Remote work (RW) is likely to become a permanent feature of organizational life. However, we lack advice on managing it and evidence to predict who will gain or lose from this change. To address this gap, we use a computational model to explore the impact of RW on organizational learning—an important determinant of performance—and highlight how structural design choices might mitigate ensuing negative consequences. We show that complexity and turbulence in the organizational environment, in conjunction with organizational structure, all play a crucial role in determining the impact of RW. While some organizations may be relatively unaffected by RW, others may need significant reorganization to maintain performance. We suggest factors to consider in its implementation and urge further research to understand this paradigmatic shift better.

Key words: Remote work, organization design, organizational learning, exploration and exploitation

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1. Introduction

The COVID-19 Pandemic accelerated the worldwide implementation of remote work (RW) as an emergency health policy measure, initially thought to be temporary in most cases.¹ Yet, while many top managers such as Tim Cook (Apple) and Jamie Dimon (JPMorgan Chase) have strongly argued for the eventual full return to the office (Bartelby 2021), it seems that a reversion to the “old normal” is unlikely. Some early projections suggest that at least 20% of all American work hours will never return and that this share will continue to rise (Barrero et al. 2021b). Tellingly, 42% of Americans who currently work from home would look for another job or just quit if asked to go back full time to the office, while the majority would at least favor some RW (Barrero et al. 2021b,a, Brynjolfsson et al. 2020).

Managing the long-term diffusion of RW is an urgent problem of unprecedented proportions, affecting most organizations across the globe and likely to permanently impact labor markets and economic output at the micro and macro levels (Dingel and Neiman 2020, Choudhury et al. 2021). Surprisingly, there is little research for policymakers, managers, or employees to consult as they navigate these uncharted waters. Therefore in this paper, we address two key questions that can guide stakeholders in formulating their RW strategy: a) under which conditions will an organization expect positive or negative effects from RW? and b) what type of managerial interventions can be used to mitigate (exploit) projected negative (positive) impacts from RW?

While there is a small but growing body of excellent empirical work on RW, the nature of this research makes its generalization challenging. In particular, most studies focus on the short-term impact on individual workers who move into RW. While these studies report

¹ Remote work can encompass a spectrum ranging from never having to be physically present at a workplace, to arrangements where only a fraction of the work hours is in non-traditional settings. RW status can be considered a continuous variable, however for ease of exposition we often discuss RW as a discrete choice.
that RW boosts personal satisfaction and productivity (e.g., Gajendran and Harrison 2007, Bloom et al. 2015, Choudhury et al. 2021), the research has tended to explore easily modularized jobs like call center employees, open-source coders, and patent examiners—jobs that have traditionally been performed by individuals in isolation regardless of workers’ physical location. It is also challenging to glean insights from extant studies that focus on less modularized jobs, like Yang et al.’s examination of emails within Microsoft during the Pandemic (2021), since the single-firm setting of the studies limits the generalizability of the findings. Conversely, while Zuzul et al. (2021) exploited email data on thousands of firms, the authors examined the impact of the Pandemic on communication patterns, not just the impact of remote work. It is reasonable to assume that in addition to forcing many employees to work from home, the conflagration of other factors surrounding the health emergency would further affect behavior, thus confounding the impact of the shift to RW. Importantly, neither of these email-based studies speaks on the effect on performance.

More broadly, the bulk of evidence gathered so far does not address long-term costs or benefits that might accrue to organizations or the economy at large, especially in settings where higher-level outcomes depend on interdependent activities and group dynamics (Thompson 1967, Milgrom and Roberts 1990, 1995, Grant 1996, Puranam et al. 2012). This should be critical for organizations engaged in knowledge-based activities, which feature interdependencies between employees’ tasks and where communication demands are fundamental (Kogut and Zander 1992, Young-Hyman 2017). For example, a remote worker may successfully continue doing a familiar job in the short run. Yet, without updating from others, their performance may deteriorate over time as the environment changes—a familiar dynamic behind competence traps (Levinthal and March 1993). Similarly, RW may hamper remote workers’ ability to bring valuable external knowledge back to the rest of the firm, eroding organizational-level competitiveness.
Performing detailed, long-term studies of such dynamics on a representative sample of firms and across the spectrum of industries would be ideal, though highly unfeasible. Within the study of organizations, an alternative to granular firm-level studies has traditionally been the large-scale, longitudinal statistical analysis of financial data, but this overlooks within-firm employee dynamics. Such trade-offs between depth and breadth hamper our understanding of the impact of RW on the world’s economy. Furthermore, given the massive and simultaneous shift towards RW, it is also societally costly to wait for reliable archival data to accrue on the long-term effects of this change.

To overcome these challenges, We use an agent-based computational simulation platform that models organizations as complex adaptive systems, where employees perform their tasks and learn from each other to improve their performance (March 1991, Ethiraj and Levinthal 2004, Fang et al. 2010, Csaszar and Siggelkow 2010). We theoretically argue that RW should slow the rate of interpersonal knowledge transfer, allowing us to operationalize the impact of RW at equilibrium on a virtually unlimited set of organizational forms operating in different types of environments and without the constraints of data and time.

The analysis of the model yields several important insights. First, we show that the complexity and turbulence of the organizational task environment play an essential role in determining the impact of a shift to RW. Under low complexity and turbulence in the task environment, RW has, on average, a positive effect on organizational learning and performance as it slows down the process of information transfer, thus benefiting more from a diversity of beliefs among employees. However, firms in complex and turbulent environments are likely to experience a negative impact from RW. Our results may thus explain why extant studies that examined firms whose employees are engaged in relatively stable and modular tasks have found consistent benefits from RW implementation in firms.
Our study thus cautions that extrapolating from limited empirical evidence may lead to incorrect prescriptions. Second, our results also show that positive individual-level outcomes may not aggregate to benefit the organization, thus countervailing the optimistic “win-win” view of RW. While individuals may benefit from shifting to RW, the aggregate impact of RW on the organization can, in many cases, produce negative consequences. Our study may thus explain why the preferences for RW differ between subordinates and superiors. Third, our results highlight an important but often overlooked moderating effect of organizational structure. We show that organizational structure can either boost or counter the effects of RW and thus should be considered a key managerial lever that urgently needs more study to provide better actionable guidance to stakeholders instituting a shift towards RW. Our analysis suggests that centralized structures, where information flows through a few well-connected hubs, are more likely to benefit from a change to RW than more modular structures. Using a genetic algorithm (Holland 1992), we also push the analysis further and show how organization designers might reshape organizational structure to accommodate a shift to RW. The results suggest that organizations do not require much or any intervention in simple and stable environments and can proceed as before the shift to RW. Such environments support modular organizational structures. However, organizations operating in complex and turbulent environments may require a very high degree of connectedness, thus making structures like the matrix form more desirable.

