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The Effects of Temporal Distance on Intra-Firm Communication: Evidence from Daylight Saving Time

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Abstract

Cross-border communication costs have plummeted and enabled the global distribution of work, but frictions attributable to distance persist. We estimate the causal effects of temporal distance, i.e., time zone separation between employees, on intra-firm communication, a critical means of coordination and knowledge transfer. We argue that temporal distance creates frictions for synchronous communication, which could be especially harmful for collaboration among employees engaged in non-routine tasks. Exploiting Daylight Saving Time (DST) as a natural experiment and detailed data from a large multinational firm, we show that among collaborators who experience an increase in temporal distance, total communication volumes drop by 9.4 percent on average, an effect fully driven by reductions in richer, synchronous communication. Further, we show that these declines are concentrated among employees in *routine* tasks. Employees in non-routine tasks, meanwhile, react to increased temporal distance by *shifting* synchronous communication across the boundary of their workday into leisure time. Additional tests show that workers' propensity to employ this adjustment mechanism is only partly explained by differences in their ability to work from home. Overall, our findings provide evidence that employees collaborating on non-routine tasks place a high premium on synchronous communication even at the cost of personal leisure. We present additional evidence and draw implications for how temporal distance relates to strategic considerations such as worker mobility, co-production of patents, and temporal boundaries of the firm.

Keywords — communication patterns, time zones, geographic frictions, knowledge workers, multinational companies

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1. Introduction

The strategy literature has long theorized the role of firms in facilitating coordination and communication between diverse workers and in their seminal paper, (Kogut and Zander 1996; p.503) argue that the cost of communication is a “primary metric that influences the boundary decisions of firms.” Although the widespread adoption of modern information and communication technologies (ICTs) has reduced communication costs to nearly zero, scholars have by now firmly established that global collaboration continues to face frictions related to multiple dimensions of distance (e.g., Ghemawat 2001; Berry, Guillén, and Zhou 2010). Understanding the sources of such frictions is increasingly relevant at a time when multinational companies (MNCs) are ever-more offshoring knowledge-intensive functions like research and development (R&D), which depend on frequent cross-border communication between collaborators and scientists (Freeman, Ganguli, and Murciano-Goroff 2014; Branstetter, Glennon, and Jensen 2018; Kerr and Kerr 2018; Catalini, Fons-Rosen, and Gaulé 2020). The rise of distributed and remote work and of “work-from-anywhere” organizational models (Stan-ton and Thomas 2019; Choudhury, Foroughi, and Larson 2021) further adds to our need to better understand what aspects of distance hinder communication and collaboration, for which workers, and the implications thereof.

One dimension of distance that is receiving increasing attention in recent management and economics literature is *temporal distance*, which results from time zone separation between firm locations. Recent papers have brought to light that temporal distance affects a number of important outcomes, including individual productivity (e.g., Mell, Jang, and Chai 2020), team performance (e.g., Cummings, Espinosa, and Pickering 2009), and knowledge transfer from headquarters to multinational affiliates (e.g., Bahar 2020). While such effects are thought to result from frictions in within-firm communication, to the best of our knowledge we lack direct, causal evidence on the size of the friction temporal distance poses for intra-firm communication as well as a nuanced conceptual understanding of how temporal distance affects communication among workers performing different tasks. Temporal distance between workers might change for many reasons, for example, when workers relocate, when they join or leave global teams, when a firm expands to new locations or relocates, and when it changes the distribution of work across global centers. Such events are

increasingly salient given the rise in geographic mobility of inventors and high-skilled workers (e.g., [Breschi and Lissoni 2009](#); [Marx, Strumsky, and Fleming 2009](#); [Kerr, Kerr, Ozden, and Parsons 2016](#)) and the acceleration of remote work. Yet debates remain on how temporal distance affects the performance of workers in different tasks, and consequently, which workers should be allowed to work-from-anywhere and how the temporal boundaries of the firm should be organized. Given this, in this paper, we ask: To what extent does temporal distance affect communication volumes between collaborators? And, how are workers performing heterogeneous tasks affected by temporal distance to collaborators?

To guide our empirical analysis, we outline a conceptual framework that integrates insights from the organizational literature on information processing and labor economics. A core insight from the organizational information processing literature is that equivocal tasks, which involve greater emphasis on establishing shared meaning and shared interpretation, require *richer* forms of communication ([Daft and Lengel 1986](#)). Synchronous modes of communication, in which participants exchange information in real-time, e.g., face-to-face meetings and voice or video calls, are considered the richest mediums. Asynchronous communication modes, which involve a temporal delay between sending and responding to information, e.g., letters, e-mail, databases, and reports, have been characterized in the literature as “lean” ([Dennis, Fuller, and Valacich 2008](#)). We connect this view of the communication needs of tasks with insights from the labor economics literature ([Autor, Levy, and Murnane 2003](#); [Acemoglu and Autor 2011](#)), which categorizes occupations according to their intensity of routine and non-routine tasks. Routine tasks can be accomplished by following explicit rules or instructions, while non-routine tasks lack clear instructions and require creative problem-solving. Combining these insights, we posit that for employees engaged in non-routine tasks which lack clear instructions, establishing shared meaning is more salient, and the need for synchronous communication is higher. In other words, we expect that workers engaged in non-routine tasks are more *synchronous communication-intensive*, i.e., all else equal, they conduct a greater share of their work-related communication via synchronous modes relative to workers engaged in routine tasks. We explore the implications of this premise for the question of how workers performing routine and non-routine tasks are affected by temporal distance to collaborators.

Temporal distance between collaborators can be conceptualized in terms of their business hour

overlap (BHO) (e.g., O’Leary and Cummings 2007). Greater temporal distance reduces BHO and shrinks the time window in which collaborators can communicate synchronously during local business hours. Intuitively, we expect that this leads to a reduction in volumes of synchronous communication. However, one adjustment mechanism that is relatively underexplored in the literature through which workers may circumvent this constraint is by shifting synchronous communication to outside of business hours. A key empirical prediction that we evaluate in this paper is that because their tasks are more synchronous communication-intensive, workers engaged in non-routine tasks will be more likely to employ this adjustment mechanism than workers performing routine tasks. Thus, our conceptual framework highlights that although employees performing non-routine tasks depend on synchronous communication *more*, their communication volumes are likely to be *less* affected by temporal distance frictions than those of employees in routine tasks. We further highlight that this result is supported by a more flexible boundary between the formal workday (e.g., 8 a.m. to 6 p.m. local time) and after-work time (e.g., after 6 p.m. local time) for non-routine workers, i.e., that they are affected by temporal distance on the margin of personal time.

We study the relationship between temporal distance, task routineness, and intra-firm communication in the context of a large, *Fortune 100* multinational company (“the Firm”) that globally distributes a variety of tasks. We have data on more than 12,000 of the Firm’s employees, including their location, and Outlook and Skype records for a 12-week period. These allow us to measure employee communication volumes for three synchronous modes (scheduled calls and meetings, unscheduled calls, instant message chats) and one asynchronous mode (e-mail), as well as the time of day (in local time) when the communication takes place. We also have data on employee job titles, which we use to construct measures of task routineness. First, we document two empirical facts in our data: Employees in non-routine tasks i) communicate significantly more and ii) conduct a significantly greater share of their communication via synchronous modes than employees in routine tasks, patterns that are consistent with the premise of our conceptual framework.

To estimate the causal effects of temporal distance on intra-firm communication, we implement a novel identification strategy using cities’ shifts to/from Daylight Saving Time (DST) as a natural experiment that creates discrete changes in temporal distance between collaborators. An ideal experiment in the context of our research questions would randomly allocate otherwise compara-

ble pairs of collaborators to locations with varying degrees of temporal distance keeping all other dimensions of distance fixed, or randomly vary only temporal distance among a fixed set of collaborators. Our identification strategy approximates the second ideal experiment. Using a difference-in-differences research design, we study how communication patterns change for pairs of collaborators that gain or lose shared business hours following the DST shift relative to those whose temporal distance remains unchanged. This design allows us to isolate the effects of temporal distance from those of other dimensions of distance (e.g., geographic distance, language differences) and to include collaborator-pair fixed effects, which control for unobserved determinants of communication, including the potential that employees who communicate frequently endogenously co-locate.

Our results provide evidence that temporal distance creates an economically large communication friction. First, we find that pairs of collaborators who experience an increase in temporal distance (and lose one-to-two shared business hours) reduce weekly communication volumes by 9.4 percent on average. This effect is entirely concentrated in volumes of synchronous communication, which fall by 11 percent from baseline levels, on average. Asynchronous communication volumes show no statistically significant responses, suggesting that the two modes of communication do not readily substitute for one another for the collaborators in our sample. In contrast, we find no evidence of increases in communication volumes for employees who experience a decrease in temporal distance. Using weekly event study models, we show that the effects we estimate are confined to the weeks following the DST shifts and that treated and untreated collaborators show parallel trends in the pre-period. We also show, using cross sectional data and two separate empirical strategies, that the effects are likely to approximate the steady-state effects of a one hour increase in temporal distance, rather than short-term responses. We subject these baseline findings to a number of robustness tests, including only considering collaborators treated at the same time, different definitions of the length of the workday (e.g., 9 hours, 11 hours), and estimation using alternative sub-samples empirical choices. The conclusions remain unchanged.

Next, we explore whether collaborators intensive in routine and non-routine tasks respond to changes in temporal distance differently. In split-sample analyses by employee type, we find that the declines in synchronous communication reported in our baseline result are driven by large reductions in synchronous communication by collaborators in *routine* tasks. In contrast, we find no evidence

that collaborators in non-routine tasks reduce synchronous communication in response to a one-to-two hour increase in temporal distance. To explain this result, we study to what extent workers shift synchronous communication across the boundary of their local workday. We find evidence for the adjustment mechanism outlined in our conceptual framework and for the prediction that non-routine workers offset increases in temporal distance with collaborators by shifting communication into leisure time. Specifically, we find that while communication taking place inside business hours drops by a similar amount for both types of employees, those in non-routine tasks increase synchronous communication taking place outside of business hours, by 18 percent from baseline levels on average, thus fully offsetting the reduction during business hours. Collaborators on routine tasks, in contrast, show no evidence of offsetting the drop by shifting synchronous communication across the workday boundary.

We further investigate whether these heterogeneous responses might be explained by an alternative mechanism: differences in employees' *ability* to work from home. Results reveal that the ability to work from home appears to be an important complement enabling workers to adjust to temporal distance to collaborators. However, they also provide further evidence supportive of our argument that the nature of the work — specifically, its non-routineness and resulting synchronous communication-intensity — drives the utility from synchronous communication and the salience of the adjustment mechanism of dipping into leisure time to conduct work-related communications.

Finally, we investigate to what extent temporal distance affects two employee-level outcomes in our sample: the probability of retention and employee relocation. We find no evidence that greater temporal distance to the team affects employee retention at least in the medium-term (over two years); but we find correlational evidence that employees more distant to their team are more likely to be relocated to different cities. However, relocated workers are often moved temporally *further* away from their team, suggesting that the Firm is potentially subjecting its human capital to an added friction. In a separate analysis, we find that inventors in the Firm are less likely to patent with inventors to whom they are more temporally distant.

Our paper has implications for the organization of temporal boundaries within the firm and contributes to the literatures on cross-national distance, communication patterns, and the global distribution of knowledge work within multinational firms (Ghoshal, Korine, and Szulanski 1994;

Gupta and Govindarajan 2000; Singh 2005; Phene and Almeida 2008; Berry et al. 2010; Ghemawat 2011; Foley and Kerr 2013; Alcácer, Kogut, Thomas, and Yeung 2017; Choudhury 2017; Kerr and Kerr 2018). We contribute to a small but growing set of studies (Cummings et al. 2009; Bøler, Javorcik, and Ulltveit-Moe 2018; Bahar 2020; Breschi, Gagliardi, Hovy, and Mariani 2020; Mell et al. 2020) focusing on a relatively understudied dimension of distance — temporal distance — and provide, to the best of our knowledge, the first set of causal results showing how it affects intra-firm communication patterns in a real-world organizational context. Espinosa, Nan, and Carmel (2015; p. 160) provide an excellent review of the literature on temporal distance and communication, and note that “the literature that focuses specifically on temporal separation is very sparse.” We document that temporal distance presents a sizable friction and reduces communication volumes between collaborators, in particular, richer, synchronous communication. Our secondary results also suggest that temporal distance between collaborators might be related to performance outcomes, such as patenting between collaborators.

Our results related to heterogeneous responses to changes in temporal distance for routine and non-routine workers bridge the literature on distributed work and the labor economics literature on heterogenous tasks performed by workers. The specific ways in which temporal distance affects communication patterns of heterogenous workers are relatively underexplored. Espinosa et al. (2015) report results from a laboratory experiment that studies the effect of temporal distance on the performance of collaborative teams. The authors conclude that task complexity, categorized in their paper as simple, complex and equivocal, did not have a significant effect in most models studying temporal distance and communication outcomes, except for in determining convergence, i.e., establishing shared meaning from information through discussion. In a recent paper, Mell et al. (2020) introduce the construct of temporal brokerage, which they define as being in a position within a team’s temporal structure that bridges subgroups that have little or no temporal overlap with each other, and provide evidence that being in positions of temporal brokerage on global teams decreases the quantity but increases the quality of an individual’s total productive output. Our theorizing and results contribute to this conversation and attempt to make progress in studying how workers performing routine and non-routine tasks react to temporal distance with collaborators.

Finally, our results highlight two managerial challenges, one involving under-provisioning of

synchronous communication resulting from temporal distance, and a second related to employees' work-life balance in the context of temporally distributed work. Our results highlight the consequences of temporal distance for the spatial/temporal organization of globally distributed work, and especially of global knowledge production. In particular, they suggest that employees engaged in collaboration on non-routine tasks place a strong premium on synchronous communication and benefit from being located in such a way as to minimize temporal distance—that is, largely on a North-South axis.

2. Theoretical Framework and Hypotheses

This section integrates key insights from the literatures on organizational communication and labor economics into a framework for analyzing employee communication and temporal distance. It presents a set of empirical predictions regarding the relationship between changes in temporal distance and volumes of intra-firm communication for collaborators performing routine and non-routine tasks. Our theorizing is based on two interrelated arguments: (i) compared to routine workers, non-routine workers perform tasks that are more synchronous communication-intensive; (ii) faced with an increase in temporal distance with collaborators, non-routine workers are more likely than routine workers to avail of an “adjustment mechanism”, i.e., shift their synchronous communication beyond local business hours into leisure hours.

2.1. Theoretical Background: Communication Synchronicity and Task Routineness

Interpersonal communication plays a central role in organizations. It is a primary means of coordinating interdependent work (March and Simon 1958; Thompson 1967; Galbraith 1973) and of transferring knowledge (Teece 1977; Kogut and Zander 1993; Roberts 2000). In a classic article, Daft and Lengel (1986) integrate multiple theoretical perspectives to propose that, at the most fundamental level, intra-organizational communication serves two functions: to reduce uncertainty and to reduce equivocality. Uncertainty is defined as a lack of information; equivocality is an absence

of shared meaning or interpretation.¹ Daft and Lengel’s central argument is that reducing equivocality calls for *rich* communication, where richness signifies “the ability of information to change understanding (of the receiver) within a time interval” or, in other words, the “learning capacity of a communication” (Daft and Lengel 1986; p.560).

