Organizational Culture, Adaptation, and Performance

Francisco Brahm and Joaquin Poblete[1]

This version: January 2024

Abstract

Prior research has emphasized how organizational culture can hinder organizational adaptation. In this study, we investigate how organizational culture can help promote organizational adaptation to environmental changes, using a formal model from cultural evolution theory. In the model, organizational members face a trade-off between innovating versus following tradition (because environmental changes are uncertain). Members can also decide to help others who are following the tradition, thereby improving its diffusion. Organizational leaders shape the culture of their organization, which influences members' decisions to choose innovation or tradition, or to help others following tradition. Culture comprises two dimensions: beliefs and prosocial values. We find that increasing the accuracy of beliefs leads to improvements both in innovation and in following tradition, thereby mitigating the trade-off between them and boosting adaptation and performance. On prosocial values, we find that increasing their intensity reduces the cost of following tradition, but at the expense of reduced adaptation, resulting in an inverted-U relationship between intensity of prosocial values and performance. Overall, we show how leaders can fine tune the dimensions of organizational culture to foster improvements in adaptation and performance. The formal model we introduce is novel to the literature and offers a way of studying adaptation to a changing environment, and to incorporate social learning into models of adaptation under bounded rationality.

Keywords: beliefs; cultural evolution; learning; organizational adaptation; organizational culture; prosocial values

Running header: Organizational culture and adaptation

[1] Brahm: London Business School, 26 Sussex Pl, London NW1 4SA, UK, fbrahm@london.edu (corresponding author); Poblete: School of Management, Pontificia Universidad Catolica de Chile (PUC), Av. Libertador Bdo. O'Higgins 440, 4to piso, Santiago 8331010, Santiago, Chile, joaco.poblete@gmail.com.

1. Introduction

Over the last few decades, research on organizational culture—broadly defined as the beliefs and values shared by organizational members—has been accumulating across diverse fields of academic inquiry (for organization theory, see Weber and Dacin 2011, Giorgi et al. 2015; for strategy, see Gibbons et al. 2021b; for organizational behavior, see Chatman and O'Reilly 2016, Srivastava and Goldberg 2017, Hartnell et al. 2011, 2019; for finance, see Grennan and Li 2022, Gorton et al. 2022; for economics, see Hermalin 2012). For this literature, it is self-evident that organizational culture affects performance. Recent evidence from firm executives confirms this: 91% of 1,348 senior executives in North America agree that culture is important for performance at their firm (Graham et al. 2022). However, several authors in this field suggest that, despite progress, there is much work to be done to understand the mechanisms through which culture affects performance (Chatman et al. 2014, O'Reilly and Chatman 2016, Chatman and Srivastava 2021, Gibbons et al. 2021b, Grennan and Li 2022).

In this paper, we use a formal model drawn from cultural evolution theory (Cavalli-Sforza and Feldman 1981, Boyd and Richerson 1985, 2005; Brahm and Poblete 2022) to study how organizational culture affects a relatively understudied mechanism, namely, an organization's capacity to adapt to environmental changes. Existing work in organizational adaptation (see the reviews by Eggers and Park 2018, Sarta et al. 2021) and in organizational culture (Sorensen 2002, Van den Steen 2010b, Hermalin 2012, Corritore et al. 2020) tends to emphasize the limitations that organizational culture imposes on organizations' ability to adapt. These limitations may stem from shared beliefs and values that focus excessively on the status quo and fail to recognize unfolding changes that call for adaptation (Eggers and Park 2018), or from shared beliefs and values that limit diversity, which is a fundamental ingredient for the experimentation needed to change and adapt (e.g., Corritore et al. 2020). For the most part, the literature has not explored whether—and how—culture can help organizations adapt to environmental changes. (We are aware of two exceptions, Chatman et al. (2014) and Gibbons et al. (2021c), which we will discuss below.) In this paper, we address that gap and show how culture, via improved adaptation, can improve performance.

In our formal model, adaptation works as follows. An organization operates in a changing environment; therefore, organizational adaptation is central to organizational performance. Organizations adapt via two types of learning. On the one hand, organizations adapt when its members choose *individual learning* (or "innovation"), which entails a costly trial-and-error effort to obtain the knowledge or technology that is adaptive for the current state of the environment. On the other hand, organizations adapt by diffusing this knowledge or technology internally, which occurs when members choose *social learning*—copying/imitating what others are doing (or following "tradition"). Crucially, it is difficult to discern whether a change has occurred in the environment; this creates a dilemma for organizational members, who must choose either to follow the less costly but potentially obsolete tradition (social learning), or to pursue the more costly but precise innovation (individual learning). The organization's leaders cannot discern whether an environmental change has occurred, but they can influence the organization's culture, which in turn affects its members' choice between tradition or innovation—and, thus, the organization's level of adaptation and performance.

In addition to the type of learning choice, when they are being copied by social learners, organization members in our model also decide whether to exert costly effort in helping them learn better (e.g., guidance, teaching) and thereby make following tradition less costly, or "more efficient." Because the benefits flow to social learners, this effort is altruistic and thus entails a social dilemma: although beneficial for the organization, it goes against the self-interest of the organization's members. As with the type-of-learning decision, this choice is also influenced by the culture set up by the organization's leaders.

Following Schein (2010) and others,[2] we conceptualize organizational culture as possessing two broad "dimensions" that organizational leaders can influence: *causal beliefs* about the problem the firm

---

[2] Kocak and Puranam (2023) distinguish between causal codes and moral codes in culture, and DiMaggio (1994) distinguishes between constitutive beliefs (taken-for-granted cognitive categories and schema necessary for parties to think) and regulative beliefs (norms, values, and conventions that may reshape an individual's pursuit of self-interest). Although Kocak and Puranam (2023) remain agnostic with respect to the content of moral codes, research in evolutionary anthropology shows that cooperation and pro-sociality is a very important and recurrent feature of moral codes across cultures around the world (Curry et al. 2019).

solves and the associated mean-ends relations (i.e., if we do 'A,' we obtain 'B'); and *prosocial values*, that is, how much helping colleagues, contributing to the whole organization (rather than focusing on one's own payoff), and being a good citizen are prioritized and emphasized by the organization.

Regarding causal beliefs, we draw from research on organizational cognition (Barr et al. 1992, Tripsas and Gavetti 2000, Tripsas 2009, Eggers and Kaplan 2009, 2013; Helfat and Peteraf 2015) that shows that causal beliefs, as a representation of underlying reality (March and Simon 1958, March 1991, Puranam 2018), can have a different level of *accuracy* or verisimilitude (ibid). Our model's analysis shows that belief accuracy allows the organization to better interpret signals from its interaction with the environment and, thus, better decide when to innovate—that is, innovate when the environment has changed. In addition to this direct effect, a secondary effect of accurate beliefs on adaptability operates through improving tradition. Improving the timing of innovation (i.e., innovating during periods of change) produces both a better timing of social learning (it occurs increasingly during periods of stability) and an overall increase in the percentage of organizational members that use it. Thus, the less costly learning strategy is used more frequently, which reduces the overall costs of carrying a tradition in the organization, and with better timing, minimizing its downside (i.e., adopting outdated knowledge/technology when the world changes). Further, having more members doing social learning promotes an increase in helping effort because its marginal benefit increases; this makes tradition even more efficient. In summary, these two effects of more accurate beliefs —"better innovation timing" and "more and less costly tradition"—improve adaptation and performance by making both innovation and tradition work better, minimizing their trade-off. These results speak to the classic tension of exploitation and exploration (March 1991, Benner and Tushman 2006, O'Reilly and Tushman 2013), in which organizational culture has been hinted, but not developed, as a potential solution (see O'Reilly and Tushman 2013, p. 239).

Regarding prosocial values, we draw from research showing that organizations vary in the intensity with which they value prosociality (Organ et al. 2005, Rand and Nowak 2013, Bolino and Grant 2016, Fehr 2018, Francois et al. 2018). We find that increasing this intensity makes the organization's

tradition—its accumulated practices, skills, technology—more efficient. This is because more intense prosocial values generate rewards (e.g., reputation, prestige, pride) that boost the altruistic effort of organizational members in helping the social learners. This lowers the cost of transmitting tradition, improving performance and buffering the organization from environmental changes. However, by promoting tradition, the intensity of prosocial values crowds out the capacity of the organization to innovate and track the environment, rendering it increasingly vulnerable to environmental changes; if intensity is sufficiently high, this effect overwhelms the efficiency gains in transmission of tradition, and performance suffers. Thus, against received wisdom—pro-sociality having a positive and *monotonic* relation with performance (Organ et al. 2005, Rand and Nowak 2013, Fehr 2018, Liao et al. 2022)—the intensity of prosocial values displays an inverted-U relationship with organizational performance.

The formal model also allows us to analyze how beliefs and prosocial values interact in affecting performance, something that eluded prior research (cf., Schein 2010). Our analysis shows that accuracy of causal beliefs and intensity of prosocial values are complementary: the impact of each cultural dimension on performance is more positive (or less negative) if the other one increases. Although not obvious a priori, the model provides a clear intuition: well-timed innovation produced by accurate beliefs produces more benefits when paired with a more efficient internal diffusion of innovation (driven by more intense prosocial values).[3] We are not aware of prior research exploring the interaction between these two dimensions of organizational culture.

We offer two main contributions to the literature. First, we expand recent work that studies the relation between beliefs, prosocial values and organizational adaptation. Regarding beliefs, prior literature shows that a strong culture—i.e., shared beliefs held intensively—promotes efficiency but limits diversity and thus restricts an organization's capacity to explore and adapt to environmental changes (March 1991, Sorensen 2002, Van den Steen 2010b, Hermalin 2012, Corritore et al. 2020).

---

[3] This also operates in the reverse direction: Efficient transmission of tradition driven by prosociality is more valuable when that tradition can be updated in a timely fashion when changes occur (by way of accurate beliefs).

However, our results suggest that if the shared beliefs are accurate, adaptation improves; this effect can counteract the loss from lack of diversity and, thus, cultural strength need not come at the expense of adaptation. Furthermore, our theory addresses some limitations of prior work that has studied how organizational culture can favor adaptation (Chatman et al. 2014, Gibbons et al. 2021c; see section 2.3 for details). Regarding prosocial values, we join a nascent stream of papers (Chatman et al. 2019, Hergeux et al. 2021) that is uncovering a "dark side" of overly intense prosocial values, namely that they can reduce performance by compromising the organization's capacity to adapt to changes. Taken together, our findings provide guidance on how organizational culture can improve adaptation to changes.