Our paper makes several contributions. First, we contribute to the growing literature on the effects of RW on organizational performance (Bloom et al. 2015, Gajendran and Harrison 2007, Choudhury et al. 2021, Zuzul et al. 2021). We show that many of the reported effects of remote work may not generalize beyond a narrow setting: The level of analysis (individual or organizational), the degree of complexity and turbulence in the
environment, and organizational structure determine whether one would expect a positive or negative impact on organizational learning.

Concerning the literature on organization design, we find that the interventions required to deal with the impacts of RW may need to involve changing the structure of an organization. While the extant literature has so far tended to recommend an increase of interactions via fixes such as regular company get-togethers (Choudhury et al. 2020), we find that designers may want to either increase or decrease interactions through modularization, depending on the initial organizational structure and the characteristics of the environment.

Our paper also makes a contribution to the literature on organizational learning. Combining an agent-based model of learning, a model of tunable complexity, and a genetic algorithm, we can consider a much broader set of permutations of environmental and organizational characteristics than prior work where results depended on a specific set of assumptions (e.g., March 1991, Lazer and Friedman 2007, Fang et al. 2010, Clement and Puranam 2018). By considering multiple variables at once, we show how the complexity and turbulence of the environment, organizational structure, and learning speed jointly shape the efficacy of organizational learning under RW.

Our paper proceeds as follows. In the next section, we review the relevant literature and position our paper with respect to existing models. In the third section, we introduce the model and map its features to the key characteristics of the phenomenon. We then discuss the model results and identify key mechanisms through a series of computational experiments. In the discussion and conclusion sections, we discuss its key implications, limitations, and future extensions.
2. Background and Theory

Well before the COVID-19 Pandemic, a small body of research has been exploring RW (Kiesler and Cummings 2002). Here, the most consistent set of findings has been at the individual level. The fundamental postulate of that research is that RW allows workers more freedom, which increases personal well-being and increases workers’ productivity (e.g., Gajendran and Harrison 2007; Sauermann and Cohen 2010; Bloom et al. 2015; Kryscynski et al. 2021; Choudhury et al. 2021). While the benefits of RW accruing to employees appear to be relatively straightforward, costs associated with employees working at a distance may be more nuanced and might manifest indirectly and with delay.

2.1. Potential costs of remote work: An organizational perspective

The dominant view on why in-person interactions are more efficient than remote ones dates back to early work showing the benefits of colocation (Oldham and Brass 1979, Allen 1977). Core mechanisms in support of colocation include communication and information theory, which posits that face-to-face (FTF) communication conveys tacit and complex communication more effectively (Carson et al. 2003, Lewis 2004), reduces information search costs, and increases serendipitous interactions (Catalini et al. 2020, Catalini 2018, Boudreau et al. 2017, Chai and Freeman 2019). Work on colocation has consistently found benefits to in-person interactions (especially in the case of inventors, e.g., Catalini et al. 2020; Catalini 2018; Boudreau et al. 2017; Chai and Freeman 2019). From a social perspective, lack of colocation makes people less aware of each other’s social context and common knowledge, making it difficult to interpret others’ behavior, diminishes social presence, reduces trust, and increases misunderstandings and conflict (Cramton 2001).

The preceding streams of literature thus suggest similar predictions for the impact of RW on firms. However, they differ in terms of their industry settings, levels of analysis,
time scales, and mechanisms linking individual actions to organizational-level performance. Similarly, the bulk of this work does not tackle the question of how individual outcomes may aggregate to the level of the organization nor speak to the long-run impacts of micro-geography. A notable exception is Yang et al. (2021), which quantified firm-level outcomes at Microsoft after RW was imposed following the pandemic. They observed that the quality of collaboration deteriorated, and collaboration communities became more siloed (but more interconnected within each silo). While suggestive, this early evidence tells us little about the long-term impact of RW, and it is difficult to generalize from the focal firm since Microsoft operates in many industries (technology, cloud computing, software) where it enjoys a unique market position, making it a less than representative organization. Similarly, the COVID-19 Pandemic has not only forced a large part of the workforce to switch to RW but has also imposed incalculable other economic, social, and personal burdens. This makes it difficult to isolate the effects of working remotely. We argue that the best way to concatenate prior findings is to integrate them into a single framework that allows us to study the impact of RW while muting potential confounds.

2.2. **Why computational models are ideal for studying RW**

Increasing our understanding of the organizational-level impact of RW is a critical challenge that must capture a) the impact on individuals, b) the impact on organizations, and c) the interaction between the two levels. To make progress on this front, we turn to computational modeling, an approach that over the past several decades has generated valuable insights about settings where the actions of individuals aggregate in non-simple ways and where the data necessary to examine an issue empirically is either not available or available only after a costly delay (Siggelkow and Rivkin 2009, Burton and Obel 2011, Puranam et al. 2015). Computational models recently gained wide notoriety as they are
being used to guide the global response to the COVID-19 pandemic. Simulations such as COVIDSim (Ferguson et al. 2020) allowed scientists to forecast possible infection and mortality scenarios, which involved carefully mapping feedback dynamics and introducing behavioral elements. However, capturing how individual-level actions aggregate to produce organizational-level outcomes is challenging and has spawned a considerable body of academic research (see Puranam et al. 2015 for an overview of main computational approaches to studying organizational phenomena). The subject of aggregation plays a particularly important role in the literature in the Carnegie School tradition (March and Simon 1958, Cyert and March 1963) and evolutionary economics (Nelson and Winter 1982), with both literatures serving as theoretical touchstones for studying organizational learning and adaptation (Levinthal 2021). Formal models of aggregation have been used to study the impact of complexity in the organizational environment (Levinthal 1997, Rivkin 2000, Rivkin and Siggelkow 2007), turbulence (Davis et al. 2009, Hsu and Marino 2010, Posen and Levinthal 2012), technological change (Aggarwal et al. 2017), organizational structure (Ethiraj and Levinthal 2004, Siggelkow and Levinthal 2003, Csaszar 2013, Fang et al. 2010, Levinthal and Workiewicz 2018), and learning rates (Lounamaa and March 1987, March 1991, Siggelkow and Rivkin 2005). In sum, for the past several decades, computational models have been widely acknowledged as powerful tools to explore organizational aggregation and dynamics.