Richness results when a communication medium provides for frequent and rapid feedback, multiple cues (e.g., tone of voice, body language), personalized messages, and language variety (Daft and Lengel 1986). One of the main correlates of medium richness is *synchronicity* (Dennis et al. 2008). Synchronous modes of communication, in which participants exchange information in real-time, e.g., face-to-face meetings and voice or video calls, are considered the richest mediums. Asynchronous communication modes, which involve a temporal delay between sending and responding to information, e.g., letters, e-mail, databases, and reports, have been characterized in the literature as “leaner” (e.g., Barry and Fulmer 2004). While the reduction of equivocality calls for rich communication, transmitting a set of clear-cut instructions that reduces uncertainty about the performance of a task, in contrast, can be most efficiently achieved via lean communication (Hinds and Kiesler 1995). As noted by Kraut, Fussell, Brennan, and Siegel (2002; p. 151), “collaborators try to use face-to-face conversation for tasks that require consensus or negotiation, while using e-mail for coordination.”

Dennis et al. (2008) further refine this perspective, proposing that most tasks require synchronous *and* asynchronous communication, in different amounts. The greater the need for transmission of information (which they term “conveyance”) in the execution of a task, they argue, the more performance will be enhanced by a greater *share* of asynchronous communication. Conversely, the greater the need for processing of ambiguous information (termed “convergence”), the more task completion will benefit from a greater *share* of synchronous communication. This theoretical refinement is consistent with the empirical observation that people typically use an array of communication modes when collaborating. For example, individuals often pursue a shared understanding of a task via a phone call and then follow up with an e-mail specifying the agreed-upon next steps.

¹Hinds and Kiesler (1995; p. 375) elaborate that “uncertainty means that data are missing; equivocality means that values, schema or meanings for interpreting events are ambiguous or conflictful.” To quote Daft and Lengel (1986; p. 554) further: “Equivocality seems similar to uncertainty, but with a twist. Equivocality presumes a messy, unclear field. An information stimulus may have several interpretations. New data may be confusing, and may even increase uncertainty. New data may not resolve anything when equivocality is high. Managers will talk things over and ultimately enact a solution. Managers reduce equivocality by defining or creating an answer rather than by learning the answer from the collection of additional data.”

Within the broad spectrum of jobs performed by workers, which will be more synchronous communication-intensive? Here, we connect the insights of the organizational literature above to the labor economics literature that provides a classification of jobs based on their task “routineness.” [Autor et al. \(2003\)](#) argue that it is necessary to study the “task content” of different occupations to theorize how changes in communication technology might affect their performance. [Autor et al. \(2003\)](#) also provide a categorization of tasks — routine, i.e., procedural, rule-based tasks and non-routine tasks, that require problem-solving, intuition, persuasion, and creativity. Building on this, [Acemoglu and Autor \(2011; p.1077\)](#) theorize that non-routine tasks require “situational adaptability, visual and language recognition.” Integrating insights from this literature with the insights from the organizational communication literature discussed earlier, we posit that employees performing jobs with a greater content of non-routine tasks (compared to routine tasks) require greater dependence on visual and language recognition, and hence are more *synchronous communication-intensive*.

While these theoretical perspectives provide useful guidance for what the optimal communication patterns among employees may be, in the next section, we will evaluate how employees are likely to respond to frictions created by temporal distance to collaborators. First, we will evaluate the baseline effect of temporal distance; and then evaluate how our premise regarding the synchronous communication-intensity of tasks informs our question of how employees performing routine and non-routine tasks are likely to be affected by temporal distance to collaborators. To do so, we build on a third stream of literature in economics and management — the literature on how workers allocate their time to work versus leisure, and the related literature on temporal/schedule flexibility.

2.2. The Effects of Temporal Distance on Employees Performing Heterogeneous Tasks

How would communication patterns of workers performing heterogenous tasks react to an increase in temporal distance (i.e., less overlap in business hours) with collaborators? Prior to theorizing about these heterogenous effects, we build on prior literature and present a baseline hypothesis on how temporal distance affects synchronous communication on average.

Existing studies from the distributed-work literature note that temporal distance makes synchronous interaction more difficult (e.g., [Hinds and Kiesler 2002](#)). Temporal distance shrinks

business-hour overlap, or the number of hours in a standard workday during which remote collaborators are likely to be available (O’Leary and Cummings 2007). While time zone differences of ten hours or more create a temporal boundary between collaborators providing no time at all for synchronous interaction during the workday (Cummings et al. 2009), even less extreme time zone differences can meaningfully reduce synchronous interaction opportunities (Espinosa and Carmel 2003). For example, a study of coordination in global software teams found that a one-hour time zone difference between two sites reduced their overlapping time by four hours: one at the beginning of the day, one at the end of the day, and one during each site’s lunch break (Grinter, Herbsleb, and Perry 1999). Based on prior literature, we suggest the following baseline hypothesis:

Baseline hypothesis (H_0): *All else equal, greater temporal distance reduces volumes of synchronous communication between collaborators.*

Asynchronous communication volumes, in contrast, might not be affected by temporal distance at all, since messages can be sent or received even when the collaborator is not contemporaneously working. However, the volume of asynchronous communication may increase with temporal distance if remote collaborators resort to asynchronous communication to make up for the lack of synchronous communication, i.e., if the two modes of communication are substitutes. Finally, if the two models of communication are complements, then asynchronous communication volumes may decrease as synchronous modes decrease. As the theoretical effects are ambiguous, we do not present hypotheses about the effects of temporal distance on asynchronous communication.²

Our baseline hypothesis implicitly assumes that faced with greater temporal distance, synchronous communication has to decline, as synchronous communication needs to be performed within the period of business hour overlap between collaborators. Yet, all employees may not be equally constrained by their business hour overlap in conducting synchronous communication. In fact, recent literature (e.g., DeFilippis, Impink, Singell, Polzer, and Sadun 2020) provides evidence that workers frequently communicate beyond the boundary of their workday, cutting into leisure time. Prior organization literature, notably Perlow (1998), conceptualizes the temporal boundary between employees’ work and life outside of work and studies mechanisms used by managers to

²However, in the empirical section, we can use patterns in the data to interpret whether the two communication modes appear to be complements or substitutes in our empirical context.

exert boundary control over knowledge workers, often by setting meetings, reviews, and internal deadlines beyond business hours.

Therefore, we reason that faced with an increase in temporal distance with collaborators, it is possible that workers engage in an *adjustment mechanism* and shift synchronous communication with distant collaborators across the temporal boundary of the workday. In summary, workers have two options: reduce overall synchronous communication given shorter temporal overlap with collaborators or move synchronous communication across the boundary of the workday, cutting into leisure time.

We argue that non-routine workers are more likely to employ the adjustment mechanism when faced with increased temporal distance with collaborators for two reasons. The first draws on the literature on time allocation by workers in economics ([Becker 1965](#); [Gronau 1976](#); [Heckman 2015](#)). A key insight of this literature is that individuals allocate time to work versus leisure by comparing the utility derived from a unit of time spent on the two activities and allocating time to the one that provides a higher return. Given that their tasks are more synchronous communication-intensive, non-routine workers (compared to routine workers) are more likely to derive greater work-related utility from shifting synchronous communication across the boundary of the workday, when faced with an increase in temporal distance with collaborators. Second, we draw on the organizational literature, notably [Perlow \(1999\)](#), that takes a more cynical view of why workers shift work across the temporal boundary of the workday. In particular, [Perlow \(1999\)](#) argues that a perpetuating reality of dealing with “crises” (crisis was defined as anything that had to be done urgently) led workers shifting work across the boundary of the workday, and this was more likely for workers performing “unplanned” and “unstructured” work. Given that non-routine work by definition is more unplanned and unstructured, workers performing non-routine tasks might have to move synchronous communication across the boundary of the workday to deal with such work-related crises. In contrast, workers performing routine tasks are less likely to either derive greater utility from shifting synchronous communication across the boundary of the workday and/or are less likely to deal with unstructured crises, given the inherent rule-based structure of their tasks. This leads us to reason:

Hypothesis 1a: *Faced with an increase in temporal distance to collaborators, workers perform-*

ing non-routine tasks are less likely to reduce synchronous communication than employees in routine tasks.

Hypothesis 1b: *Faced with an increase in temporal distance to collaborators, workers performing non-routine tasks are more likely to shift synchronous communication across the temporal boundary of the workday, cutting into leisure time, than employees in routine tasks.*

Next, we hypothesize how workers performing routine and non-routine tasks might react to decreases in temporal overlap with collaborators, i.e., when they have greater business hour overlap with collaborators. If ex ante, synchronous communication volumes are below optimal levels, we could observe employees increasing synchronous communication with collaborators during the extended period of business hour overlap. Given the additional time to engage in synchronous communication during the regular workday, we expect that non-routine workers would have less need to employ the adjustment mechanism and shift communication outside the workday boundary. In contrast, given that their tasks are less synchronous intensive, routine workers are likely to increase synchronous communication during the workday less, despite the increased business hour overlap with collaborators. This leads us to hypothesize:

Hypothesis 2: *Faced with a decrease in temporal distance with collaborators, workers performing non-routine tasks are more likely to increase synchronous communication during regular business hours, compared to workers performing routine tasks.*

3. Empirical Setting and Data

3.1. Empirical Setting

Our empirical setting is the largest division of a U.S.-headquartered *Fortune 100* multinational company (“the Firm”). The Firm provides a highly suitable setting because it operates in each region of the world and geographically and temporally distributes various business functions, including production, R&D, information technology, and others. We have detailed data on 12,089 employees in the Firm’s largest division (“the Division”), including information on each employee’s work location (building address, city, and country), job title, and business function. Out of these, 12,038

employees communicate at least once with other employees in the data during the period of study and constitute our sample (“the sample”). As can be seen in Figure 1, the sample employees are distributed across 167 different cities in 48 countries. North America hosts 40 percent of the employees; Asia, the Middle East, and Europe also account for sizeable percentages. Next, we describe the construction of key variables used in the study.

[Figure 1 about here]

3.2. Dependent Variable: Communication Volume

Measures of intra-firm communication between sample employees are constructed from the employees’ Outlook and Skype records. Outlook and Skype are the Firm’s primary communication-management tools. These data cover a 12-week period (September 10–November 30, 2017). The raw records are used to estimate volumes of bilateral communication for each pair of sample employees and each week via four different media: 1) scheduled calls and meetings, 2) unscheduled calls, 3) instant message chats, and 4) e-mail.³ Each measure is described in more detail below; however, all follow two common principles. First, any minute of an individual’s day is allocated to no more than one communication activity. In other words, communication is measured around the clock but cannot exceed 24 hours per day.⁴ Second, when communication involves more than one counterpart, the focal individual’s attention is allocated to them equally. Next we describe the construction of the measures in more detail.

Synchronous communication. Following prior studies in the distributed work literature (e.g., Hinds and Kiesler 1995), we sum communication conducted via scheduled calls and meetings, unscheduled calls, and instant message (IM) chats to calculate total synchronous communication.

- *Scheduled calls and meetings.* Communication volume via scheduled calls and meetings is estimated using the beginning and end timestamps of Outlook calendar events. All employees

³The Firm’s raw data is processed by a human capital analytics firm before being shared with us. More information on the measures that we describe is available in: Kim, T.J., Bradbury, M.S. and Olguin, D.O., Sociometric Solutions inc, 2020. *System and Method for Transforming Communication Metadata and Sensor Data into an Objective Measure of the Communication Distribution of an Organization*. U.S. Patent Application 16/532,835.

⁴If an individual is multi-communicating (Reinsch, Turner, and Tinsley 2008) (e.g., composing an e-mail while participating in a scheduled call or meeting), the time is allocated to only one activity, with scheduled calls and meetings prioritized.

that share a focal Outlook event are considered co-participants and constitute the set of employee pairs (*dyads*) among whom positive communication volume is recorded.⁵ The measure is symmetric; thus if individuals A and B are co-participants in a 30-minute event, the link $A \rightarrow B$ and the link $B \rightarrow A$ each equal 30 minutes. Because time is allocated equally for events involving more than two co-participants, a 30-minute meeting involving individuals A, B, and C, for example, results in six dyads ($A \rightarrow B, A \rightarrow C, B \rightarrow A, B \rightarrow C, C \rightarrow A, C \rightarrow B$), with communication volume of 15 minutes each.⁶ As a result, scheduled events involving many participants, for example a Division-wide conference call, carry little weight. In practice, the measure of scheduled call and meetings can pick up scheduled communication across multiple media types (e.g., Zoom, Skype, dial-in conference calls).⁷

- *Unscheduled calls.* The volume of unscheduled calls is calculated like that of scheduled calls and meetings, with the difference that it is estimated from the beginning and end timestamps of Skype call records. Also, the measure counts only call minutes that fall outside of a scheduled Outlook calendar event (that is, outside of any scheduled call or meeting) to prevent overlap with the measure of scheduled calls and meetings, some of which take place over Skype.⁸
- *Instant message chats.* The volume of instant-message chats is estimated using a count of messages. Specifically, for each instant message, 40 seconds of time is allocated to the sending employee. For example, a chat session consisting of six messages sent from A to B yields 240 seconds, or 4 minutes, for the $A \rightarrow B$ dyad. Time is not allocated for reading the message; thus, the $B \rightarrow A$ dyad is not allocated communication volume unless B replies. Therefore, unlike scheduled calls and meetings and unscheduled calls, the measure of instant-message chat volume is *asymmetric*. When a message is directed to more than one recipient, the time spent composing the message is allocated equally among them.⁹

⁵Specifically, the Firm counts all individuals whose schedule it appears on and who did they not decline the event as a participant. Outlook calendar events without co-participants (e.g., blocked-off private time) are not included.

⁶More generally, a meeting with N participants yields $N(N - 1)$ dyads; meeting volume for each dyad is equal to the length of the meeting divided by $N - 1$.

⁷Regrettably, we lack information on the specific medium used for a scheduled call or meeting. Though scheduled calls and meetings could also include face-to-face interactions, we expect their contribution in our analysis to be small since we focus our study communication between non-co-located employees and thus in-person meetings would require travel.

⁸According to our analysis of Division data, 3.9 percent of scheduled calls and meetings occur via Skype.

⁹Therefore an instant-message chat involving N recipients yields N dyads, each with communication volume equal

Asynchronous communication. We measure asynchronous communication as the total volume of communication via e-mail. Communication volume via e-mail is calculated like that of instant-message chats, with the difference that time spent composing each e-mail is estimated from message length, with a maximum value of 10 minutes per message. Anyone named in the “To” or “Cc” field is considered a recipient; the time spent composing the message is allocated among them equally. For example, if A sends an e-mail message whose length has a value of 10 minutes to B and C , then $A \rightarrow B$ and $A \rightarrow C$ equal 5 minutes each.

Communication inside / outside business hours. Each instance of communication generates a time stamp—the time of day in each participant’s local time—when the communication is sent or received.¹⁰ Using the time stamp, we code each instance of communication as occurring either inside business hours (*IBH communication*) or outside business hours (*OBH communication*). We code scheduled calls and meetings and unscheduled calls at the employee-pair level as inside business hours if *both* participants are within local business hours (8 a.m.–6 p.m.) and otherwise as outside business hours. We code instant-message chats and e-mail as occurring inside business hours if the *sending* party is within local business hours, and otherwise outside.

