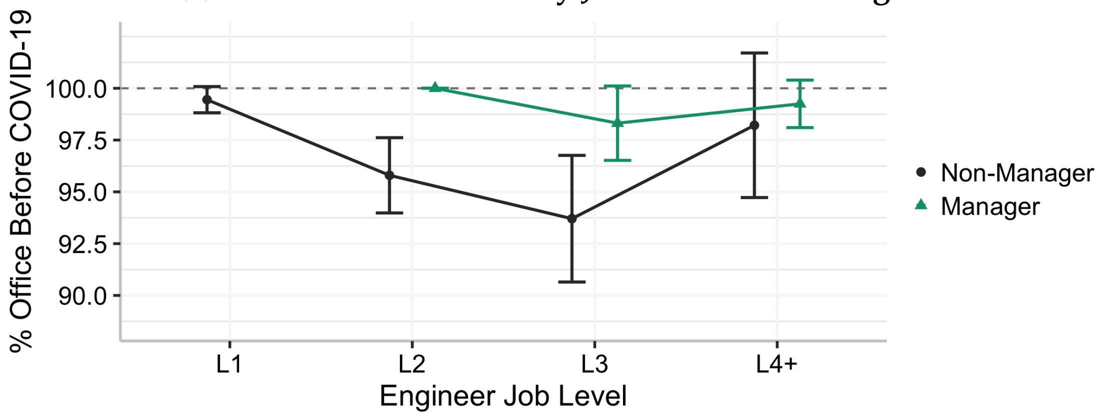
Panel (c): By Gender



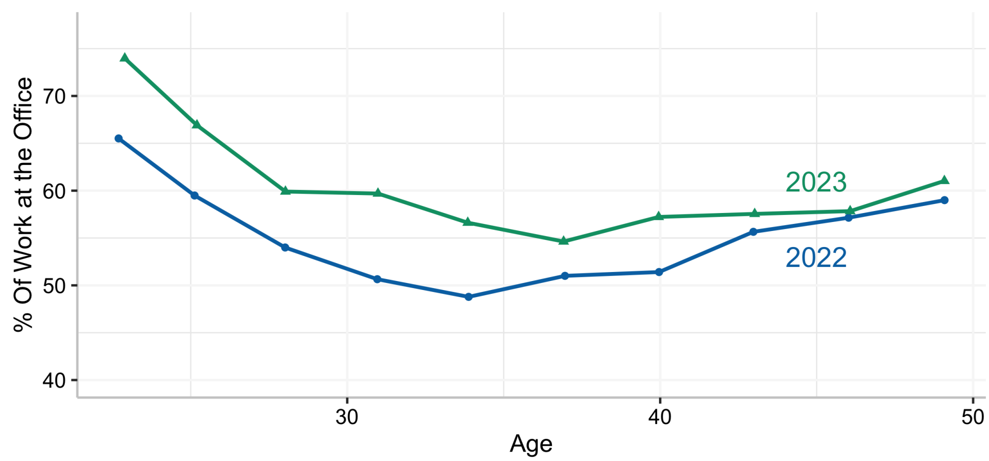
Notes: This figure illustrates the effects of proximity on quits (a) overall, (b) by pre-COVID tenure, and (c) by self-identified gender. Each plot shows the raw quit rates for engineers on one-building and multi-building teams. The annotated coefficients use our preferred set of controls for engineering group and engineer tenure. Standard errors are clustered by engineering team. The sample includes engineers who worked on the main code-base, whose teammates were all in the main campus, and who were hired before the start of our sample. *p<0.1; **p<0.05; ***p<0.01.

Figure 7: Who Works in the Office

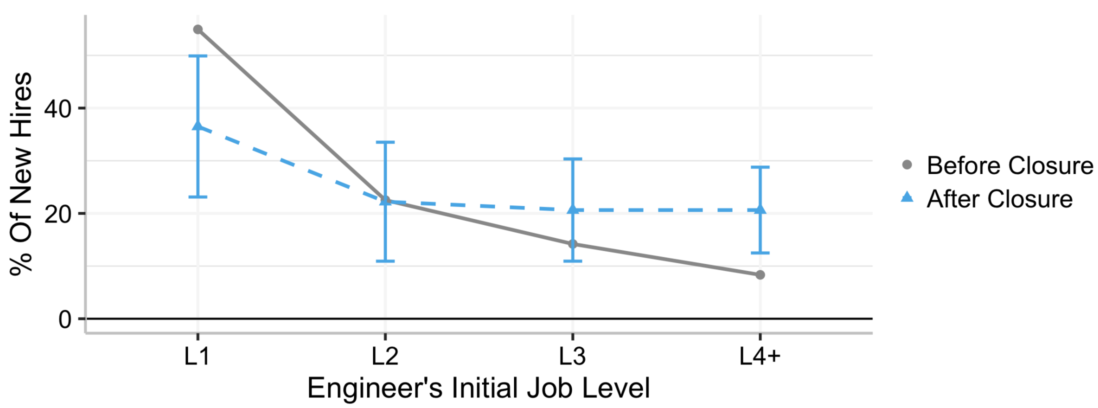
Panel (a): Percent in the Office by Job Level and Manager Status



Panel (b): Percent College-Educated, Non-Parents in the Office Nationally



Panel (c): Workers Hired Before and After the Pandemic by Job Level



Notes: Panel (a) shows which engineers at the firm worked on-site versus remotely before the pandemic's office closures. Panel (b) uses data from the Household Pulse Survey, limiting to college-educated workers without children. Panel (c) shows the share of new hires at each job level before and after the office closures. Error bars reflect 95% confidence intervals.

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

	Mean	One-Building	Multi-Building	Δ_0	
% Work on Internal Tools	60.5	37.2	90.1	-52.9***	0
				(5.26)	(0)
# Teammates	5.98	5.72	6.57	-0.851**	-0.425
				(0.418)	(0.466)
Engineer Traits					
% Female	18.7	19.5	17.3	2.19	-2.75
				(2.78)	(3.26)
% BIPOC	24.0	21.8	26.2	-4.32	-2.12
				(3.07)	(3.71)
% Parent	16.0	17.0	16.5	0.457	8.30
				(4.91)	(6.32)
Age (Years)	28.9	28.5	29.1	-0.586	0.365
				(0.416)	(0.557)
Job Traits					
Firm Tenure (Years)	1.63	1.21	1.56	-0.344***	-0.419***
				(0.110)	(0.123)
Job Level	1.81	1.62	1.82	-0.196***	-0.058
				(0.063)	(0.075)
Hourly Pay	55.8	53.7	55.6	-1.89***	-0.172
				(0.694)	(0.852)
Manager Traits					
Manager Tenure	2.77	2.75	2.73	0.023	-0.376
				(0.295)	(0.332)
Manager Job Level	3.28	3.21	3.42	-0.206**	-0.077
				(0.093)	(0.099)
Manager Pay	70.6	69.7	72.6	-2.91**	-0.690
				(1.21)	(1.38)
Engineer Group Controls					✓
# Software Engineers	1,055	637	418	1,055	1,055

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

Table 2: Proximity to Teammates and Online Feedback

	Comments per Program						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post x One-Building Team	-1.29^{***}	-1.58^{***}	-1.52^{***}	-1.16^{***}	-1.18^{***}	-1.50^{***}	-1.13^{**}
	(0.48)	(0.50)	(0.45)	(0.43)	(0.44)	(0.46)	(0.47)
One-Building Team	1.16^{**}	1.45^{**}	2.35^{***}	1.80^{***}			
	(0.52)	(0.61)	(0.53)	(0.49)			
Post	-1.22^{***}						
	(0.36)						
Pre-Mean, One-Building Team	8.04	8.04	8.04	8.04	8.04	8.04	8.04
Percentage Effects							
Post x One-Building Team	-16.1%	-19.7%	-18.9%	-14.4%	-14.6%	-18.7%	-14%
One-Building	14.5%	18.1%	29.2%	22.4%			
% One-Building Team	58.3	58.3	58.3	58.3	58.3	58.3	58.3
Engineer Group x Post FE		✓	✓	✓	✓	✓	✓
Program Scope Quartics			✓	✓	✓	✓	✓
Months at Firm x Post FE				✓	✓	✓	✓
Engineer FE					✓	✓	✓
Engineer Traits x Post FE						✓	✓
Main Building x Post FE							✓
# Teams	304	304	304	304	304	304	304
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055	1,055
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304	9,304
R^2	0.02	0.02	0.29	0.36	0.49	0.50	0.50

Notes: This table investigates the relationship between sitting near teammates and the online feedback that engineers receive on their computer code. Each observation is an engineer-month. The dependent variable is the average number of comments that the engineer receives on each program. Each column estimates Equation 1, which compares engineers who were in the same building as all of their teammates before COVID-19 to those on teams already distributed across multiple buildings. Column 1 presents the raw estimates corresponding to Figure 1. Column 2 includes time-varying controls for engineering group (e.g., front-end website design). Column 3 adds controls for program scope (quartics for the number of lines added, number of lines deleted, and number of files changed). Column 4 allows for differential changes in feedback for engineers with different tenure (in months). Column 5 includes engineer fixed effects. Column 6 adds additional controls for engineer age (in years), gender, home zipcode, and job level. Columns 6 includes building-by-post fixed effects to allow programmers who sat in the main and auxiliary buildings to experience different changes in feedback around the office closures. The sample includes engineers who submit programs to the firm's main code-base in the month and whose teams are all in the firm's main campus. Standard errors are clustered by team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 3: Proximity and Dimensions of Online Feedback

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

	Comments per Program (1)	Total Characters (2)	Hours to Comment (3)	% Other Online Convo (4)
Post x One-Building Team	-1.16^{***}	-135.70^{**}	1.01^{*}	-1.23
	(0.43)	(57.93)	(0.60)	(0.82)
One-Building Team	1.80^{***}	201.60^{***}	-1.43^{**}	2.39^{***}
	(0.49)	(62.44)	(0.59)	(0.88)
Pre-Mean, One-Building Team	8.04	833.24	16.02	4.06
Post x One-Building Team as %	-14.4%	-16.3%	6.3%	-30.5%
One-Building Team as %	22.4%	24.2%	-8.9%	58.8%

Panel (b): Intensive and Extensive Margins

	Comments per Commenter (1)	Commenters per Program (2)
Post x One-Building Team	-0.35^{*}	-0.10^{**}
	(0.20)	(0.05)
One-Building Team	0.51^{**}	0.20^{***}
	(0.21)	(0.06)
Pre-Mean, One-Building Team	4.36	1.77
Post x One-Building Team as %	-8%	-5.7%
One-Building Team as %	11.7%	11.5%

Panel (c): Back-and-Forth Conversations

	Commenter's	Program Writer		Commenter's
	Initial Comments	Replies	Questions	Follow-up Comments
	(1)	(2)	(3)	(4)
Post x One-Building Team	-0.48^{*}	-0.63^{**}	-0.14^{***}	-0.68^{**}
	(0.26)	(0.26)	(0.05)	(0.34)
One-Building Team	0.76^{***}	0.68^{**}	0.11^{**}	1.04^{***}
	(0.26)	(0.29)	(0.05)	(0.39)
Pre-Mean, One-Building Team	4.91	2.14	0.24	3.13
Post x One-Building Team as %	-9.8%	-29.4%	-58.3%	-21.8%
One-Building Team as %	15.5%	31.6%	47.5%	33.2%

Notes: This table considers alternative metrics of (a) the extent and timeliness of feedback, (b) the intensive and extensive margins of feedback, and (c) the back-and-forth conversation between the commenter and program writer. Each specification replicates Column 4 of Table 2, reported in Column 1 of Panel (a) for reference. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 4: Proximity to Teammates and Engineer Output

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel (a): Programs per Month					
Post x One-Building Team	0.47***	0.45***	0.41***	0.35***	0.32***	0.32**
	(0.11)	(0.13)	(0.13)	(0.11)	(0.12)	(0.13)
One-Building Team	−0.48***	−0.33**	−0.32**			
	(0.16)	(0.16)	(0.16)			
Pre-Mean, One-Building Team	1.71	1.71	1.71	1.71	1.71	1.71
Post x One-Building Team as %	27.5%	26.3%	24.1%	20.4%	18.9%	18.7%
One-Building Team as %	-28.1%	-19.1%	-19%			
R^2	0.01	0.05	0.08	0.46	0.46	0.46
	Panel (b): Lines Added per Month					
Post x One-Building Team	104***	90**	92**	89**	80**	111***
	(36)	(38)	(39)	(38)	(39)	(41)
One-Building Team	−190***	−155***	−166***			
	(42)	(43)	(45)			
Pre-Mean, One-Building Team	317	317	317	317	317	317
Post x One-Building Team as %	32.8%	28.5%	28.9%	28.1%	25.1%	34.8%
One-Building Team as %	-59.8%	-48.9%	-52.4%			
R^2	0.02	0.03	0.04	0.34	0.35	0.35
	Panel (c): Files Changed per Month					
Post x One-Building Team	1.80**	1.58*	1.41	1.17	0.90	1.34
	(0.88)	(0.95)	(0.96)	(0.91)	(0.94)	(0.98)
One-Building Team	−3.70***	−3.39***	−3.52***			
	(1.03)	(1.06)	(1.08)			
Pre-Mean, One-Building Team	9.15	9.15	9.15	9.15	9.15	9.15
Post x One-Building Team as %	19.7%	17.3%	15.4%	12.8%	9.9%	14.7%
One-Building Team as %	-40.5%	-37.1%	-38.4%			
R^2	0.01	0.02	0.04	0.33	0.33	0.33
Engineer Group x Post FE		✓	✓	✓	✓	✓
Months at Firm x Post FE			✓	✓	✓	✓
Engineer FE				✓	✓	✓
Engineer Traits x Post FE					✓	✓
Main Building x Post FE						✓
# Teams	304	304	304	304	304	304
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304

Notes: This table investigates the relationship between sitting near teammates and monthly output of (a) programs submitted to the main code-base, (b) lines of code added, and (c) files changed. Each specification estimates Equation 1, with controls defined in Table 2. The sample includes engineers who ever submitted a program to the firm's main code-base and whose teammates are all in the firm's main campus. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Effect of Proximity to Teammates on Pay Raises

	% Pay Raise					
	Offices Open			Offices Closed		
	(1)	(2)	(3)	(4)	(5)	(6)
One-Building Team	-3.22^{**}			7.08^{**}		
	(1.54)			(3.40)		
Junior (< 16mo) x One-Building Team		-5.46^{**}			9.32^{**}	
		(2.32)			(3.68)	
Senior (≥ 16mo) x One-Building Team		-1.35			2.01	
		(4.01)			(5.37)	
Female x One-Building Team			-6.73			14.90^{**}
			(4.44)			(6.84)
Male x One-Building Team			-3.66^{*}			5.63
			(2.20)			(3.53)
Dependent Mean	13.52	13.52	13.52	41.24	41.24	41.24
Junior (< 16mo) Mean	17.16	17.16	17.16	17.16	17.16	17.16
Senior (≥ 16mo) Mean	23.64	23.64	23.64	42.68	42.68	42.68
Female Mean	20.85	20.85	20.85	41.98	41.98	41.98
Male Mean	19.06	19.06	19.06	41.08	41.08	41.08
Percentage Effect						
One-Building Team	-23.8%			17.2%		
Junior (< 16mo) x One-Building Team		-31.8%			23%	
Senior (≥ 16mo) x One-Building Team		-5.7%			4.7%	
Female x One-Building Team			-32.3%			35.5%
Male x One-Building Team			-19.2%			13.7%
Preferred Controls	✓	✓	✓	✓	✓	✓
# Teams	262	262	262	256	256	256
# Engineers	801	801	801	720	720	720
# Engineer-Review	1,988	1,988	1,988	1,851	1,851	1,851

Notes: This table investigates how the likelihood of a pay raise differs for engineers on one-building teams while the offices were open (Columns 1−3) and after the offices closed (Columns 4−6). Each column includes our preferred, time-varying controls for engineering type and firm tenure. Each observation is an engineer for a given tri-annual review-period that end in October, March, and July. The March 2020 review period is included in the pre-period since it is based on pre-closure performance. The sample includes engineers who worked on the main code-base, whose teammates were all in the main campus, and who were hired before the start of our sample. Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.