To maintain continuity and facilitate comparisons with prior work, we build on two seminal models, March’s (1991) model of organizational learning and the Kauffman/Levinthal

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2 While we also use computational simulation, our model differs in some respects from those used in guiding the response to the pandemic. These models aim at forecasting the most likely trajectory of an infection in a specific setting as realistically as possible. These models take into account detailed information such as regarding demographics, travel patterns, behavioral habits and are continuously calibrated using real-time data. Because our aim is to examine the impact of RW on a broad spectrum of organizations, rather than a specific example, our model is necessarily more general in design and decontextualized. Instead, our goal is to examine key mechanisms and the direction of effects rather than offer a precise estimate.
NK model of search (Kauffman 1993, Levinthal 1997). This allows us to incorporate dynamics between agents (e.g., workers), the organization, and the environment and examine the mechanisms and interactions over many conditions. Following Fang et al. (2010) and Koçak et al. (2021), we model organizational structure as the communication pattern imposed by management among actors, muting the confounding impact from social or informal networks that might arise organically in a real-world setting. Consistent with prior work, organizational structure arises within our model from the grouping and linking of decisions made by an organizational designer while allowing the resulting pattern of communication to be non-deterministic (Nadler and Tushman 1997, Smith-Dor and Powell 2005, Clement and Puranam 2018, Puranam 2018). We can thus simulate the impact of RW on the performance of organizations characterized by several archetypal structures (e.g., centralized, decentralized, semi-isolated teams, etc.). To complete our analysis, we use a genetic algorithm (Holland 1992) that lets an optimal structure emerge organically when RW is imposed under various combinations of complexity and turbulence in a task environment. This approach allows us to identify subtler features and mechanisms that may benefit organizations forced to implement RW and frees us from the constraints of conforming to canonical structural archetypes.

2.3. Operationalizing RW: Why RW is not a structural change

RW may, on the surface, appear to be an organizational structure change insofar as it shifts the distance among components of the organization (workers). However, the study of organizational structure and design is theoretically concerned with the delegation of decision rights (Blau, 1968) through the arrangements between formal divisions, groups, or departments in relation to the headquarters and each other (Milgrom and Roberts

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3 See Lavie et al. (2010), and Baumann et al. (2019) respectively for an overview of the literature and impact of these seminal models.
Conversely, RW entails the physical separation of individuals from the organization, impacting how individual workers interact with each other, both within and across their units, while maintaining the existing authority structure. For example, if we consider geographic decentralization, workers within a distant unit still interact with each other, and the typical focal issue is the organizational-level flows of rights and resources between the units and the headquarters. This is different from RW, which impacts individual workers’ interactions with each other and the organization. Put simply, the employee working remotely still reports to the same manager and oversees the same subordinates—the formal structure has not changed.

Thus, switching to RW in our model does not in and of itself engender changes to the organizational structure (e.g., it does not make it more or less “centralized”). One could argue that in a real-world setting, a switch to RW might affect the nature of the social interactions between employees and, in turn, the pattern of those interactions, perhaps through changing power dynamics, perceptions of status, or similar social channels. However, our study mutes the interplay between formal and informal structures, focusing only on the formal structure. Our analysis makes the structure of interactions the key variable of interest, and we explore how slowing down the rate of learning affects organizations with different structures. Thus, instead of answering how RW might change the organizational structure, we answer the question: given a task environment, what changes to the structure should be made to increase or maintain performance after the shift to RW.

2.4. Why RW throttles the rate of information transfer

In this section, we describe how our model operationalizes RW by focusing on one important feature of RW that should impact both the individual and organizational levels and

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4 Some recent COVID studies have indeed reported changes correlated with RW that would be consistent with such mechanisms (e.g., Yant et al., 2021; Zuzul et al., 2021), though future work still needs to systematically document the relationship between RW, social dynamics, and organizational structure.

5 See Clement and Puranam 2018, for a discussion on the interplay between formal and informal interactions.
manifest itself in the broadest of contexts: Moving worker interactions to a virtual setting should cause a reduction in the speed of information exchange among individuals.

Despite the lack of coherent research specifically relating RW to organizational performance, several studies have explored features of the employment relationship that should be relevant as we investigate remote work. Research from various disciplines has shown that the rate of information transfer between individuals drops in organizations where face-to-face interactions (FTF) are reduced or where individuals are spatially separated. Physical proximity generally promotes more frequent and spontaneous interactions (Allen 1977, Kiesler and Cummings 2002), an essential factor influencing the design of working spaces for knowledge transfer (Oldham and Brass 1979, Catalini 2018). More importantly, FTF interactions promote more efficient (higher bandwidth) communication and learning (Cardon et al., 2003; Lewis 2004). FTF interactions also reduce misunderstandings and conflict, both of which impede information exchange between individuals (Cramton 2001, O’Leary and Mortensen 2010) (see also the excellent review of the literature by Ren 2020).

The literature suggests that individuals’ learning is moderated by several features distinguishing RW from FTF. Namely, a) RW offers a less salient learning environment, b) the frequency of interactions and hence learning is lower, and c) the noise to signal ratio increases, making learning more difficult. Subsequently, we argue that the shift to RW can, on average, be construed as a reduction in the learning rate among the individuals in an organization.⁶ We, therefore, operationalize the switch between FTF and RW as a decrease in the average speed at which knowledge flows between workers. Put simply, a lower learning rate captures the expected drop in knowledge transfer associated with decreasing FTF interactions. As detailed in the Model section, the variable \( p \) captures

⁶While we recognize that other factors are affected by RW, we focus here on what a preponderance of diverse literatures supports as one primary effect of RW.
the throttling of the channel between individuals and is agnostic with regards to which specific factor underlies the reduction (e.g., knowledge, socio-cultural cues, frequency of exchanges, etc.). Our approach thus is to isolate the impact of RW through one specific channel: knowledge flow. We do not claim that this is always the case, as there can be meaningful differences between different types of knowledge, tasks, hierarchical levels, or the personalities of the individuals involved; however, a robust pattern identified by the literature is that FTF interactions improve, rather than attenuate, learning and knowledge transfer among individuals (Ren 2020).