3.3. Other Measures

Temporal distance. Following recent studies (e.g., Cummings et al. 2009; Mell et al. 2020), we measure temporal distance using the concept of business-hour overlap (BHO), or the number of shared work hours between two employees in a standard workday. To calculate BHO, we use data on the time zone of the city where each employee is located and assume that business hours range from 8 a.m. to 6 p.m. local time, that is, a 10-hour workday (in section 6, we show robustness to alternative definitions of business hours). BHO thus ranges from zero hours for employees that are located in cities more than ten time zones apart, to ten hours for employees located in the same time zone.¹¹ For city pairs in which at least one member of the pair observes DST, we calculate

to the estimated time spent composing the message divided by N . The same is true for e-mail.

¹⁰For ease of data processing, we aggregate time stamps within 30-minute time slots.

¹¹City-level time zone data is provided by geonames.org. Though our communication data was collected in 2017, we use time zone data from 2018. None of the cities in our sample changed time zones between 2017 and 2018. Our sample includes a small number of employees in city pairs whose overlaps are fractional (e.g., 8.5 hours of time zone difference). In these cases, we round up to a full hour; thus BHO always takes an integer value between zero (no

BHO twice: Once using each city’s local time in effect before the shift to/from DST (*Pre-period BHO*), and once following the shift (*Post-period BHO*).

Employee task routineness. We construct measures of employee task routineness from employee job titles and publicly available data. Because the Firm’s job titles are non-standard, we first manually code them to Standard Occupational Classification (SOC) codes.¹² Then we calculate the [Acemoglu and Autor \(2011\)](#) measures of task routineness for each SOC code using their replication files and publicly available O*NET data.¹³ We are able to calculate routineness measures for 8,276 sample employees who have valid job titles and whose SOC occupation contains O*NET data. We create an indicator variable *Non-routine*, which takes the value one if an employee’s score on the “Non-routine cognitive: Analytical” metric is above the median value among sample employees. We will refer to employee jobs with below-median values of the non-routine score in the sample as *Routine*.

4. Descriptive Patterns

Because our objective is to study the effects of temporal distance between collaborators on their communication volumes, the majority of our analysis is conducted at the employee-pair level. With 12,038 sample employees, the number of potential pairs is very large. However, most employee pairs never communicate during the sample period and, because all our analyses will include employee-pair fixed effects, would drop out the sample. Hence, our employee-pair sample consists of all pairs of sample employees who communicated *at least once* via any mode during the 12-week sample period (“collaborators”). Excluding collaborators located in the same office (i.e., who have the same work address), we have 859,092 pairs of collaborators in our sample.¹⁴ Panel A of Table 1 shows

overlap in business hours) and ten (complete overlap in business hours).

¹²The list of SOC codes was downloaded from: <https://www.bls.gov/soc/2010/#materials> in January, 2021. In the coding process, approximately 5,000 unique job titles were initially coded to the 1,110 SOC codes. Each title was initially coded by two independent coders; then, a third coder reviewed the choices and selected the best match. Finally, the research team coded a five percent random sample of titles and calculated rates of overlap with the final choice of the independent coders. These checks reached north of 80 percent inter-coder overlap.

¹³The replication files were downloaded from David Autor’s homepage (<https://economics.mit.edu/faculty/dautor/data/acemoglu>). O*NET version 25.0 data were downloaded from https://www.onetcenter.org/db_releases.html.

¹⁴We exclude co-located collaborators because they can also engage in impromptu, face-to-face communication, a mode that we do not observe.

summary statistics at the collaborator-pair level. Their mean weekly communication volume is 1.69 minutes, as most collaborators do not communicate in a given week. However, some collaborator pairs communicate quite intensively, with a maximum value of 36 hours per week. One fact evident in the data and confirmed by conversations with Firm employees is the prominence of synchronous communication, in particular via scheduled calls and meetings, in total communication. On average, collaborators have 5.7 hours of BHO (prior to the moves to/from DST) and conduct 68 percent of their communication inside business hours.

Panel B of Table 1 presents summary statistics for the 12,038 sample employees. As a check on the communication measures, we sum total communication by employee-week. The average employee in the sample spends a total of 14.3 hours per week communicating via the four measured modes. These estimates of communication volumes appear reasonable and to capture a large share of weekly communication. The average normalized non-routine score of the sample employees is 1.1, which indicates that the occupations represented in the sample are, on average, more non-routine than the set of SOC occupations. However, significant heterogeneity exists among the sample employees, ranging from a minimum normalized score of -1.7 to a maximum score of 2.5. As a check on the metric, we summarize the routineness score by the employees' business function in Table 2. Reassuringly, employees in a priori more complex functions (specifically, R&D and "other", which includes roles in marketing, law, tax, etc.) exhibit significantly higher non-routineness scores than production employees.

[Table 1 about here]

Our conceptual framework predicts that employees in non-routine tasks are more synchronous communication-intensive. Next, we examine whether this premise is confirmed by the data. Figure 2 plots the average weekly communication separately for non-routine and routine employees and the share of synchronous communication in the total. The figure shows that employees whose jobs are more non-routine spend significantly more time communicating via the measured communication modes than employees in routine jobs (left panel). Consistent with our theoretical framework, they also conduct a significantly higher share of their communication via synchronous modes (right panel).

[Figure 2 about here]

5. Empirical Strategy

Our empirical strategy for identifying the causal effects of temporal distance on intra-firm communication exploits changes in temporal distance between employees induced by cities' shifts into and out of Daylight Saving Time (DST). This section describes our empirical strategy and research design in more detail.

5.1. Shifts into/out of Daylight Saving Time in 2017

Cities' shifts into and out of Daylight Saving Time in 2017 occurred on different dates but all overlapped with the 12-week period of our study (Figure 3). During this period, cities in the Northern Hemisphere that observe DST (e.g., most cities in the United States, Canada, Mexico, many European countries) shifted out of DST and moved their clocks backward by one hour. Cities in the Southern Hemisphere that observe DST (e.g., most cities in Brazil, Australia, New Zealand) shifted into DST and moved their clocks forward by one hour. A third group of cities in our sample does not observe DST and, hence, did not move its clocks. Cities' shifts into/out of DST discretely changed the business hour overlap for some pairs of employees but not for others. For example, as DST came to an end in the United States on November 5, 2017 and Houston set its clocks backward by one hour, employees in Houston lost an hour of BHO with employees in Moscow and gained an hour of BHO with employees in Seoul, neither of which observe DST. Houston experienced no change in BHO with Vancouver, which observes DST but also moved its clocks backward. Meanwhile, Houston lost *two* hours of BHO with Rio de Janeiro, a Southern Hemisphere city that moved its clocks *forward* by one hour. These discrete changes in temporal distance between collaborators induced by DST offer a natural experiment that can allow us to estimate the causal effects of changes in temporal distance on employee communication.

[Figure 3 about here]

5.2. Empirical Model

Our empirical model uses a standard difference-in-differences (DiD) research design to compare changes in communication volumes for pairs of collaborators who experienced an increase or decrease in temporal distance relative to those whose temporal distance remained unchanged before and after cities’ moves to/from DST. We estimate:

$$Comm_{ijt}^m = \alpha + \beta^m D_{ijt} + \eta_{ij} + \delta_t + \varepsilon_{ijt} \quad (1)$$

where $Comm_{ijt}^m$ is communication volume in mode m for collaborator pair ij in week t , D_{ijt} is a binary treatment indicator, η_{ij} are collaborator-pair fixed effects, δ_t are week fixed effects, and ε_{ijt} is an idiosyncratic error term. β^m is the treatment effect of interest.

We separately estimate the effects of increases and decreases in temporal distance on communication by defining two distinct treatment groups. In each case, collaborators whose temporal distance did not change constitute the control group. The first treatment group are collaborators who lost BHO. We create a binary variable $D_{ijt} = Increased\ Distance_{ij} \times Post_t$, which equals one for this group starting the first week in which the pair experiences a reduction in BHO and zero for the control group.¹⁵ The second treatment group are collaborators who gained BHO. We create the binary variable $D_{ijt} = Decreased\ Distance_{ij} \times Post_t$, which equals one for this group starting the first week in which the pair experienced an increase in BHO and zero for the control group.¹⁶ From the beginning to the end of the sample period, 22 percent of the collaborators experienced an increase in temporal distance, 10 percent experienced an decrease, and 68 percent saw no change in temporal distance. Figure 4 shows the timing of treatment.

[Figure 4 about here]

¹⁵As cities move into/out of DST at different times, some collaborators experience an initial change in BHO when one city in the dyad shifts and a second change when the other city does so. For example, collaborators between Australia and the United States gain one hour of BHO when Australian cities shift their clocks forward on October 1, and a second hour when U.S. cities shift their clocks backward on November 5. For such dyads, we define treatment using the week of the earliest shift.

¹⁶Because we measure BHO assuming an 8 a.m.–6 p.m. workday, some employee pairs experience a change in time zone difference but not in BHO. For example, the U.S. East Coast and Singapore have a time zone difference of 12 hours during DST and 11 hours outside of DST, but no change in business-hour overlap, which remains at zero. In a robustness check, we use alternative definitions of BHO assuming a 9-hour and 11-hour workday, in which case some such dyads become “treated”.

The main advantage of our empirical design is that the model in Equation (1) can include fixed effects for each pair of collaborators, η_{ij} . These control both for unobserved heterogeneity (e.g., the fact that some pairs of collaborators communicate more than others for unobserved reasons) and for reverse causality (e.g., the fact that the Firm may co-locate collaborators who need to communicate frequently). With the collaborator pair fixed effect in place, the effect of temporal distance is identified from changes in communication volumes within each pair of collaborators before and after moves to and from DST, relative to the changes among untreated collaborators. The main assumption for this effect to be causally identified is that the treated and control groups would have followed parallel trends in the absence of treatment. A second, implicit, assumption is that employees are not perfectly forward-looking; that is, that they do not fully anticipate the changes in temporal distance with collaborators and adjust to them in advance. We will validate both of these assumptions of the DiD framework directly by estimating Equation (1) with weekly leads and lags, which will allow us to observe whether treated and control groups show any differences prior to treatment, and whether any differences are confined to the period after treatment. Finally, recent developments in the empirical literature point out potential biases that can arise in estimation of DiD models with time-varying treatment due to comparisons between units treated earlier and those treated later when treatment effects are not constant over time (e.g., [Goodman-Bacon 2021](#); [Borusyak, Jaravel, and Spiess 2021](#)). We will show robustness of our analysis to the exclusion of such, potentially problematic, comparisons.

6. Results

6.1. Effects of Temporal Distance on Intra-Firm Communication

Table 3 presents the results of the difference-in-differences analysis, focusing on the effects of increased temporal distance. We estimate Equation 1 with a Poisson pseudo maximum likelihood (PPML) regression model with the dependent variable measured in levels and present robust standard errors conservatively clustered at the city-pair level to allow for error correlation both within pairs of collaborators over time as well as collaborators who are subject to the same temporal dis-

tance shocks.¹⁷ Column 1 shows the effect of increased temporal distance on total communication between collaborators and Columns 2 and 3 examine differential effects of increased distance on total synchronous and asynchronous communication.

The results show that a one-to-two hour increase in temporal distance led to a $(e^{-0.099} - 1) * 100 = 9.4$ percent decline in total communication among collaborators, on average. Consistent with the expectation that temporal distance should be most relevant for synchronous communication, Column 2 shows that the decline in total communication is fully accounted for by declines in synchronous modes. The estimated coefficient in Column 2 implies that a one-to-two hour increase in temporal distance led to a 11.0 percent decline in total synchronous communication. These results provide support for the baseline hypothesis, namely, that greater temporal distance reduces volumes of synchronous communication between collaborators. We had no strong prior as to whether asynchronous communication would substitute for lost synchronous communication in our sample. The estimate in Column 3 implies that in our sample, synchronous and asynchronous communication do not appear to be close substitutes. The coefficient in Column 3 is not statistically significant, and in terms of magnitude, very close to zero. In contrast, we find no significant changes in communication volumes as a result of decreases in temporal distance (Table 4). All estimated coefficients are close to zero and not statistically significant. Overall, the baseline results show that increases in temporal distance reduce synchronous communication. They provide no evidence that decreases have the opposite effect.

[Table 3 and Table 4 about here]

Validating the Parallel-Trends Assumption. Before we proceed, we validate the baseline results by testing the key assumptions behind the difference-in-differences analysis: parallel trends among the treated and control groups and no anticipatory effects. To do so, we estimate Equation (1), replacing the D_{ijt} dummy indicating the period after treatment with a set of indicator variables for each of the weekly periods before and after treatment, defining *Week 0* as the week in which a

¹⁷We use the *ppmlhdfe* Stata package developed by [Correia, Guimarães, and Zylkin \(2019\)](#). The PPML model has become a preferred choice in data where the dependent variable is nonnegative and features a large number of zeros, making traditional log-linear OLS models inconsistent ([Silva and Tenreyro 2006](#)). For example, it has become the standard choice in gravity-style frameworks from the international trade literature ([Fally 2015](#)). Like international trade flows, our communication data features a large number of zeros, as most collaborators do not communicate with each other each week. In section 6.2, we show the robustness of our results to estimation via OLS.

pair of collaborators first experiences a change in BHO due to DST practices.¹⁸ For example, in the sample of collaborators that experienced an increase in temporal distance, the indicator $Week(-1)$ denotes the week prior treatment and $Week(1)$, the week after. This analysis allows us to observe both any differences in pre-trends as well as the timing of the effects following treatment.

Figure 5 presents coefficients estimates of the event study model graphically, showing the effects of changes in temporal distance for each of five weeks following treatment and pre-trends for five weeks before treatment (Table A1 includes up eight pre-period leads).¹⁹ Consistent with the DiD results, in Panel A we observe negative effects on total and synchronous communication following treatment for pairs that experience an increase in temporal distance (four of the six estimated coefficients are negative and statistically significant). Moreover, these results show that the negative effects are not confined to the week or two following the switch to/from DST (which could reflect temporary confusion), but rather persist in later weeks, as well. In contrast, none of the pre-period coefficients are statistically different from zero. Turning to asynchronous communication, consistent with the results in Table 3, we observe neither a pre-trend nor a significant trend after treatment for asynchronous communication. Panel B shows the estimated coefficients for dyads experiencing a decrease in temporal distance. Here we do not observe systematic differences in synchronous communication volumes prior to or after treatment between treated pairs and the control group. While a positive jump in synchronous communication volume appears in the first period of treatment, $Week 0$, it does not persist. Moreover, in this sample, asynchronous communication volumes see uptick after treatment, although the pre-period coefficients suggest that this may reflect an anticipatory effect or pre-period trend.

Overall, the analysis lends support to the parallel trends assumption and fails to detect anticipatory effects in regards to the baseline finding of increases in temporal distance. Estimates for decreases in temporal distance are noisier, potentially reflecting a smaller number of treated pairs, but also fail to detect systematic pre-period trends.