Our second contribution is to introduce a formal model from cultural evolution theory (Cavalli-Sforza and Feldman 1981, Boyd and Richerson 1985, 2005; Mesoudi 2017, Boyd 2018, Henrich 2016, 2020, Brahm and Poblete 2021, 2022) to the literature on organizations. Our model (like most cultural evolution models) is consistent with the Carnegie school (CS) tradition by emphasizing bounded rationality and adaptation via learning. We contend that our model can be a fruitful addition to the menu of formal models in this tradition (see Puranam et al. 2015 for an overview of models in the CS spirit) as it allows for expanding the set of phenomena that can be formally studied. In particular, unlike the CS tradition—which focuses on adaptation to a fixed but unknown and potentially complex environment—our model, at its core, is about adaptation to a constantly changing environment. Furthermore, our model (and cultural evolution models in general) focuses on social learning, contributing technique, evidence, and theory on a phenomenon that has been relatively neglected by the CS in favor of individual reinforcement learning (the main exception being March 1991 and its follow-up by Fang et al. 2010).

2. Literature background

2.1. Formal models of organizational adaptation and organizational culture

Organizational adaptation is a concept with a long and important history (Lawrence and Lorsch 1958, Cyert and March 1963, Chakravarty 1982, Levinthal 1997, Sarta et al. 2021).[4] The CS tradition has used formal models to study organizational adaptation (see Puranam et al. 2015 for an overview), and we share with CS an emphasis on bounded rationality; the imperfect representations of the underlying reality; learning as behavioral tool to navigate and adapt to an uncertain world; a focus on how the population evolves out of simple rules of behavior; exploration triggered by performance feedback (i.e., problemistic search); and the emphasis that, at the core of organizational adaptation, there is a tension between the "exploitation of old certainties" with the "exploration of new possibilities" (March 1991, p. 71). However, our model (like cultural evolution models in general) differs from the CS tradition in two important ways.[5]

The first difference is that in cultural evolution the environment is constantly changing; in contrast, in the CS tradition the focus is on a fixed but unknown, and potentially complex, environment. Of course, in the CS the environment can change (and some researchers have explored that), but it is not the central/defining feature of the environment (as it is in cultural evolution).

The second difference emanates from the first. In a fixed environment an agent can learn from his/her own actions in order to slowly but surely "discover" what works (even if the environment is complex); accordingly, reinforcement learning (a type of individual learning) is emphasized in the CS. In contrast, when the world is changing, agents' fitness drops severely after a change occurs, and thus reinforcement learning might not be ideal. Instead, the game is about using a more expensive and

---

[4] The review by Sarta et al. (2021) defines organizational adaptation as "intentional decision making undertaken by organizational members, leading to observable actions that aim to reduce the distance between an organization and its economic and institutional environments" (p. 44).

[5] In addition to these two substantive differences, cultural evolution models also can contribute on the "technical" side. In addition to simulations, which are central to the agent-based models of the CS, cultural evolution models also rely on analytical solutions to a model's equilibrium using the concept of evolutionary stable strategies (ESS). In a model with a constantly changing environment, behavior does not converge toward a "set/immutable" behavior, and thus using simulation analysis alone may not be enough; instead, behavior "circles around a point of attraction" described by the ESS and, thus, this solution technique (or equilibrium concept) is necessary.

effective individual learning, which can pull back the agent more quickly when the world changes (compared to reinforcement learning), versus relying on what others have been doing (i.e., social leaning) when the world is stable. Given that it is difficult to recognize when the world has changed, a fundamental trade-off arises for agents: rely on less costly but vulnerable-to-change social learning versus more costly but adaptive individual learning. Thus, *cultural evolution models bring to the forefront social learning as an alternative strategy to individual learning*. Cultural evolution models have developed a sophisticated understanding of social learning (Kendal et al. 2018), which allows them to study the phenomena of tradition, culture, habit, and other socially transmitted behaviors that have been largely neglected by the CS in favor of an emphasis on decision making and reinforcement learning (under bounded rationality) (see the "critique" by Cohen 2007a, b). In the CS tradition, social learning has been modeled using the approach proposed by March (1991); another (small) strand is imitation in NK models, started by Rivkin (2000). However, compared to the voluminous literature on Bandit, NK, coupled learning/search, project screening, and other model types (Puranam et al. 2015), research expanding March's model has been meager (Wilden et al. 2018).

The CS model closest to ours is March (1991) and its follow-up by Fang et al. (2010), as it focuses on social learning. As we discuss in more detail below in section 4.2, our model differs from that of March (1991) in that the trade-off between tradition and innovation (or, exploitation and exploration) arises from a different source. In March (1991), the trade-off arises from the tension between having homogeneity versus diversity of beliefs across members in the organization. In our model, the organizational culture's beliefs and values are homogeneous across members by default, and the trade-off arises from assuming a tension/dilemma when members choose between (accurate but expensive) innovation and (cheap but possibly outdated) tradition when change is uncertain and difficult to decipher. In a sense, the trade-off between tradition and innovation (or, exploitation and exploration) that March explains is a "point of departure" in our case, because it is deeply embedded in the basic mechanics of how agents operate in our model.

Regarding previous models of organizational culture, an important share of the work has been done in organizational economics (Hermalin 2012 for a review). Some notable efforts are: Cremer (1992), who focuses on the role of common language, knowledge and routines; Van den Steen (2010a), who studies the emergence of shared (and homogeneous) beliefs via self-selection of workers; Gibbons et al. (2021a), who study how shared cognition in the form of mental frames constrains or enhances the performance level that agents can attain; and Kreps (1990) and Gibbons et al. (2021c), who view the repeated-game equilibrium as a shared understanding of "how things are done," that is, general principles/beliefs about proper behavior. We differ from these models in that they assume rationality and use optimization or (classical) game-theory methods (whereas we assume bounded rationality), and in that they focus on the homogeneity of beliefs arising from heterogeneous agents whereas we assume homogeneity in the beliefs and values of the organizational culture; as before, these models are our "point of departure" for the assumption of culture homogeneity in our model. The models by Dessein and Prat (2022) and Besley and Persson (2022) are closer in spirit to ours: while retaining optimization assumptions and a concern for shared beliefs, they add dynamics and evolutionary elements (e.g., a birth and death process) to their analysis.

Beyond economics, our model is close to the Harrison–Carroll model of organizational culture (Harrison and Carroll 1991, 1998, 2001), which focuses on the transmission of culture by specifying a socialization function, which, similar to ours, allows for influence both from the top (e.g., ideal culture that management advocates for) as well as from peers (e.g., what others believe, on average). Unlike ours, the Harrison–Carroll model does not specify performance consequences for culture; instead, they complement socialization processes with hiring, turnover and (exogenously determined) growth, and study the properties of the equilibrium culture that arises (e.g., time to equilibrium, homogeneity versus heterogeneity of beliefs) with the purpose—in the original 1991 paper—of characterizing the culture that emerges in different organizational forms, such as the Japanese "long-term" organizations, government bureaucracy, and American "arm's-length" corporations.

2.2. Two basic dimensions of organizational culture

Schein's influential book *Organizational Culture and Leadership* (2010), defines culture as "a pattern of shared basic assumptions that was learned by a group as it solved its problems of external adaptation and internal integration, that has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, and feel in relation to those problems" (p. 17). According to this view, organizational culture has two essential dimensions (namely, *external adaptation* and *internal integration*), which are sufficiently distinct and rich to consider and analyze separately (as Schein does in his 2010 book). All organizations face the following two generic problems, which are reflected in their culture: identifying and understanding their "role for society" (external adaptation—what problems they solve) and "how they come together as a group" (internal integration—social rules). We call the former "beliefs" and the latter "prosocial values."

2.2.1. Causal beliefs (of varying accuracy)

Beliefs related to external adaptation are those that define a "basic sense of core mission, primary task, or 'reason to be'" (Schein 2010, p. 89), plus all the beliefs about aspects, as conceptualized by Schein, that derive from having a mission, namely: *goals* ("here, we believe X is the crucial goal"), means ("here, we believe that in order to achieve X, doing Y is crucial"), *measurement* ("here, we believe on a specific criteria Z and a specific review process to track progress"), and *correction* ("here, we take action W when V happens").[6] We refer to these as "causal beliefs." These beliefs are similar to what Kocak and Puranam (2023) refer to as "causal codes," which "map actions to their consequences" and that are related to the concept of "representations in behavioral strategy, which refers to agents' understanding of their task environment, connecting actions to their payoffs" (p. 5). This way of understanding causal beliefs of agents is also similar to the idea of the "theory of the business" in some recent work in strategy (Drucker 1994, Zenger 2013, Felin and Zenger 2017).

---

[6] Most of the elements in "means" and "measurement" could be labelled as "practices" amenable to formalization and codification (e.g., functional practices in sales, finance, HR). However, these are "culturally" produced in the sense that, as highlighted by Gibbons and Henderson (2013), they do not necessarily rely on formal contracts. Instead, due to many of the subtleties involved in creating them, these elements frequently rely on informal understandings rooted in principles and beliefs.

In contrast to previous formal models of culture—which have tended to focus around the emergence of shared beliefs from heterogeneous individuals—in our model all individuals share the same causal beliefs (i.e., culture is maximally "strong") and then we vary the verisimilitude/accuracy of these beliefs. To justify varying belief accuracy, we rely on the organizational adaptation literature showing that: (i) organizations vary in their capacities to adapt (Ahuja and Katila 2003, Teece 2007, Helfat and Martin 2015); (ii) an important determinant of this capacity are the cognitive representations (i.e., beliefs, mental models, dominant logics, cognitive frames) that managers, and the organization in general, have about the environment, about itself and what it is capable of (Barr et al. 1992, Barr 1998, Tripsas and Gavetti 2000, Tripsas 2009, Danneels 2011, Eggers and Kaplan 2009, Helfat and Peteraf 2015, Eggers and Park 2018); and that (iii) cognitive representations differ in their degree of accuracy or verisimilitude (i.e., the degree to which they correctly reflect the underlying reality), and the more accurate/verisimilar they are, the better for adaptation (Barr et al. 1992, Tripsas and Gavetti 2000, Eggers and Park 2018).[7] The latter is consistent with the CS view of bounded rationality, in which agents have an imperfect representation of the world that they update via learning over time and thus, can have different degrees of verisimilitude or accuracy (March and Simon 1958, March 1991, Puranam 2018).[8]

2.2.2. Prosocial values (of varying intensity)

The cultural dimension of internal integration refers to all aspects that determine how the group comes together (Schein 2010), such as language (i.e., concepts and categories the group uses), boundary and membership (e.g., what defines group membership, necessary/legitimate credentials), power/status (e.g., who is admired), values regarding cooperation and mutual help (e.g., level of cooperation-

---

[7] For example, Eggers and Park (2018) indicate in their review that "cognition and identity *incompatible* with a new technology hinder the acquisition of new knowledge or assets" (p. 363; emphasis added) but also that "*adequate* cognitive frame or vision of management, however, can also reverse the firm's fate and lead to successful adaptation" (p. 368; emphasis added)

[8] As Puranam (2018) states: "Cognitive representations are conceptual structures in individuals' minds that encapsulate simplified understanding of the reality these individuals face […] However, representations are *imperfect* [and] […] learning may lead individuals to learn the *wrong lessons* from experience and fall victim of *superstitious learning*. […] However, representations held by an agent need not be perfect (even if that was ever possible) to be useful. They may be *better than*, or at least not worse, than that of others" (pp. 27, 29, 30; emphasis added).

prosociality versus individualism-competition), and rewards and punishment (e.g., what informal rules regulate salary levels and changes).