2.5. How our approach differs from previous modeling investigations

While, to our knowledge, there are no modeling papers tackling the question of remote work, there have been several streams of modeling literature examining the effect of a reduced learning rate. We build on and extend this discussion by synthesizing the insights of independent modeling works on three distinct pillars: organizational learning, organizational structure, and environmental complexity. Although prior works have revealed a valuable understanding of individual components or dyadic relations between those components, the lack of study on their triadic interplay makes it challenging to provide managerial recommendations given various organizational contingencies. The second limitation comes from the implicit differences in the multiple operationalizations of ‘learning rate’, hindering a direct application of these insights to the RW setting. We discuss below how our model complements these prior works on learning, complexity, and structure.

The first stream of related models focuses on the intra-organizational learning process laid out in the seminal piece of March (1991). By analyzing the role that learning plays, March showed that the lower learning speed of employees preserves diversity and improves long-term performance. However, environmental complexity and organizational structure
were outside of the scope of this paper. Indeed, considering the effect of these two contingencies, we show conditions under which slowing down the learning rate can be detrimental to organizational performance. We also show that organizational structure can be a powerful complement to the learning speed.

The second related literature concerns organizational adaptation on a rugged (NK) landscape (Levinthal 1997). Here the learning rate is captured in imitation breadth or imitation accuracy (Rivkin 2000, Csaszar and Siggelkow 2010). These NK models generally conceptualize an organization as a unitary actor, therefore being agnostic about the role of organizational structure and interpersonal learning. Furthermore, since these works modeled imitation coupled with individual local search, authors generally confirmed the benefit of reduced learning rate exclusively in the presence of complexity by helping to dislodge firms from their local peaks. In contrast, we demonstrate that in the presence of learning, throttling the learning speed can be more likely to backfire in a complex environment.

The third related modeling approach focuses on the efficacy of different organizational structures on interpersonal learning, notably the papers of Fang et al. (2010) and Schilling and Fang (2014). The authors make important extensions to March’s original model by considering the effect of specific structures like semi-connected subgroups and hubs on social learning performance. We depart from their conceptualization in two ways. First, we examine the role of dropping the learning rate on learning efficacy, while Fang et al. (2010) didn’t vary the learning rate to focus on the structure instead. Second, we consider complexity as the presence of substitution effects among decision choices. While there are many possible complexity measures, the existence of multiple locally superior solutions is tied to substitution among the choices, not complementarity (Rivkin 2000, Rahmandad 2019). While in their paper, the authors use the word “complexity,” their $ms$ landscape
is single-peaked, and their conceptualization of complexity is that of a credit assignment problem, where the contribution of a given decision is hidden until a certain threshold is reached (Sutton & Barto, 1998). In contrast, we show the substitution effects present in an NK model’s multi-peaked conceptualization of complexity. We find that these substitutions have important consequences that make semi-isolated organizational units less effective and allow centralized hubs to triumph over moderately hubby or modular structures.

A model that has incorporated all three elements of social learning, organizational structure, and environmental complexity on a rugged landscape is the work of Lazer and Friedman (2007). The authors found that structural connectivity increases short-term organizational performance under complexity at the expense of long-term performance. Similar to the previous NK papers, this paper confounded local search with social learning such that all organizations would converge on a peak (local or global) given enough time. Furthermore, it is also important to note that their ‘velocity’ of learning is not our learning rate since, regardless of the velocity, the authors endow the agents with the ability to perfectly copy the whole knowledge vector of the best performer in a given period, which is equivalent to $p_{learning}$ rate of 1. The effect of ‘error rate’ in this model is partially muted since the agents only conduct offline learning. Therefore, connectivity is equated with an efficient network. More importantly, the authors didn’t examine the effects of reducing information velocity beyond a fully connected graph, making the study not applicable to studying the impact of a shift to RW. In contrast, by focusing on the reduction in learning rate specifically, we show conditions when connectivity to multiple different superiors can destroy performance in learning complex knowledge. Finally, the paper focused on a small number of structures and did not consider their interaction effects with learning speed and environment. Indeed, examining a broader range of structures in search for one that fared
well in both the short and long run was proposed by Lazer and Friedman as a direction for future research. We thus further expand this line of work by examining a large number of possible organizational structures with the help of a genetic algorithm. We also show the mechanisms that allow the caveman structure to outperform other generic structures in very simple and complex environments.

Finally, the paper by Clement and Puranam (2018) focused on the role of formal structure and environment in shaping the evolution of the patterns of information exchange. The authors argued that formal structure helps to regenerate and maintain the pattern of interactions among employees. While we allow the structure to emerge naturally in the last part of our analysis, our goal is very different. Their paper was interested in the process of evolution, whereas we explored the structures that proved most successful in the end. Importantly we add the speed of learning among employees and model it explicitly. This allows us to examine the impact of RW on learning efficacy.

Taken together, while prior formal investigations have contributed significantly to our understanding of learning processes in organizations in the presence of complexity and time constraints, extant work has not been able to include an integrative comparison of learning performance or given structures operating in given environments and under different work modalities. In our approach, we build on this earlier pioneering work to tackle the implications of shifting to RW.

3. Model

Following prior literature, we conceptualize the organization as a complex adaptive system that interacts with its environment by learning from performance feedback (March 1991, Levinthal 1997, Siggelkow and Rivkin 2005). Our model highlights that learning in organizations doesn’t occur in isolation but is influenced by organizational structure and
the task environment (Argote and Miron-Spektor 2011). We build on the seminal work by March (1991) to study the impact of RW in the manipulated and controlled experimental settings of an agent-based computational simulation. This allows us to examine the effects of organizational context on organizational learning. In our model, we include agents and their representations of the task environment, a process for enacting their representations, environmental feedback, and finally, a process through which the initial representations are updated (March and Olsen 1976, Puranam et al. 2015). Consequently, our model needs to specify three key elements: the organizational parameters, the task environment, and the learning process.

3.1. The organization.

The organization consists of $m$ employees embedded in an organizational structure, represented by a graph of bi-directional communication links between those employees. In our model, connected employees learn from each other by observing the outcome of each other’s decisions (defined below). The pattern of communications determines the dynamics of learning among the individuals or the structure. The structure thus determines the degree of centralization and isolation of subunits to which employees belong (Fang et al. 2010).