[Figure 5 about here]

¹⁸All cities in our sample shift clocks on Sunday (with the exception of cities in New Zealand, which shift clocks on Monday), which is also defined as the first day of the week in our data. Hence $Week 0$ denotes the first seven days over which treated pairs experience treatment.

¹⁹Only two percent of observations experience more than five weeks of treatment (dyads involving New Zealand, Australia, and Brazil), hence we consolidate weeks 5+ into the $Week 5$ indicator.

6.2. Robustness of the Main Effect

Table 5 presents a series of robustness tests of the main results for alternative empirical choices and sub-samples. The first robustness test is designed to address potential biases uncovered by a recent empirical literature on DiD research designs with time-varying treatment, i.e., event study designs (e.g., [Goodman-Bacon 2021](#); [Borusyak et al. 2021](#)). This literature highlights that traditional DiD estimation can lead to biased estimates of the true treatment effect when units are treated at different points in time and the treatment effect is heterogeneous in time. The bias is potentially severe when the control group is small – i.e., when identification fully relies on comparisons among earlier and later treated units. In our setting, we have a large group of never-treated units — collaborators who experience no change in BHO — which reduces the likelihood of such biases. In addition, in column (2) of Table 5 we present the estimates of Equation (1) including only units treated at the same time — in week 9 of the sample period — along with the never-treated control group.²⁰ The estimated coefficient in this sample is very close to the original estimate shown for comparison in column (1). In our setting, we also have a small number of city pairs that are treated only temporarily. For example, countries in Europe shift from DST one week prior to the United States. While ultimately U.S.-Europe dyads see no change in BHO (and are hence included in the control group), they experience a temporary shift. Excluding these “temporarily-treated” dyads from the control group does not substantially change the baseline results (column (3)).²¹

[Table 5 about here]

A second set of robustness tests uses different definitions of the length of a workday to calculate BHO and hence, change in temporal distance. Defining the workday with shorter length — e.g., 9 hours instead of 10 — means that some units which in our baseline analysis were considered treated now enter the control group; in contrast, a longer workday definition implies more units are treated and fewer are in the control group. As the results in columns (4) and (5) show, the

²⁰Week 9 is the period when the largest number of dyads is treated, as this is when North America shifts its clocks.

²¹We have also performed an analysis that explores whether communication volumes of such “temporarily treated” dyads respond in the period of treatment. Specifically, we compare the weekly communication volumes of U.S.-Europe dyads (temporarily treated group) to those of U.S.-Canada dyads (control group) to check whether U.S.-Europe dyads see an uptick in communication volumes during the week when they are temporarily closer. Consistent with our main results on the dyads whose temporal distance decreased, we fail to find systematic treatment effects of these short-term changes. These analyses are available from the authors.

results are not very sensitive to the alternative choices. Column (6) excludes dyads which saw a two-hour change in BHO, thus only considering the average effects of a one-hour increase or decrease in temporal distance. The magnitude of the coefficient for the effects of increased distance drops to 6.6 percent and remains significant. In column (7) we exclude the week of Thanksgiving (sample week 11), which sees significantly less communication than other weeks. While our week fixed effects should absorb the effects of such shocks, this robustness tests ensures that our main results are not potentially driven by differential adjustment of treated and control pairs during that period. The coefficient estimate in column (7) suggests that this is not the case. In column (8), we estimate Equation (1) using OLS rather than PPML. While the model fit appears worse per the R^2 , the coefficient estimate is of similar magnitude and statistical significance. In column (9), we add fixed effects for each city in addition to the collaborator-pair and week fixed effects to control for any potential differences affecting all employees in a city. Finally, in column (10), we seek to address concerns around the communication measures being potentially sensitive to the prevalence of economically insignificant collaborations (e.g., two employees copied on the same division-wide email). To do so, in this analysis we only include collaborators who have a minimum of 5 minutes of dyadic communication volume. While this sample restriction drastically reduces the number of observations in the model, the estimated effects in column (10) are very similar to the baseline estimates.

Validating the Size of the Baseline Effect.

Our analysis using DST shifts is designed to uncover the causal effects of temporal distance on communication volumes. One limitation is that with only a few weeks of data in the post period, we cannot directly observe whether the estimates in Table 5 reflect short-term or steady-state effects. To provide additional evidence on the likely magnitude of steady-state effects, we conduct two analyses of cross-sectional communication flows using data from the pre-DST period, weeks 1–5 of our sample.²² In the first analysis, we estimate a gravity model of communication flows, which models communication volumes between collaborators as a function of their temporal and geographic distance, controlling for fixed effects of each employee and week. While the correlation

²²We exclude Australia and New Zealand from this analysis, as they already moved to DST by week five. These dyads constitute a vary small share of the data.

between BHO and geographic distance is very high ($\text{corr}=-0.86$), this approach exploits variation in temporal distance among geographically equidistant collaborators (e.g., those located on an East-West versus North-South axis). Table A2 reports the results of the analysis, first with only temporal distance and subsequently adding the geographic distance control. The results show that a one hour higher BHO is associated with 6.3 percent more communication volume in our sample, on average. The size of this effect is very much in line with the causal estimate of a one-hour increase in temporal distance shown in column (6) of Table 5. Consistent with expectations, the effect of temporal distance is much more pronounced for synchronous relative to asynchronous communication volumes. Meanwhile, geographic distance does not contribute much incremental explanatory power to predicting communication volumes once temporal distance is accounted for.

The second analysis uses a regression-discontinuity style design to address some limitations of the gravity model (especially, the high correlation between geographic and temporal distance). For this analysis we use the approach developed by Bahar (2020) and identify, for each focal employee, collaborators who are located within narrow distance bands on either side of a timezone line.²³ We then estimate the communication volumes of a focal employee to collaborators as a function of the collaborator being on the side of the timezone line that is “closer” to the focal employee (i.e., that is one hour more temporally proximate). The results of this analysis are presented in Table A3. The estimates suggests a 12 percent increase in communication volume associated with being on the more proximate side of the timezone line.

While these two cross-sectional analyses do not fully address the potential for endogenous co-location of collaborators, they provide a range of estimates that help us to interpret and validate the causal estimate using the DST strategy.

²³For this analysis, each employee is assigned to the time zone lie to which they are most geographically proximate. We present results using collaborators located within a distance band of 250 km to a timezone line, though analyses using other bands (e.g., 150 km) yield similar results.

7. Changes in Temporal Distance and Employee Task Routineness

Next, we test our hypotheses about task routineness and employees' responses to temporal distance. To do so, we perform split-sample analyses of non-routine and routine collaborator pairs. Since the data are dyadic, we define the *Non-routine* collaborators subsample as the pairs of collaborators where both employees in the dyad have above-median values of the non-routine score in the sample. Similarly, we define the *Routine* collaborators subsample as the pairs of collaborators where both employees have a below-median value. Fifty-nine percent percent of the collaborator pairs in the sample constitute employees in the same routineness category, a pattern that echoes prior findings of homophilous intra-organizational communication patterns (e.g., [Kleinbaum, Stuart, and Tushman 2008](#)). Therefore, the split-sample analyses account for a large share of total communication flows included in the baseline analyses.

Columns 1–3 of Table 6 show the results of estimating Equation (1) in the sample of i) all collaborators, ii) non-routine collaborators, and iii) routine collaborators. The dependent variable is total synchronous communication. The results show that the main effect described in Section 6 — an 11 percent reduction in synchronous communication — is driven by large reductions in synchronous communication among collaborators in routine tasks. The coefficient estimate of -0.229 indicates that these collaborators reduce synchronous communication by 20 percent from baseline levels, on average. The coefficient estimate for non-routine collaborators, meanwhile, is much smaller (-0.058) and not statistically significant. A formal test of the difference of the coefficients among the two groups confirms that the differences are statistically significant. These results provide support for Hypothesis 1a, namely that faced with an increase in temporal distance with collaborators, workers performing non-routine tasks are less likely to reduce synchronous communication than employees in routine tasks.

[Table 6 about here]

7.1. Evidence of Mechanism: Dipping into Leisure Time

The results presented so far are consistent with our theoretical arguments that temporal distance constrains richer, synchronous communication and that workers in non-routine tasks attribute a higher marginal value to synchronous communication than workers in routine tasks. In our theoretical framework, a higher marginal value of synchronous communication will make employees more likely to shift work-related communication into leisure time in response to temporal-distance constraints. Next, we empirically test for evidence of this mechanism. Specifically, we investigate whether employees increase the volume of their work communication outside of business hours when they experience an increase in temporal distance with collaborators; and conversely, whether they shift work-related communication into business hours when they experience a decrease in temporal distance. We expect that, faced with an increase in their temporal distance from collaborators, workers will shift communication to early mornings and late evenings, encroaching on their personal and family time, and that this margin of adjustment will be greater among non-routine employees who value synchronous communication more. We also expect employees who experience a decrease in temporal distance from their collaborators to reduce communication during early mornings and late evenings, i.e., encroaching less on personal and family time outside regular business hours. We expect this margin of adjustment to be lower among non-routine workers (who continue to attribute a higher marginal value to shared time even as more opportunities for synchronous communication arise) than among workers in routine tasks.

Focusing on the effects of increased temporal distance, the results of the analysis of employee work-shifting appear in Columns 4–9 of Table 6. Columns 5–6 show that increases in temporal distance led to large and statistically significant reductions in synchronous communication taking place inside business hours (IBH) for both routine and non-routine collaborators. The estimated coefficients imply a 24 percent reduction in synchronous communication taking place inside business hours, on average, with meaningfully larger negative coefficients for routine than non-routine collaborators (although, given large standard errors, the differences are not statistically significant). As IBH communication volumes fell, communication outside of business hours (OBH) shows statistically significant increases; however, only among non-routine collaborators. Column 8 shows that these collaborators increase OBH synchronous communication by 18 percent, thus effectively offset-

ting the reduction of communication taking place inside business hours. In contrast, collaborators in routine tasks show no significant increases in the volume of communication conducted outside business hours. The estimated coefficient in Column 9 is very small (-0.034) and not statistically different from zero. The lack of adjustment by routine workers rationalizes the fall in total communication volumes among this group observed in Column 3. Overall, the analysis of work-shifting in response to increases in temporal distance provides support to Hypothesis 1b, namely that faced with an increase in temporal distance with collaborators, workers performing non-routine tasks are more likely to shift synchronous communication across the temporal boundary of the workday, cutting into leisure time, than employees in routine tasks.

Finally, we report how employees' allocation of work across the workday reacts to decreases in temporal distance to collaborators. Panel B in Table 7 shows that while total communication volumes remain unchanged (as reported in our prior results), the distribution of work across employees' workday changes. Specifically, Columns 4–6 show that communication volumes taking place inside business hours increase for both routine and non-routine collaborators. While the size of the coefficient is larger for non-routine collaborators, given the standard errors, the differences are not statistically significant, thus offering only weak support for Hypothesis 2. Columns 7–9 further show that communication volumes taking place outside of business hours fall for both types of employees.²⁴

[Table 7 about here]

Overall, we find several clear-cut patterns. Temporal distance frictions have sizable effects on the volumes of communication and the nature of the employee workday. We find evidence that temporal distance reduces total communication and in particular, rich synchronous communication. We also find evidence that employees adjust to temporal distance by dipping into leisure time and communicating outside of regular business hours when opportunities to communicate synchronously with collaborators during business hours shrink and shift communication back into regular business hours as opportunities to do so increase. Finally, we find that while the margin of adjustment

²⁴Note however, that this second result reflects the behavior of collaborators who have communicated outside of business hours at least once during the sample period, since those who have not done so drop out of this analysis due to the collaborator-pair fixed effects. We can note by comparing the number of observations across columns 1–3 and columns 7–9 of Tables 6 and 7, however, that a smaller share of routine than non-routine collaborators communicate OBH.

happens primarily on volumes of synchronous communication for workers in routine tasks, it happens primarily on the labor/leisure margin for workers engaged in non-routine tasks. Overall, the results so far are consistent with employees in non-routine tasks valuing synchronous communication more. At the same time, they lead to the initially counter-intuitive finding that their total communication volumes are *less* affected by temporal distance, a result of their more intensive use of the adjustment mechanism.

7.2. Alternative Mechanism: Ability to Work from Home

Our interpretation of the patterns in the data and the arguments of our conceptual framework rest on the view that non-routine employees' greater need for synchronous communication is a key factor driving their responses to temporal distance. An alternative explanation rests on employees' *ability* to work from home. For example, routine and non-routine employees may value synchronous communication equally but may differ in their ability to conduct work-related communication from home. For example, employees in routine tasks may lack the complementary technologies (e.g., access to conferencing technology, access to complementary inputs like databases or machinery) needed to perform work-related tasks at home.

To tease apart the explanatory power of the *willingness* to work from home due to a higher value of synchronicity from the *ability* to work from home, we introduce a measure of whether an employee's job can be preformed at home constructed by [Dingel and Neiman \(2020\)](#) using O*NET data.²⁵ We are able to match [Dingel and Neiman \(2020\)](#)'s measure for 7,496 employees in our sample using the SOC code. The measure implies that in our sample, 68 percent of the employees' jobs can be performed at home. Not surprisingly, this share is higher for sample employees in non-routine jobs (84 percent) than in routine jobs (42 percent). We will use the differences in ability to work from home among employees within each group to tease apart its role. A priori, we expect that if for routine workers the ability to work from home is the main constraint, then we should observe that the subset of routine workers who *can* work from home react similarly to

²⁵The measure is a dummy variable constructed using questions from O*NET which ask survey respondents to assess whether factors like "Majority of time wearing protective or safety equipment" are important for the performance of their job. If, for any question, the median responder answered "Yes", then the job is coded as "cannot be performed at home." Overall, the authors find that 37 percent of U.S. jobs can be performed at home.

non-routine collaborators. This implies that the reductions in communication we observed should be concentrated among collaborators who *cannot* work from home.

Table 8 presents the results of analyses that split the subsamples of routine and non-routine collaborators by whether their jobs can be preformed from home.²⁶ Among non-routine collaborators, comparing the effect of increases in temporal distance for collaborators whose jobs can be performed at home (Columns 1–3) to those whose cannot (Columns 4–6), we see that our baseline result — non-routine workers maintaining synchronous communication by shifting it into OBH — depends on the workers who can work from home. Those who cannot lose out on synchronous communication. The differences in the behaviors of these two groups are large and statistically significant. While it was not the primary aim of our analysis, this result suggests an important implication: that work from home technology is a critical complement in collaborators’ ability to offset frictions stemming from temporal distance. Turning to the main question that we are interested in, Columns 7–9 show that routine workers do not compensate by working outside business hours, even when their jobs *can* be performed at home (Columns 7–9). Among routine workers, both employees who can work from home and those who cannot see a reduction in synchronous communication following increases in temporal distance. Moreover, neither type compensates for this drop by shifting communication into outside business hours.

Overall, the results of the work-from-home mechanism provide evidence consistent our argument that non-routine workers have a higher value of synchronous communication than routine workers, rather than with an explanation that solely rests on the two types of employees differing in their ability to work from home. In addition, they reveal another important finding – that work-from-home technologies are an important complement in employees’ ability to adjust to temporal distance.

²⁶As before, because the data are dyadic, we code a collaborator pair as able to work from home if both members have an able to work from home dummy equal to one; and as not otherwise.