In our model, we focus on one central element of this dimension, namely the values around cooperation and helping other group members—prioritizing the group rather than the self, and displaying honesty, trust, and goodwill towards group members (Organ et al. 2005, Bowles 2009, Rand and Nowak 2013, Bolino and Grant 2016, Fehr 2018). We call these "prosocial values." A central focus of the literature is trying to explain why some groups display intense prosocial values. There are many theories and mechanisms that can support prosociality within groups: for example, Francois et al. (2018) points to the intensity of inter-group competition, Barnard (1938) to leadership, and Nowak and Sigmund (2005) to reputation (for reviews, see Rand and Nowak (2013), Bolino and Grant (2016), and Henrich and Muthukrishna (2021)). Thus, it is natural to focus in our model on the intensity of these prosocial values: We exogenously vary their intensity and focus on the downstream consequences in terms of behaviors, adaptation, and performance.

2.3. Organizational culture and adaptation

In this section, we survey how the literature has addressed the impact of organizational culture on organizational adaptation.

The literature in organizational culture has shown, via theoretical models (Cremer 1993, Van den Steen 2010a, Fehr 2018, Gibbons et al. 2021a) and robust empirical evidence (Sørensen 2002, Weber and Camerer 2011, Chatterji et al. 2016, Marchetti 2019, Marchetti and Puranam 2020, Corritore et al. 2020, Grennan 2020, Grennan 2022, Graham et al. 2022,), that high consensus/intensity in causal beliefs (i.e., a strong culture) has a positive impact on the alignment of expectations, the smoothness of communication and coordination, and the overall efficiency of the organization. However, this generates a trade-off: A strong culture, by limiting diversity and thus the exploration of new/innovative ideas, constrains the capacity to adapt to environmental changes (March 1991, Sorensen 2002, Van den Steen 2010b, Hermalin 2012, Corritore et al. 2020).

Two papers in the literature have tried to propose ways in which organizations can break away from the "cultural strength trade-off": Chatman et al. (2014) and Gibbons et al. (2021c).[9] Chatman et al. (2014) argues that a strong culture may favor adaptation by strongly emphasizing adaptability in its content. A limitation of assuming adaptability in the culture's content is that adaptability is relevant in some settings (such as high tech) but not others (such as stable and mature industries). Our model does not prescribe a specific content for causal beliefs, and thus we do not "assume away" the trade-off.

Gibbons et al. (2021c) draws from Kreps (1990), who interpreted a repeated-game equilibrium as a shared understanding of "how things are done"; this usually takes the form of general principles/beliefs about proper behavior (e.g., "when in conflict, always defer decision making to the senior party," "seek fairness within the organization," "prioritize customers") to argue that when the circumstances change (e.g., a change in payoffs of the game) and agents must adapt in response, the presence of principles/beliefs provided by culture ("how things are done here") allows agents to know what to expect from others' behavior, thereby facilitating mutual adaption into a new equilibrium. In simple terms, shared principles/beliefs act as "focal points" that facilitate coordinated adaptation among agents. Li et al. (2021) provides supportive empirical evidence exploiting the COVID shock. A limitation of this idea is its assumption that change is immediately and effortlessly understood by all agents involved. In the real world, however, change is quite often far from obvious. Organizational members may not know whether the signals they are receiving (e.g., a drop in sales, a change of customer type, a drop in profitability, worse customers reviews) point to a change in the environment or are simply noise. Answering the question "do we need to adapt?" is not easy, as it is endogenous to hard-to-falsify causal beliefs. Our model provides a role for culture in answering this question: More

---

[9] There is a third way in which culture can facilitate adaptation without necessarily sacrificing strength (and thus, coordination and efficiency), which is the idea of culture as a toolkit (Swidler 1986, Howard-Grenville et al. 2020); that is, people have more beliefs and values than those currently being displayed/used and thus can rely on that deeper repertoire to adapt when change strikes. Lix et al. (2022) provide evidence in favor of this view, showing that teams can modulate their "group cognition" to fit the demands of different tasks: more diverse when innovation is required, and less diverse when coordination is required.

accurate causal beliefs allow for better signal interpretation and, thus, to choose innovation when it is most required.

Regarding prosocial values (the second half of organizational culture), recent efforts in the literature are uncovering how, contrary to received wisdom, prosocial values are not monotonically associated with higher performance because, if overly intense, they can reduce performance by compromising the capacity of the organization to adapt to changes (Hergeux et al. 2021, Chatman et al. 2019). On the received wisdom of a positive–monotone relationship, we can point to the big literature that has developed showing that prosociality—understood broadly as organizational members helping one another (Barnard 1937, Rand and Nowak 2013, Fehr 2018, Francois et al. 2018, Henrich and Muthukrishna 2021), favoring the collective instead of the individual (Akerlof and Kranton 2005, Chatman et al. 2019), and being a good organizational citizen (Organ et al. 2005)—increases members' efforts toward organizational goals and thereby increases the organization's performance. However, Chatman (2019) indicates that "examining the empirical research more closely, however, reveals that the seemingly obvious relationship between collectivism and group performance is neither straightforward nor entirely robust […] [and that] despite decades of research, researchers still do not fully understand how collectivism influences group performance" (pp. 236–236). Chatman et al. (2019) argues (and empirically demonstrates) that the downside of collectivism—which they define equivalently to how we define prosociality—is that it can limit performance in certain tasks that require constant adaptation to changing circumstances; they point to prosociality blurring perceived individual differences and thus reducing the capacity to draw from diverse ideas, skills, and backgrounds. Our paper complements Chatman et al. (2019) in emphasizing the costs of prosociality in terms of reduced adaptation. In our model, we fully blur differences—all agents are the same—and thus, we add an additional layer: if sufficiently intense, prosociality can be detrimental to performance because the gains from a more efficient tradition are not enough to compensate for the losses in adaptation produced by the crowding out of innovation.

3. The model

We base our model on a workhorse model of cultural evolution labelled "selective learning" (Boyd and Richerson 2005, chapters 1 and 2; Boyd 2018), a model of adaptation to changes via learning.

Our model revolves around three endogenous variables that capture behavior and adaptation, two culture parameters, and one parameter that reflects the environment uncertainty. The three endogenous variables are: (i) the share of agents that have the technology that is appropriate for the state of nature, denoted by r (this can also be understood as the "stock of adaptive knowledge/technology" in the organization); (ii) the extent that learning is guided by innovation (or, individual learning) versus following tradition (or, social learning), which is regulated by d; and (iii) the helping effort that agents exert in diffusing tradition, denoted by a. The two culture parameters are: (a) the "causal beliefs" (i.e., beliefs about the role of the organization, the problems they solve and how they create value), denoted by λ; and (b) "prosocial values" (i.e., the emphasis placed on prosocial behavior, helping others, citizenship, etc. denoted by μ. The parameter of environmental uncertainty (i.e., the likelihood of a change in the environment) is captured by p. At equilibrium, the three endogenous variables define one another, and the equilibrium, in turn, is affected by the three exogenous parameters.[10]

When introducing these three variables and three parameters, and the mechanics of the model, we will use a running example to better convey the model's intuition. We will use the example of a sales force where individual salespersons sell goods and services to customers, have a selling technique/technology that they obtain via learning, receive a performance signal, and face a changing environment. In Table 1, we provide an integrated view of the example.

---

[10] In defining λ and μ as culture, we are following Schein's definition of culture as "deeply held values and beliefs." However, in other schools of thought, behaviors a and d may be part of organizational culture. For example, a and d would be captured as the presence (or absence) of "cooperation" and "innovation" in the culture of an organization by the survey-based literature (Denison and Mishra 1990, Cameron and Quinn 2011, Chatman et al. 2014, Groysberg et al. 2018); other schools of thought, such as cultural evolution, would indicate that the technology r is part of culture (as well as a and d), because it can be socially learned and is not instinctual/genetic (Boyd and Richerson 2005). For the "relational contracting" work by Gibbons and Henderson (2012) and Gibbons et al. (2021c), to the extent that r connotes practices/routines rooted in subtle, informal understandings underpinned by principles and beliefs (rather than contracts), r would be part of organizational culture.

Our model applies to organizations because we assume that, although it may not be easy, parameters λ and u can be manipulated and affected in a top-down fashion. Influencing these parameters is a fundamental aspect of CEOs' and top management teams' role (Schein 2010, Barnard 1938, Hermalin 2012). We are confident that this is feasible in groups up to a certain scale, such as teams, divisions, and firms/corporations. In larger units—such as cities or countries—history, politics, and institutions tend to play a much larger role than leadership alone.[11]

[Insert Table 1 around here]

3.1. The environment, learning a technology and beliefs

Throughout the model, we assume that the organization is large; to simplify the exposition, we assume it is populated by a continuous of agents with measure N. In our running example, this is a group of salespersons.

Many environmental states are possible. In each period, the state may change with probability p. For every state, there is a unique knowledge set, which we call "technology," that provides higher benefits to agents. Technology captures all the knowledge that agents require in order to be successful in a particular state; it includes skills, tools, routines, practices and processes, all of which may be tacit or explicit. By a normalization, we can assume, without loss of generality, that if an agent carries a technology that is tuned to match the state, then it generates a benefit of 1, and if it is not tuned, it generates a benefit of 0. Generally, these changes in the environment capture many forces that may leave an extant technology at a relative disadvantage, such as disruption by new entrants, a more successful strategy by competitors, changes in the demographic or political environment, changes in the climate, and pandemics.

---

[11] Two additional clarifications are necessary. First, even if λ and u cannot be manipulated top-down by the organization, there would still be value in exploring how stable culture heterogeneity across groups might affect adaptation and performance. Second, if λ and u can be manipulated top down, this does not mean that the behavioral rule d and the behavior a can also be easily manipulated: one the one hand, the ideal d and a are not obvious for organization leaders, and on the other, training members to change behavior can be very difficult and costly—at least compared to beliefs and values, which humans seem particularly attuned to adopt when in a group. Nonetheless, we invite research to devise extensions of our model in which d and a can also be affected by top-down choices.