3.2. The task environment.

Following a large body of work, our task environment consists of $N$ binary decision variables $f = \{d_1, d_2, \ldots, d_N\}$ that can be either -1 or 1 and represent two possible discrete choices an individual or organization can make. The task environment represents an objective reality independent of employees’ beliefs. Decisions may be independent or interdependent. For example, the appropriate battery size in an electric vehicle depends on the size and weight of the car itself and its intended use (city or highway driving), and the choice of
battery size affects several other design decisions. Such interdependence is captured by parameter $K$, which describes the average number of other decision variables interacting with a focal decision variable. Thus, when parameter $K = 0$, the decision variables are independent of each other, and when $K > 0$, whether a given decision makes sense depends on the other $K$ decisions, as in the above electric vehicle example. Formally, the overall fitness (performance) of a given combination of decision variables is defined as:

$$V(f) = \frac{1}{N} \sum_{i}^{N} V(d_i, d_{-i}), \text{where } i \neq -i$$

(1)

where $d_{-i}$ are the $K$ other variables with which focal variable $d_i$ is interdependent. This operationalization means that the task environment is rugged, with multiple local optima (Levinthal 1997). Organizational performance is calculated as the average performance across all employees at the end of $t$ periods, where $t$ is a parameter controlling for the turbulence of the environment. Lower values of $t$ increase the environmental “turbulence” because an organization has less time to learn and disseminate information among its employees (Siggelkow and Rivkin 2005).

3.3. The learning process.

Employees hold beliefs about the external reality. The belief vector of an employee $i$ consists of beliefs regarding the $N$ elements of the task environment $B_i = \{b_{i1}, b_{i2}, \ldots, b_{iN}\}$. A belief can be -1, 0, or 1, where -1 or 1 means that the employee has a position on the decision and considers their belief the correct one. A belief of 0 means that the employee is uncertain regarding which value for this variable will lead to better performance.

At each round, individuals execute their actions according to their beliefs. If an individual holds a belief 0 (where they do not have a position), a value of -1 or 1 is chosen randomly because they always have to act. Individual actions are then compared with
objective reality, and a corresponding performance value is recorded for each individual. Each employee observes all other employees to whom they are connected and compares their own belief for each decision with the actions of their better-performing colleagues and, with probability $p$ revises their own belief according to what the majority of superior colleagues have done. If there is a tie, the employee’s belief remains unchanged.\(^7\)

4. Results

We ask: I) How do the features of the organizational task environment and organizational structure moderate the effects of switching to remote work? And II) What is the appropriate organizational design response to the increase in the share of remote work in the organization?

4.1. Organizational impact of remote work

Following prior work, we utilize tools developed in the study of network structure to analyze our synthetic organizational structure (See Fang et al. 2010, Koçak et al. 2021), while being clear that as discussed above, these are not social networks, since our agents are devoid of social dimensions. In the following analysis, we examine the impact of switching to RW by observing the change in organizational performance when we drop the value of $p$ from 0.7 (FTF) to 0.3 (RW).\(^8\) We set the number of decision variables to $N = 12$ and the number of employees to $m = 20$. We then varied the complexity and turbulence of the organizational task environment. Both factors have been previously associated with greater demand for information processing in organizations (Galbraith 1977, Siggelkow and Rivkin 2005, Joseph and Gaba 2020). We looked at four levels of task-environment complexity:

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\(^7\) In his original model, March (1991) used organizational code and associated learning rate to model how both organizations and individuals learn from each other. Because the organizational structure is one of our variables of interest, we follow Fang et al. (2010), who themselves adapted March’s model to study the role of organizational structure. Consequently, in our model, individuals learn from their local organizational code, which is represented by their better-performing direct contacts.

\(^8\) We also checked the results for different values of $p$, lowering the value from 0.8 to 0.2 and from 0.6 to 0.4 to capture the effects of an organization switching to RW. The results were qualitatively the same.
negligible \((K = 0)\), low \((K = 3)\), moderate \((K = 6)\), and high \((K = 11)\). For each level of complexity, we considered four levels of environmental turbulence, ranging from negligible \((t = 400)\) to low \((t = 100)\), moderate \((t = 50)\), and high \((t = 25)\). We chose these values to correspond to the model dynamics. In a moderately complex environment, a random graph with an average degree of 4 would generally take around 94 periods to fully converge in the RW condition and 45.5 periods in the FTF condition. Setting the values between 25 and 400 allows us to examine a broad spectrum of conditions. Altogether, we calculated the net effect of switching to RW for 16 different combinations of complexity and turbulence.

We embedded the employees in an organization. For each combination of complexity and turbulence, we considered four widely used archetypes: a random graph (Erdős & Rényi, 1959), scale-free (Barabási and Albert 1999), connected caveman (Watts 1999), and small-world (Watts and Strogatz 1998). To facilitate comparisons, we set the parameters of the structure-generating algorithms so that all resulting graphs had the same average degree of 4 (same average number of connections between employees), which isolates the impact of structure, apart from connectedness. Our intention here was not to do an exhaustive review of all possible organizational structures but simply to examine whether there is a difference in the impact of RW for a few representative canonical examples that differ in terms of the degree of centralization as well as presence and degree of isolation of subunits. Finding differences would support a call for further study into how organizational structure moderates the impact of RW. Table 1 summarizes the key characteristics of each structure.

Finally, to ensure the statistical validity of our results, we ran 10,000 simulations per each combination of parameters and for each organizational structure (100 organizations x 100 landscapes) and reported the average values. All reported results are statistically significant at a one percent level.
Table 1 Descriptions of selected structural archetypes

<table>
<thead>
<tr>
<th>Graph structure</th>
<th>Description</th>
<th>Visualization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>Random graphs where edges are created with pre-defined probability.</td>
<td></td>
</tr>
<tr>
<td>Erdős and Rényi, 1959</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scale-free</td>
<td>Graph dominated by a few central hubs, degree distribution follows a power law resulting from a preferential attachment algorithm.</td>
<td></td>
</tr>
<tr>
<td>Barabaši and Albert 1999</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Connected</td>
<td>Graphs with several nearly isolated subgroups/highly modular cliques.</td>
<td></td>
</tr>
<tr>
<td>Caveman</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Watts 1999</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small-world</td>
<td>Graphs where nearest neighbors are connected, and most nodes are not neighbors but can reach any other nodes via a few edges.</td>
<td></td>
</tr>
<tr>
<td>Watts and Strogatz 1998</td>
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</table>

4.2. Task environment and organizational structure

Figure 1 illustrates the relative impact of moving from FTF into RW for the four organizational archetypes. To simplify the interpretation of our analysis, Figure 1 reports only the direction of performance change after introducing RW, with white regions with “+” signs representing an improvement in organizational performance and darker quadrants
Figure 1  Performance change following a shift to RW for four archetypes.
Note: This figure presents the effects of switching to RW on performance across four archetypal structures. The key insight is that even when operating in the same task environment, organizations may experience different outcomes upon switching to RW, depending on their organizational structures.

with “-” symbols representing combinations of parameters for which a shift to RW leads to worse outcomes. We refer to the specific numerical values in the following discussion of results.