A Appendix

I.A Principal Component Analysis

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

Table A.1: Example Emblematic Comments of Principal Components

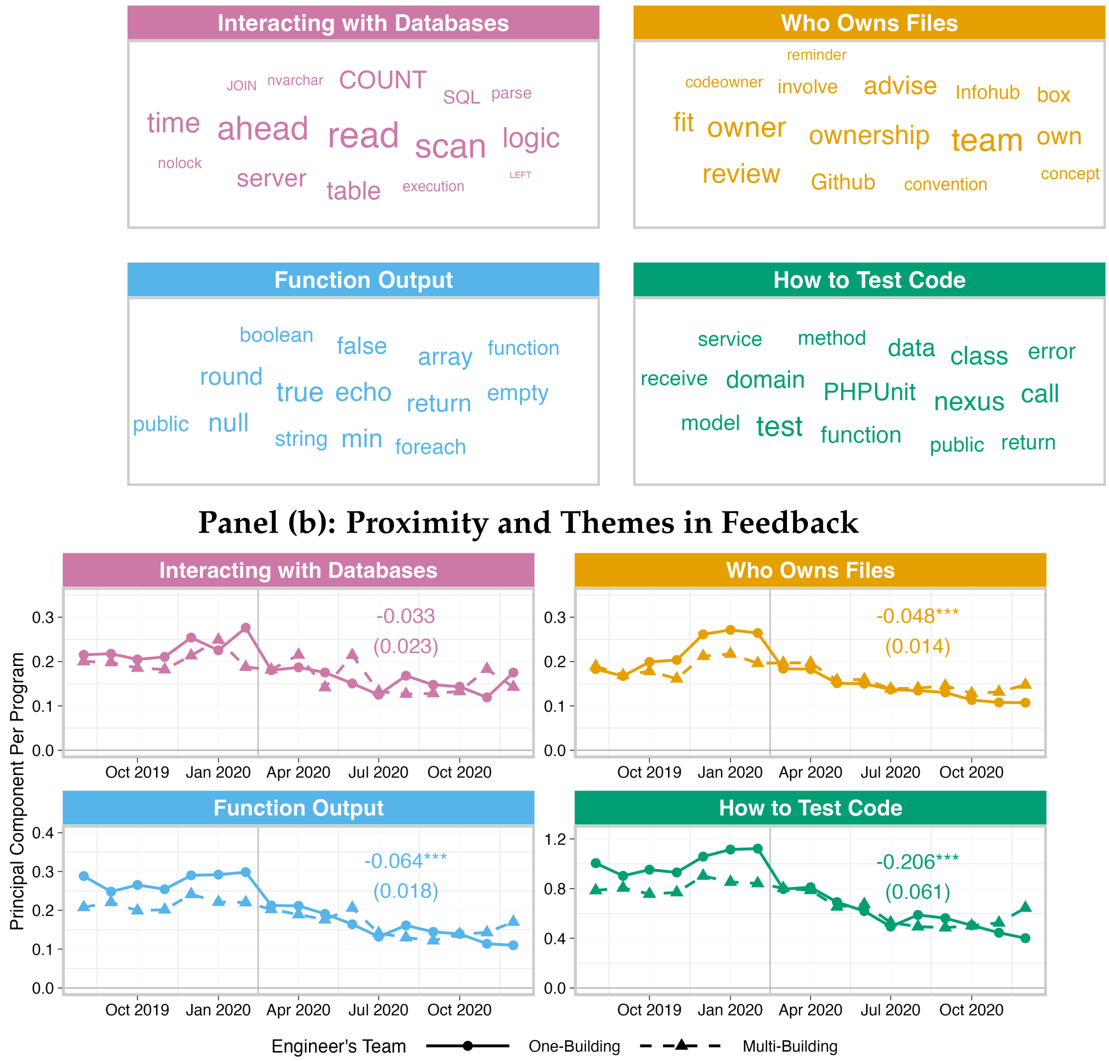
PCA	Total Load	Text of Comment
1	1.25	This **logic** is very confusing to **read** for the first **time**. Please add a paragraph in the comment section to clearly explain the **logic**.
1	0.98	So, you are still **reading** all jobs and then **counting** in PHP. I would think you want to make a **count**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

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

Figure A.1: Themes in Programmers' Online Peer Feedback

Panel (a): Word Loadings in Principal Components

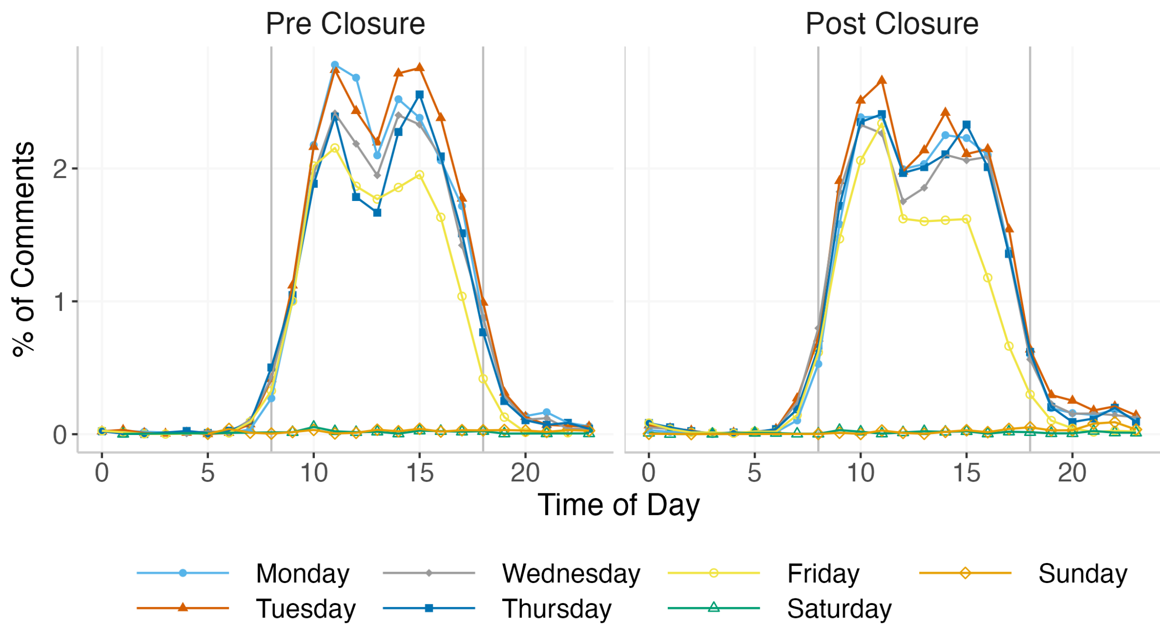
Panel (b): Proximity and Themes in Feedback



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

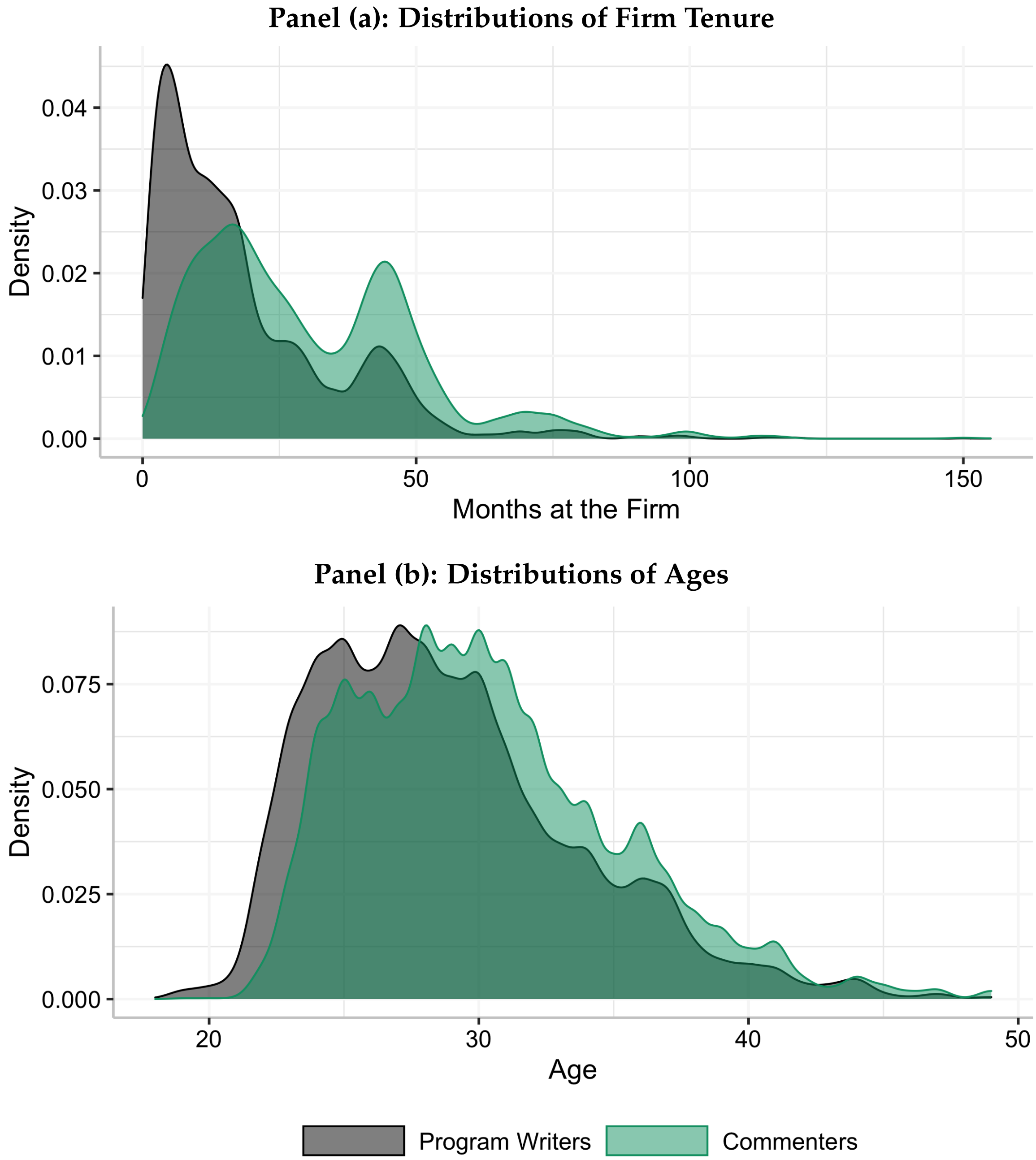
I.B Figures & Tables

Figure A.2: Timing of Comments Over the Course of the Day



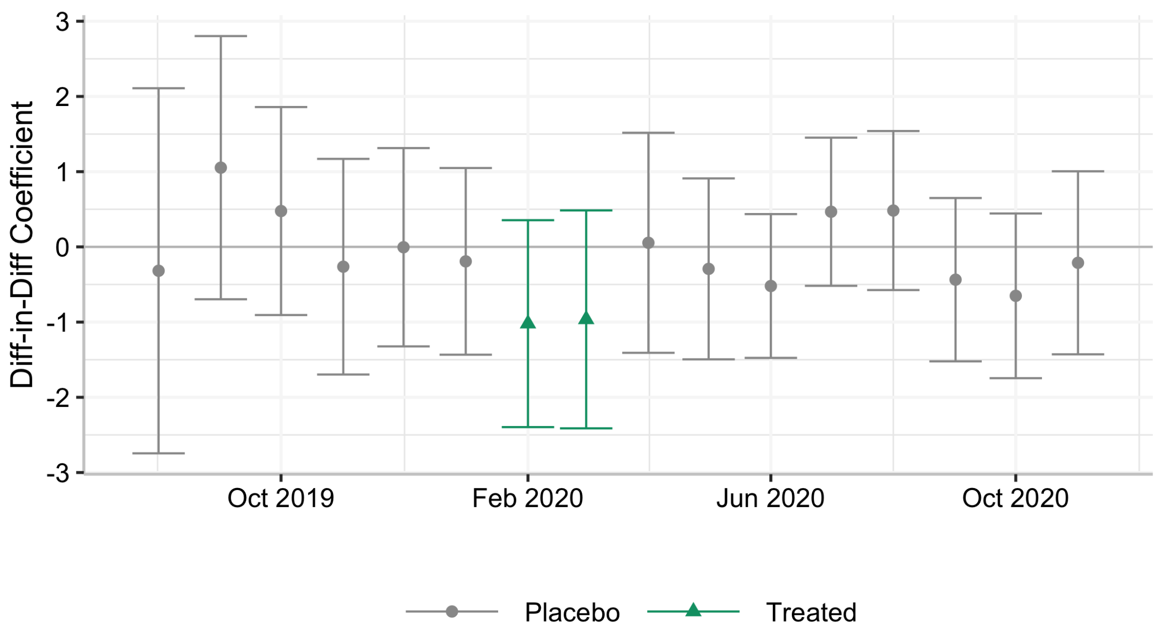
Notes: This figure plots the timing of comments over the course of the day. The x-axis plots the time of day in military time. The y-axis is the percent of comments that occur in that particular time of day on that particular day of week. The left plot is the period before the office closures of COVID-19. 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.3: Program Writer and Commenter Age and Experience



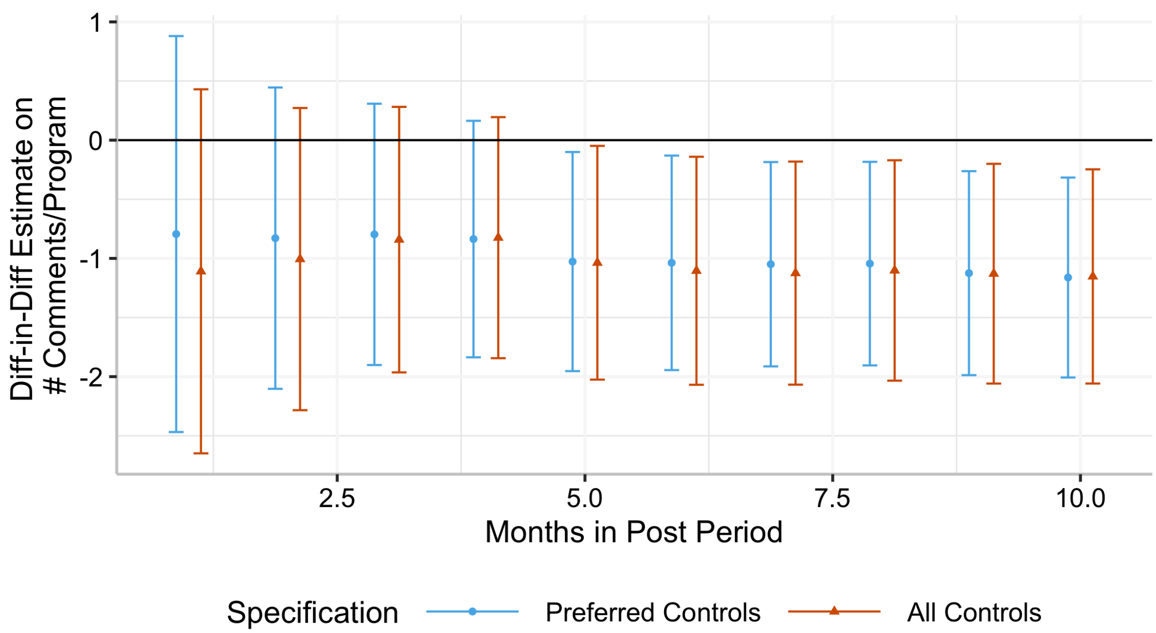
Notes: These figures contrast the experience of program writers and comments (a) at the firm and (b) in their careers. The grey histogram shows the densities for engineers who write programs, weighted by the number of programs that they write. The green distributions show the densities for engineers who write comments on code, again weighted by the number of programs they comment upon.