Organizational adaptation corresponds to the adoption of tuned technology by agents. At the organization level, the variable r captures the share of agents in the organization who possess a technology that is tuned to the state of the world at one point in time. We call this variable the organization's "share of agents with tuned technology." This variable reflects the technological "tradition" that the firm has accrued over time—its stock of adaptive knowledge—and, thus, as we detail below, the pool of knowledge that social learners access as it "follows tradition." A second way to think about adaptation in our setting is dynamically, by exploring how quickly the organization responds to a change in the environment.

In our sales force example, an environmental state is captured by customers' tastes and preferences; the presence, type and behavior of competing sales forces (e.g., remote, in-person, hybrid); the technology that is used by the actors in this market/industry (e.g., use of digital tools); and the presence of substitutes, among other factors. One or many of these elements may change from one period to another—let us say between years. The "technology" that salespersons possess includes the sales technique they use, the amount/type of preparation they do before approaching a customer or a sales opportunity, the techniques used to scan opportunities in the market, and pricing strategy. Depending on the state of the environment on a given year, a particular sales technology is superior, which provides an advantage with respect to all other technologies in terms of performance (e.g., revenue growth, market share, mark-up) (and thus, we can normalize the benefits of technology to 1 and 0 for superior technology and others, respectively).

Agents in the organization obtain technology via learning. In particular, they can resort to two types of learning behavior: individual learning or social learning. Individual learning requires investing time and effort to study and understand the environment, which allows the agent to discover the technology that is tuned to the current environment. This learning behavior relies on different tactics, such as rational deduction, systematic experimentation, or trial and error. Individual learning has a cost C, which is bounded between 0 and 1 ($0 < C < 1$). Social learning consists of observing what a randomly chosen member of the organization did in the previous period and then copying their

technology. Social learning has a cost c, which is bounded between 0 and C ($0 < c < C$). This strategy is less costly because the agent does not need to invest time and effort to understand the underlying environmental state. Thus, these two behaviors display a trade-off for agents: Whereas individual learning allows an agent to "get it right" by paying a high cost, social learning is cheaper but bears the risk of a change in nature that renders its technology obsolete. To allow social learning to evolve, we assume that $C - c > p$ (see Online Appendix A.3.2 for details).

Individual learning can be understood as innovation, without which the organization cannot survive changes in the environment. Social learning can be understood as conformism or following tradition, and it is crucial to diffuse adaptive technologies from individual learners (or "innovators") to the rest of the organization. Innovation allows the organization to adapt to changes and, over time, in combination with diffusion via social learning, the organization builds a stock of adaptive knowledge.

With benefits and costs defined, we can start specifying the fitness that the agents receive. If the state of the world remains unchanged, the fitness an agent obtains with individual learning is $1 - C$ and with social learning is $r - c$. Social learners obtain the right technology, and thus the fitness of 1, only when they copy tuned agents (which occurs at the rate r). If the state of the world changes, the fitness of individual learning is $1 - C$ and of social learning is $- c$. Before we can write down a formal expression for fitness, we first must understand how agents decide their learning behavior.

Agents in the organization choose between individual and social learning after observing a signal s, which is drawn from a distribution that depends on whether the state of the world has changed. This signal can be understood as any feedback the organization receives from its interaction with the environment, such as operational and financial data, customer feedback, or investor reactions. Models of selective learning based on signals are well established in the literature on cultural evolution (Boyd and Richerson 2005, Boyd 2018). We follow this literature and model selective learning in a simple way. If the state of the world has not changed, the signal s is distributed exponentially with parameter $\lambda = 1$, which we denote as $f_{\lambda=1}(s)$; if the state of the world has changed, then the distribution is exponential with parameter $\lambda < 1$, which we denote as $f_{\lambda<1}(s)$ (we use $f_\lambda(s)$ to denote the density

function and $F_\lambda(s)$ to denote the cumulative function). Assuming an exponential distribution means that $s > 0$.[12] Given that $\lambda < 1$, when the environment changes, larger values of s are more likely to come from $f_{\lambda<1}(s)$ rather than $f_{\lambda=1}(s)$ (the exponential function flattens out when λ goes down). Thus, large values of s are interpreted by the agent as something "out of the ordinary," which is indicative of a change in the environment, whereas low values of s are indicative of "business as usual." In our sales force example, consider a salesperson who, for every period, closely tracks the number of lost sales opportunities (such as in a B2B context). If a competitor has created a much better product or service (i.e., the world has changed), then the likelihood of observing a large number of lost sales opportunities would increase. If the salesperson observes too many lost opportunities, it is likely that this will be interpreted as a change in the world (i.e., the realization of s is more likely to come from $F_{\lambda<1}(s)$ than from $F_{\lambda=1}(s)$); thus, it may be a good idea to innovate and re-think aspects of the sales technology that they use.

The closer λ gets to zero, when s grows in value, the difference between $f_{\lambda<1}(s)$ and $f_{\lambda=1}(s)$ becomes larger; thus, a lower λ improves the informativeness of the signal.

Notice that the value λ corresponds to the agents' capacity to interpret signals that come from the interaction between the organization and the environment. A lower value of λ may come from different sources. These include, among others: (i) the "scanning" or "sensing" capabilities that a firm has to detect changes in the environment (e.g., Teece 2007), embodied, in part, in a dedicated market intelligence unit within the organization that communicates what it "senses" to all its members; (ii) the education level of agents, which may help them better interpret signals; and (iii) the experience of the organization leader, who may better perceive changes and communicate them effectively. In this paper, we focus on a specific but important source rooted in organizational culture, namely the "causal beliefs" members hold (i.e., the beliefs about the role of the organization in the environment, the problems it

---

[12] Our results hold for any probability distribution with positive support that fulfills the monotone likelihood ratio property condition; see Online Appendix A.1. However, our proof of uniqueness of the equilibrium relies on the exponential assumption.

solves and how it creates value; see March 1991, Schein 2010, Kocak and Puranam 2023). It is important to emphasize that these beliefs are *not about changes in the environment*, but about the "structure" of the world—what audiences/customers want, what players believe and how they behave, how profits are made in this setting, what values are in place, etc.—and what problems the organization is solving and how (i.e., the role it is playing in this "structure") (see section 2.2.1 above). For example, Disney Inc. has a particular understanding of the world, the audience, workers, animators, etc., as well as an understanding of its role, purpose, and associated means–ends relationships (e.g., their business model); this has been documented by Argyres and Zenger (2012), Zenger (2013), and others.

Causal beliefs can differ in their verisimilitude; that is, they can be a more or less accurate reflection of reality (Puranam 2018, March and Simon 1958, March 1991). An organization can have naïve or accurate beliefs about the "structure" of the world, about its purpose/role in it, and how to fulfill that purpose (i.e., beliefs about the action–consequence pairs, usually embedded in a business model). Drawing from the literature on organizational adaptation (Tripsas and Gaveti 2000, Tripsas 2008, Eggers and Kaplan 2013, Eggers and Park 2018), we assume that when these beliefs are more accurate, the interpretation of signals improves, and thus, firms are able to recognize whether the environment has changed (e.g., change in customers/audiences' values and preferences).[13]

Continuing with the sales force example, sales forces have different beliefs about customers. Some beliefs are simplistic and inaccurate (e.g., believing that "all customers are driven exclusively by price" in a market with vertical differentiation); more often than not, this will lead to signal misinterpretation (such as not realizing that a drop in sales was caused by many customers increasingly valuing quality over price). Other beliefs are more accurate (e.g., "some customers prioritize price, but others prioritize quality and service"), thereby improving signal interpretation. Salespersons would also have beliefs

---

[13] The classic example of Polaroid is enlightening: Polaroid, although it held correct/accurate beliefs (and developed the corresponding knowledge and technology) about the future of imaging (i.e., digital), it had inaccurate beliefs about how profits are made (i.e., profits coming from printing, rather than the camera) and thus about its value and the problem digital imaging really solves (i.e., physical storage of memories instead of digital) as well as how to solve it (i.e., maintain marketing and salesforce choices). These inaccurate beliefs prevented Polaroid from correctly interpreting a myriad of signals coming from sales, customer reviews, sales force feedback, etc.

about the role of the sales force—some simplistic and inaccurate (e.g., believing that "we simply take sales orders because customers are captive" in a market with intense competition), which will often lead to signal misinterpretation (such as not realizing that a drop in sales was driven by a new service-oriented strategy by a competitor)—whereas others are more sophisticated and accurate (e.g., "we provide solutions—a bundle of the right products, at the right price, and a great good service—to the customer's unique problem").

The parameter λ is the same for all members of the organization, and thus it is a maximally strong culture: Everyone shares the same causal beliefs—the same "story" about the organization's role in the world, the problem it solves and how it creates value. This allows us to focus in our model on varying the accuracy/verisimilitude of beliefs. Also, the parameter λ is stable, it doesn't change over time, such as in response to changes in the environment. This is similar in spirit to the idea of Kreps (1990) and Gibbons et al. (2021c) that culture comprises high-level and time-invariant principles that guide the behavior of organization members. Of course, this does not mean that causal beliefs cannot change; indeed, Schein (2010) provides an interesting discussion on how they may change. In the discussion section, we suggest how our model could be extended to incorporate heterogeneous and time-variant beliefs.

In this setup, how do agents decide their behavior after they receive the signal s? As is standard in Bayesian decision theory, the optimal strategy is a cut-off strategy in which agent i will choose individual (social) learning if the signal s is above (below) a threshold value d_i (Boyd and Richerson 2005).[14] This threshold indicates how innovative or traditionalist the agent is: The higher (lower) the value, the greater the likelihood that the agent will choose social (individual) learning and thus display traditionalism (innovation). Every agent has a unique threshold. In our sales force example, salespersons have rules of this type: "If year-to-year sales drop by more than XX%, then I will innovate" (e.g., try

---

[14] The optimal behavioral strategy is a threshold because the relative advantage of individual learning compared to social learning is monotonic in the signal; therefore, there is only one signal level for which both behaviors are equivalent. Above this threshold, individual learning is advantageous; below it, social learning is. See Online Appendix A.1 for a detailed mathematical treatment.

new sales techniques, reroute clients, change discounts and promotions); if not, I will follow tradition (i.e., "I will use the technology/practices/skills that my peers have been using in the past"). Note that XX varies across salespersons.

Now we can write down a fitness expression for agents. Given a level of d_i, if the state of the world does not change, the individual fitness of an agent is:

$$h_i^u(d_i, r) = F_{\lambda=1}(d_i)(r - c) + (1 - F_{\lambda=1}(d_i))(1 - C) \tag{1}$$

If the state of the world changes, the agent's fitness is:

$$h_i^c(d_i, r) = F_{\lambda<1}(d_i)(-c) + (1 - F_{\lambda<1}(d_i))(1 - C) \tag{2}$$

Therefore, the expected fitness of agent i will be

$$h_i^e(d_i, r) = (1 - p)h_i^u(d_i, r) + p \cdot h_i^c(d_i, r) \tag{3}$$

In our sales force example, payoff h can be understood as the added value that the salesperson generates for the organization (e.g., price minus cost C or c).[15]

Later on, in section 3, we explain how the variable d_i evolves and tends toward an equilibrium value for all agents. Notice also that our model allows performance (fitness h) and adaptation (variable r) to be decoupled as different constructs. The organizational adaptation literature so far has tended to conflate these two, leading to some complications (Sarta et al. 2021).