8. Exploratory Analysis of Employee- and Firm-Level Outcomes

8.1. Temporal Distance and Employee Retention

Finally, we complement our main analysis by exploring whether, in the context of the Firm, employees' temporal distance to collaborators is correlated with a number of important employee- and firm-level outcomes. Using additional data, in particular, a directory of Firm employees in March 2018 and January 2020, we measure two outcomes at the employee-level: i) retention and ii) relocation.²⁷ We construct the dummy variable *Retained* which equals one if a sample employee who is employed in March 2018 is still employed with the Firm in January 2020.²⁸ We construct the dummy variable *Relocated* which equals one if an employee, conditional on being employed in January 2020, is based in a different city. Finally, using information on each employee's manager from the directory, we construct an empirical definition of an employee's "team", which are all other sample employees who share the same manager. We measure the variable *Temporal distance to team* as 10 minus the average BHO between an employee and their team. The variable ranges from zero (for employees with ten hours of overlap with all members of their team) to ten (for those with none). We empirically explore whether employees who were more temporally distant from their team in the baseline period (March 2018) had a different probability of being retained or relocated over the subsequent two years.

Table 9 shows the results of the employee retention and relocation analysis. In these analyses, we find no evidence that employees located at a greater temporal distance from their team exhibit different rates of retention, neither in simple bivariate models (not shown) nor when we control for employees' team size, tenure in the Firm, city, and business function (Columns 1–3). The coefficient on the distance to team variable is close to zero and not statistically significant in the full sample of employees (Column 1) and in the subsamples of only non-routine and only routine employees (Columns 2 and 3). In Columns 4–6, we explore whether, conditional on being retained, employees

²⁷We use March 2018 as the starting point for this analysis because we do not know the employees' manager in Fall 2017, which is the period of our main communication-level dataset. As a result, the number of employees drops (to 11,354), which reflects the fact that some sample employees were no longer in the March 2018 directory.

²⁸We can observe the employee in the January 2020 directory even if they are employed in a different business unit or a different Division in the Firm.

are more likely to be relocated if their temporal distance to team is higher. We find some evidence of this pattern. The sizes of the estimated coefficients suggest that employees who are one hour more distant from their team were on average 1.6 percent more likely to be relocated over the two-year period. The size of effect is similar for non-routine (Columns 5 and 6) and routine employees. However, measuring employees' BHO with their team in the baseline period (March 2018) and end period (January 2020), we find no evidence that those who relocated were brought closer to their team. On average, the change in BHO between the two periods is -0.03 hours for this group and 0.17 for the group who did not relocate (and whose BHO to team may also change due to a different manager assignment, relocation of team members, or change in the composition of their team) (Figure 6). Thus, we find no evidence in this analysis that the Firm is strategically using relocation to temporally co-locate dispersed teams.

8.2. Temporal Distance and Patenting Collaborations

Finally, we complement our main analysis with a second, publicly-available dataset on the Firm's patenting activity from *PatentsView* for the years 2000-2015. These data contain detailed information on 12,218 utility patents assigned to the Firm during this period, as well as the names and locations of patent inventors. We define the years that an inventor is active within the Firm as all years between the first and the last year in which they are observed on a patent assigned to the Firm and create an inventor-pair-year dataset that represents the set of possible collaborations. We define the indicator variable *Collaboration* which takes the value one if an inventor-pair actually collaborated in a year, and zero otherwise.

We perform a descriptive analysis asking whether the amount of BHO between two of the Firm's inventors is correlated to the likelihood of co-patenting. The results are presented in Table 10. Column (1) presents a simple model with BHO along with year and each-inventor fixed effects. Columns (2) and (3) further control for geographic distance between the inventors and additional controls. The columns suggest that, other things equal, inventors who share one extra hour of BHO are 3 percent more likely to have collaborated on a patent. While these results cannot leverage the same causal identification strategy as our main results, they are robust to standard gravity-model controls, including geographic distance, inventor, and year fixed effects and are consistent

with similar findings in the literature (e.g., [Montobbio and Sterzi 2013](#); [Bircan, Javorcik, and Pauly 2021](#)).

9. Discussion and Conclusion

This paper uses intra-firm data from a large multinational firm to demonstrate how temporal distance affects communication patterns among more than 12,000 of the firm’s employees, located across 48 countries. Our novel identification strategy exploits the annual shift of clocks into and out of Daylight Saving Time. This research design enables us to control for all other dimensions of distance between units of a multinational firm, and to present clean estimates of how changes in temporal distance affect communication patterns. We document that an increase in temporal distance has a negative and statistically significant effect on synchronous communication volumes; this negative effect is concentrated among workers in routine tasks. We also show no significant reductions in communication for employees in non-routine tasks. We show that increases in temporal distance lead employees to dip into an adjustment mechanism – spending more leisure time on work-related communication. Reductions in temporal distance reverse this tendency.

Our paper has several limitations. First, our analysis is specific to a single multinational firm and a single three-month period. The patterns we found should be validated across an array of contexts, and especially at organizations that have adopted more cutting-edge asynchronous communication technologies like Slack that offer greater synchronicity and richness than e-mail. We also acknowledge several limitations in our data: [Espinosa et al. \(2015\)](#) build on [O’Reilly and Pondy \(1979\)](#) to argue that both “communication patterns” (measured using such variables as “turn-taking in communication”) and “communication content” shape how temporal distance affects communication outcomes. Given that our data comes from a real-world setting, confidentiality concerns prevent us from observing either the content of communication or such features of the data as turn-taking. Nor do we observe communications sent and received using employees’ private accounts or other communication technologies.

Despite these limitations, our paper contributes to several literatures, notably that on how distance affects communication patterns within multinational firms, and has implications for the

organization of temporal boundaries within firms. This literature, beginning with [Tushman \(1977\)](#) and [Gupta and Govindarajan \(2000\)](#), has posited the important effect of “richness in transmission channels” on communication patterns within MNCs. A separate strand of the literature, including an editorial by [Alcácer et al. \(2017\)](#), has made a case for studying the role of “figurative distances” in hindering value creation for MNCs; [Ghemawat \(2007; p. 11\)](#) has questioned why “most types of economic activity that can be conducted either within or across borders are still quite localized by country.” An important paper by [Berry et al. \(2010\)](#) documents nine dimensions of distance relevant for MNCs; temporal distance is conspicuously missing from the list.²⁹ Even so, as our research design indicates, controlling for all other dimensions of distance, temporal distance affects patterns of communication between units of a multinational firm. It is important to document these effects of temporal distance given the increase in global co-production of knowledge at MNCs ([Singh 2005](#); [Phene and Almeida 2008](#); [Alcácer and Zhao 2012](#); [Foley and Kerr 2013](#); [Choudhury 2017](#); [Kerr and Kerr 2018](#)) which critically depends on intra-firm communication and knowledge-exchange.

Second, our study contributes to the literature on distributed work ([Hinds and Kiesler 1995, 2002](#); [Cummings et al. 2009](#); [Olson, Olson, and Venolia 2009](#); [Edmondson 2012](#); [Espinosa et al. 2015](#)). Time zone differences are often acknowledged as a challenge in global work. [Olson and Olson \(2000\)](#) and [Edmondson \(2012\)](#) describe various difficulties in coordination between workers in different time zones and on different diurnal rhythms. [Cummings et al. \(2009\)](#) theorize that the likelihood of coordination delays on globally distributed projects is a function of temporal boundaries; they use survey data to demonstrate that greater use of asynchronous e-mail does not reduce coordination delay between pairs with non-overlapping work hours. [O’Leary and Cummings \(2007\)](#) theorize that, for workers in knowledge-intensive tasks, temporal distance shrinks time available for problem solving and decreases the likelihood of synchronous communication; in a more recent paper, [Espinosa et al. \(2015\)](#) posit that greater temporal distance is associated with more asynchronous communication and vice-versa, and test their thesis using a laboratory experiment. To the best of our knowledge, our study offers the first set of causal results of the effects of temporal distance on communication patterns in a real-world setting. Our results are directionally related to the [O’Leary](#)

²⁹The dimensions of distance specified in the paper are economic, financial, political, administrative, cultural, demographic, knowledge (differences in patent and scientific production), connectedness (differences in tourism and internet use), and geographic.

and Cummings (2007) proposition; we find less evidence for the Espinosa et al. (2015) proposition that temporal distance leads to more asynchronous communication. The contrast we find in the communication patterns of collaborators in routine and non-routine tasks mirrors the findings of Hinds and Kiesler (1995), who studied lateral communication among technical and administrative workers. Our unique contribution is to provide causal estimates of the size of temporal distance friction on communication volumes and to exploit heterogeneity in job functions to provide estimates of how temporal distance affects communication patterns of employees performing different tasks.

Third, our study contributes to the literatures on information processing in organizations, temporal structuring and remote work. In the literature on information processing in organizations, Daft and Lengel (1986; p. 560) argue that managers work under conditions of “time constraints”; they also define “information richness” as “the ability of information to change understanding within a time interval.” Our empirical study examines how exogenous changes to time constraints affect communication patterns at global firms. In the organizations literature, Orlikowski and Yates (2002) posit that organizational actors, via their every action, produce and reproduce “temporal structures” that shape the temporal rhythm of their ongoing practices. The authors also link these temporal structures to time management on the part of individual workers: “Temporal structures, because they are constituted in ongoing practices, can also be changed through such practices. Like all social structures, they are ongoing human accomplishments, and thus provisional. They are always only ‘stabilized-for-now’” (Orlikowski and Yates 2002; p. 687). Our contribution to this literature is to document how natural phenomena, such as the annual shift of clocks out of Daylight Saving Time, can impact organizations’ temporal structures and communication patterns. Our findings are also relevant to the literature on remote work practices (Bloom, Liang, Roberts, and Ying 2015; Choudhury and Salomon 2020). Choudhury and Salomon (2020) document an emerging form of remote work—“work from anywhere,” whereby a firm grants employees the geographic flexibility to live in any location; our study indicates that, for workers who self-select to locate within an East–West continuum, greater temporal distance can generate frictions in their synchronous-communication patterns.

Our results are also relevant to the literature on time famine and time-budget allocation (Perlow 1999). Numerous studies have richly documented the prevalence of feelings of time scarcity

(Whillans, Dunn, Smeets, Bekkers, and Norton 2017) and anxiety, among both men and women, brought on by the 24/7 work culture (Padavic, Ely, and Reid 2020). Organizations have tried to handle this situation by introducing temporal flexibility as a work practice (Briscoe 2007). Temporal flexibility has been defined as ceding to individual workers control over how they allocate their time (Evans, Kunda, and Barley 2004). However, flexibility comes at a cost. Golden (2001; p. 50) reports that “work is increasingly being spread out, performed on the fringes of the typical workday, extending earlier in the morning or later into the evening.” While Perlow (1997) asserts that workers view longer hours as a signal of their commitment, which they believe firms demand in return for raises, promotions, and continued employment—a pattern confirmed by other recent studies (e.g., Gonsalves 2020)—Goldin (2014) argues that ridding firms of the expectation that individuals labor not only long but *particular* hours is the last necessary step in the “grand gender convergence.” Our paper contributes to this literature by documenting that temporal distance to collaborators is an understudied variable relevant to time-budget allocation on the part of workers, especially workers in non-routine tasks. Empirically, we show direct evidence that temporal distance to collaborators shifts work into leisure time, a mechanism consistent with the findings of two recent studies related to ours, which show that temporal distance to customers (Bøler et al. 2018) and to headquarters (Breschi et al. 2020) increases the gender wage gap and reduces promotion rates for women.

More broadly, while our study highlights a friction in managing within-firm temporal boundaries for distributed work; this friction has broader implications for the related literatures on global outsourcing and online labor markets (e.g., Ghani, Kerr, and Stanton 2014; Goldfarb, Greenstein, Tucker, Agrawal, Horton, Lacetera, and Lyons 2015; Stanton and Thomas 2016). The effects that we document are likely to be magnified in inter-firm settings: in the intra-firm context, managers and employees have access to multiple coordination mechanisms, such as management by authority, tacit procedures, blueprints, or company directives (Srikanth and Puranam 2011; Mani, Srikanth, and Bharadwaj 2014); these mechanisms are largely unavailable to agents operating at arm’s length, who are therefore apt to rely more on communication as the primary mechanism of coordination.

Our findings also have practical implications for managers of global companies and for firm-location strategy. “Follow-the-sun” arrangements (Espinosa and Carmel 2003), whereby globally distributed locations work sequentially around the clock, can be very effective for employees engaged

in non-complex, administrative, or predictable patterns of collaboration, who can communicate asynchronously; they may be less so for non-routine workers. Our results suggest that employees engaged in non-routine collaboration place a strong premium on synchronous communication, and benefit from being located in such a way as to minimize temporal distance—that is, largely on a North-South axis. For example, though Seattle and San Francisco, or New York and Sao Paulo, are geographically distant, workers in the two locations will experience near complete business-hour overlap. Overall, our study calls for carefully weighing locations’ benefits as sites of distributed or offshored work (e.g., access to human capital, lower wage rates) against the incremental coordination costs created by temporal-distance frictions.

In conclusion, as multinational firms continue to distribute work globally, and as firms explore such novel models of remote work as “work from anywhere,” our study identifies temporal distance as a friction that markedly affects within-firm communication patterns. Our results have practical implications for managers for organizing within-firm temporal boundaries, suggesting that North–South geographic corridors (where there is no temporal distance between dispersed units) might lead to more efficient synchronous-communication patterns among workers at distributed/multinational firms, compared to when workers are distributed in an East-West geographic corridor.