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



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

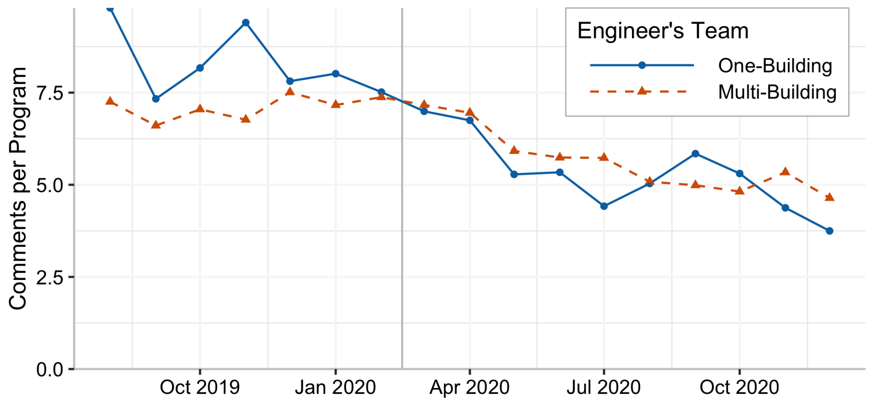
Figure A.5: Robustness of Effect of Proximity on On-the-Job Training from Coworkers to Alternative Post-Periods



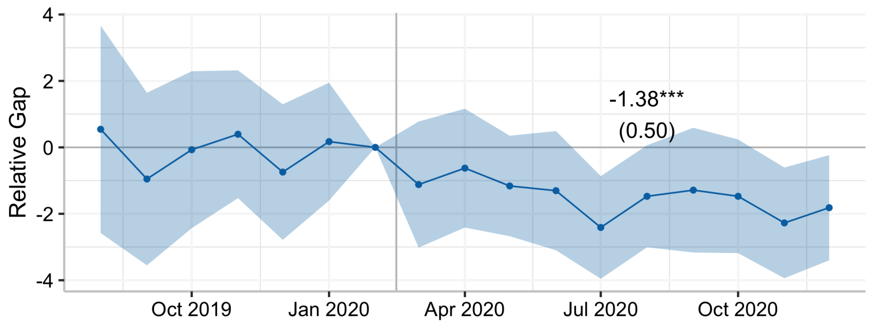
Notes: This figure illustrates how the difference-in-differences estimate from Equation 1 — that compares engineers on one- and multi-building teams, before and after the office closures — varies with the number of months in the post period. The blue circles are the coefficients using our preferred controls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

Figure A.6: Proximity to Teammates and Online Feedback for Engineers Working on Internal Tools

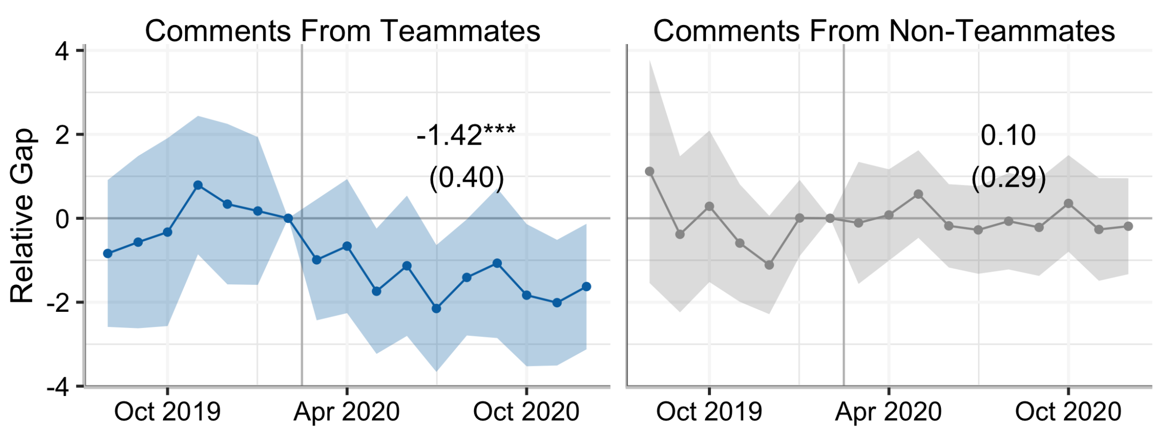
Panel (a): Raw Averages of Comments Per Program



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



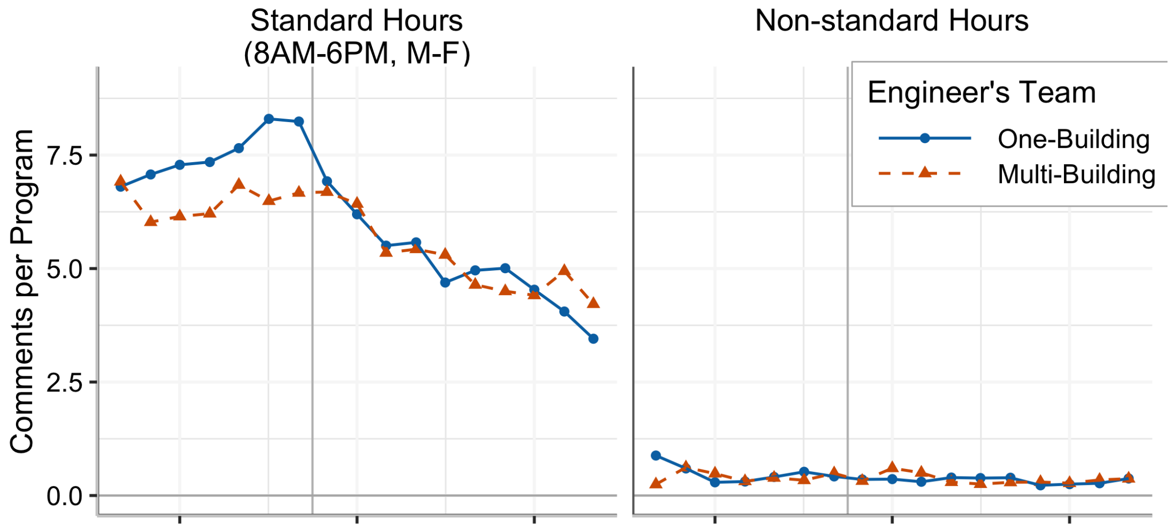
Panel (c): Placebo Check with Comments from Teammates or Non-Teammates



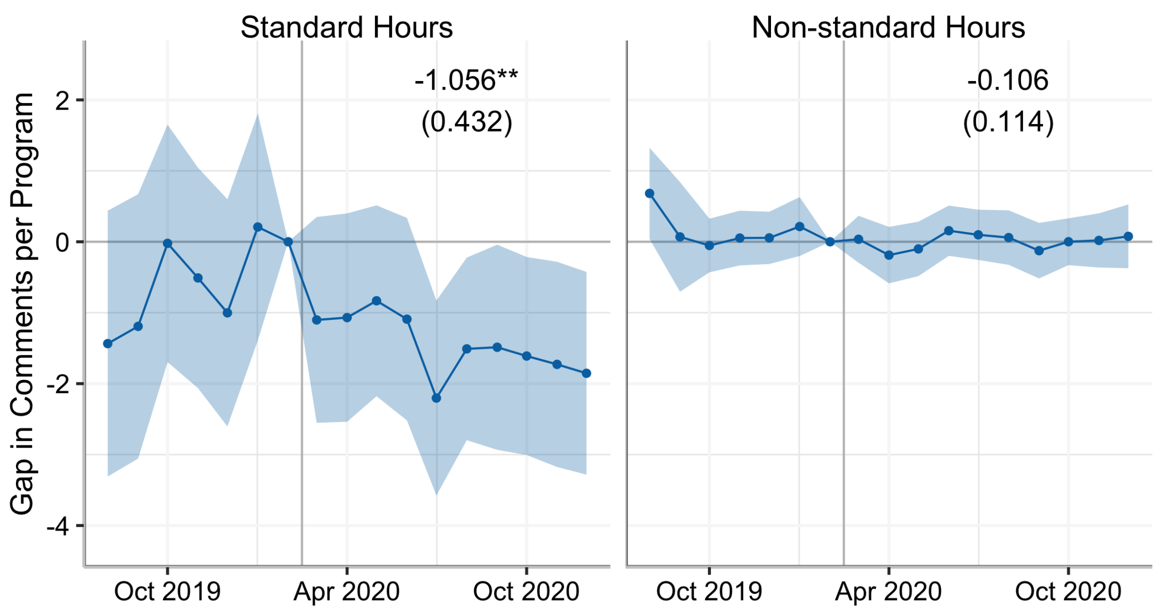
Notes: This figure replicates Figure 1 but limits the sample to the 588 engineers who built internal tools (i.e., software used by others in the firm). Since it is useful for these workers to sit near those who use their tools (e.g., sales workers), it is more likely that their teams end up split across the two office buildings. The analysis compares engineers who had sat with all their teammates in the same building before the offices closed (N=215) to engineers on multi-building teams (N=373). *p<0.1; **p<0.05; ***p<0.01.

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



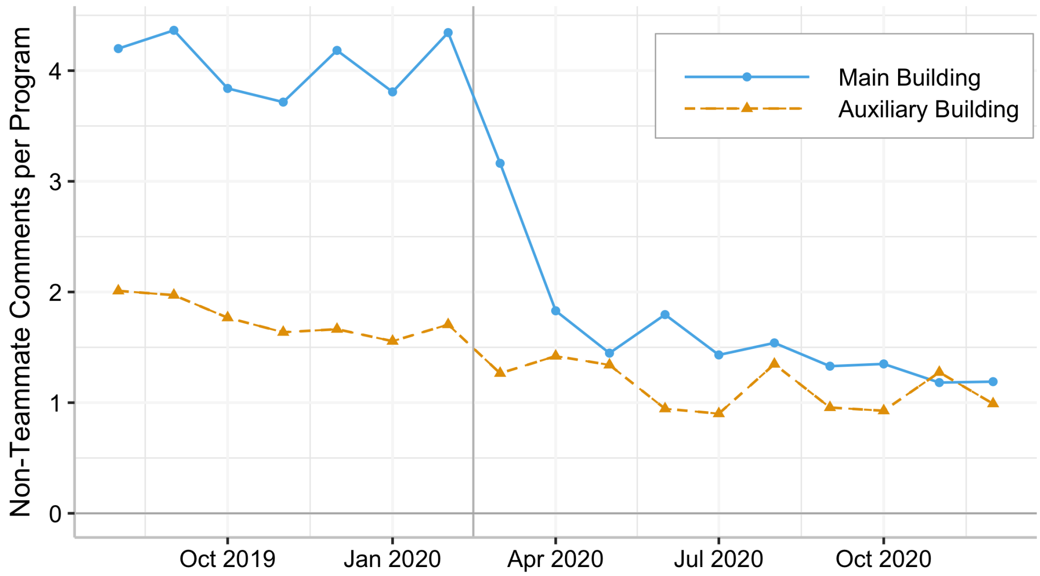
Panel (b): Dynamic, Conditional Differences



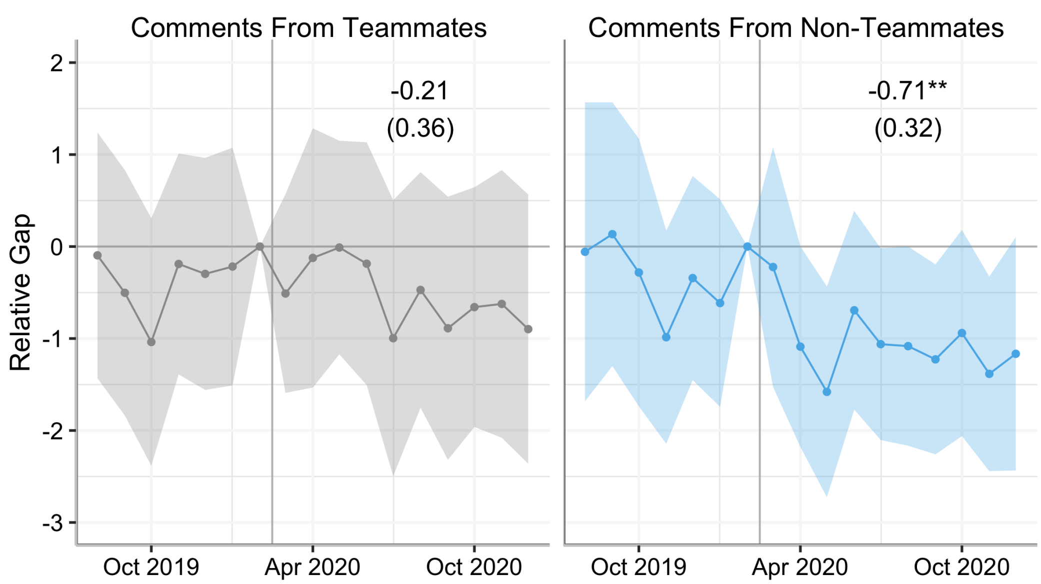
Notes: This figure illustrates the online feedback received by engineers in one-building teams (N=637) and engineers on multi-building teams (N=418) before and after the offices closed for COVID-19 (the grey vertical lines). The left plots consider comments given in standard work hours (8AM to 6PM, Monday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