It is important to clarify two elements: agents' information set and types of innovations. First, agents know only about their own d_i, the signal s_i they receive, and their beliefs (which they share with others). They don't need to know about the probability function F or the value of λ; that is, they don't need to know about the accuracy of their beliefs. This is intuitive, because complex beliefs (as is the case for "causal beliefs") are difficult—if not impossible—to falsify. Second, innovation may happen in two circumstances: when the state of the world has not changed, and when it has. In the former case, the agent who receives a very large signal decides to innovate, only to find that the technology it

---

[15] Although we do not model value capture for the firm and employee (i.e., a salesperson's compensation plan), we nonetheless can assume that part of this added value will be captured by the salesperson in the form of compensation, and that this share will increase with added value.

develops is the same as—or different, but not superior to—other technologies already present in the organization and that they could have obtained via social learning. In the latter case, when the state of the world has changed, innovation occurs when it is fully necessary. We label these two types of innovation "ill-timed" and "timely," respectively.[16]

3.2. Knowledge, technology and practices

The share of agents with tuned technology r is determined endogenously within the organization as a function of d and the state of the world. To fix ideas, let us assume that all agents in the organization have the same behavior d. In such a case, we can formalize the equation that rules the evolution of the share of agents with tuned technology r. When the state of the world does not change, the evolution of this variable is given by the following difference equation between periods t and $t + 1$:

$$r(t + 1) = [1 - F_{\lambda=1}(d)] + F_{\lambda=1}(d) \cdot r(t) \tag{4}$$

This equation shows that the share of agents with tuned technology in $t + 1$ depends on the share of agents who innovate, plus the share of conformists multiplied by the share of agents with tuned technology in t. When the state of the world changes, only those who decide to engage in individual learning end up being tuned to the state; therefore, the equation is as follows:

$$r(t + 1) = [1 - F_{\lambda<1}(d)] \tag{5}$$

Thus, the expected level of the share of agents with tuned technology conditional on the current stock is equal to

$$r^e(t + 1) = p[1 - F_{\lambda<1}(d)] + (1 - p)\big([1 - F_{\lambda=1}(d)] + F_{\lambda=1}(d) \cdot r(t)\big) \tag{6}$$

3.3. Cooperation and prosocial values

A large body of literature on organizational learning has documented that the members and productive units of an organization learn from one another, harness one another's experiences to improve practices, processes, routines, and productivity (Argote and Miron-Spektor 2011, Argote et al. 2021). However,

---

[16] If beliefs are perfectly accurate ($\lambda \to 0$), it means that agents know perfectly when the state of the world has changed and when it has not. This implies that when the state of the world changes, everyone engages in individual learning, and that when it does not, everyone engages social learning and $r = 1$ always. Thus, there is no "ill-timed" innovation.

the transmission and sharing of knowledge/information inside the organization is not free of hazards. Knowledge and information are non-rival, non-excludable goods and are thus subject to problems of free-riding and under-provision. Therefore, the quality and extent of knowledge/information transmission is not a given, because agents may not exert effort so that others learn better from them (e.g., Sandvik et al. 2020). To tackle this problem, organizations may need to actively promote prosocial values that support sharing of knowledge/information (Morrison and Wilhem 2004, Fehr 2018). Creating conditions for the sharing of knowledge is a core function of organizations (Grant 1996, Kogut and Zander 1996, Brahm and Poblete 2021) as well as a crucial dimension of corporate culture (Fehr 2018).

To incorporate these ideas into our model, we add: (i) a cooperative effort that agents can exert to facilitate social learning by others (which we label "help in diffusing tradition"), and (ii) the organization's values about help, cooperation, and the importance of the group (i.e., "prosocial values") (see section 2.2.2). Help in diffusing tradition is an endogenous variable; the prosocial values are a parameter. Agents observe prosocial values.

We first detail the help in diffusing tradition and how it enters the fitness function. An agent can exert effort $a_i \geq 0$ in order to facilitate other organizational members' learning from them—for example, by actively sharing insights while mentoring and helping the learner (instead of merely "allowing themselves to be copied"). Agents who are engaging in either individual or social learning can exert this effort. This helping effort is costly, reducing the agent's fitness h_i by an amount $m(a_i)$; however, at the same time, it reduces the social learning cost of whomever is copying the agent by an amount equal to the agent's effort a_i. We assume that $m(a_i)$ is increasing and convex, and that, for sufficiently low effort levels, $a_i > m(a_i)$, and thus effort a_i is a social dilemma. Formally, we assume that $m'(0) = 0$ and $m'(c) = \infty$ so that some interior level of helping effort is always socially optimal.

It is important to clarify here that our model only considers innovation brought about by individual experimentation, and not the type of "collaborative" innovation arising from the combination of specialized individuals who create something that none of them could have achieved alone. Thus, we

24

do not consider how a_i may affect innovation. See section 5.1 for a discussion of this boundary condition in our model.

Consider an organization in which one agent i exerts effort a_i, but all the others exert an average helping effort denoted by $\bar{a}$. Now we can expand the expression for agents' fitness, adding helping effort. The expected individual fitness of agent i is as follows. If the state of the world does not change, fitness is

$$h_i^u(d_i, \bar{a}, a_i, r) = F_{\lambda=1}(d_i) \cdot (r - c + \bar{a}) + \left(1 - F_{\lambda=1}(d_i)\right) \cdot (1 - C) - m(a_i) \qquad (7)$$

If the state of the world changes, fitness is

$$h_i^c(d_i, \bar{a}, a_i, r) = F_{\lambda<1}(d_i) \cdot (-c + \bar{a}) + \left(1 - F_{\lambda<1}(d_i)\right) \cdot (1 - C) - m(a_i) \qquad (8)$$

Thus, the expected fitness of the agent will be

$$h_i^e(d_i, \bar{a}, a_i, r) = (1 - p) \cdot h_i^u(d_i, \bar{a}, a_i, r) + p \cdot h_i^c(d_i, \bar{a}, a_i, r) \qquad (9)$$

Thus, expected individual fitness is increasing in other members' effort and decreasing in the agent's own effort.

It is useful to measure agent i's contribution to the organization via help in diffusing tradition as the difference between (i) the actual fitness of all other agents in the organization when they exert helping effort $\bar{a}$ and (ii) the fitness that would exist if the focal agent were to exert no helping effort at all, instead of effort a_i. This contribution by the agent to the organization corresponds to the effort a_i times the likelihood of social learning by other members in the organization. To see why this is the case, consider an organization with N members in which everyone has learning rule d (the same for all) and exerts a helping effort $\bar{a}$. The expected fitness of the whole organization is given by $N \cdot h(d, \bar{a}, r)$ (which is equivalent to the "profit" of the organization). If agent i exerts no effort instead of exerting a_i, everyone else's fitness will be decreased by an amount a_i whenever they learn socially from agent i. Agents learn socially with probability $(1 - p) F_{\lambda=1}(d) + p F_{\lambda<1}(d)$ and they copy from agent i with probability $1/N$. Therefore, the fitness of the organization becomes

$$N \cdot \left\{ h(d, \bar{a}, r) - \frac{1}{N} [(1 - p) F_{\lambda=1}(d) + p F_{\lambda<1}(d)] \, a_i \right\} \qquad (10)$$

and, thus, the expected contribution of the agent to the organization is

$$\psi_i(d, a_i) = [(1 - p)F_{\lambda=1}(d) + p \, F_{\lambda<1}(d)] \, a_i \tag{11}$$

Now we return to "prosocial values" and address their connection to "help in diffusing tradition," which we model by making the contribution of agents $\psi_i(\vec{d}, a_i)$ important and valued in the organization. We expand the fitness h_i^e of agents by adding this contribution, and we label the resulting quantity as "payoff." We represent the expected payoff for an agent as follows:

$$q_i^e(\vec{d}, \bar{a}, a_i, r) = h_i^e(d_i, \bar{a}, a_i, r) + \mu \cdot \psi_i(a_i) \tag{12}$$

A positive μ captures how much the agent stands to benefit from their contribution ψ_i. Organizations can influence this using several levers, including: symbolic rewards/punishment (e.g., creating status/prestige around helping effort); tying awards to sharing knowledge/information; stimulating peer pressure/punishment of free-riders who do not exert helping effort; formal levers such as establishing and enforcing processes of knowledge sharing (e.g., mentoring schemes); creating pecuniary incentives (e.g., bonuses tied to group performance); and adding formal criteria for performance assessment and promotions. We assume that a very powerful driver for organizations using these levers is the presence of "prosocial values," that is, how much the organization values cooperation; helping other group members; prioritizing the group rather than the self; and displaying honesty, trust, and goodwill toward group members. Extant literature on organizational culture has documented considerable variation in the intensity/emphasis of "prosocial values" among organizations (Denison and Mishra 1995, Cameron and Quinn 2011, Chatman and O'Reilly 2016, Chatman et al. 2019, Graham et al. 2022). When prosocial values display high intensity, then it is expected that the aforementioned levers would increase in strength, and thus μ would increase in size. The same is true in the opposite direction: low intensity prosocial values would mean that μ would be small. As with λ, we assume that "prosocial values" (and thus μ) are shared by all in the organization; this allows us to focus on the impact of varying their intensity.

Returning to our running example of a sales force, when salespersons learn from one another about how things are done (e.g., sales techniques, daily route planning, priorities in terms products/customers)

they may receive help (or not) from the salesperson from whom knowledge/tradition is sought. The salesperson who helps transmit tradition to others generates a benefit to others and the organization as a whole, but at a cost to themselves. Motivation to help is generated if the culture of the sales force emphasizes prosociality in its values.

Notice that, whereas the organization cares about the expected fitness of the whole organization—$N \cdot h_i^e(d_i, \bar{a}, a_i, r)$, which we label "profits" or "performance"—the agents care about expected payoff $q_i^e(\vec{d}, \bar{a}, a_i, r)$. This discrepancy can introduce a tension between the organization and its agents because $h_i^e(d_i, \bar{a}, a_i, r)$ and $q_i^e(\vec{d}, \bar{a}, a_i, r)$ may respond differently to changes in parameters.

4. Solution and findings

In this section, we first present the criteria (i.e., evolutionary stable strategies) and the equations that describe the equilibrium of the model; we then present our findings exploring how the equilibrium changes when the cultural parameters λ and μ are modified.