References

- Acemoglu D, Autor D (2011) Skills, tasks and technologies: Implications for employment and earnings. *Handbook of labor economics*, volume 4, 1043–1171 (Elsevier).
- Alcácer J, Kogut B, Thomas C, Yeung B (2017) Geography, location, and strategy. Alcácer J, Kogut B, Thomas C, Yeung B, eds., *Geography, location, and strategy*, 1–6 (Bingley, England: Emerald Publishing Limited).
- Alcácer J, Zhao M (2012) Local R&D strategies and multilocation firms: The role of internal linkages. *Management Science* 58(4):734–753.
- Autor DH, Levy F, Murnane RJ (2003) The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics* 118(4):1279–1333.
- Bahar D (2020) The hardships of long distance relationships: time zone proximity and the location of mnc’s knowledge-intensive activities. *Journal of International Economics* 103311.
- Barry B, Fulmer IS (2004) The medium and the message: The adaptive use of communication media in dyadic influence. *Academy of Management Review* 29(2):272–292.
- Becker G (1965) A theory of the allocation of time. *Economic Journal* 75(299):493–517.
- Berry H, Guillén MF, Zhou N (2010) An institutional approach to cross-national distance. *Journal of International Business Studies* 41(9):1460–1480.
- Bircan C, Javorcik B, Pauly S (2021) Creation and diffusion of knowledge in the multinational firm .
- Bloom N, Liang J, Roberts J, Ying ZJ (2015) Does working from home work? Evidence from a Chinese experiment. *The Quarterly Journal of Economics* 130(1):165–218.
- Bøler EA, Javorcik B, Ulltveit-Moe KH (2018) Working across time zones: Exporters and the gender wage gap. *Journal of International Economics* 111:122–133.
- Borusyak K, Jaravel X, Spiess J (2021) Revisiting Event Study Designs: Robust and Efficient Estimation.
- Branstetter LG, Glennon B, Jensen JB (2018) The IT revolution and the globalization of R&D. *Innovation Policy and the Economy* 19:1–37.
- Breschi S, Gagliardi L, Hovy D, Mariani M (2020) Overtime work, (in) flexible schedules and women’s career progression.
- Breschi S, Lissoni F (2009) Mobility of skilled workers and co-invention networks: An anatomy of localized knowledge flows. *Journal of Economic Geography* 9(4):439–468.
- Briscoe F (2007) From iron cage to iron shield? How bureaucracy enables temporal flexibility for professional service workers. *Organization Science* 18(2):297–314.
- Catalini C, Fons-Rosen C, Gaulé P (2020) How Do Travel Costs Shape Collaboration? *Management Science* 66(8):3340–3360.
- Choudhury P (2017) Innovation outcomes in a distributed organization: Intrafirm mobility and access to resources. *Organization Science* 28(2):339–354.
- Choudhury P, Foroughi C, Larson B (2021) Work-from-anywhere: The Productivity Effects of Geographic Flexibility. *Strategic Management Journal* 42(4).
- Choudhury P, Salomon E (2020) GitLab and the future of all-remote work (A).
- Correia S, Guimarães P, Zylkin T (2019) ppmlhdf: Fast poisson estimation with high-dimensional fixed effects. *arXiv* 1–19, URL <http://arxiv.org/abs/1903.01690>.
- Cummings JN, Espinosa JA, Pickering CK (2009) Crossing spatial and temporal boundaries in globally distributed projects: A relational model of coordination delay. *Information Systems Research* 20(3):420–439.
- Daft RL, Lengel RH (1986) Organizational information requirements, media richness and structural design. *Management Science* 32(5):554–571.
- DeFilippis E, Impink SM, Singell M, Polzer JT, Sadun R (2020) Collaborating during coronavirus: The impact of covid-19 on the nature of work. *NBER Working Paper* (w27612).

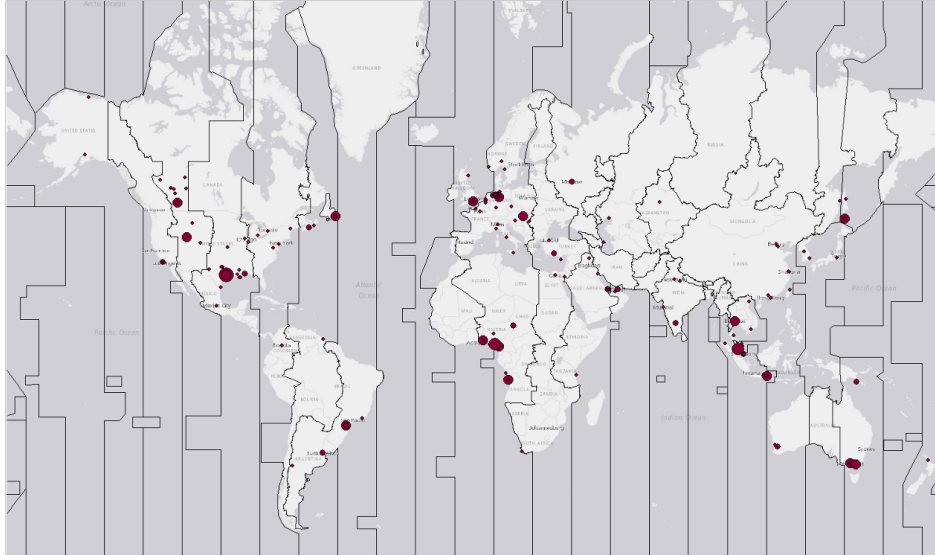
- Dennis A, Fuller R, Valacich J (2008) Media, tasks, and communication processes: A theory of media synchronicity. *MIS Quarterly* 32(3):575–600.
- Dingel JI, Neiman B (2020) How many jobs can be done at home? *Journal of Public Economics* 189.
- Edmondson A (2012) *Teaming: How organizations learn, innovate, and compete in the knowledge economy* (San Francisco: Jossey-Bass), 1st edition.
- Espinosa JA, Carmel E (2003) The impact of time separation on coordination in global software teams: A conceptual foundation. *Software Process Improvement and Practice* 8(4):249–266.
- Espinosa JA, Nan N, Carmel E (2015) Temporal distance, communication patterns, and task performance in teams. *Journal of Management Information Systems* 32(1):151–191.
- Evans JA, Kunda G, Barley SR (2004) Beach time, bridge time, and billable hours: The temporal structure of technical contracting. *Administrative Science Quarterly* 49(1):1–38.
- Fally T (2015) Structural gravity and fixed effects. *Journal of International Economics* 97:76–85.
- Foley CF, Kerr WR (2013) Ethnic innovation and U.S. multinational firm activity. *Management Science* 59(7):1529–1544.
- Freeman RB, Ganguli I, Murciano-Goroff R (2014) Why and wherefore of increased scientific collaboration. *The changing frontier: Rethinking science and innovation policy.*, 17–48 (University of Chicago Press).
- Galbraith JR (1973) *Designing complex organizations* (Addison-Wesley Longman Publishing Co., Inc.).
- Ghani E, Kerr WR, Stanton C (2014) Diasporas and outsourcing: Evidence from oDesk and India. *Management Science* 60(7):1677–1697.
- Ghemawat P (2001) Distance still matters. *Harvard Business Review* 79(September):137–147.
- Ghemawat P (2007) *Redefining global strategy: Crossing borders in a world where differences still matter* (Harvard Business School Press).
- Ghemawat P (2011) *World 3.0: Global prosperity and how to achieve it* (Boston: Harvard Business Review Press).
- Ghoshal S, Korine H, Szulanski G (1994) Interunit communication in multinational corporations. *Management Science* 40(1):96–110.
- Golden L (2001) Flexible work schedules: What are we trading off to get them? *Monthly Labor Review* 124(3):50–67.
- Goldfarb A, Greenstein SM, Tucker CE, Agrawal A, Horton J, Lacetera N, Lyons E (2015) Digitization and the contract labor market: A research agenda. *Economic Analysis of the Digital Economy*, 219–256 (University of Chicago Press).
- Goldin C (2014) A grand gender convergence: Its last chapter. *American Economic Review* 104(4):1091–1119.
- Gonsalves L (2020) From face time to flex time: The role of physical space in worker temporal flexibility. *Administrative Science Quarterly* .
- Goodman-Bacon A (2021) Difference-in-differences with variation in treatment timing. *Journal of Econometrics* 225(2):254–277.
- Grinter RE, Herbsleb JD, Perry DE (1999) Geography of coordination: Dealing with distance in R&D work. *Proceedings of the International ACM SIGGROUP Conference on Supporting Group Work* 306–315.
- Gronau R (1976) Leisure, home production and work - The theory of the allocation of time revisited. *NBER Working Paper Series* .
- Gupta AK, Govindarajan V (2000) Knowledge flows within multinational corporations. *Strategic Management Journal* 21(4):473–496.
- Heckman JJ (2015) Introduction to a theory of the allocation of time by Gary Becker. *Economic Journal* 125(583):403–409.
- Hinds P, Kiesler S (1995) Communication across boundaries: Work, structure, and use of communication technologies in a large organization. *Organization Science* 6(4):373–393.
- Hinds P, Kiesler S (2002) *Distributed work* (Cambridge, MA: MIT Press).

- Kerr SP, Kerr W, Ozden C, Parsons C (2016) Global talent flows. *Journal of Economic Perspectives* 30(4):83–106.
- Kerr SP, Kerr WR (2018) Global collaborative patents. *Economic Journal* 128(612):F235–F272.
- Kleinbaum AM, Stuart TE, Tushman ML (2008) Communication (and coordination?) in a modern, complex organization. *Harvard Business School Working Paper* 69.
- Kogut B, Zander U (1993) Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science* 3(3):383–397.
- Kogut B, Zander U (1996) What Firms Do? Coordination, Identity, and Learning. *Organization Science* 7(5):502–518, ISSN 10477039.
- Kraut RE, Fussell SR, Brennan SE, Siegel J (2002) Understanding effects of proximity on collaboration: Implications for technologies to support remote collaborative work. Hinds PJ, Kiesler S, eds., *Distributed Work* (Cambridge, MA: MIT Press).
- Mani D, Srikanth K, Bharadwaj A (2014) Efficacy of R&D work in offshore captive centers: An empirical study of task characteristics, coordination mechanisms, and performance. *Information Systems Research* 25(4):846–864.
- March JG, Simon HA (1958) *Organizations* (New York: Wiley).
- Marx M, Strumsky D, Fleming L (2009) Mobility, Skills, and the Michigan Non-Compete Experiment. *Management Science* 55(6):875–889.
- Mell J, Jang S, Chai S (2020) Bridging Temporal Divides: Temporal Brokerage in Global Teams and Individual Performance. *Organization Science* 2020(1):13037, ISSN 0065-0668.
- Montobbio F, Sterzi V (2013) The Globalization of Technology in Emerging Markets: A Gravity Model on the Determinants of International Patent Collaborations. *World Development* 44:281–299.
- O’Leary MB, Cummings JN (2007) The spatial, temporal, and configurational characteristics of geographic dispersion in teams. *MIS Quarterly* 31(3):433–452.
- Olson GM, Olson J, Venolia G (2009) What still matters about distance. *Proceedings of HCIC* .
- Olson GM, Olson JS (2000) Distance matters. *Human-Computer Interaction* 15(2-3):139–178.
- O’Reilly C, Pondy L (1979) Organizational communication. Kerr S, ed., *Organizational Behavior*, 119–150 (Columbia, Ohio: Grid).
- Orlikowski W, Yates J (2002) It’s about time: Temporal structuring in organizations. *Organization Science* 13(6):684–700.
- Padavic I, Ely RJ, Reid EM (2020) Explaining the persistence of gender inequality: The work–family narrative as a social defense against the 24/7 work culture. *Administrative Science Quarterly* 65(1):61–111.
- Perlow LA (1997) *Finding time: How corporations, individuals, and families can benefit from new work practices*. (Cornell University Press).
- Perlow LA (1998) Boundary control: The social ordering of work and family time in a high-tech corporation. *Administrative Science Quarterly* 43(2):328–357.
- Perlow LA (1999) The time famine: Toward a sociology of work time. *Administrative Science Quarterly* 44(1):57–81.
- Phene A, Almeida P (2008) Innovation in multinational subsidiaries: The role of knowledge assimilation and subsidiary capabilities. *Journal of International Business Studies* 39(5):901–919, ISSN 00472506.
- Reinsch NL, Turner JW, Tinsley CH (2008) Multicommunicating: A practice whose time has come? *Academy of Management Review* 33(2):391–403.
- Roberts J (2000) From know-how to show-how? Questioning the role of information and communication technologies in knowledge transfer. *Technology Analysis and Strategic Management* 12(4):429–443.
- Silva JMCS, Tenreyro S (2006) The log of gravity. *The Review of Economics and Statistics* 88(4):641–658.
- Singh J (2005) Collaborative networks as determinants of knowledge diffusion patterns. *Management Science* 51(5):756–770.
- Srikanth K, Puranam P (2011) Integrating distributed work: comparing task design, communication, and tacit coordination mechanisms. *Strategic Management Journal* 32(8):849–875.

- Stanton CT, Thomas C (2016) Landing the first job: The value of intermediaries in online hiring. *Review of Economic Studies* 83(2):810–854.
- Stanton CT, Thomas C (2019) Missing trade in tasks: Employer outsourcing in the gig economy.
- Teece DJ (1977) Technology transfer by multinational firms: The resource cost of transferring technological know-how. *Economic Journal* 242–261.
- Thompson JD (1967) *Organizations in action* (New York: McGraw-Hill).
- Tushman ML (1977) Special boundary roles in the innovation process. *Administrative Science Quarterly* 22(4):587–605.
- Whillans AV, Dunn EW, Smeets P, Bekkers R, Norton MI (2017) Buying time promotes happiness. *Proceedings of the National Academy of Sciences of the United States of America* 114(32):8523–8527.

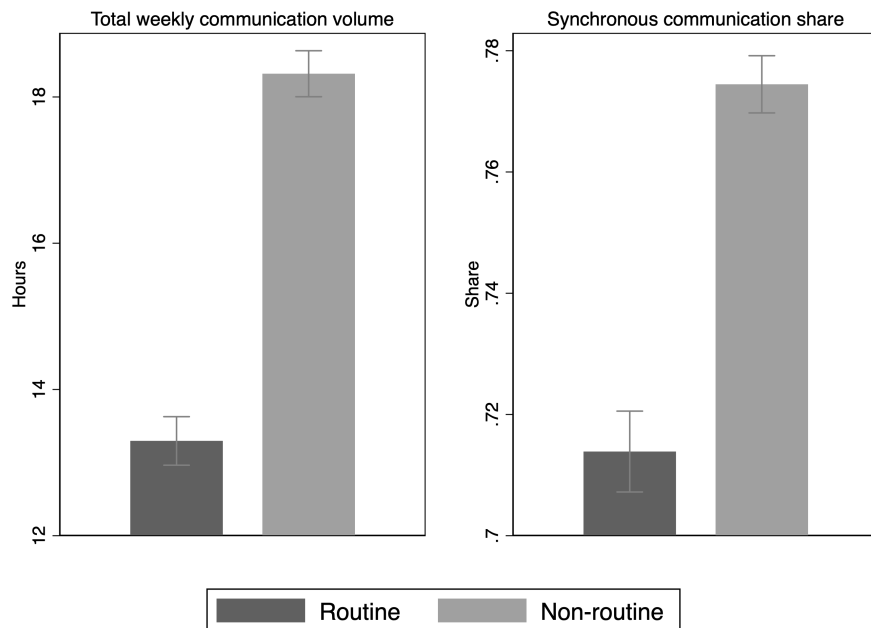
Tables and Figures

Figure 1: Employee Locations and Time Zone Lines



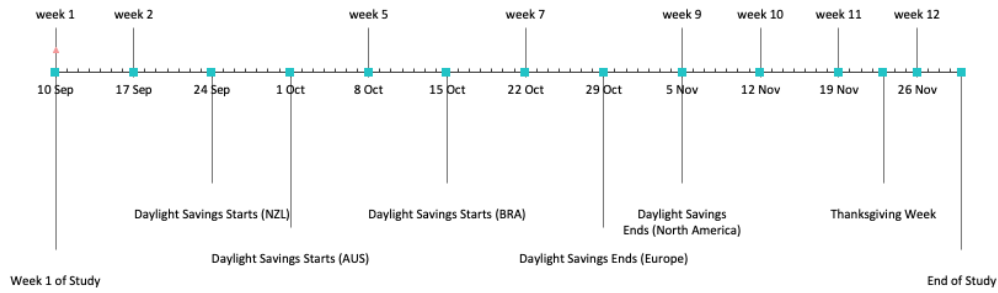
Notes: The figure shows the locations of sample employees. Node size is proportional to the number of employees. Vertical lines are time zone lines.