There are two important observations stemming from this analysis. First, the environment matters. The results show that organizations operating in task environments characterized by low complexity and low turbulence will, on average, experience a boost in organizational performance. With low complexity and low turbulence, it is easy to reach a high level of performance. Yet, organizations can still experience further performance growth ranging from 0.26 to 1.62 percent by switching to RW across all four structural archetypes. These baseline results point in the same direction as prior findings showing
that RW has a positive impact when employees work in relatively modular and stable environments such as call centers and patent offices (Choudhury et al., 2020; Bloom et al. 2015). However, an increase in either environmental turbulence or complexity makes RW detrimental to organizational performance, leading to a drop of 3.69 percent in moderately complex and turbulent environments, up to a 14.35 percent plunge in highly complex and turbulent ones compared with the FTF condition. Turbulent environments call for the speedy information assimilation provided by FTF interactions, where it is better to disseminate and implement partially imperfect knowledge that responds to the urgent needs demanded by the environment rather than waiting until employees search for and agree on a perfect approach.

The effect of complexity is equally important. Our results suggest that the well-documented benefit of slow, individual-level learning (March 1991) does not generalize to settings with high levels of interdependence. A shift to RW under complexity is more likely to lead to the exchange of incomplete information and, in turn, to lower organizational performance even when turbulence is low. This happens because, under complexity, sharing incomplete information produces detrimental effects (Milgrom and Roberts 1995, Levinthal 1997). In summary, this calibration experiment shows that RW can positively or negatively affect organizational performance depending on the nature of the organizational task environment. We argue that RW would have been beneficial for some organizations even before the current health crisis, while for others, managers may have a point in insisting on a return to the office.

Second, organizational structure matters too. Even for organizations operating in identical task environments, a shift to RW can lead to heterogeneous outcomes depending on their organizational structure. In all four cases, RW benefits organizations in simpler and less turbulent environments; however, structures characterized by higher centralization (scale-free)
benefit from RW in more combinations of environmental parameters. Conversely, organizations where organizational structures are characterized by higher modularity (caveman) will only benefit from a shift to RW if they operate in the simplest and most stable of environments. The key to explaining these results is that organizational structure moderates the speed of information diffusion throughout the organization. Centralized structures allow for faster overall information exchange, while structures with many weakly connected subunits (clusters) are generally slower to diffuse information. The insight here is that when organizational structure results in information disseminating too rapidly, given the environmental parameters, a shift to RW can help by slowing down information diffusion. RW can thus complement or even substitute for organizational structure in modulating the speed of information exchange and balancing organizational exploration and exploitation (March 1991). This result leads to a follow-up question: Since task environments are generally exogenous, which type of structure is best for companies implementing RW in a given task environment? We explore this question next.

4.3. Relative comparison of the four organizational structures

As argued above, a switch to RW by itself is not a modification of the organizational structure. In typical cases, workers continue to work under the same hierarchy and reporting structure. Any additional “decision rights” given will entail personal choices such as what to wear or when to complete a task. Conversely, organizational structure can be a powerful managerial lever to assist in managing the switch to RW. For example, managers can use formal design to change the degree of centralization and isolation of organizational subunits to influence the degree of exploration and exploitation in an organization (Csaszar 2013; Ethiraj and Levinthal 2004; Fang et al. 2010; O’Reilly & Tushman 2004; Siggelkow and Levinthal 2003; Siggelkow and Rivkin 2005). A divisional structure such as the classic
M-Form resembles the “connected caveman” archetype, where individuals are tightly clustered within their division but have only sparse and infrequent ties with other divisions. Similarly, an organization designer may increase centralization to achieve a structure with “scale-free” properties. The small-world structure can be induced by introducing a bossless form, like in the American company Valve, where employees periodically move between teams and are temporarily isolated (Puranam et al. 2015, Ketkar and Workiewicz 2022).

Thus, this section analyzes and compares how different organizational structures fare within different task environments and work modes (FTF vs. RW). In the next set of tests, we focused on four canonical structures that have featured prominently in the literature on organizational learning (random, scale-free, connected caveman, and small-world) to see how each performs in a given task environment. A description of each structure can be found in Table 1. Figure 2 presents the simulation results for different combinations of complexity and turbulence. For both RW and FTF, the caveman archetype remains best under negligible complexity and turbulence. However, in task environments with low/medium complexity/turbulence, the best structure changes from small-world in FTF to more random structures for RW. Small-world structures, in turn, become a better choice as task-environment complexity increases, as long as there are negligible levels of turbulence. In other words, after the shift to RW, small-world structures lose much of their appeal. Centralized structures (scale-free) should be more favorable in very turbulent but moderately complex task environments and ones with medium turbulence and high complexity.

Surprisingly, the caveman structure performs best in extreme combinations: when task environments are simple and stable but also when they are complex and turbulent. At first glance, this seems surprising. An explanation for this lies in the mechanisms of knowledge diffusion in such organizations. Recall that the caveman structure consists of several
smaller, densely connected groups, where members of each group are well connected with
the members of their group but only occasionally share a link with someone from outside
that group. In such a structure, the search occurs in two waves. First, the team mem-
bers quickly arrive at a shared solution at the team level. However, under complexity,
the initial solutions that individual teams adopt are different most of the time. In other
words, each team finds and adopts a local solution, which occurs quickly, with over 90%
local convergence (within the team) in $t = 25$, averaged for all levels of $K$. After each
team finds a solution, the weak links start to exert influence. Some teams realize that few
of their members are aware of different but superior solutions adopted by other teams.
Slowly these superior solutions are disseminated across the other teams, further increas-
ing organizational performance. However, this process takes time, and we only see 75%
organization-wide convergence at $t = 400$. Thus, the caveman structure quickly arrives at
an initial set of good but diverse solutions. Each team quickly climbs its local peaks (hence good performance when complexity and turbulence are high). When given more time, this structure preserves diversity in its members’ beliefs, which increases the chances of finding a globally superior solution.

Interestingly, a structure with a random pattern of connections also becomes more attractive in specific environments, producing the highest performance in environments with modest complexity and turbulence or when only one of these features of the task environment is high. This last finding suggests that there is something that the other canonical structures do not capture that allows a random graph to achieve superior performance. This prompts the next set of investigations.