Before proceeding, it is important to clarify that our agents are bounded rational, having access to the following information: An agent knows μ, d_i, the signal s_i, a_i, and the payoff q_i^e the agent obtains at the end of the period. As discussed above, although the agent knows their causal beliefs, they do not know their accuracy, and thus do not know the value of λ. Also, the agent can "tell" which agents receive the highest payoffs at the end of each period.

4.1. Evolutionary stable strategies

We assume that in each period, a small share of agents decides to copy the traits help in diffusing tradition a_i and learning threshold d_i of the agents who have the highest payoff q_i^e (this is independent of the copy involved in social learning, and we assume that agents can observe a and d of the agent they decide to copy). In evolutionary modelling, this updating process is known as "replicator dynamics": In biology, replication means that fitter organisms have more offspring, and in social science, more successful traits or strategies are copied with higher likelihood. Whereas in biology, replicator dynamics means that various species increase or decrease in number, in social science it

means that the behavioral repertoire (in our case, d_i and a_i) diffuses or vanishes. As a result of this updating process, over time, agents "converge" to a particular set of values for a and d. To determine whether such values exist—and whether they are unique—we rely on the concept of evolutionarily stable strategies (ESS) (Maynard Smith 1982).[17]

We follow Boyd and Richerson (2005) in defining a symmetric ESS as a situation in which a small set of agents who deviate from a^* and d^* perform strictly worse in expectation compared to other agents in the organization. The pair a^* and d^* are said to be "stable" because, given that agents copy from more successful behaviors, deviations will not spread in the organization. (As indicated above, it is not the case that agents will have fewer offspring if they deviate from ESS; rather, their behavioral repertoire diffuses or vanishes via replicator dynamics because they have a lower payoff.)

To find the ESS, first consider possible deviations in the effort exerted in helping diffuse traditions. The expected payoff of an agent in ESS is given by $q_i^e(a^*, d^*, r) = h_i^e(a^*, d^*, r) + \mu \cdot \psi_i(a^*, d^*)$. An agent who deviates to an effort level $a^* + \varepsilon$ will achieve a lower fitness h_i^e by exerting more effort in helping others, but their contribution to the organization ψ_i increases; these two effects are reflected in its payoff:

$$q_i^e(a^* + \varepsilon, d^*, r) = [h_i^e(a^*, d^*, r) + m(a^*) - m(a^* + \varepsilon)] + \mu \cdot \{\psi_i(a^*, d^*) + \varepsilon[(1-p)F_{\lambda=1}(d^*) +$$
$$p\, F_{\lambda<1}(d^*)]\} \qquad (13)$$

In an ESS, the expected payoff of the "mutation" should be less than the payoff of the members of the organization and, therefore, the condition for ESS is $q_i^e(a^* + \varepsilon, d^*, r) \leq q_i^e(a^*, d^*, r)$ for every possible deviation ε. A necessary condition for this is that $\partial q_i^e(a^* + \varepsilon, d^*, r)/\partial \varepsilon$ evaluated at $\varepsilon = 0$ must be 0 because we are in maximum. This is equivalent to the requirement that $\partial q_i^e(a^*, d^*, r)/\partial a_i$ be equal to zero at $a_i = a^*$, which, after reordering, yields the following:

$$m'(a^*) = u[(1-p)F_{\lambda=1}(d^*) + p\, F_{\lambda<1}(d^*)] \qquad (14)$$

---

[17] This convergence toward an ESS does not mean that changes cease to occur. Rather, it means that in the long run, the variables continue to change—albeit doing so around the neighborhood of the set of "equilibrium" or "long-run" values for a and d defined by the ESS.

This is a standard first-order condition that equalizes the marginal cost of helping effort $m'(a^*)$ to its marginal benefit, which is the weight u times the probability of being copied $[(1-p)F_{\lambda=1}(d^*) + p\,F_{\lambda<1}(d^*)]$.

Analogously, mutations with respect to the learning parameter d^* should not increase the payoff of agents in the organization. Observe that at the maximum, these mutations affect only the fitness h_i^e and not the contribution ψ_i in the agent's payoff; therefore, d^* satisfies the first-order condition $\partial q_i^e(a^*, d^*, r)/\partial d_i = \partial h_i^e(a^*, d^*, r)/\partial d_i = 0$ at $d_i = d^*$, which yields the following:

$$(1-p)f_{\lambda=1}(d^*)(r - c + a^* - [1 - C]) + p\,f_{\lambda<1}(d^*)(-c + a^* - [1 - C]) = 0 \tag{15}$$

In Equation (15), the first term represents the change in fitness from increasing social learning (and a corresponding decrease in individual learning) when it does not cause harm—that is, when the world has not changed; this must be equal to the case in which it does cause harm (the second term)—that is, when the world has changed.

Finally, to calculate the long-term unconditional expected level of the share of agents with tuned technology, we use the difference Equation (6), which shows how this share changes from one period to the next. The unconditional expected share is reached when it does not change from one period to the next—that is, when $r(t) = r^e(t+1) = r$. Using this steady-state condition, we can obtain the long-term level of the share of agents with tuned technology r:

$$r = \frac{p\big(1 - F_{\lambda<1}(d^*)\big) + (1-p)\big(1 - F_{\lambda=1}(d^*)\big)}{1 - (1-p)F_{\lambda=1}(d^*)} \tag{16}$$

Equations (14), (15), and (16) characterize the ESS. In Online Appendix A.2, we prove that the equilibrium exists and that it is unique.

4.2. Trade-off between innovation and help in diffusing tradition

The first result we wish to highlight is the negative relationship between innovation (measured as the share of agents who perform individual learning) and help in diffusing tradition (measured by a). This negative relationship comes directly from Equation (14), which clearly describes a trade-off between help in diffusing tradition and innovation. Intuitively, more innovation implies less social learning,

which reduces the benefits—and thus, frequency—of helping effort a. Mathematically, if the share of social learning $[(1-p)F_{\lambda=1}(d^*) + p\,F_{\lambda<1}(d^*)]$ increases (for example, due to a more stable environment[18]), then for a given u, the helping effort a^* would also need to increase in order for the marginal costs to equalize the marginal benefit in Equation (14). If the strength of prosocial values u increases, the situation is the same: Social learning would be favored and increase—and, thus, a^* would increase because it has a larger marginal benefit. Figure 1 illustrates this trade-off by graphing how the ESS equilibrium shifts by changing p.

This trade-off suggests that we should observe a tendency for the culture of organizations to focus on either innovation or tradition. This prediction is consistent with the view that emerges from three prominent organizational culture frameworks (Denison and Mishra 1990, Cameron and Quinn 2011, Groysberg et al. 2018), which indicate that there will be a tension between innovation and tradition—and in the case of Cameron and Quinn (2011), a trade-off as well.[19]

Furthermore, this result is consistent with the literature highlighting the tension that organizations exhibit between exploration and exploitation (March 1991, Benner and Tushman 2006, Uotila et al. 2008, Lavie et al. 2010, O'Reilly and Tushman 2013). However, unlike the model by March (1991), where the trade-off arises due to the presence or lack of diversity of beliefs across organizational members, in our model we assume homogeneity of cultural beliefs and values (u and λ, respectively),[20] and thus the trade-off arises from a different source: In every period, agents must decide—under conditions of uncertainty—whether to experiment/innovate (individual learning) or follow tradition (social learning). In our model, the trade-off arises from the difficulty of choosing innovation or

---

[18] In Online Appendix A.3, we detail the impact of changing environmental uncertainty p on the model equilibrium. In Online Appendix A.4, we also explore how changes in C and c affect the equilibrium.

[19] Cameron and Quinn (1983) indicate the following: "From the external view, […] the emphasis is on the overall competitiveness of the organization in sometimes changing environments. From the internal view, the organization is a socio-technical system. Participants have unique feelings, likes and dislikes, and require consideration […]. *When the external value on the overall organization is maximized, the internal emphasis on the socio-technical equilibrium may be reduced; and when the emphasis on internal harmony grows, it may tend to shift emphasis away from overall competitiveness*" (p. 370; emphasis added).

[20] It could be interpreted that, because agents' fitness realizations differ depending on the technology they possess at any point in time (i.e., they get 1 or 0 in fitness if the technology is tuned or not tuned, respectively), they may develop different beliefs about technology, which would be heterogeneous (at least bi-modal). Given that agents have different threshold d, belief heterogeneity may also occur regarding the relative value of innovation versus of tradition.

tradition when change is uncertain—not by the homogeneity versus diversity of agents as in previous work (e.g., March 1991, Van den Steen 2010a, b).

[Insert Figure 1 around here]

4.3. Accuracy of beliefs

We split the discussion of the findings in two. First, we discuss the impact on adaptation and performance, as well as the empirical evidence consistent with our findings, and then we discuss in detail where these results come from—that is, what mechanisms drive the impact of λ.

To discuss performance and adaptation, we rely on Figures 2 and 5. In Figure 2, we illustrate how the ESS of the model changes when "causal beliefs" in the organization increase in accuracy from $\lambda = 0.7$ to $\lambda = 0.1$ (remaining parameters are set as in Figure 1 and $p = 0.1$). In the graphs of Figure 5, we illustrate the dynamics of adaptive knowledge (left-hand graph) and fitness (right-hand graph) for different values of λ.

Regarding performance, we find a monotonic increase in fitness as beliefs become more accurate (see bottom-left graph of Figure 2). This means that the organization will always improve its performance—organizational performance is equal to N times fitness—when its beliefs increase in accuracy. Regarding adaptation, we look at r and adaptation to shocks (i.e., realization of $p = 1$). As for the former, we see in the top-left graph of Figure 2 that the r—which can be conceptualized as the stock of adaptive knowledge—increases. As for the latter (adaptation to shocks), Figure 5 shows that when λ is lower, adaptation to shocks improves. The left-hand graph of Figure 5 shows that the drop in the share of agents with tuned technology when the world changes (in period 10) is much smaller, and the same can be appreciated for fitness (right-hand graph of Figure 5).

In sum, more accurate beliefs improve the share of agents with tuned technology (a "cross-section" measure of adaptation) as well as the response to shocks (a "dynamic" measure of adaptation), and generates higher performance for the organization. Research on cognition and adaptation cited in section 2.2.1 (e.g., Barr et al. 1992, Tripsas and Gavetti 2000, Tripsas 2009) provides supportive evidence for this result. However, this research takes the form of qualitative, in-depth case studies (e.g.,

Polaroid in Tripsas and Gaveti 2000) and we are not aware of any large-scale quantitative studies that have tested this finding thoroughly (most likely because it is notoriously difficult to measure the accuracy of beliefs for many organizations at once). There is, nonetheless, some evidence we can point to, depending on how far one stretches the interpretation of the concepts and measures. First, Costanza et al. (2016), using a sample of 95 firms, found increased odds of survival over the next 70 years for those firms that in 1940 held three values of adaptability, namely: (i) "the organization pays attention to its external environments and values reading and interpreting signals from their environments," (ii) "the organization proactively works to identify internal and external problems; the organization focuses on future problems or environment changes," and (iii) "the organization believes that it has the ability to change"), provided that these values were backed by the capacity to change. Second, Vicinanza et al. (2023) show that firms capable of better vision (i.e., firms with more accurate beliefs about what will happen) enjoy higher stock returns.