Figure 2: Total Communication and Synchronous Communication Share by Employee Task Routineness



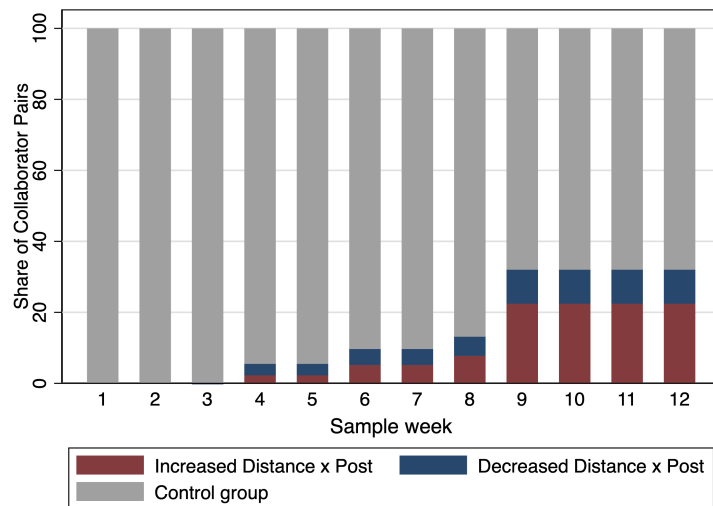
Notes: The figure shows the mean weekly total communication (left) and the mean synchronous communication share (synchronous communication / total communication) (right) for *Routine* and *Non-Routine* employees. Vertical bars represent 95% confidence intervals. Means calculated using data from the pre-DST period.

Figure 3: Timeline of Events



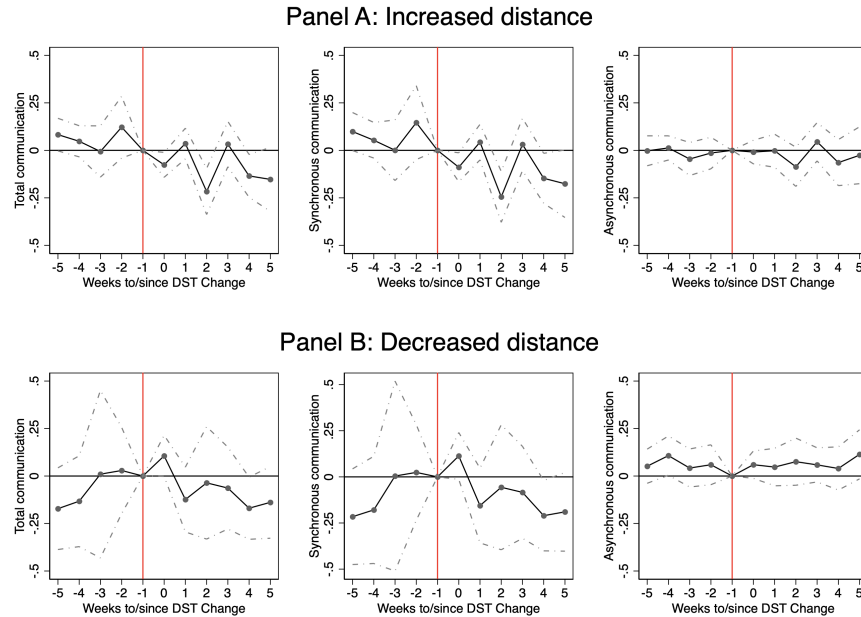
Notes: The figure shows the dates and weeks in the sample period during which countries where sample employees are located shifted to/from Daylight Saving Time.

Figure 4: Timing of Treatment for Collaborator Pairs, Weekly



Notes: The figure shows the share of collaborator pairs in each week of the sample period who experienced an increase, a decrease, or no change in temporal distance. Week count is relative to the start of the sample period (week of September 10, 2017).

Figure 5: Effects of Changes in Temporal Distance on Communication, Weekly Estimates



Notes: The figures report coefficients from estimating Equation (1) with weekly leads and lags. The coefficients represent changes in the weekly volume of communication for collaborators who lost (top) or gained (bottom) business hour overlap due to cities' shifts into/out of Daylight Saving Time (DST) relative to pairs of collaborators whose BHO remained unchanged in the five weeks before and after the change in BHO. The sample includes all pairs of employees who communicated at least once via the relevant medium during the sample period. The reference period for this comparison is the week prior to when a pair experiences a change in BHO. Estimation using Poisson Pseudo Maximum Likelihood models with employee-pair and week fixed effects. Error bars represent 95 percent confidence intervals based on robust standard errors clustered at the employee city-pair level.

Figure 6: Employee Relocation and Change in Temporal Distance to Team

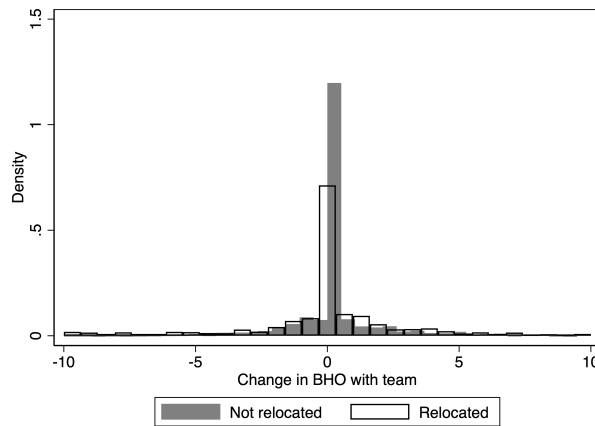


Table 1: Summary Statistics

	Mean	Std. dev.	Min	Max
Panel A: Employee-pair level (N=859,092)				
<i>Total communication (mins./week)</i>	1.69	9.75	0.00	2187.37
<i>Synchronous comm. (mins./week)</i>	1.44	8.63	0.00	2164.84
<i>Asynchronous comm. (mins./week)</i>	0.25	1.94	0.00	210.63
<i>IBH comm. (mins./week)</i>	1.15	7.55	0.00	2092.89
<i>OBH comm. (mins./week)</i>	0.54	4.07	0.00	516.76
<i>Pre-period BHO (hours)</i>	5.70	3.71	0.00	10.00
<i>Post-period BHO (hours)</i>	5.58	3.69	0.00	10.00
<i>Geographic distance (km)</i>	6522.65	5587.45	0.62	19629.61
Panel B: Employee level (N=12,038)				
<i>Total communication (hours/week)</i>	14.30	10.61	0.02	73.28
<i>Synchronous comm. (hours/week)</i>	11.30	9.10	0.00	73.16
<i>Asynchronous comm. (hours/week)</i>	3.01	2.53	0.00	18.87
<i>Non-routine score, normalized</i>	1.10	0.66	-1.73	2.53
<i>Non-routine, dummy</i>	0.46	0.50	0.00	1.00
<i>Job can be performed at home, dummy</i>	0.68	0.47	0.00	1.00
<i>Temporal distance to team (hours)</i>	1.08	2.22	0.00	10.00
<i>Team size</i>	9.74	10.63	0.00	94.00
<i>Tenure at firm (years)</i>	14.74	9.24	0.00	46.00
<i>Retained</i>	0.87	0.33	0.00	1.00
<i>Relocated</i>	0.16	0.36	0.00	1.00

Table 2: Summary Statistics of the Non-routine Score by Employee Function

<i>Non-routine score, normalized</i>	Mean	Std. dev.	Min	Max	Difference		
					Other-R&D	R&D - IT	IT - Prod.
Other (e.g., tax, legal, marketing)	1.39	0.67	-0.47	2.53			
R&D	1.29	0.64	-0.96	2.53	0.096***		
IT	1.22	0.67	-1.16	2.36		0.069**	
Production	0.95	0.63	-1.73	2.53			0.273***
All	1.10	0.67	-1.73	2.53			

Notes: The observations are 8,276 sample employees for whom routineness measures could be calculated. Non-routine scores are calculated by matching employee job titles to U.S. SOC job codes, then calculating non-routine scores using O*NET version 25.0 data and the [Acemoglu and Autor \(2011\)](#) replication code. ** p<0.05, *** p<0.01.

Table 3: Effects of Increased Temporal Distance on Communication Volumes

DV: Communication	(1) <i>Total</i>	(2) <i>Synchronous</i>	(3) <i>Asynchronous</i>
<i>Increased Distance</i> × <i>Post</i>	-0.099*** (0.033)	-0.116*** (0.037)	-0.007 (0.031)
Constant	2.763*** (0.003)	2.633*** (0.003)	1.772*** (0.003)
Employee-pair fixed effects	Y	Y	Y
Week fixed effects	Y	Y	Y
pseudo R-squared	0.6794	0.6558	0.5508
Employee pairs	776,581	716,974	153,248
Observations (employee-pair-weeks)	9,318,972	8,603,688	1,838,976

Notes: The dependent variable is weekly communication (measured in minutes) between pairs of employees. *Synchronous* includes scheduled calls and meetings, unscheduled calls, and instant message chats. *Asynchronous* is e-mail. *IncreasedDistance* × *Post* is an indicator variable that takes a value of 1 for pairs of employees who lost business-hour overlap (BHO) as a result of Daylight Saving Time (DST) in the weeks after the switch to/from DST. The table presents Poisson pseudo maximum likelihood (PPML) model estimates with fixed effects for each employee pair and each week. Heteroskedasticity-robust standard errors in parentheses, clustered at the employee city-pair level. Employee pairs are included in a model if they had non-zero and time-varying communication volume in that mode over the 12-week sample period. *** p < 0.01.

Table 4: Effects of Decreased Temporal Distance on Communication Volumes

DV: Communication	(1) <i>Total</i>	(2) <i>Synchronous</i>	(3) <i>Asynchronous</i>
<i>Decreased Distance</i> × <i>Post</i>	-0.026 (0.059)	-0.036 (0.069)	0.027 (0.028)
Constant	2.726*** (0.003)	2.601*** (0.003)	1.728*** (0.001)
Employee-pair fixed effects	Y	Y	Y
Week fixed effects	Y	Y	Y
pseudo R-squared	0.6739	0.6505	0.5454
Employee pairs	666,427	613,070	137,070
Observations (employee-pair-weeks)	7,997,124	7,356,840	1,644,840

Notes: The dependent variable is weekly communication (measured in minutes) between pairs of employees. *Synchronous* includes scheduled calls and meetings, unscheduled calls, and instant message chats. *Asynchronous* is e-mail. *DecreasedDistance* × *Post* is an indicator variable that takes a value of 1 for pairs of employees who gained business-hour overlap (BHO) as a result of Daylight Saving Time (DST) in the weeks after the switch to/from DST. The table presents Poisson pseudo maximum likelihood (PPML) model estimates with fixed effects for each employee pair and each week. Heteroskedasticity-robust standard errors in parentheses, clustered at the employee city-pair level. Employee pairs are included in a model if they had non-zero and time-varying communication volume in that mode over the 12-week sample period.

Table 5: Robustness Tests of Main Effect

Panel A: Increased Distance	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DV: Total Communication	Baseline	Treated week 45	Excl. temp. treated	9-hour day	11-hour day	Excl. 2-hour changes	Excl. Thanksg.	OLS	Each City FE	Collab. > 5 mins
<i>Increased Distance</i> × <i>Post</i>	-0.099*** (0.033)	-0.104*** (0.0383)	-0.102*** (0.0331)	-0.102*** (0.0329)	-0.0880** (0.0351)	-0.0684** (0.0328)	-0.0661** (0.0318)	-0.128** (0.0574)	-0.116*** (0.0373)	-0.100*** (0.0331)
Employee-pair fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
(pseudo) R-squared	0.6794	0.677	0.682	0.680	0.678	0.676	0.680	0.401	0.656	0.554
Employee pairs	776,581	563,968	708,062	787,472	723,419	752,395	701,252	776,581	716,974	223,966
Observations (employee-pair weeks)	9,318,972	6,767,616	8,496,744	9,449,664	8,681,028	9,028,740	8,415,022	9,318,972	8,603,688	2,687,592
Panel B: Decreased Distance	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DV: Total Communication	Baseline	Treated week 45	Excl. temp. treated	9-hour day	11-hour day	Excl. 2-hour changes	Excl. Thanksg.	OLS	Each City FE	Collab. > 5 mins
<i>Decreased Distance</i> × <i>Post</i>	-0.026 (0.059)	0.0912 (0.0628)	-0.0288 (0.0584)	-0.0410 (0.0673)	-0.0590 (0.0426)	0.00708 (0.0463)	-0.0172 (0.0610)	-0.0194 (0.0807)	-0.0258 (0.0587)	-0.0282 (0.0636)
Employee-pair fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
(pseudo) R-squared	0.6739	0.673	0.677	0.675	0.673	0.674	0.675	0.398	0.674	0.548
Employee pairs	666,427	474,055	597,908	688,088	654,863	635,265	601,751	666,427	666,427	200,500
Observations (employee-pair weeks)	7,997,124	5,688,660	7,174,896	8,257,056	7,858,356	7,623,180	7,221,016	7,997,124	7,997,124	2,406,000

Notes: The dependent variable is weekly total communication (measured in minutes) between pairs of employees, which includes scheduled calls and meetings, unscheduled calls, instant message chats, and e-mail. *IncreasedDistance* × *Post* is an indicator variable that takes a value of 1 for pairs of employees who lost business-hour overlap (BHO) as a result of Daylight Saving Time (DST) in the weeks after the switch to/from DST. *DecreasedDistance* × *Post* is an indicator variable that takes a value of 1 for pairs of employees who gained business-hour overlap. The table presents Poisson pseudo maximum likelihood (PPML) model estimates with fixed effects for each employee pair and each week. Column (9) further adds fixed effects for each city in the pair. Heteroskedasticity-robust standard errors in parentheses, clustered at the employee city-pair level. Employee pairs are included in a model if they had non-zero and time-varying communication volume in that mode over the 12-week sample period. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Effects of Increased Distance on Communication Volume by Employee Routineness

DV: Synchronous Communication	<i>Total</i>			<i>IBH</i>			<i>OBH</i>		
	<i>All</i>	<i>Non-routine</i>	<i>Routine</i>	<i>All</i>	<i>Non-routine</i>	<i>Routine</i>	<i>All</i>	<i>Non-routine</i>	<i>Routine</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Increased Distance</i> × <i>Post</i>	-0.116*** (0.037)	-0.058 (0.045)	-0.229*** (0.064)	-0.278*** (0.022)	-0.292*** (0.048)	-0.402*** (0.066)	0.124*** (0.025)	0.203*** (0.059)	-0.034 (0.084)
Test of H ₀		(2) = (3)			(5) = (6)			(8) = (9)	
p-value		0.068			0.406			0.017	
Employee-pair fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
(pseudo) R-squared	0.6558	0.6514	0.6519	0.6445	0.6459	0.6335	0.6040	0.5941	0.6053
Employee pairs	716,974	145,251	86,226	510,231	98,046	61,279	380,148	90,749	45,952
Observations (employee-pair-weeks)	8,603,688	1,743,012	1,034,712	6,122,772	1,176,552	735,348	4,561,776	1,088,988	551,424