Panel (a): Raw Averages of Non-Teammate Comments per Program

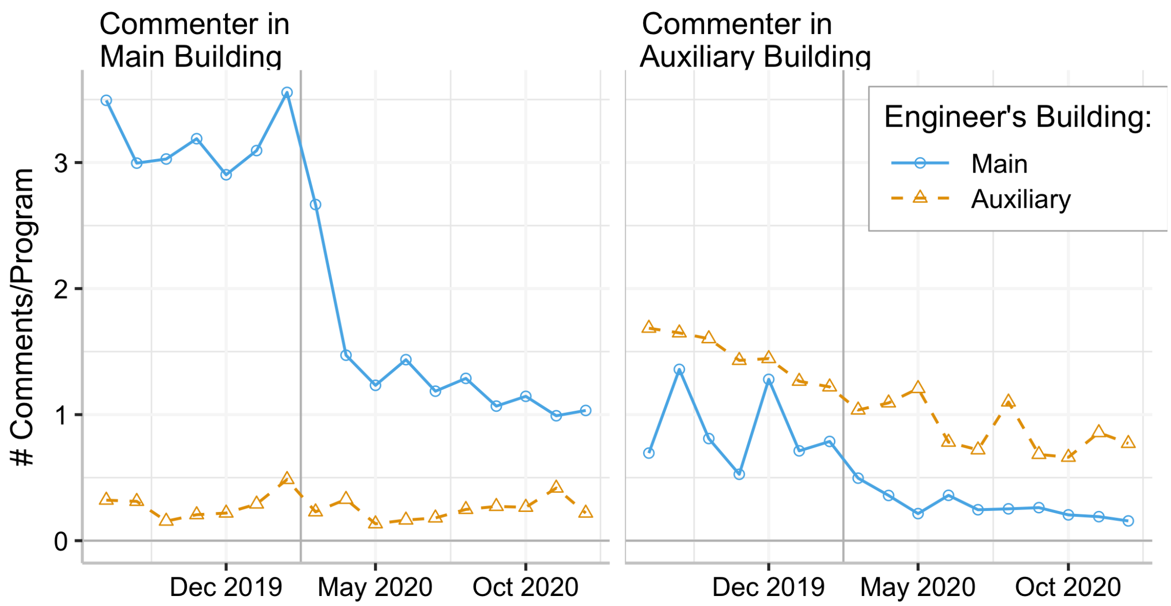


Panel (b): Dynamic, Conditional Differences Placebo and Treated



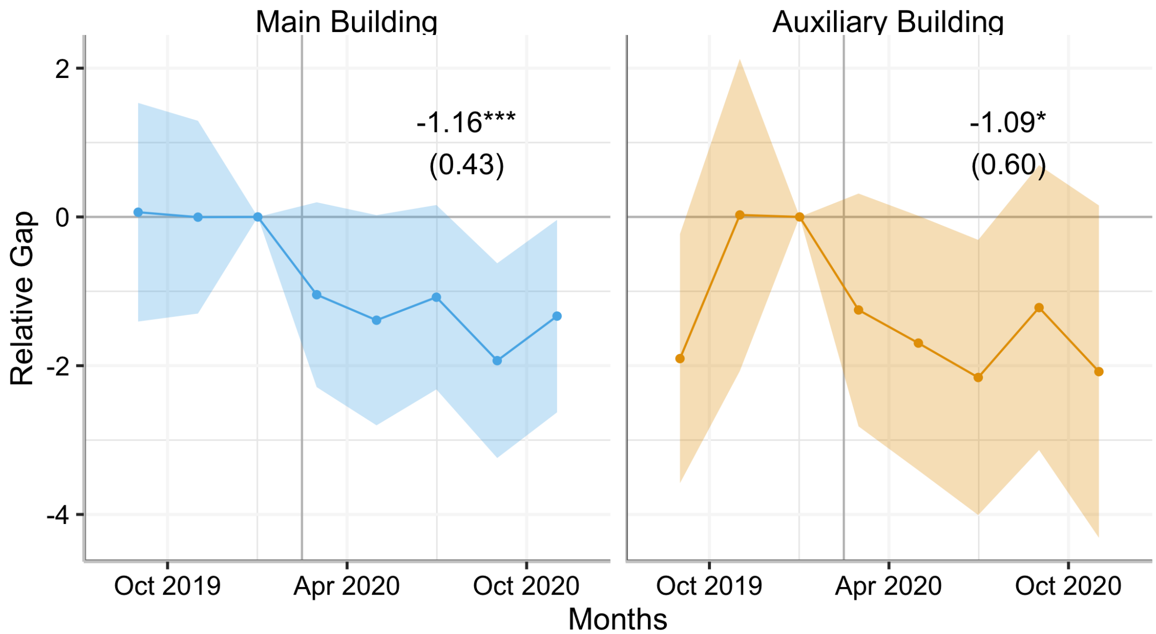
Notes: This figure compares the feedback received by the engineers who sat in the main building (N=788) and the engineers who sat in the auxiliary building (N=277) around the office closures. Panel (a) plots raw averages in the number of non-teammate comments that engineers receive on their code. Panel (b) presents the conditional differences between engineers in the main and auxiliary buildings, controlling for our preferred controls and the engineers' proximity to their teammates (the analogue of Equation 1 for building rather than team-type). The left plot shows a placebo check with teammate comments. The right plot shows non-teammate comments which should be impacted. Ribbons are 95% confidence intervals with clustering by engineering team. Only engineers whose teammates all worked in the main campus are included. The grey vertical lines mark the COVID-19 office closures. *p<0.1; **p<0.05; ***p<0.01.

Figure A.9: Proximity and Online Feedback from Non-Teammates



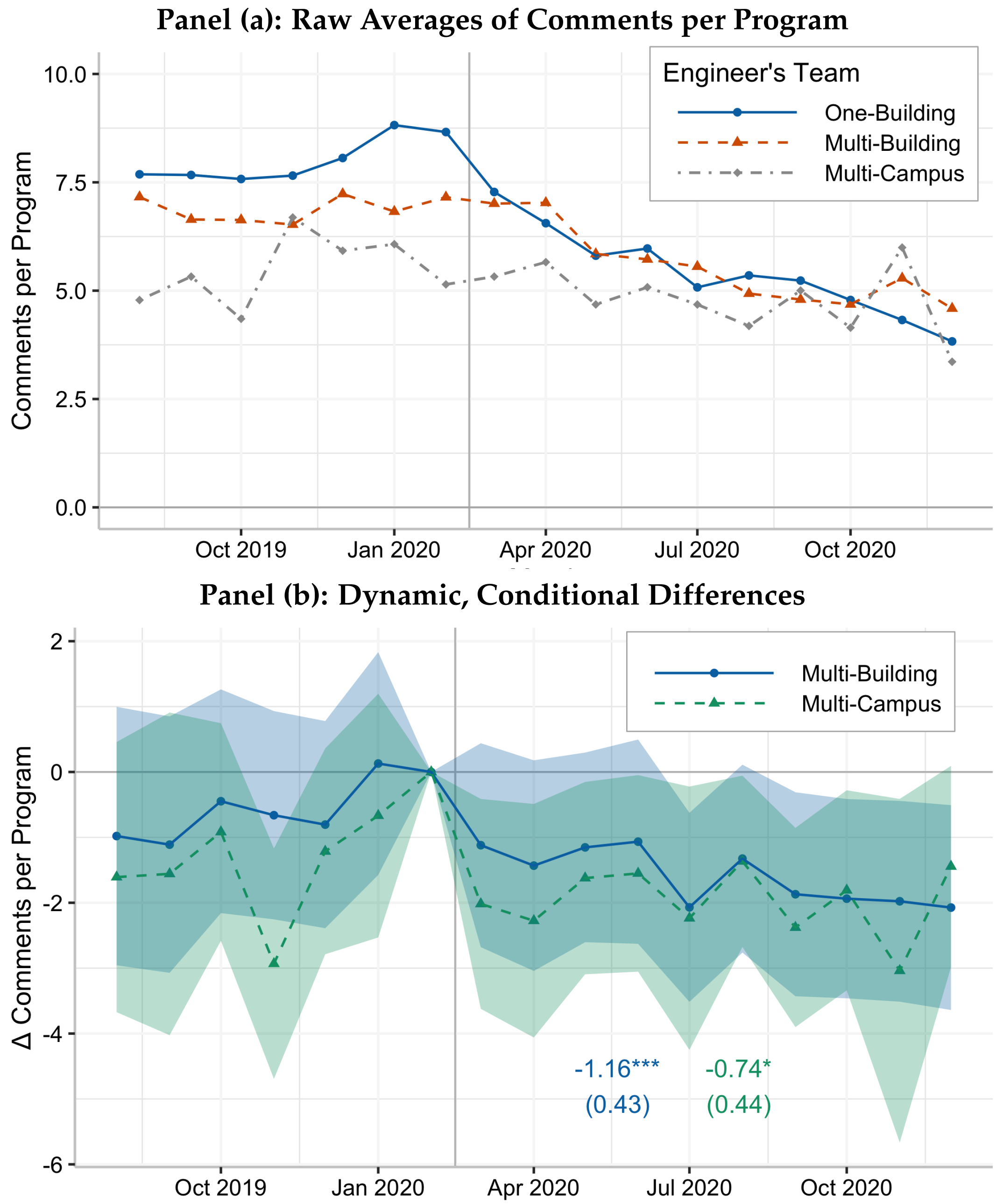
Notes: This figure compares the change in peer feedback from non-teammates around the COVID-19 office closures for engineers in the firm's main building (in blue circles) to engineers in an auxiliary building (in orange triangles) based on the commenter's location. In both plots, the x-axis represents the month, with the grey line highlighting the COVID-19 office closures. In the left plot, the y-axis represents the quantity of comments from non-teammates in the main building. In the right plot, the y-axis represents the quantity of comments from non-teammates in an auxiliary building.

Figure A.10: Proximity to Teammates and their Feedback: In the Main and Auxiliary Buildings



Notes: This figure compares the change in peer feedback from teammates around the COVID-19 office closures for engineers in one-building teams versus those on multi-building teams. The left panel focuses on engineers in the main building. The right panel focuses on engineers in the auxiliary building. The annotated coefficients compare the difference between engineers in one- and multi-building teams after the closure to the same difference before the closure as in Equation 1 with the preferred set of controls (as in Column 4 of Table 2). The points come from a dynamic version of this regression, bimonthly rather than monthly to increase precision. Ribbons reflect 95% confidence intervals. Standard errors are clustered by engineering team. *p<0.1; **p<0.05; ***p<0.01.

Figure A.11: Proximity to Teammates, by Distance

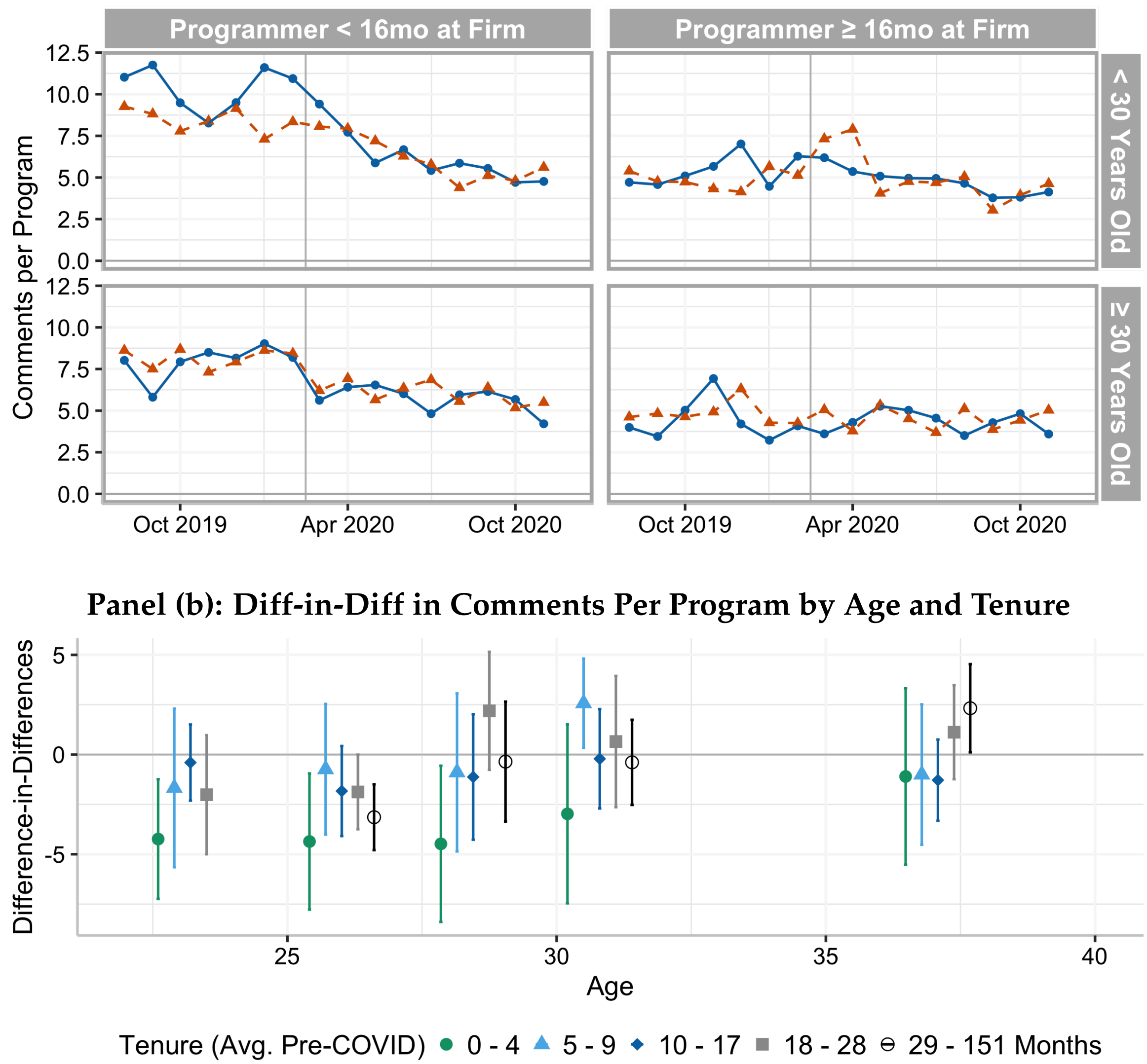


Notes: This figure illustrates the online feedback received by engineers in one-building teams (N=637), multi-building, single-campus teams (N=418), and multi-campus teams (N=215) before and after the offices closed for COVID-19 (the grey vertical lines). The sample includes all engineers who are all themselves in the main campus, regardless of their teammates' locations. Panel (a) plots the raw averages; Panel (b) plots the differences from Equation 2, conditional on our preferred set of controls listed in Subsection IV.B. The ribbons reflect 95% confidence intervals with clustering by engineer. The annotated coefficients come from the analogue of Equation 1. *p<0.1; **p<0.05; ***p<0.01.