4.4. Finding an optimal structure for remote work

In this section, we push beyond four canonical types since neat structures are unlikely to be found in real organizations, where the number of subunits and the degree of coupling between them (modularity) are refined through repeated interactions and experimentation (Ethiraj and Levinthal 2004, Clement and Puranam 2018). Interestingly, the robust performance of the random structure suggested that in some cases, the three archetypes were suboptimal. This prompts further questions: What would be the ideal organizational structure for a given task environment if the organization designer was not constrained to strict archetypes? What features of the organizational structure would be beneficial when shifting to RW?

To answer these questions, we employed a genetic algorithm (GA) that approximates the optimal organizational structure by allowing it to naturally emerge through a recurrent process of mutations and selection (Holland 1992). We started with an initial population of 1,000 organizations, each with an independently generated random graph of employee
connections. We then allowed each organization to learn following the procedure outlined in
the first experiment. We ran each of the 1,000 organizations on 1,000 randomly generated
NK landscapes of a given complexity (K) and averaged each organization’s performance to
arrive at a performance value in time \( t \), which was determined by the respective turbulence
level. Next, we created a second generation of organizations. First, we selected the 50 best-
performing organizations to be carried over unchanged to the second generation. This elitist
selection allowed us to avoid genetic drift because there is no guarantee that the desired
features of the high-performing organizational structures will be preserved with mutation
and crossover. Without elitist selection, a given population may lose its advantageous
features. Keeping the best performing specimens prevents this.

Next, using crossover and mutation, we generated the remaining 950 organizations for
the second generation by mutating the prior organizations. Specifically, we selected 475
pairs of parents using a rank-based roulette wheel procedure, where organizations with
higher performance had a higher chance of being selected and could enter the pool multiple
times. For each pair of parents, we generated two-child organizational structures, which
average the two parents’ structures. We introduced small random mutations in the child
organizations by rewiring some of the connections between employees. Setting a maximum
probability of changing a given connection at 5\% ensured that the evolution did not stop
prematurely, allowing us to explore the maximum number of configurations. This proce-
dure was repeated until there was no further change in the elite pool for ten consecutive
generations. We then recorded the structures of the top-performing organizations. We ran
this procedure for each of the 32 combinations of parameters (4 levels of complexity x 4
levels of turbulence x 2 modes of work) to obtain the results. To measure the differences
between the organizational structures best adapted to FTF and RW, we recorded the
average_degree (the average number of connections per employee), path_length (average geodesic distance between any pair of employees), and modularity. Specifically, to obtain the modularity measure, we ran a community detection algorithm to partition the graph using the Louvain method (Blondel et al., 2008). The resulting modularity measure is the observed fraction of edges inside subgroups minus the expected value for such a fraction in equivalent random graphs (Newman 2006). In our case, modularity ranges from 0 to 1, where 1 means the structure is fully modular with no edges connecting the subgroups, and 0 corresponds to a random structure. The detailed numerical results can be found in Figure 3. Figure 4, in turn, presents examples of optimal organizational structures in each scenario identified by the GA.

The results present several important insights. First, under negligible levels of complexity and turbulence, a structure with a few semi-isolated teams is optimal for both work modes, as average_degree, path_length, and modularity remain roughly the same (Figure 3).\(^9\) There is also little difference between examples shown in Figure 4, panel a).

With increasing complexity (Figure 4, Panel b), the number of connections rises for both work modes compared with a stable and simple environment, but there is also a more pronounced decrease in modularity with RW (Figure 3 and Figure 4, panel b). Interestingly, the organizational structure adjustment helps counter the shift to RW almost entirely in terms of performance (fitness drops from 0.84 to 0.83).

A similar situation occurs with low complexity but higher turbulence (Figure 4, Panel c); however, the optimal organizational structure is much flatter for RW, with a pronounced increase in average_degree, reduction in path_length, and a sharp decrease in modularity

\(^9\) In our discussion of the results, we will use “optimal” to denote the best organizational structure obtained through the GA. This is a simplification, as these are approximations of the optimal structure. Identifying the optimal structure is an NP complete problem, i.e., the optimal solution cannot be determined algorithmically due to a huge number of possible permutations (Rivkin 2000).
Figure 3  Selected structural metrics from GA analysis.

Note: The figure shows the fitness and main measures of the optimal structures for FTF and RW conditions, which are the best performers in the last generation of our GA. Fitness (panel a) is the normalized organizational performance at the end of $t$ periods, with 1 representing all employees having discovered and converged on the global peak. Average_degree (panel b) is the average number of edges per node. Path_length (panel c) is the average geodesic distance between all possible pairs of nodes in the graph. Finally, modularity (panel d) captures the relative density of intra-subgroup links versus inter-subgroup links (Newman 2006) when subgroups are detected with the Louvain modularity-greedy method (Clauset et al. 2004).

(Figure 3). Furthermore, the analysis again demonstrates that reorganization can be a powerful tool in accommodating RW in an organization. Shifting to a new optimal form helps to restore previous performance levels (fit of 0.99 vs. 0.98).

Under high complexity and turbulence (Figure 3 and Figure 4, Panel d), optimal structures for both work modes exhibit high connectivity (high average_degree and short path_length) and a high level of structural integration (low modularity). However, in a turbulent and complex environment, rearranging organizational structure can no longer fully counter the effects of a drop in $p$ resulting from the shift to RW, and performance (fitness) drops from 0.78 to 0.7.
Overall, these results suggest that in settings characterized by low turbulence and low complexity, *few or no, interventions to the organizational structure will be needed to accommodate the shift to RW.* At least from an organizational learning perspective, some of the recommendations to always increase interactions among remote workers may have to be reconsidered. Perhaps some activities can be initiated to maintain the structure from before the shift to RW, but not much more. However, in the presence of complexity, organizations that rely on well-defined, integrated teams may need to dissolve some of those boundaries to create additional avenues for knowledge flows. However, the most significant change occurs in highly turbulent environments where many more connections must be added to counteract the overall drop in knowledge transfer. While the distributed struc-
tures of semi-connected FTF teams are superior in turbulent environments, much denser structures must be induced after a shift to RW. This result suggests that organization designers should go beyond simple restorative actions and consider reducing the isolation of different subunits and flattening their organizational structures.