The finding so far is intuitive, and admittedly close to the model's assumptions. Nonetheless, we are confident that there is value in formalizing such intuition emerging from a literature that has been, to date, predominantly conceptual in its theory development. We now turn to a more subtle finding, uncovering the mechanisms by which more accurate beliefs generate these benefits to adaptation and performance.

This increase in fitness from lower λ comes from three sources: (i) an increase in the share of agents with tuned technology r (top-left graph of Figure 2), (ii) an increase in the less costly social learning strategy (top-tight graph of Figure 2) without sacrificing adaptiveness, and (iii) an increase in helping effort a (bottom-right graph of Figure 2). Perusing Figure 2 and Equations (7)–(9) reveals that these three sources are roughly equal in magnitude (with source (iii) weighing slightly less than the other two). We unpack each one in turn.

The share of agents with tuned technology increases because, even though total innovation is decreasing (top-right graph of Figure 2), agents' innovations are more timely because the agents are more accurate when inferring from the signal whether the world has changed. Recall that innovation

can happen in two circumstances: when the world has not changed ("ill-timed" innovation) and when the world has changed ("timely" innovation). In the former, the amount of innovation is $1 - F_{\lambda < 1}(d^*)$; in the latter, it is $1 - F_{\lambda = 1}(d^*)$. The left-hand graph of Figure 3 depicts these two proportions against the value of λ. The figure shows that innovation becomes more timely—that is, it occurs increasingly when the world changes, and occurs less frequently when it doesn't change. This better timing of innovation is reflected in Figure 5, which shows that the decrease in adaptive knowledge and fitness when change strikes is less severe when beliefs are more accurate. Innovation also becomes "more productive": in Figure 2, the share of agents with tuned technology increases (top-left graph) at the same time that innovation is decreasing (top-right graph), indicating an increase in the amount of adaptive knowledge per innovation unit. In short, adaptive knowledge increases because innovation becomes better-timed and more productive.

In turn, focusing innovation on periods of change enables increased use of social learning when it is most useful, that is, during periods of stability. As "ill-timed" innovation decreases (left-hand graph of Figure 3), social learning in times of stability rises. This leads to an overall increase in social learning (top-right graph of Figure 2), a less costly learning strategy that now—given that innovation is well focused—does not bring with it increased vulnerability to environmental changes. The benefit of more social learning during stability is reflected in the period immediately after a shock. In Figure 5, fitness in period 11 bounces back more quickly from period 10 (when the shock $p = 1$ occurs) when λ is lower because more social learning transmits the higher stock of knowledge in period 10 more quickly within the organization.

Then, in response to more social learning, more help in diffusing tradition is produced (bottom-right graph of Figure 2). This increases fitness by reducing the cost of tradition in the organization. As can be appreciated in Equation (14) and the discussion in subsection 4.2, this occurs because the marginal return for help in diffusing tradition increases.

At the heart of these mechanisms is the fact that more accurate beliefs mitigate—or minimize— the trade-off between innovation and tradition. In our model, this trade-off arises from the difficulty in

33

choosing a learning strategy—tradition or innovation—under uncertainty. In Figure 4, we plot the relationship between total innovation (left-hand graph), timely innovation (middle graph) and ill-timed innovation (right-hand graph) on the one hand and help in diffusing tradition on the other, as the organization moves from high to low λ (using the same range as in Figures 2 and 3). The middle graph shows that a positive relationship is formed between innovation and help diffusing tradition during periods of environmental change. This occurs because the reduction of λ increases help in diffusing tradition (bottom-right graph of Figure 2) while timely innovation also increases (Figure 4). Notice that the trade-off persists for total innovation: Equation (14) means that there will always be a trade-off, however small, although it is weaker in comparison to Figure 1; only for "timely" innovation is the trade-off broken.[21]

The image that emerges from this discussion is that an organization with accurate beliefs will be very responsive during a period of change (or disruption), innovating more than an organization with less accurate beliefs during that period—and that, after the new technology is generated, the organization with accurate beliefs is capable of diffusing that technology more rapidly during periods of stability thanks to more abundant and less costly tradition. Overall innovation cedes terrain to tradition, but both become more efficient, thereby minimizing the trade-off between them.

Overall, we summarize the findings on the mechanisms of λ with the following proposition:

> _Proposition 1_: _Increasing the accuracy of beliefs focusses innovation on periods of environmental change, makes innovation more productive, reduces (increases) the frequency of innovation (tradition), increases help in diffusing tradition, and reduces the trade-off between innovation and help in diffusing tradition._

These mechanisms are not entirely obvious ex ante—not without a formal model. Furthermore, this proposition provides empiricists with precise, testable predictions.

---

[21] In Figure A.2 of the Online Appendix A.3, we show that the effect of more accurate beliefs on the use of social learning and the amount of help is more significant when environmental uncertainty p is higher. This is intuitive because the importance of timely innovation—as well as the consequences it has on "freeing up" time for agents to pursue social learning during periods of stability (which then boosts help in teaching others)—is greater when the environment is more volatile.

This proposition is consistent with research on ambidexterity, which indicates that organizational culture is one way for organizations to minimize or break through the trade-off between exploration and exploitation (O'Reilly and Tushman 2013). In particular, our model is in line with the idea of "contextual ambidexterity" introduced by Gibson and Birkinshaw (2004) wherein the organization provides the right context—including culture—that "encourages individuals to make their own judgments as to how to best divide their time between the conflicting demands for alignment and adaptability" (ibid, p. 211). O'Reilly and Tushman (2013) indicate that contextual ambidexterity is "a function of a *culture* that supports workers to pursue exploration and exploitation" (p. 329; emphasis added). However, although this idea emphasizes engaging with exploration and exploitation simultaneously, our model and finding emphasizes the importance of timing in deciding when to explore and when to exploit. This connects with the idea of "sequential ambidexterity" wherein exploration and exploitation are pursued at different moments in time (O'Reilly and Tushman 2013), and is in line with the effort by Randle and Pisano (2021), which indicate that—consistent with our model—the within-firm evolutionary process that generates innovations "begins with a period of exploration, which is followed by a period of exploitation" (ibid, p. 291).

[Insert Figures 2, 3, 4 and 5 around here]

4.4. Intensity of prosocial values

As in section 4.3, we split this discussion into two parts as well. First, we describe how the intensity of prosocial values affects helping effort, the extent of tradition versus innovation, and adaptation. Second, we describe the impact on organizational performance (fitness). The former finding is closer to the assumptions we make in the model, whereas the latter is more unexpected and novel.

In Figure 6, we display how the model's ESS changes when the intensity of prosocial values is increased from 0 to 0.6. We find that increasing u leads to a large increase in help in diffusing tradition (see the bottom-right graph of Figure 6). This is to be expected because u increases agents' payoffs if they help others to better follow tradition (see Equation (14)). In turn, this promotion of helping effort by the cultural values generates consequences for innovation and adaptation: Increasing u lends an

advantage to social learning and tradition (it becomes less costly) and, thus, as we see in the top-right graph, tradition substitutes for innovation as μ grows. The right-hand graph of Figure 3 shows that innovation decreases as u increases for both timely and ill-timed innovation. This leads to a reduction in the share of agents with tuned technology (top-left graph of Figure 6) as well as a reduction in the capacity to adapt to environmental changes when these occur: both graphs in Figure 7 show that the drop in r and fitness when the environment changes is more precipitous when μ is larger. All of this is reflected in that changes in u generate a larger trade-off between innovation and help in diffusing tradition (see Figure 8) than the trade-off produced when p changes (see Figure 2) or when λ changes (see Figure 4).

Several lines of research provide evidence consistent with the result depicted so far, namely that when tradition is favored (in our case via prosocial values that boost help in diffusing tradition), innovation and adaptation tend to suffer (see the review by Sarta et al. 2021). This result is intuitive.

The second result on how u affects performance is less intuitive. As can be appreciated in the bottom-left graph of Figure 6, we find that fitness—and, by extension, organizational performance—has an inverted-U relationship with μ; the highest fitness is attained around $\mu \approx 0.24$. The intuition for this inverted-U result is that when μ is growing, at first it provides benefits to the organization because social learning is not only increasing but also, more importantly, it is becoming less costly because helping effort grows (bottom-right graph of Figure 6), thereby reducing the overall cost of tradition in the organization more rapidly than the decline in fitness that results from possessing a less adaptive technology due to lower innovation (top-left graph of Figure 6). However, when u grows too large, there comes a point when the gains in terms of less costly, more efficient tradition are eventually outweighed by the reduction in innovation and the share of agents with tuned technology; at this point, fitness begins to decline. This inverted-U finding is counterintuitive—and even surprising—because the literature, for the most part, tends to posit that stronger prosocial values in a group always increase organizational performance (Boyd and Richerson 2005, Fehr 2018). By contrast, our results suggest

that prosocial values have an important downside that prior literature has largely overlooked, namely that of reducing innovation and adaptation. We summarize this finding in the following proposition:

> <u>Proposition 2:</u> *For low levels of prosocial values, there is a positive relationship between prosocial values and performance, but this relationship turns negative after a threshold, creating an inverted-U relationship.*

Regarding empirical evidence, our best efforts found only two previously published papers that document how prosociality and cooperation can be detrimental to organizational performance; both showed that it does so by hindering adaptation to changes/shocks. The paper closest to our own is that by Hergeux et al. (2021), who studied reciprocity-based cooperation (i.e., cooperating with others if they respond in kind) in the context of open-software development teams. They found that reciprocity in the team had a non-linear relationship with its performance: More reciprocity generates better performance, but also makes the teams more likely to fail. This is because, although reciprocity can build up and sustain cooperation in good times—team members' feeding of one another's effort—if "something" happens that makes a team member cooperate significantly less (e.g., a personal matter, better projects to work on elsewhere), then cooperation may unravel because it is conditional. However, the paper does not specify what this "something" is; we contend that it can certainly be environment shocks/changes as we model them in our paper (although there could be other reasons, such as a software developer giving attention to an alternative project that is unobserved by the rest of the team).