Figure A.12: Proximity and Mentorship of Young Engineers

Panel (a): Comments per Program by Program Writer's Tenure and Age

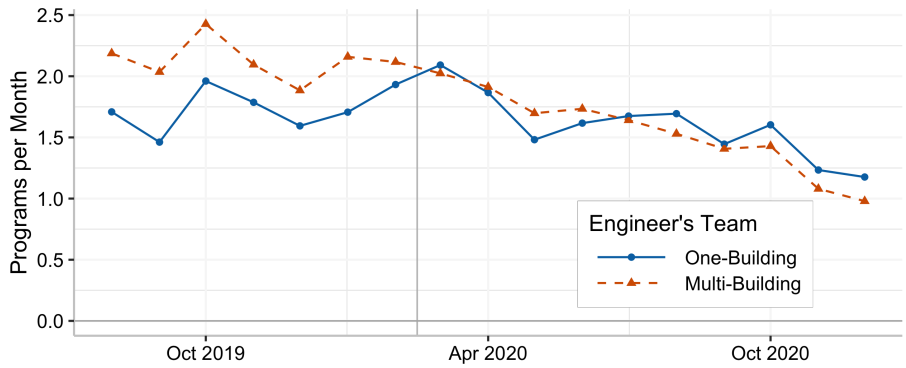
Panel (b): Diff-in-Diff in Comments Per Program by Age and Tenure



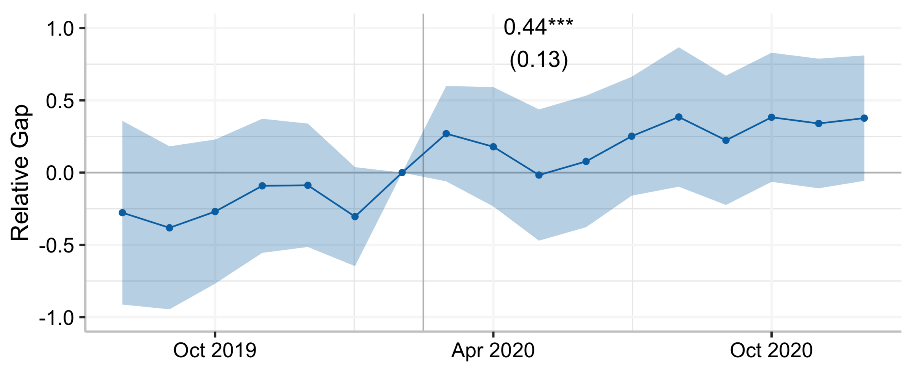
Notes: Panel (a) shows the effects of proximity on online feedback received by engineers of different tenures and ages. It shows the raw monthly averages of comments received per program for engineers on one- and multi-building teams, separately by those below and above the median tenure of 16 months and those below and above the average age of 30. Panel (b) shows the estimated difference-in-differences coefficient from Equation 1 for different age quintiles separately by tenure quintile. Each specification includes our preferred controls for program scope, programmer tenure, and engineering type. Error bars represent 95% confidence intervals with standard errors clustered by team.

Figure A.13: Proximity to Teammates and Engineer Output for Engineers who Build Internal Tools

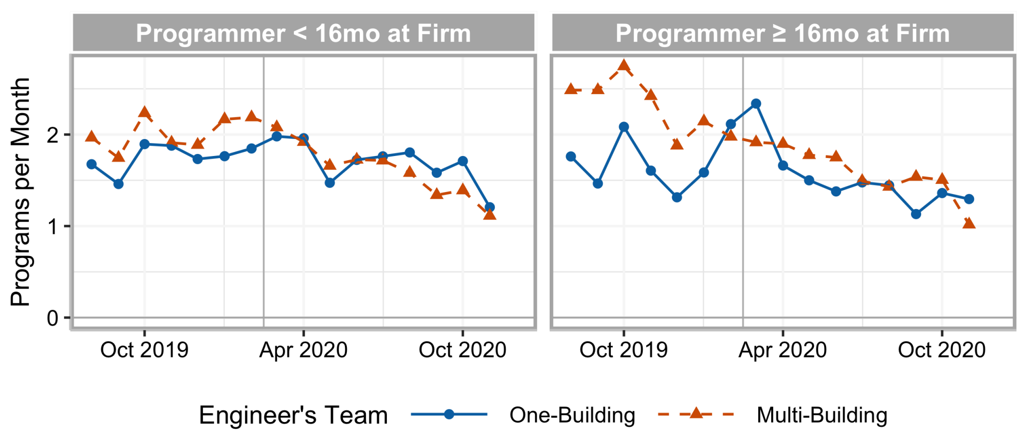
Panel (a): Raw Averages of Programs Written Per Month



Panel (b): Dynamic, Conditional Differences in Programs Per Month

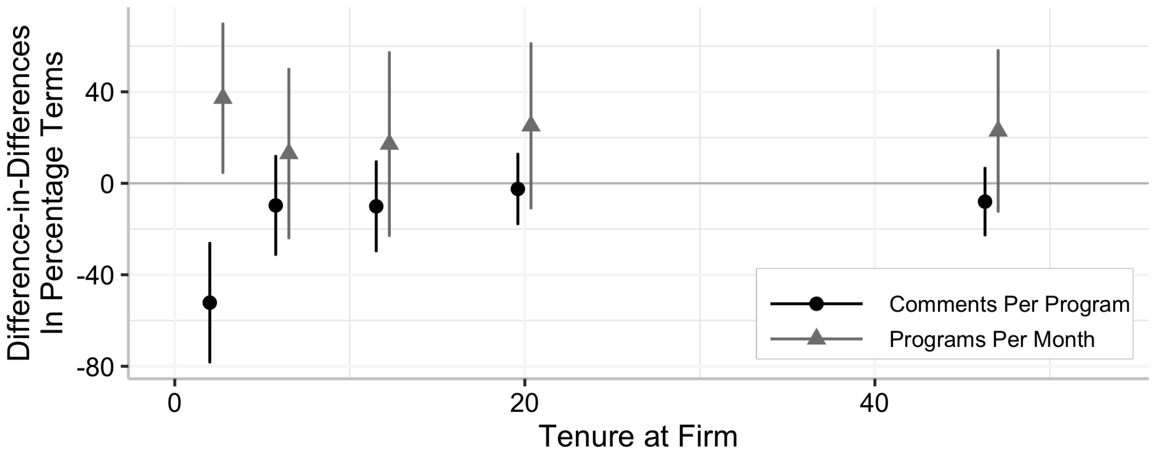


Panel (c): Programs Per Month by Program Writer's Tenure



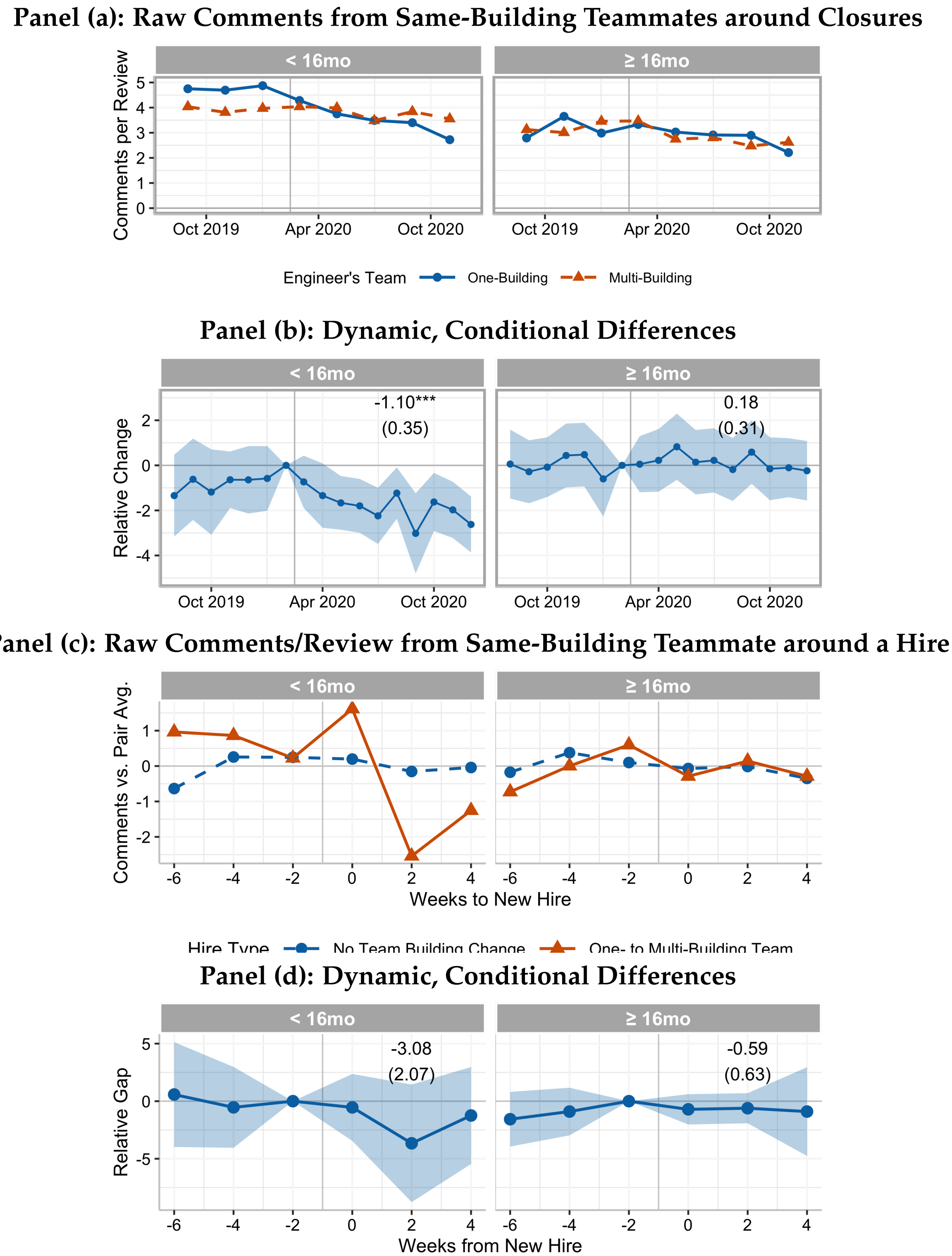
Notes: This figure replicates Figure A.13 but limits the sample to the 588 engineers who worked on internal tools (i.e., software used by others in the firm). Since it is useful for these workers to sit near those who use their tools (e.g., sales workers), it is more likely that these teams are split across the two office buildings. The analysis compares engineers who had sat with all their teammates in the same building before the offices closed (N=215) to engineers on multi-building teams (N=373). Standard errors are clustered by engineering team. *p<0.1; **p<0.05; ***p<0.01.

Figure A.14: Proximity to Teammates and Engineer Output and Feedback by Baseline Tenure



Notes: This figure illustrates the effects of losing proximity to teammates on feedback and programming output for engineers of different tenure at the firm. Each point represents a quintile of baseline tenure at the time that the offices closed. The y-axis plots the difference-in-differences coefficient from Equation 1 with our preferred set of controls for the scope of the program (quartics in files changed, lines added, and lines deleted), the engineer's tenure at the firm (in months) and the engineering role (e.g., website design versus database management). The error bars represent 95% confidence intervals with standard errors clustered by team.

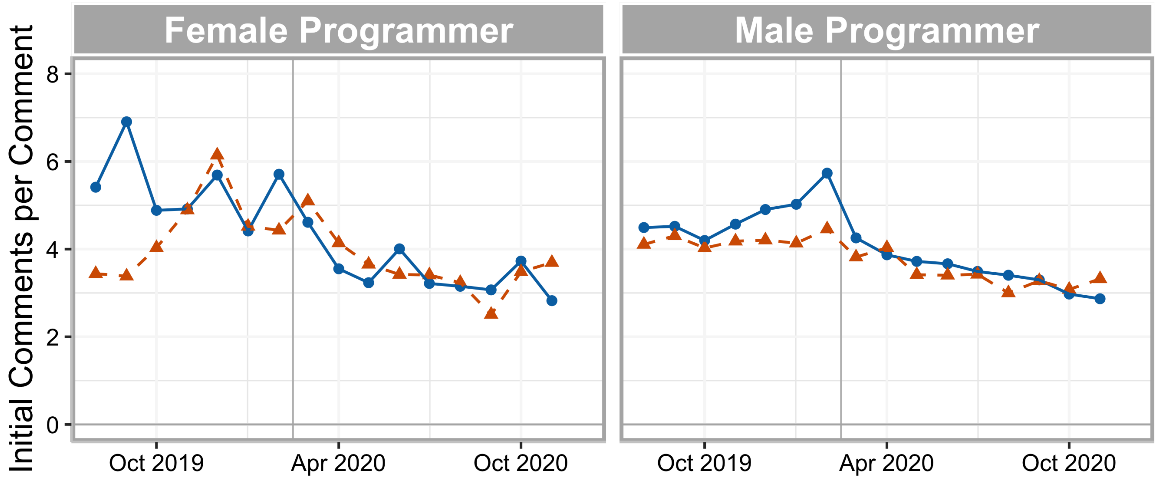
Figure A.15: Externalities from Distant Teammates By Tenure



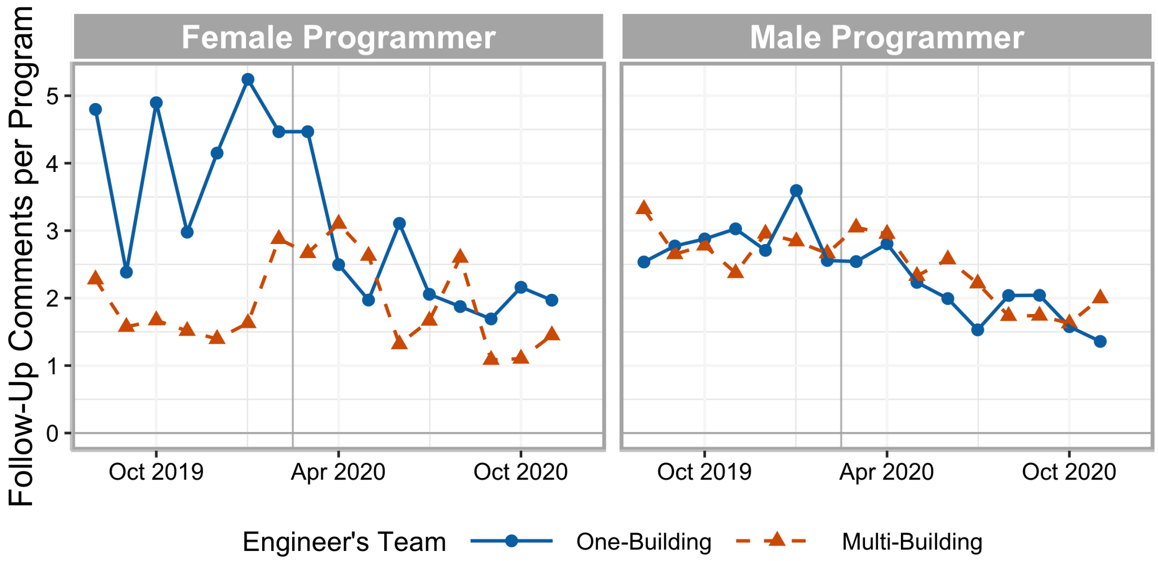
Notes: This figure replicates Figure 3 but differentiates between more and less experienced engineers.