4.5. Robustness checks

To check the robustness of our results to alternative model specifications we ran the model with different values of $p$ for FTF and RW ($p = [0.8, 0.2]$ and $p = [0.6, 0.4]$ for FTF and RW, respectively). We also tested alternative sizes of the organization ($m = \{6, 20, 60\}$), other organizational structures (fully connected graph, one- and two-star graphs, random graphs with different edge probability values, lattice and caveman archetypes with different rewiring probability values), and different specifications for the GA (fitness-based vs. rank-based, linear vs. non-linear probability of selection, different values of mutation rates and elitists). The results were qualitatively the same.

5. Discussion and Conclusion

To our knowledge, this study is the first to provide systematic insights into the long-term impact of RW across a representative spectrum of organizations—arguably one of the most pressing issues facing managers today. Building on two well-established computational modeling platforms to capture interactions between individual- and organizational-level dynamics, we simulated a battery of scenarios to advance our understanding of how RW will impact a wide variety of organizations facing different environments and suggest ways in which organizations may deliberately adjust their internal structures to adapt to RW.

We find that the increasingly common prescription offered to managers to embrace RW can significantly hurt learning and performance in some organizations. By identifying specific mechanisms and conditions that can drive these effects, we also show that some
of the strategies that have been suggested to improve performance under RW, such as organizing intra-organizational get-togethers to increase the number of interactions among remote employees, may, in some cases result in worse performance. Our paper thus extends the prior discussion of the effects of remote work by accounting for critical organizational-level factors that have thus far been overlooked, such as the nature of the task environment and organizational structure.

Our paper makes several contributions. First, we present direct and immediate ramifications for both scholars and managers concerning the impact of remote work on organizational learning and performance. We highlight the importance of the context as it conditions the degree to which extant empirical studies may generalize across different scenarios. In particular, the impact of RW on a given firm will be biased depending on a) whether measurements are made at the individual vs. organizational level, b) the degree of complexity and turbulence in the task environment, and c) organizational structure. We show that RW can, on average, benefit companies operating in simple and stable environments but harm those in complex and turbulent environments. We then used classic organizational forms and algorithmically generated graphs to show that these average effects can be further decomposed once we take organizational structure into account. For example, an organization with semi-isolated teams handles RW best in very high and very low complexity/turbulence environments. Conversely, flatter, less modular forms perform best under modest complexity and turbulence.

Our paper also calls for urgent follow-on research to develop a targeted and coherent body of knowledge on the topic of RW. It provides a roadmap for both theoretical and empirical scholars to pursue, connecting individual and organizational dynamics and internal and external factors. As evident from our review of the related literature, there is little
direct study of RW at the organizational level and much ancillary work that offers conflicting perspectives on what its impact may be. Similarly, while we recognize the difficulty of conducting detailed studies on a large sample of firms, our results caution against simple extrapolations from findings conducted in a single-firm setting.

Our paper also contributes to the organizational design literature. While the modeling approach prevents us from predicting the direction in which the organizational structure will change through informal networks in response to a shift to remote work (such would ultimately be an empirical question), we highlight two important factors. First, our study suggests that the eventual changes in organizational structures will depend on the initial conditions, like the nature of the task environment and the original organizational structure. Second, we show the direction towards which an organizational designer should push the structure of interactions in their organizations to counter the effects of decreased information transfer. Thus, we don’t model what will be but rather what ought to be concerning organizational structure. Third, we contribute theoretically by clarifying why RW in and of itself should not be considered a form of formal decentralization. Decentralization connotes the transfer of authority and power from the central (or higher level) to a lower hierarchy level (Milgrom and Roberts 1992). We point out that in terms of formal lines of authority, RW implementation does not need to correlate with decentralization. This is a critical clarification to guide future work because some recent scholars have equated the two (e.g., Zhang et al. 2021), and there is a vast body of work looking at trade-offs between centralization and decentralization, with findings that might be erroneously extrapolated to the dynamics of RW.

Our results suggest that for many organizations, especially those operating in complex and dynamic environments, a full or partial shift to RW should be accompanied by interventions beyond occasional company get-togethers and online networking events and may
require more profound changes to the company’s structure. However, given the pressure on managers to quickly implement permanent RW policies across the world, it is likely that many firms will adapt by copying practices from firms that they consider their peers (DiMaggio and Powell 1983). Our paper can help firms better identify which peers are most similar to them on the relevant dimensions and should encourage them to think carefully about what their structure is and whether or how much it can be adjusted. At an extreme, our findings are intuitive; for example, it would make little sense for a pharmaceutical firm to emulate the RW practices of a call center, no matter how successful they may have been for the call center because their activities differ so much. However, in practice, most firms will face comparison sets that are much more subtly differentiated or consider advice that has been separated from its original setting. Our study provides a much-needed checklist of internal and external factors to consider.

This paper also contributes to the organizational learning literature. We combine an agent-based model of organizational learning with a model of complexity that introduces substitution effects between the decision variables in the environment. This, together with the use of a genetic algorithm, allows us to examine a large number of permutations of key variables, like complexity, turbulence, learning speed, and organizational structure, to examine the efficacy of organizational learning in the face of RW. Our work thus extends prior research that has only looked at narrower subsets of these conditions (March 1991, Lazer and Friedman 2007, Fang et al. 2010, Clement and Puranam 2018). Our analysis shows that many of the prior findings are contingent on the type of interdependencies in the environment, learning speed, or organizational structure.

A limitation of our study is that it relies on a computational simulation platform, which may omit other relevant real-world dynamics or factors. In other words, unlike real workers,
our simulated agents are not driven by things like affect, homophily, status, bias, etc. However, this allows us to focus on the role of organizational structure and the specific features of the task environment in isolation. We further mitigate this concern by relying on two well-tested and understood modeling platforms in the management literature, previously used to study organizational learning and adaptation under complexity, namely the March (1991) and NK models. In the immortal words of George Box, “All models are wrong, but some are useful” (Box 1979, page 202). Indeed, computational models have recently proved particularly useful in guiding the global response to the COVID-19 Pandemic under extreme uncertainty and complexity conditions and with no access to relevant data that could be used to predict the evolution and impact of the disease. We hope that, while imperfect, our modeling effort will serve as a helpful step towards a deeper examination of the impact of RW on the functioning of organizations.

In sum, we offer new insights into the debate about the likely implications of RW for both individuals and organizations. Our findings provide specific, actionable insights for managers dealing with RW—whether they want to or not. It is important to note that this impacts “managers” well beyond the traditional corporate context and encompasses everyone from school administrators to small shop owners, civil servants, and of course, run-of-the-mill CEOs. Our work contributes to this critical area at a time when decisions about the nature of the future global workforce are being made around the world.

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