Notes: The dependent variable is weekly synchronous communication (measured in minutes) between pairs of employees, which includes scheduled calls and meetings, unscheduled calls and instant message chats. The *Non-routine* sub-sample includes pairs where each employee has an above-median value of the “Non-routine cognitive: analytical” score in the sample. The *Routine* subsample includes employees where each has a below-median value of the “Non-routine cognitive: analytical” score in the sample. *Synchronous IBH* includes synchronous communication taking place when both collaborators are inside their local business hours (8 a.m. – 6 p.m.). *Synchronous OBH* includes synchronous communication taking place when at least one collaborator is outside their local business hours. *IncreasedDistance* × *Post* is an indicator variable that takes a value of 1 for pairs of employees who lost business-hour overlap (BHO) as a result of Daylight Saving Time (DST) in the weeks after the switch to/from DST. The table presents Poisson pseudo maximum likelihood (PPML) model estimates with fixed effects for each employee pair and each week. Heteroskedasticity-robust standard errors in parentheses, clustered at the employee city-pair level. Employee pairs are included in a model if they had non-zero and time-varying communication volume in that mode over the 12-week sample period. * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Effects of Decreased Distance on Communication Volume by Employee Routineness

DV: Synchronous Communication	<i>Total</i>			<i>IBH</i>			<i>OBH</i>		
	<i>All</i>	<i>Non-routine</i>	<i>Routine</i>	<i>All</i>	<i>Non-routine</i>	<i>Routine</i>	<i>All</i>	<i>Non-routine</i>	<i>Routine</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Decreased Distance</i> × <i>Post</i>	-0.036 (0.069)	0.020 (0.061)	-0.041 (0.069)	0.222*** (0.030)	0.342*** (0.043)	0.257*** (0.063)	-0.216*** (0.037)	-0.203** (0.090)	-0.172* (0.096)
Test of H ₀ p-value		(2) = (3) 0.803			(5) = (6) 0.450			(8) = (9) 0.771	
Employee-pair fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
(pseudo) R-squared	0.6505	0.6484	0.6448	0.6338	0.6335	0.6279	0.6055	0.5949	0.5873
Employee pairs	613,070	119,175	78,752	402,719	67,920	54,691	339,187	80,961	42,014
Observations (employee-pair-weeks)	7,356,840	1,430,100	945,024	4,832,628	815,040	656,292	4,070,244	971,532	504,168

Notes: The dependent variable is weekly synchronous communication (measured in minutes) between pairs of employees, which includes scheduled calls and meetings, unscheduled calls and instant message chats. The *Non-routine* sub-sample includes pairs where each employee has an above-median value of the “Non-routine cognitive: analytical” score in the sample. The *Routine* subsample includes employees where each has a below-median value of the “Non-routine cognitive: analytical” score in the sample. *Synchronous IBH* includes synchronous communication taking place when both collaborators are inside their local business hours (8 a.m. – 6 p.m.). *Synchronous OBH* includes synchronous communication taking place when at least one collaborator is outside their local business hours. *DecreasedDistance* × *Post* is an indicator variable that takes a value of 1 for pairs of employees who gained business-hour overlap (BHO) as a result of Daylight Saving Time (DST) in the weeks after the switch to/from DST. The table presents Poisson pseudo maximum likelihood (PPML) model estimates with fixed effects for each employee pair and each week. Heteroskedasticity-robust standard errors in parentheses, clustered at the employee city-pair level. Employee pairs are included in a model if they had non-zero and time-varying communication volume in that mode over the 12-week sample period. * p<0.10, ** p<0.05, *** p<0.01.

Table 8: Alternative Explanation: Ability to Work from Home

<i>Job can be performed at home?</i>	Non-routine						Routine					
	Yes			No			Yes			No		
DV: Synchronous Communication	<i>Total</i>	<i>IBH</i>	<i>OBH</i>	<i>Total</i>	<i>IBH</i>	<i>OBH</i>	<i>Total</i>	<i>IBH</i>	<i>OBH</i>	<i>Total</i>	<i>IBH</i>	<i>OBH</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<i>Increased Distance × Post</i>	-0.008 (0.048)	-0.183*** (0.052)	0.208*** (0.073)	-0.641*** (0.172)	-0.992*** (0.214)	-0.196 (0.152)	-0.206 (0.128)	-0.421*** (0.131)	0.016 (0.163)	-0.183*** (0.062)	-0.306*** (0.083)	-0.068 (0.064)
Employee-pair fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
(pseudo) R-squared	0.6293	0.6234	0.5794	0.6554	0.6451	0.5975	0.6822	0.6623	0.6454	0.6494	0.6250	0.5991
Employee pairs	64,118	44,043	40,499	18,852	11,720	12,269	15,197	10,683	8,824	39,175	27,632	21,289
Observations (employee-pair-weeks)	769,416	528,516	485,988	226,224	140,640	147,228	182,364	128,196	105,888	470,100	331,584	255,468

Notes: The dependent variable is weekly synchronous communication (measured in minutes) between pairs of employees which includes scheduled calls and meetings, unscheduled calls and instant message chats. *IBH* includes synchronous communication taking place when both collaborators are inside their local business hours (8 a.m. – 6 p.m.). *OBH* includes synchronous communication taking place when at least one collaborator is outside their local business hours. The Non-routine sub-sample includes pairs where each employee has an above-median value of the “Non-routine cognitive: analytical” score in the sample. The Routine subsample includes employees where each has a below-median value of the “Non-routine cognitive: analytical” score in the sample. Employees are coded as being able to work from home or note using the [Dingel and Neiman \(2020\)](#) measure. *IncreasedDistance × Post* is an indicator variable that takes a value of 1 for pairs of employees who lost business-hour overlap (BHO) as a result of Daylight Saving Time (DST) in the weeks after the switch to/from DST. The table presents Poisson pseudo maximum likelihood (PPML) model estimates with fixed effects for each employee pair and each week. Heteroskedasticity-robust standard errors in parentheses, clustered at the employee city-pair level. Employee pairs are included in a model if they had non-zero and time-varying communication volume in that mode over the 12-week sample period. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: Temporal Distance to Team and Employee Outcomes

DV:	<i>Retained (0/1)</i>			<i>Relocated (0/1) Retained</i>		
	<i>All</i>	<i>Non-routine</i>	<i>Routine</i>	<i>All</i>	<i>Non-routine</i>	<i>Routine</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Temporal distance to team</i>	0.001 (0.002)	0.004 (0.003)	-0.001 (0.003)	0.016*** (0.002)	0.023*** (0.005)	0.018*** (0.005)
<i>Team size</i>	0.016*** (0.001)	0.017*** (0.003)	0.012*** (0.003)	0.003** (0.001)	-0.002 (0.003)	0.004 (0.003)
<i>Tenure at firm (years)</i>	0.001* (0.000)	0.001 (0.001)	0.000 (0.001)	-0.001 (0.000)	0.002 (0.001)	-0.000 (0.001)
<i>Tenure at firm squared (years)</i>	-0.001*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000** (0.000)
Observations	11,354	3,514	4,171	9,685	3,031	3,564
R-squared	0.121	0.097	0.163	0.208	0.125	0.255
City fixed effects	Y	Y	Y	Y	Y	Y
Business function fixed effects	Y	Y	Y	Y	Y	Y

Notes: The dependent variable *Retained* is an indicator which takes the value one if a sample employee that was employed in the firm in March 2018 was still employed in the Firm in January of 2020. The dependent variable *Relocated* take the value one if a sample employee that was retained was located in a different city in January 2020 compared to March 2018. *Temporal distance to team* is calculated as 10 minus an employee's average BHO with other Division employees who share the same functional manager. *Team size* is the number of such employees. *Tenure* is the number of years from the employee's contract start year to year 2018. The table presents linear probability model estimates with fixed effects for each city and business function. Heteroskedasticity-robust standard errors in parentheses.

Table 10: Temporal Distance to Collaborators and Patenting Collaborations

DV:	<i>Collaboration (0/1)</i>		
	(1)	(2)	(3)
<i>Temporal Distance</i>	-0.278*** (0.005)	-0.023*** (0.005)	-0.031*** (0.007)
<i>Log of Geographic Distance (km)</i>		-0.363*** (0.005)	-0.351*** (0.005)
<i>Fixed effects</i>			
Year	Y	Y	Y
Each Inventor	Y	Y	Y
Controls included	N	N	Y
pseudo R-squared	0.114	0.141	0.190
Obs. (inventor-pair-years)	11,649,794	11,649,794	11,649,794

Notes: The dependent variable is an indicator variable that takes the value of 1 if a pair of inventors collaborated on at least one patent in a year. Data downloaded in June 2021 from PatentsView: <https://patentsview.org/download/data-download-tables>. Inventors are included in the model from the earliest to the last year in which they are observed patenting in the Firm. *Temporal Distance* between inventors is calculated as 10 minus their average value of BHO in the year. Geographic distance is calculated using inventor latitudes and longitudes. Column (3) also includes controls for total count of other inventors that a focal inventor collaborated with in a year as well as an indicator variable that takes the value one if both inventors are located in a country where English is the primary language. The table presents Poisson pseudo maximum likelihood (PPML) model estimates with fixed effects for each each employee in the pair and each year. Heteroskedasticity-robust standard errors in parentheses, clustered at the employee-pair level.

Additional Tables and Figures

Table A1: Effects of Temporal Distance on Communication Volume: Weekly Event Study Coefficients

DV: Communication	Panel A: Increased Distance			Panel B: Decreased Distance		
	<i>Total</i>	<i>Synchronous</i>	<i>Asynchronous</i>	<i>Total</i>	<i>Synchronous</i>	<i>Asynchronous</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Difference-in-differences Model:</i>						
Increased Distance × Post	-0.099***	-0.116***	-0.007			
Decreased Distance × Post				-0.026	-0.036	0.027
<i>Event Study Model:</i>						
Week 5+	-0.181*	-0.217**	0.015	-0.108	-0.159	0.140**
Week 4	-0.164**	-0.189**	-0.024	-0.136	-0.176	0.065
Week 3	-0.000	-0.017	0.092**	-0.028	-0.049	0.088**
Week 2	-0.249***	-0.291***	-0.041	-0.001	-0.021	0.104*
Week 1	0.002	-0.005	0.045	-0.088	-0.120	0.076*
Week 0	-0.110*	-0.138**	0.038	0.142**	0.149*	0.089**
Week -1 (omitted)	0	0	0	0	0	0
Week -2	0.089	0.098	0.034	0.066	0.061	0.089*
Week -3	-0.042	-0.051	0.003	0.046	0.040	0.072
Week -4	0.014	0.004	0.062	-0.094	-0.140	0.138**
Week -5	0.047	0.047	0.049	-0.136	-0.180	0.084
Week -6	-0.115	-0.138	0.021	0.212**	0.235**	0.009
Week -7	-0.010	-0.031	0.101	0.083	0.085	0.062
Week -8	-0.040	-0.074	0.119*	-0.210	-0.275	0.098
Employee pairs	776,581	716,974	153,248	666,427	613,070	137,070
Observations (employee-pair-weeks)	9,318,972	8,603,688	1,838,976	7,997,124	7,356,840	1,644,840

Notes: This table displays weekly event study coefficient estimates of Equation (1) alongside the coefficients from the difference-in-differences models. The dependent variables are measured as in Tables 3 and 4. *Week 0* is the week in which a pair of collaborators first experiences a change in business-hour overlap (BHO) as a result of Daylight Saving Time (DST) practices. The omitted category is the week preceding the treatment, *Week -1*. The table presents Poisson pseudo maximum likelihood (PPML) model estimates with fixed effects for each employee pair and each week. Significance levels based on heteroskedasticity-robust standard errors, clustered at the employee city-pair level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Gravity Model Estimates of Communication Flows

DV: Communication	<i>Total</i>	<i>Synchronous</i>	<i>Asynchronous</i>	<i>Total</i>	<i>Synchronous</i>	<i>Asynchronous</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Pre-period BHO (hours)</i>	0.050*** (0.009)	0.049*** (0.009)	0.018*** (0.005)	0.065*** (0.015)	0.068*** (0.015)	0.017** (0.008)
<i>Log of Geographic distance (km)</i>				0.033 (0.035)	0.041 (0.034)	-0.003 (0.015)
Constant	1.514*** (0.062)	1.503*** (0.063)	1.195*** (0.033)	1.191*** (0.322)	1.098*** (0.316)	1.222*** (0.143)
Each employee fixed effects	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y
pseudo R-squared	0.261	0.278	0.235	0.261	0.278	0.235
Employee pairs	428,904	388,921	92,059	428,904	388,921	92,059
Observations (employee-pair-weeks)	2,144,520	1,944,605	460,295	2,144,520	1,944,605	460,295

Notes: This table displays estimates of a gravity model of collaborator-pair communication as a function of their business hour overlap (BHO) and geographic distance (in logs). The dependent variables are measured as in Tables 3 and 4. Estimation uses only sample weeks 1–5 and drops any collaborators already affected by switches to/from DST. Collaborators appear each model if they had non-zero communication volume in that mode over the 5-week period. The table presents Poisson pseudo maximum likelihood (PPML) model estimates with fixed effects for each employee and each week. Heteroskedasticity-robust standard errors presented in parentheses, clustered at the employee city-pair level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A3: RDD Model Estimates of Communication Flows

DV: Communication	<i>Total</i>	<i>Synchronous</i>	<i>Asynchronous</i>	<i>Total</i>	<i>Synchronous</i>	<i>Asynchronous</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Closer</i>	0.134*** (0.043)	0.117*** (0.045)	0.093* (0.049)	0.133*** (0.043)	0.116*** (0.045)	0.100** (0.049)
<i>Log distance to tz line</i>	0.050*** (0.018)	0.068*** (0.018)	-0.009 (0.023)	0.084*** (0.029)	0.096*** (0.028)	0.049 (0.037)
<i>Closer × Log distance to tz line</i>				-0.063 (0.045)	-0.050 (0.044)	-0.115* (0.061)
Constant	1.600*** (0.026)	1.601*** (0.027)	1.114*** (0.027)	1.630*** (0.032)	1.625*** (0.033)	1.165*** (0.038)
Focal employee fixed effects	Y	Y	Y	Y	Y	Y
Nearest tz line fixed effects	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y
pseudo R-squared	0.212	0.232	0.186	0.212	0.232	0.186
Employee pairs	386,671	346,177	88,585	386,671	346,177	88,585
Observations (employee-pair-weeks)	1,933,355	1,730,885	442,925	1,933,355	1,730,885	442,925

Notes: This table displays estimates of a regression discontinuity-style model of a focal employee’s communication with collaborators in a defined distance band on either side of the same time zone line (all collaborators are coded with respect to the time zone line to which they are most proximate). *Closer* is an indicator variable for a collaborator being on the side of the time zone line that is closer to the focal employee. *Log of geographic distance to timezone line* is the logged distance of the collaborator to their nearest time zone line measured in kilometers and divided by 100. Estimation uses only sample weeks 1–5 and drops any collaborators already affected by switches to/from DST. Collaborators appear each model if they had non-zero communication volume in that mode over the 5-week period. Collaborators only appear in the model if they are located within a bandwidth of 250 km from a timezone line. All models include focal employee-, week-, and timezone line fixed effects. The table presents Poisson pseudo maximum likelihood (PPML) model estimates. Heteroskedasticity-robust standard errors presented in parentheses, clustered at the focal employee- nearest timezone line level. * p < 0.10, ** p < 0.05, *** p < 0.01.