Figure A.16: Gendered Impacts of Proximity to Teammates on Initial and Follow-up Feedback

Panel (a): Initial Comments Received Per Program

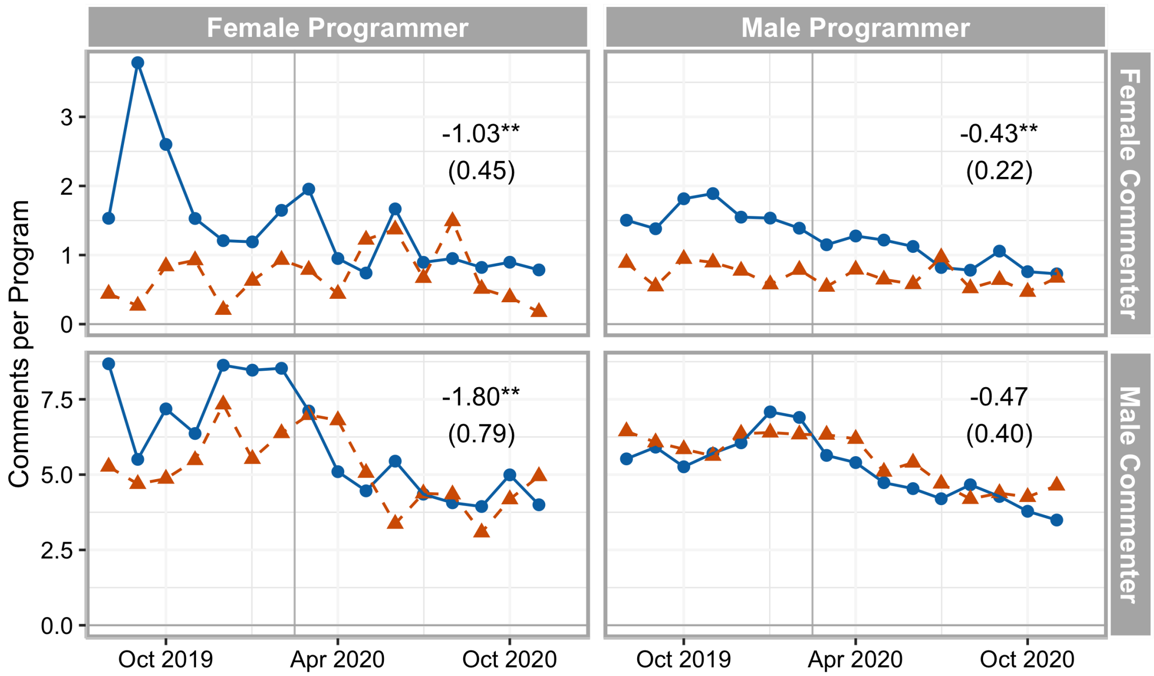


Panel (b): Follow-up Comments Received Per Program



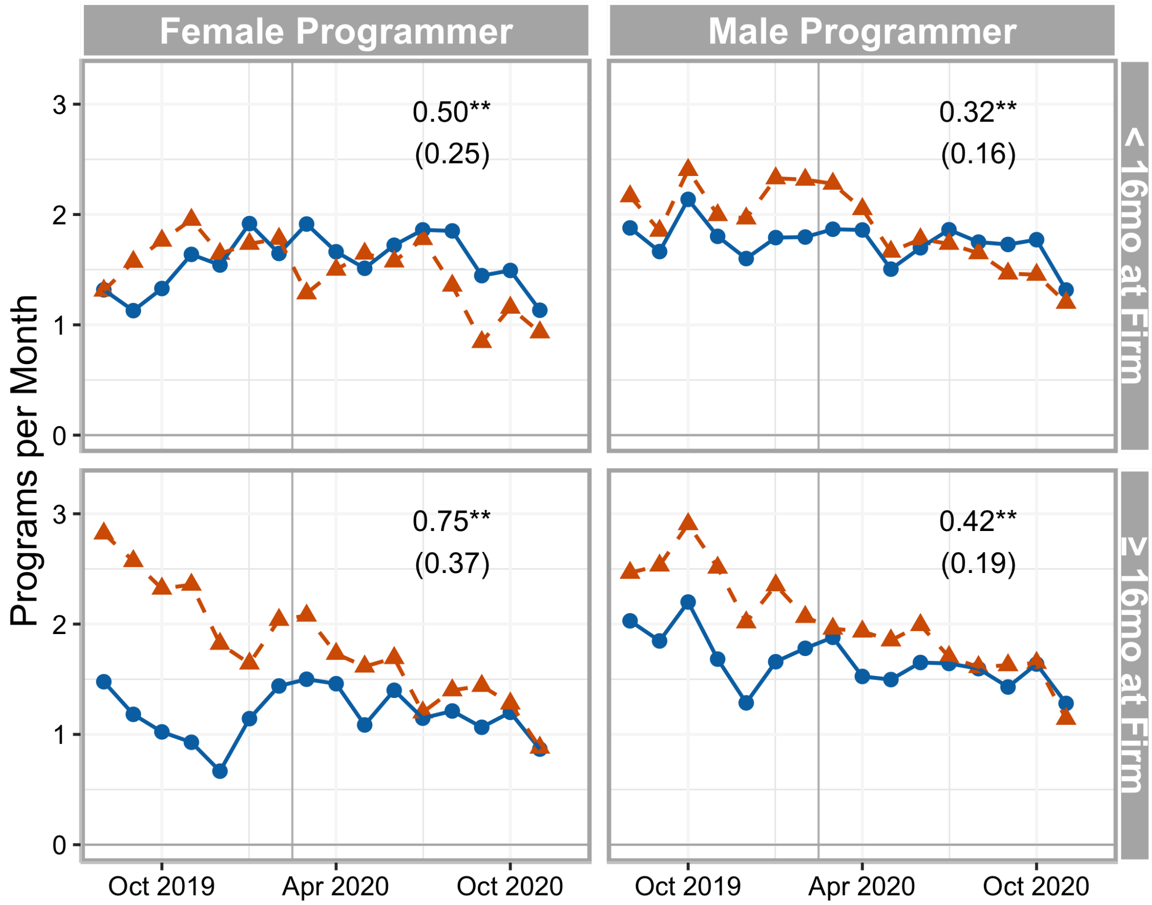
Notes: This figure illustrates the gendered impact of proximity on the feedback that an engineer receives on their code. Panel (a) plots the initial feedback on their code, defined as the average number of comments that an engineer receives on their programs before they send a follow-up reply. Panel (b) plots the average number of comments that an engineer receives on their code after they send a reply. The sample limits to engineers whose teammates all worked in the main campus.

Figure A.17: Gendered Effects of Proximity on Comments from Male and Female Commenters



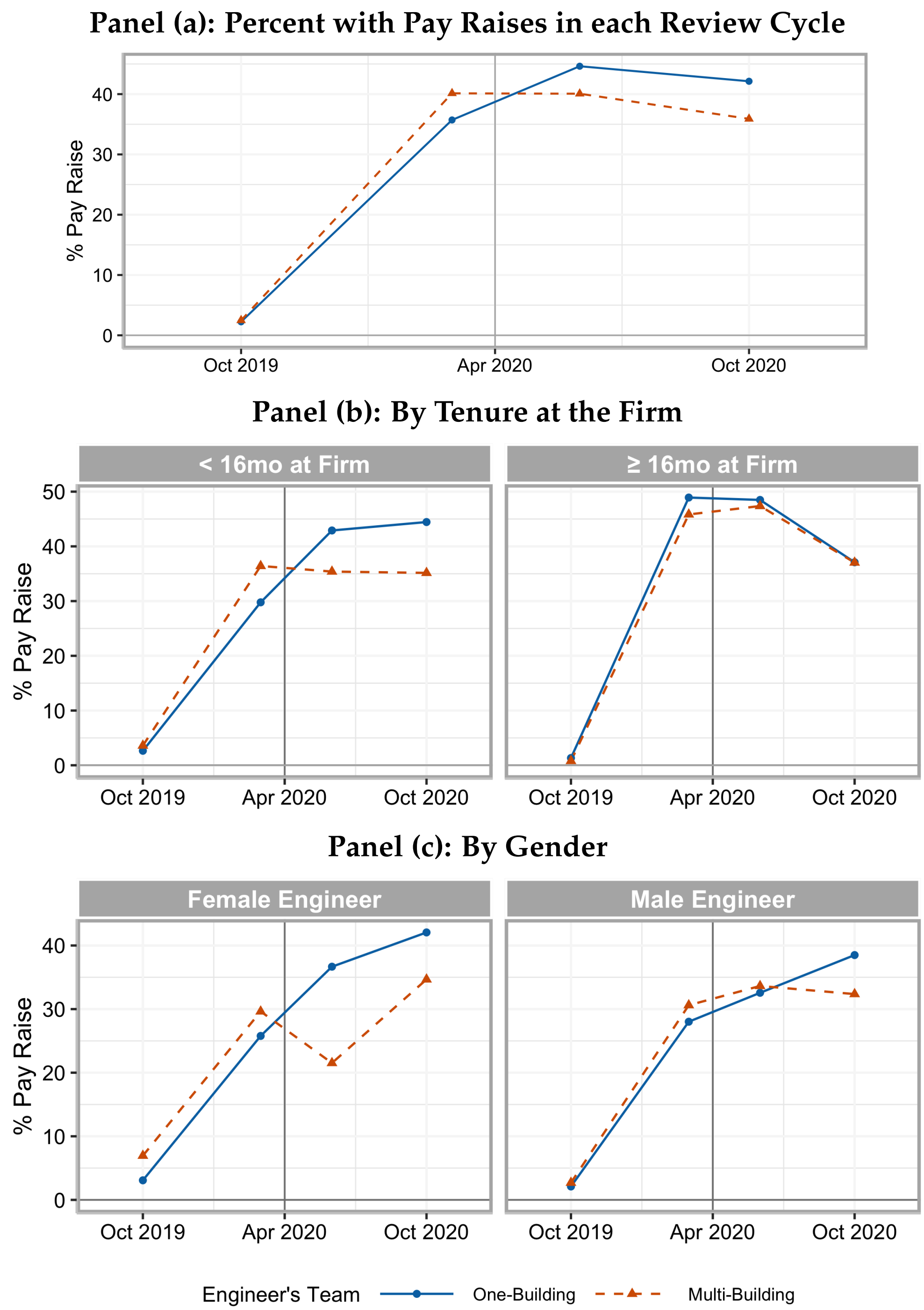
Notes: This figure illustrates the gendered impact of proximity on feedback from male and female comments. Each plot shows the raw monthly averages of comments received per program for engineers on one- and multi-building teams, separately by female and male engineers and for comments from male and female comments. The sample limits to engineers who submitted a program to the main code-base in that month and whose teammates all worked in the main campus. The annotated coefficient reflects Equation 1 with our preferred set of controls for program scope, engineering type, and engineer tenure. Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.

Figure A.18: Gendered Impacts of Proximity to Teammates on Programming Output by Seniority



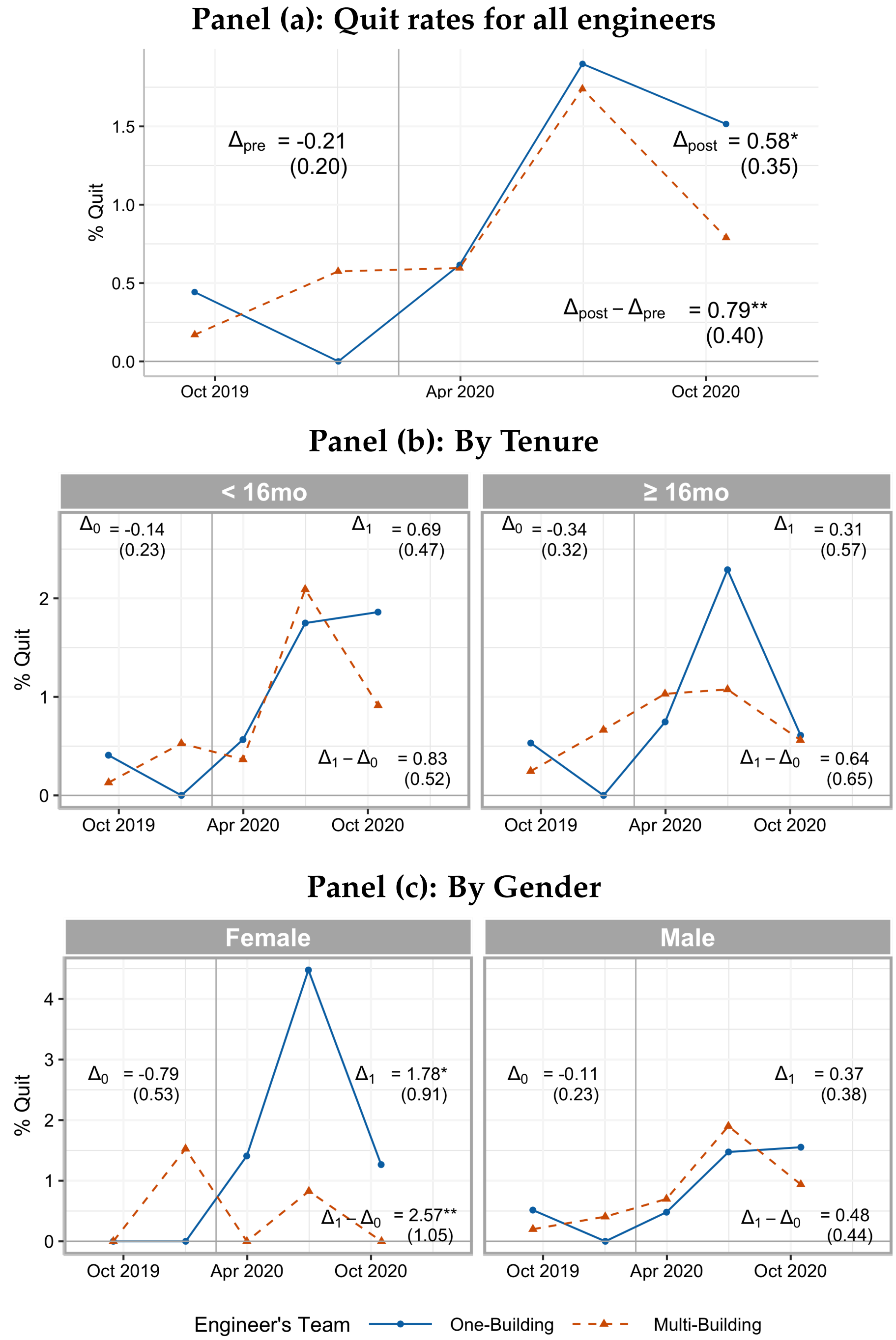
Notes: This figure illustrates the gendered impact of proximity on programming output. Each plot shows the raw monthly averages of programs per program for engineers on one- and multi-building teams, separately by female and male engineers and for those with above and below the median tenure of 16 months. The sample limits to engineers whose teammates all worked in the main campus. The annotated coefficient reflects Equation 1 with our preferred set of controls for engineering type and engineer tenure. Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.

Figure A.19: Impacts of Proximity on Pay Raises



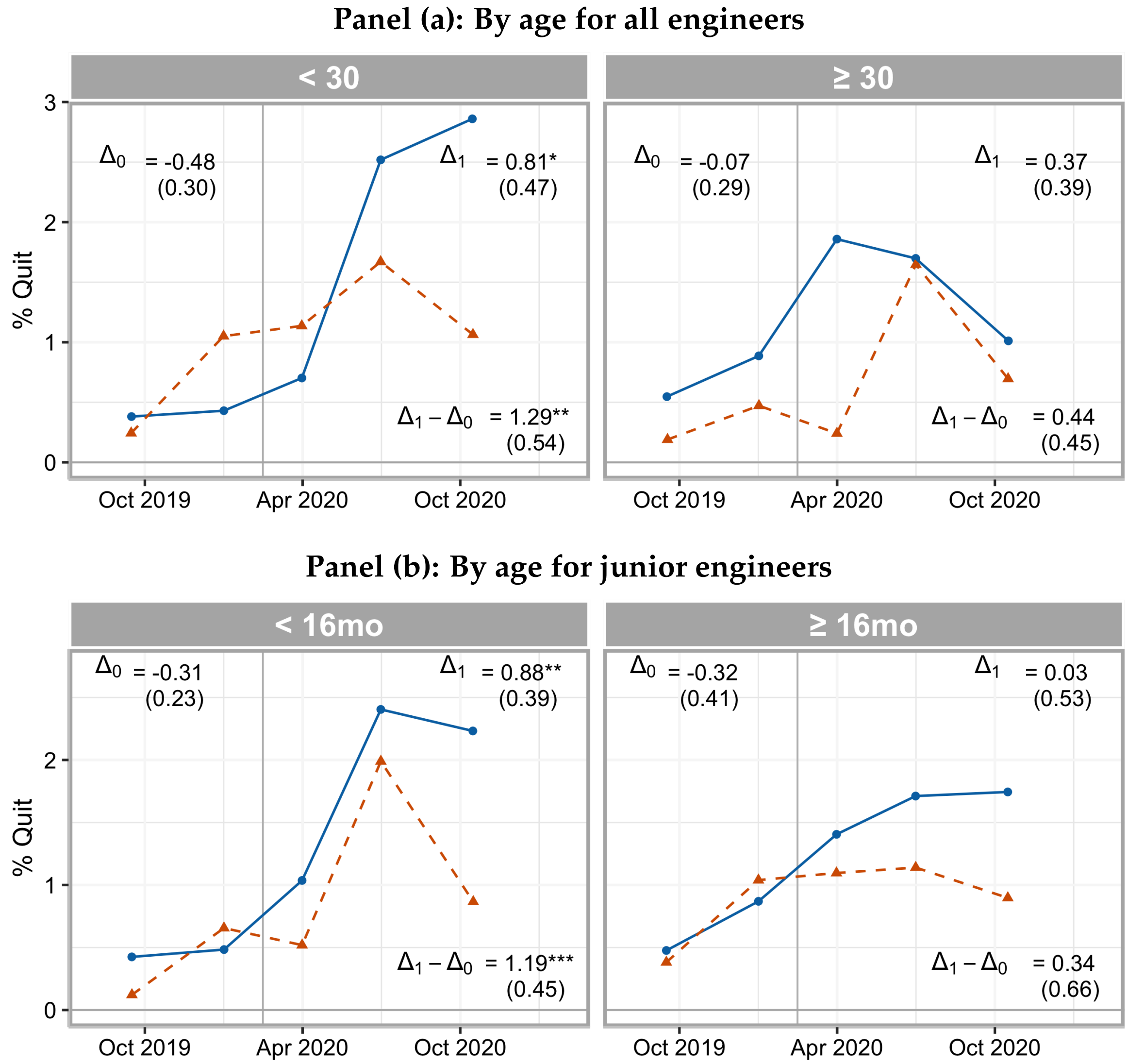
Notes: This figure illustrates the impact of proximity on the likelihood of a pay raise. Each point reflects the percent of engineers with pay raises at the end of each tri-annual review period. The post period is defined as starting in April 2020 since March 2020 pay raises were based on winter 2019-2020 reviews. The sample includes engineers who worked on the main code-base, whose teammates were all in the main campus, and who were hired before the start of our sample.

Figure A.20: Impacts of Proximity on Quits for Engineers who Work on Internal Tools



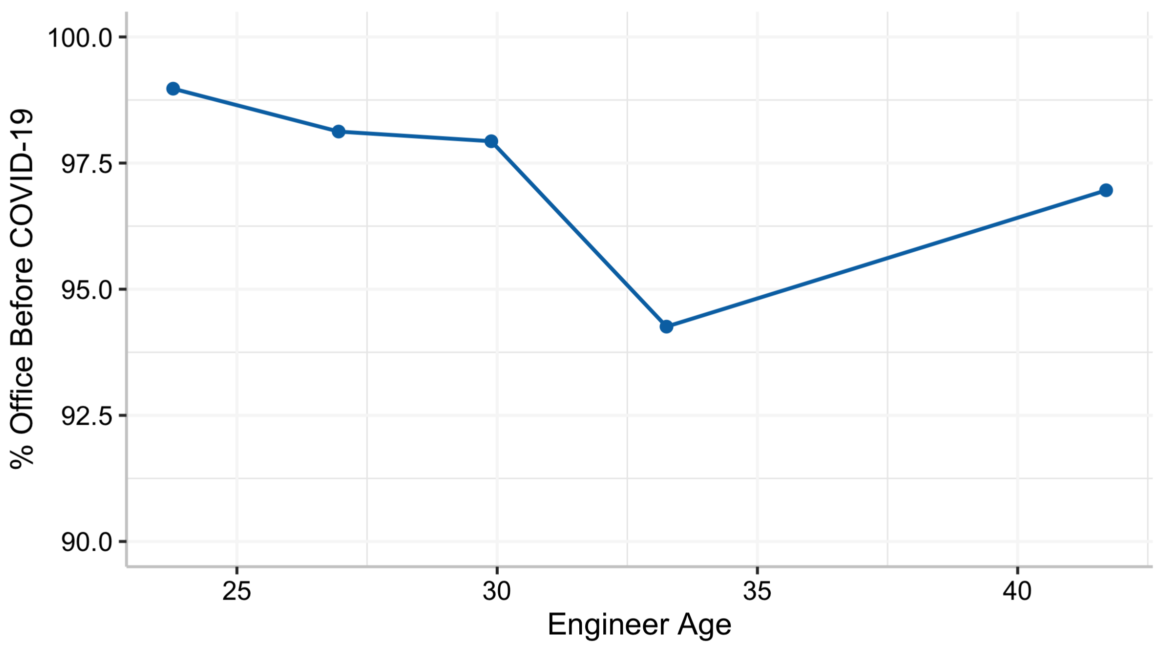
Notes: This figure replicates Figure 6 but limits the sample to the 588 engineers who worked on internal tools. Since it is useful for these workers to sit near those who use their tools (e.g., sales workers), it is more likely that these teams are split across the two office buildings. The analysis compares engineers who had sat with all their teammates in the same building before the offices closed (N=215) to engineers on multi-building teams (N=373). Standard errors are clustered by engineering team. *p<0.1; **p<0.05; ***p<0.01.

Figure A.21: Impacts of Proximity on Quits by Age



Notes: This figure illustrates the effects of proximity on quits for older and younger engineers (a) overall and (b) for relatively junior engineers before COVID (with less than the average sixteen months of experience). Each plot shows the raw quit rates for engineers on one-building and multi-building teams. The annotated coefficients use our preferred set of controls for engineering group and engineer tenure. Standard errors are clustered by engineering team. The sample includes engineers who worked on the main code-base, whose teammates were all in the main campus, and who were hired before the start of our sample. *p<0.1; **p<0.05; ***p<0.01.

Figure A.22: Office Work at the Firm by Engineer Age



Notes: This figure plots the share of engineers at the firm who were working in the office rather than from home before the pandemic as a function of the engineer's age.

Table A.2: Testing Robustness of Results to Local-Linear Time-Trends

	Comments per Program					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x In One-Building Team	-1.29^{***}	-1.72^{**}	-1.16^{***}	-1.41^{**}	-1.13^{**}	-1.35^{**}
	(0.48)	(0.86)	(0.43)	(0.63)	(0.47)	(0.64)
One-Building Team	1.16^{**}	1.82^{**}	1.80^{***}	2.50^{***}		
	(0.52)	(0.93)	(0.49)	(0.66)		
Post	-1.22^{***}	-0.24				
	(0.36)	(0.63)				
Pre-Mean in One-Building Teams	8.04	8.04	8.04	8.04	8.04	8.04
Percentage Effects						
Post x One-Building Team	-16.06%	-21.35%	-14.45%	-17.58%	-14.04%	-16.74%
One-Building	14.46%	22.63%	22.38%	31.15%		
% One-Building Team	58.33	58.33	58.33	58.33	58.33	58.33
Local-Linear Time-Trends		✓		✓		✓
Team Composition x Post FE			✓	✓	✓	✓
Program Scope Quartics			✓	✓	✓	✓
Engineer Traits x Post FE					✓	✓
Engineer FE					✓	
Main Building x Post FE					✓	
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055
# Months	17	17	17	17	17	17
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304
R^2	0.02	0.02	0.36	0.36	0.50	0.50

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

Table A.3: Proximity to Teammates and Online Feedback for Engineers who Work on Internal Tools

	Comments per Program					
	(1)	(2)	(3)	(4)	(5)	(6)
Post x One-Building Team	-1.52^{***}	-1.58^{***}	-1.38^{***}	-1.15^{**}	-1.77^{***}	-1.04^{**}
	(0.59)	(0.51)	(0.50)	(0.48)	(0.50)	(0.50)
One-Building Team	1.16	2.28^{***}	1.98^{***}			
	(0.74)	(0.65)	(0.59)			
Post	-1.36^{***}					
	(0.39)					
Pre-Mean, One-Building Team	8.27	8.27	8.27	8.27	8.27	8.27
Percentage Effects						
Post x One-Building Team	-18.3%	-19.1%	-16.7%	-13.9%	-21.4%	-12.6%
One-Building	14.1%	27.6%	24%			
% One-Building Team	36.8	36.8	36.8	36.8	36.8	36.8
Program Scope Quartics		✓	✓	✓	✓	✓
Months at Firm x Post FE			✓	✓	✓	✓
Engineer FE				✓	✓	✓
Engineer Traits x Post FE					✓	✓
Main Building x Post FE						✓
# Teams	140	140	140	140	140	140
# Engineers	588	588	588	588	588	588
# Engineer-Months	5,630	5,630	5,630	5,630	5,630	5,630
R^2	0.02	0.28	0.36	0.49	0.50	0.50

Notes: This table replicates Table A.3 but limits the sample to engineers who built internal tools for others in the firm. Since it was useful for these engineers to sit near the other engineers who used their tools, these engineers' teams were more likely to end up being split across the two buildings on the firm's main campus. Standard errors are clustered by team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.4: Proximity to Teammates and Mentorship

Panel (a): Comments Received by Seniority

	Comments per Program					
	Received by Junior (< 16mo)			Received by Senior (≥ 16mo)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x One-Building Team	-1.40^{**}	-1.72^{***}	-2.01^{***}	-0.41	-0.38	0.25
	(0.65)	(0.60)	(0.63)	(0.45)	(0.42)	(0.67)
One-Building Team	1.27^{*}	2.61^{***}		0.13	0.58	
	(0.68)	(0.69)		(0.39)	(0.41)	
Post	-2.17^{***}			-0.04		
	(0.50)			(0.32)		
Pre-Mean, One-Building Team	9.56	9.56	9.56	4.99	4.99	4.99
Percentage Effects						
Post x One-Building Team	-14.7%	-18%	-21%	-8.2%	-7.7%	4.9%
One-Building Team	13.2%	27.3%		2.5%	11.7%	
Preferred Controls		✓	✓		✓	✓
All Controls		✓	✓		✓	✓
# Engineer-Months	6,056	6,056	6,056	3,248	3,248	3,248

Panel (b): Comments Written by Seniority

	Comments per Program					
	Written by Junior (< 16mo)			Written by Senior (≥ 16mo)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x One-Building Team	-0.41^{*}	-0.25	-0.37	-0.95^{**}	-1.00^{***}	-0.84^{*}
	(0.24)	(0.26)	(0.32)	(0.38)	(0.36)	(0.45)
One-Building Team	0.15	0.39		1.07^{***}	1.47^{***}	
	(0.28)	(0.30)		(0.37)	(0.40)	
Post	-0.74^{***}			-0.42		
	(0.18)			(0.30)		
Pre-Mean, One-Building Team	2.94	2.94	2.94	3.73	3.73	3.73
Percentage Effects						
Post x One-Building Team	-13.9%	-8.6%	-12.7%	-25.4%	-26.8%	-22.4%
One-Building Team	5.1%	13.3%		28.7%	39.4%	
Preferred Controls		✓	✓		✓	✓
All Controls		✓	✓		✓	✓
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304

Notes: This table investigates the relationship between sitting near teammates and (a) the feedback received by junior and senior engineers and (b) the feedback given by these engineers. The preferred controls reflect Column 4 of Table 2; all controls reflect Column 7. Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.

Table A.5: 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	-1.16^{***}	-0.54^{**}	-1.56^{***}	-0.71^{**}
	(0.43)	(0.26)	(0.46)	(0.28)
On One-Building Team	1.80^{***}	0.71^{***}		
	(0.49)	(0.28)		
Pre-Mean, One-Building Team	8.04	4.17	8.04	4.17
Percentage Effects				
Post x On One-Building Team	-14.45%	-12.98%	-19.36%	-17.1%
On One-Building Team	22.38%	17.07%		
Avg. on Multi-Building Teams				
# Teammate Commenters	1.71	1.71	1.71	1.71
% From Proximate Teammates	39.39	39.39	39.39	39.39
# Proximate Teammate Commenters	0.67	0.67	0.67	0.67
Back-of-the-envelope Calculations				
% Initial Gap Explained		26.59%		
% Differential Change Explained		31.33%		30.8%
Controls	Preferred	Preferred	All	All
# Engineers	1,055	934	1,055	934
# Engineer-Months	9,304	7,174	9,304	7,174
R^2	0.36	0.24	0.50	0.46

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 team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.6: 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	-1.483^{**}	-1.710^{*}	-1.332
	(0.640)	(1.017)	(1.062)
Post Hire	-0.302	-0.068	0.010
	(0.987)	(1.151)	(1.008)
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	0.236	0.407	0.552

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

Table A.7: Gendered Impacts of Proximity

	Panel (a): Difference-in-Differences in Feedback Per Program				
	Comments	# Commenters	Commenter Initial Comments	Author Follow-up Questions	Commenter Follow-up Comments
	(1)	(2)	(3)	(4)	(5)
Female: Post x One-Building Team	-2.83^{***}	-0.31^{***}	-1.02^{**}	-0.17^{*}	-1.81^{***}
	(0.81)	(0.09)	(0.52)	(0.10)	(0.70)
Female: One-Building Team	3.84^{***}	0.37^{***}	1.15^{**}	0.23^{**}	2.69^{***}
	(0.77)	(0.09)	(0.48)	(0.09)	(0.66)
Male: Post x One-Building Team	-0.83^{*}	-0.06	-0.37	-0.14^{***}	-0.46
	(0.45)	(0.05)	(0.27)	(0.05)	(0.34)
Male: One-Building Team	1.38^{***}	0.17^{***}	0.68^{**}	0.09^{*}	0.70^{*}
	(0.52)	(0.06)	(0.27)	(0.05)	(0.40)
Pre-Mean, One-Building Team	8.04	1.77	4.91	0.24	3.13
Percentage Effects					
Female: Post x One-Building Team	-35.3%	-17.3%	-20.8%	-72.6%	-57.9%
Female: One-Building	47.7%	20.9%	23.4%	96.5%	85.8%
Male: Post x One-Building Team	-10.3%	-3.4%	-7.6%	-56.4%	-14.5%
Male: One-Building	17.2%	9.6%	13.8%	37.7%	22.3%

	Panel (b): Triple Difference in Feedback Per Program				
	Comments	# Commenters	Commenter Initial Comments	Author Follow-up Questions	Commenter Follow-up Comments
	(1)	(2)	(3)	(4)	(5)
Female x Post x One-Building Team	-2.01^{**}	-0.25^{***}	-0.65	-0.04	-1.36^{**}
	(0.82)	(0.08)	(0.50)	(0.09)	(0.67)
Female x One-Building Team	2.46^{***}	0.20^{***}	0.47	0.14^{*}	1.99^{***}
	(0.76)	(0.08)	(0.47)	(0.08)	(0.61)
Percentage Effects					
Female x Post x One-Building Team	-24.9%	-13.9%	-13.2%	-16.2%	-43.4%
Female x One-Building	30.6%	11.3%	9.5%	58.8%	63.5%
# Teams	304	304	304	304	304
# Engineers	1,055	1,055	1,055	1,055	1,055
# Engineer-Months	9,304	9,304	9,304	9,304	9,304

Notes: This table investigates the gendered impacts of proximity to teammates. Panel (a) shows difference-in-differences designs, conditional on our preferred set of controls (as in Table 3), for male and female programmers. Panel (b) shows the triple difference design, testing the difference in the estimated effects for female and male engineers. The sample includes engineers who submit programs to the firm's main code-base in the month and whose teams are all in the firm's main campus. Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Gendered Impacts of Proximity Conditional on Tenure & Age

	Comments per Program					
	(1)	(2)	(3)	(4)	(5)	(6)
Female x Post x One-Building Team	-2.01^{**}	-1.98^{**}	-1.83^{**}	-1.65^{*}	-1.83^{*}	-1.68^{*}
	(0.82)	(0.81)	(0.86)	(0.88)	(0.97)	(1.01)
Female x One-Building Team	2.46^{***}	2.42^{***}	2.47^{***}	2.32^{***}	2.42^{***}	2.28^{**}
	(0.76)	(0.75)	(0.80)	(0.82)	(0.93)	(0.97)
Pre-Mean, One-Building Team	8.04	8.04	8.04	8.04	8.04	8.04
Percentage Effects						
Female x Post x One-Building Team	-24.9%	-24.7%	-22.8%	-20.5%	-22.7%	-20.9%
Female x One-Building	30.6%	30.1%	30.7%	28.9%	30.1%	28.3%
Diff-in-Diff Interaction						
Junior (Months at Firm < 16mo)		✓	✓	✓	✓	✓
Months at Firm FE			✓	✓	✓	✓
Age < 30				✓	✓	✓
Age FE					✓	✓
Age < 30 x Junior						✓
# Teams	304	304	304	304	304	304
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055
# Engineer-Months	9,304	9,304	9,304	9,304	9,304	9,304

Notes: This table investigates the gendered impacts of proximity to teammates while allowing for differential effects of proximity by gender and age. Column 1 repeats Column 1 of Table A.7(b) for reference. Column 2 allows for the effect of being on a one-building team to vary for junior versus senior engineers. Column 3 allows this interaction to vary by the precise number of months that the worker has been at the firm. Column 4 further allows the effect of proximity to differ for young engineers under 30. Column 5 allows for the effect of proximity to differ for engineers of each age. Column 6 allows for an interaction between being junior and young. Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.

Table A.9: Gendered Impacts of Proximity on Mentorship and Output

	Panel (a): Difference-in-Differences in Feedback Per Program			
	Comments per Review	Programs	Lines of Code	Files Changed
	(1)	(2)	(3)	(4)
Female: Post x One-Building Team	-1.31^{**}	0.62^{***}	134.70^{**}	3.77^{**}
	(0.60)	(0.22)	(57.73)	(1.51)
Female: One-Building Team	1.13^{**}	-0.39^{*}	-128.50^{*}	-3.89^{**}
	(0.57)	(0.24)	(68.82)	(1.81)
Male: Post x One-Building Team	-0.20	0.37^{***}	82.21^{*}	0.88
	(0.22)	(0.14)	(43.28)	(1.06)
Male: One-Building Team	0.32	-0.32^{*}	-176.00^{***}	-3.50^{***}
	(0.27)	(0.17)	(48.84)	(1.14)
Pre-Mean, One-Building Team	8.04	1.77	4.91	0.24
Percentage Effects				
Female: Post x One-Building Team	-32.7%	36.1%	42.5%	41.3%
Female: One-Building	28.3%	-22.9%	-40.5%	-42.5%
Male: Post x One-Building Team	-5%	21.4%	25.9%	9.6%
Male: One-Building	8%	-18.8%	-55.5%	-38.2%

	Panel (b): Triple Difference in Feedback Per Program			
	Comments per Review	Programs	Lines of Code	Files Changed
	(1)	(2)	(3)	(4)
Female x Post x One-Building Team	-1.11^{*}	0.25	52.48	2.89^{*}
	(0.62)	(0.24)	(62.84)	(1.64)
Female x One-Building Team	0.81	-0.07	47.52	-0.39
	(0.57)	(0.24)	(74.43)	(1.86)
Percentage Effects				
Female x Post x One-Building Team	-27.8%	14.7%	16.6%	31.6%
Female x One-Building	20.2%	-4%	15%	-4.3%
# Teams	304	304	304	304
# Engineers	1,055	1,055	1,055	1,055
# Engineer-Months	16,058	16,058	16,058	16,058

Notes: This table investigates the gendered impacts of proximity to teammates on mentorship and output. Panel (a) shows difference-in-differences designs, conditional on our preferred set of controls for engineering type and tenure at the firm, for male and female programmers. Panel (b) shows the triple difference design, testing the difference in the estimated effects for female and male engineers. The sample includes engineers who ever submit programs to the firm's main code-base and whose teams are all in the firm's main campus. Standard errors are clustered by team. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.10: Proximity to Teammates and Engineer Output Who Work on Internal Tools

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel (a): Programs per Month					
Post x One-Building Team	0.47***	0.47***	0.44***	0.39***	0.38***	0.43***
	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.15)
One-Building Team	−0.42**	−0.42**	−0.39**			
	(0.19)	(0.19)	(0.19)			
Pre-Mean, One-Building Team	1.82	1.82	1.82	1.82	1.82	1.82
Post x One-Building Team as %	25.8%	25.8%	24.2%	21.4%	20.8%	23.7%
One-Building Team as %	-23.2%	-23.2%	-21.6%			
R^2	0.01	0.01	0.04	0.42	0.43	0.43
	Panel (b): Lines Added per Month					
Post x One-Building Team	100**	100**	103**	95**	84*	146***
	(43)	(43)	(44)	(43)	(43)	(47)
One-Building Team	−197***	−197***	−202***			
	(52)	(52)	(53)			
Pre-Mean, One-Building Team	332	332	332	332	332	332
Post x One-Building Team as %	30.1%	30.1%	30.8%	28.6%	25.3%	43.9%
One-Building Team as %	-59.4%	-59.4%	-60.9%			
R^2	0.02	0.02	0.05	0.34	0.35	0.35
	Panel (c): Files Changed per Month					
Post x One-Building Team	1.50	1.50	1.41	1.03	0.83	1.92*
	(1.05)	(1.05)	(1.04)	(1.03)	(1.05)	(1.11)
One-Building Team	−4.12***	−4.12***	−4.11***			
	(1.25)	(1.25)	(1.27)			
Pre-Mean, One-Building Team	9.03	9.03	9.03	9.03	9.03	9.03
Post x One-Building Team as %	16.6%	16.6%	15.7%	11.4%	9.2%	21.3%
One-Building Team as %	-45.7%	-45.7%	-45.5%			
R^2	0.01	0.01	0.04	0.32	0.33	0.33
Engineer Group x Post FE		✓	✓	✓	✓	✓
Months at Firm x Post FE			✓	✓	✓	✓
Engineer FE				✓	✓	✓
Engineer Traits x Post FE					✓	✓
Main Building x Post FE						✓
# Teams	140	140	140	140	140	140
# Engineers	588	588	588	588	588	588
# Engineer-Months	9,624	9,624	9,624	9,624	9,624	9,624

Notes: This table replicates Table 4 but limits the sample to engineers who built internal tools for others in the firm. Since it was useful for these engineers to sit near the other engineers who used their tools, these engineers' teams were more likely to end up being split across the two buildings on the firm's main campus. *p<0.1; **p<0.05; ***p<0.01.

Table A.11: Proximity to Teammates and Engineer Output by Seniority

	Monthly Programming Output					
	Programs		Lines of Code		Files Changed	
	(1)	(2)	(3)	(4)	(5)	(6)
Junior x Post x One-Building Team	0.35**	0.26*	92.29**	92.99**	0.93	0.73
	(0.14)	(0.14)	(46.23)	(46.16)	(1.16)	(1.11)
Junior x One-Building Team	−0.13		−160.40***		−2.86**	
	(0.18)		(53.49)		(1.28)	
Senior x Post x One-Building Team	0.49***	0.47**	90.34*	151.60**	2.11	2.74**
	(0.18)	(0.19)	(53.16)	(60.58)	(1.29)	(1.38)
Senior x One-Building Team	−0.64***		−176.00***		−4.54***	
	(0.21)		(57.58)		(1.40)	
Junior Pre-Mean, One-Building Team	1.75	1.75	339.27	339.27	9.62	9.62
Senior Pre-Mean, One-Building Team	1.65	1.65	278.17	278.17	8.32	8.32
Percentage Effects						
Junior x Post x One-Building Team	19.9%	14.7%	27.2%	27.4%	9.7%	7.6%
Junior x One-Building Team	-7.3%		-47.3%		-29.7%	
Senior x Post x One-Building Team	29.5%	28.3%	32.5%	54.5%	25.3%	32.9%
Senior x One-Building Team	-38.5%		-63.3%		-54.6%	
Preferred Controls	✓	✓	✓	✓	✓	✓
All Controls		✓		✓		✓
# Teams	304	304	304	304	304	304
# Engineers	1,055	1,055	1,055	1,055	1,055	1,055
# Engineer-Months	16,058	16,058	16,058	16,058	16,058	16,058

Notes: This table investigates the relationship between sitting near teammates and monthly programming output, separately for junior engineers and senior engineers. Junior engineers are defined as those with less than 16 months of experience at the firm before the office closures and senior engineers as those with at least 16 months at the firm (the average tenure). The preferred controls and full set of controls are described in Section IV. *p<0.1; **p<0.05; ***p<0.01.

Table A.12: Effect of Proximity to Teammates on Pay Raises for Engineers Who Worked on Internal Tools

	% Pay Raise					
	Offices Open			Offices Closed		
	(1)	(2)	(3)	(4)	(5)	(6)
One-Building Team	-5.04^{***}			7.33^{**}		
	(1.62)			(3.62)		
Junior (< 16mo) x One-Building Team		-6.68^{***}			7.15^{*}	
		(2.40)			(3.72)	
Senior ($\geq$ 16mo) x One-Building Team		-7.67			7.93	
		(5.94)			(7.79)	
Female x One-Building Team			-17.71^{***}			16.81^{*}
			(5.76)			(9.11)
Male x One-Building Team			-5.28^{**}			5.91^{*}
			(2.33)			(3.53)
Dependent Mean	13.53	13.53	13.53	38.72	38.72	38.72
Junior (< 16mo) Mean	17.21	17.21	17.21	17.21	17.21	17.21
Senior ($\geq$ 16mo) Mean	24.46	24.46	24.46	42.97	42.97	42.97
Female Mean	21.67	21.67	21.67	36.36	36.36	36.36
Male Mean	19.19	19.19	19.19	39.1	39.1	39.1
Percentage Effect						
One-Building Team	-37.3%			18.9%		
Junior (< 16mo) x One-Building Team		-38.8%			19.5%	
Senior ($\geq$ 16mo) x One-Building Team		-31.3%			18.5%	
Female x One-Building Team			-81.7%			46.2%
Male x One-Building Team			-27.5%			15.1%
Preferred Controls	✓	✓	✓	✓	✓	✓
# Teams	262	262	262	256	256	256
# Engineers	801	801	801	720	720	720
# Engineer-Review	1,988	1,988	1,988	1,851	1,851	1,851

Notes: This table replicates Table 5 but limits the sample to engineers who worked on internal tools used by other workers at the firm. Since it was useful for these engineers to sit near the other engineers who used their tools, these engineers' teams were more likely to end up being split across the two buildings on the firm's main campus. Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.

Table A.13: Effect of Proximity to Teammates on Firings

	% Fired					
	Offices Open			Offices Closed		
	(1)	(2)	(3)	(4)	(5)	(6)
One-Building Team	-0.04			-0.18		
	(0.09)			(0.12)		
Junior (< 16mo) x One-Building Team		-0.12			-0.17	
		(0.12)			(0.13)	
Senior ($\geq$ 16mo) x One-Building Team		0.11			-0.21	
		(0.11)			(0.29)	
Female x One-Building Team			0.01			-0.32
			(0.06)			(0.34)
Male x One-Building Team			-0.06			-0.15
			(0.11)			(0.13)
Dependent Mean	0.07	0.07	0.07	0.18	0.18	0.18
Junior (< 16mo) Mean	0.08	0.08	0.08	0.08	0.08	0.08
Senior ($\geq$ 16mo) Mean	0.05	0.05	0.05	0.24	0.24	0.24
Female Mean	0	0	0	0.3	0.3	0.3
Male Mean	0.08	0.08	0.08	1.83	1.83	1.83
Percentage Effect						
One-Building Team	-59.2%			-97.2%		
Junior (< 16mo) x One-Building Team		-150.2%			-101.9%	
Senior ($\geq$ 16mo) x One-Building Team		213.4%			-88.4%	
Female x One-Building Team			NA			-106.7%
Male x One-Building Team			-66%			-8%
Preferred Controls	✓	✓	✓	✓	✓	✓
# Teams	303	303	303	297	297	297
# Engineers	1,055	1,055	1,055	994	994	994
# Engineer-Month	6,812	6,812	6,812	9,288	9,288	9,288

Notes: This table investigates how the likelihood of being fired differs for engineers on one-building teams while the offices were open (Columns $1-3$) and after the offices closed (Columns $4-6$). Each column includes our preferred, time-varying controls for engineering type and firm tenure. Each observation is an engineer-month. The sample includes engineers who worked on the main codebase, whose teammates were all in the main campus, and who were hired before the start of our sample. Standard errors are clustered by team. *p<0.1; **p<0.05; ***p<0.01.