The second is Chatman et al. (2019), which studied the role of collectivism—defined as "a norm in which the demands and interests of groups are prioritized above individual needs and desires to achieve collective goals" (p. 235) and whose primary/defining feature is "cooperation with relevant group members" (p. 235)—in the context of mountain-climbing groups in the Himalayas. They found that collectivism blurs individual differences, which hurts the group in tasks in which performance is a function of the most expert member ("safety" task) but helps the group in tasks that all group members must do ("reaching the summit" task). By finding that prosociality can be detrimental in a context of adaptation to changing circumstances, this study is consistent with our theory.

Proposition 2 has three corollaries, all amenable to empirical study. The first corollary is: "*There is a degree of intensity of prosocial values that maximizes the performance of the organization.*" In a context of competition among organizations—what is called "group selection" in cultural evolution theory (Boyd and Richerson 2005)—it is possible that over time, organizations with the "right" amount of prosociality will be selected. Additionally, this may explain why large firms persistently struggle to attain large-scale cooperation; for example, a survey of 1,348 CEOs of large US firms ranked cooperation among employees as the main driver of an effective culture, and 84% believed the cooperation level should be higher (Graham et al. 2022). In contrast to the usual explanations for the difficulty of sustaining cooperation in large groups (which tend to emphasize the increasing temptation of free-riding), it may be that, in many cases, a scaled-back prosociality is beneficial and thus selected (independent of the CEOs' opinions).

The second corollary is an extension of the first: "*The optimal level for the intensity of prosocial values increases with the degree of environmental uncertainty* p." In Figure A.3 of Online Appendix A.3, we provide analysis that supports this statement. This is consistent with evidence indicating that within-group prosociality increases when the group faces external threats (e.g., war, natural disasters, pandemic) (Bowles 2009, Gelfand et al. 2011, Bohm and Rockenbach 2012, Bauer et al. 2016, Francois et al. 2018). Again, group selection can select organizations that display the "right" amount of prosociality for the environmental instability they face.

These first two corollaries suggest that a cultural evolution approach to organizational culture—via group selection—can refocus attention on the environment as a driver of organizational culture. For example, the classic work by Deal and Kennedy (1982) suggests that cultures arise from the nature of workflow and risk/reward in the environment. Along the same lines, Sorensen (2002) showed that strong culture produces more reliable performance only in stable industries. More recently, Ulrich et al. (2009) recommended building "outside-in" cultures where customers—and the problem the firm/organization solves for them—are central in informing the desired culture. For their part, Francois et al. (2018) showed that cooperation is higher in firms that operate in more competitive settings. In a

way, by emphasizing culture as the repository of beliefs that proved successful/adaptive to external challenges, Schein (2010) also belongs to this camp.

The third corollary of Proposition 2 is: "*More intense prosocial values always increases the payoff of organizational members but not that of the organization (see Corollary 1 above) and thus, this creates a tension with the organization with respect to the optimal intensity level*." This can be appreciated in the bottom-left graph of Figure 6. This difference arises because agents receive benefits in the form of recognition and rewards beyond fitness (see Equations (11) and (12)). This misalignment between agents and the organization suggests that there may be a risk of prosocial values becoming too strong if they are left to emerge spontaneously from agents' interactions (and if group selection is weak). We are not aware of prior studies documenting this phenomenon.[22]

[Insert Figures 6, 7 and 8 around here]

4.5. Complementarity between causal beliefs and prosocial values

In Figure 9, we display the impact on fitness by varying λ and μ simultaneously. We find that the accuracy of beliefs and the intensity of prosocial values are complementary; that is, if one increases, the impact on fitness and organizational performance improves more (or is less detrimental) if the other increases as well. We can see this result when comparing the slopes of the two graphs of Figure 9. The mechanism that drives this result is that making innovation more efficient—in the sense of innovating when it is needed (driven by more accurate beliefs)—will be even more useful when knowledge is more effectively spread internally, so that the new adaptive technology spreads more rapidly after an environmental change has occurred. The same occurs in the other direction; the value of internally spreading knowledge increases when the knowledge being spread is better tuned to the state of nature.

Overall, we summarize this discussion in the following proposition:

Proposition 3: The intensity of prosocial values and the accuracy of causal beliefs are complementary.

---

[22] Another source of conflict between agents and the organization also arises in our model. In Figure A.1 of Online Appendix A.3, we show that organizational members would rather have less uncertainty than what the organization would prefer; this is because members seek payoff, which includes the benefit gained from helping others obtain tradition, but tradition (i.e., social learning) is less used when uncertainty is high.

[Insert Figure 9 around here]

As with Proposition 1, given the difficulty in measuring the accuracy of beliefs, quantitative evidence is hard to obtain. An alternative is to look at studies that measure the mechanism: Knowledge sharing is more impactful if the innovation being shared is better and, vice-versa, improving innovation is more impactful if the sharing of the innovation is more efficient. Franchise systems are an exemplary setting for this: Watson et al. (2014) used a large sample of UK franchisees (across many sectors) and showed that (i) at least 40% of franchisees innovate locally (a new product, service or process created in a specific franchisee) and (ii) there is variation in the extent to which these innovations are shared across franchisees that share a franchisor. They then conducted in-depth interviews of 29 franchisees, which showed that cooperation and good relations among franchisees increased local innovation as well as the sharing of such innovations among franchisees. Several quotes suggest that this is due to sharing and innovation being complementary: both are better together. Using quantitative and qualitative techniques, respectively, Colla et al. (2019) and Dada et al. (2012) report findings broadly consistent with those of Watson et al. (2014).[23]

5. Discussion

5.1. Extensions to the model

All models make simplifying assumptions about the world. We would like to highlight four assumptions in our model and speculate how lifting them may yield novel findings. We believe them to be fruitful avenues for future research.

First, because technology travels between individuals in our model, it applies well to: (i) organizations where individuals are productive units performing similar activities, such as in service industries (e.g., law, consulting, accounting, medicine, education); (ii) sub-units within organizations that rely on individuals executing similar activities (e.g., sales organizations, customer service,

---

[23] Additional indirect evidence for the mechanism underlying Proposition 4 (albeit less precise than the franchise research) is the ambidexterity literature, which persuasively links better performance with firms' ability to exploit and explore (O'Reilly and Tushman 2013).

logistics); or (iii) organizations comprising a collection of productive units (e.g., franchises, stores, plants) that each can be interpreted as a "unitary entity" on its own, and can thus be treated as an agent in our model for analytical purposes. However, this inventory excludes many organizations whose output is the outcome of a web of collaborative effort across many specialized individuals and units. Consider, for example, the assembly of complex capital goods such as airplanes; this would require quite a different modelling approach, which is still in its infancy in the field of cultural evolution (Smaldino 2014). In such complex product/services scenarios, innovation is a process that involves many specialized individuals and units coming together to produce something they would not be able to produce individually. One simple way to start exploring this is to allow for the fitness of innovation to be increasing on the share of innovators; this could capture productive collaborations among specialized innovators.

Second, our model assumes the absence of organizations' internal structure (i.e., all agents are undifferentiated and can connect with one another with the same probability). A good way to lift this assumption is to allow social learning to be non-random, so that agents learn disproportionately from a subset, such as the most prestigious, or the majority. Such "biases" in social learning are extensively modeled in the literature on cultural evolution (Boyd and Richerson 2005, Kendal et al. 2018).

Third, our model assumes that culture is homogeneous (i.e., that all agents have the same λ and μ). This allows us to "shut down" the issue of cultural strength and instead focus on how culture affects adaptation. However, it would be very interesting to allow these dimensions to vary across individuals. One could explore more nuanced questions regarding the relationship between cultural strength and organizational adaptation. For example, research on "groupthink" warns that homogeneity of beliefs can lead to worse outcomes (Janis 2008) and investigations of "group polarization" show that, in general, groups generate more extreme beliefs/opinions than their individual members (Isenberg 1986, Friedkin 1999, Zhu 2013). Thus, one could add a cost of beliefs homogeneity alongside the benefits of heterogeneity (March 1991).

Fourth and finally, our model assumes the "stability of beliefs" (i.e., λ does not change over time). We argue that when λ is smaller, environmental changes are easier to identify and innovation is triggered when most needed, thereby improving the stock of adaptive technology r. Given that tradition and help diffusing it are promoted by a smaller λ, technology discovered by well-timed innovation diffuses more quickly within the organization. However, given a change in environment—and thus a change in technology r—it is not obvious that these cultural beliefs can be stable. In order to be stable, our model assumes either that (i) λ captures beliefs at a high level of abstraction such that they need not change (at least, not in the short/medium term) to be "applicable" to any environment—echoing the view of Gibbons et al. (2021c); or that (ii) λ can actually change over time in a seamless, costless way. Both assumptions entail pros and cons. To lift these assumptions, one could model the adjustment process of beliefs in response to environmental changes (perhaps following the ideas from the Carnegie School; see Puranam et al. 2015). Furthermore, one could create a hierarchical structure of beliefs such that a subset of beliefs "at the top" do not change, whereas a majority of lower-level and "closer-to-the-action" beliefs must change to accommodate to a new environment (this subset can be a part of r because many "practices" are in fact cultural—not formal—elements; see Gibbons and Henderson 2013, Howard-Grenville et al. 2020). Empirical inspiration for these efforts can be taken from the literature on narratives and stories, which has pointed to their importance for organizational change both in providing stability and in enabling change (e.g., Vaara et al. 2016, Dal Piaz and Di Stefano 2018, Gibbons 2021a).

5.2. Problemistic search

Although empirical research on problemistic search (Cyert and March 1963) has thrived, the "development of the theory has not kept pace" (Posen et al. 2018, p. 208). We believe cultural evolution models that rely on signals (such as the selective learning we use in this paper) can be used to formally model problemistic search. Consider that in problemistic search, "a firm's recognition of performance below aspirations, which is the level of future performance deemed acceptable, leads to a process of

search to discover a solution to the problem" (ibid). Our model is consistent with this description, and we believe future research could explore this connection.

6. Conclusion

With this paper, we answer calls to study the mechanisms driving the impact of organizational culture on organizational performance (Chatman et al. 2014, O'Reilly and Chatman 2016, Chatman and Srivastava 2021, Gibbons et al. 2021b, Grennan and Li 2022). More precisely, we study how organizational culture can affect organizational adaptation to a changing environment. This mechanism has received less attention than others, such as cultural strength (exceptions are Schein 2010, Chatman et al. 2014, Gibbons et al. 2021c), but it is nonetheless fundamental.

Following Schein (2010), we divide culture into two dimensions: *beliefs* about the structure of the world/environment and the firm's role in it (its mission, means to achieve goals) and *prosocial values* (values that prioritize help to colleagues and contributions to the whole organization, rather than focusing on one's own payoff). Using a cultural evolution model (Boyd and Richerson 2005, Brahm and Poblete 2021), we show that *increasing the accuracy/verisimilitude of beliefs* improves the firm's capacity to detect that a change in the environment has occurred, thereby enabling it to better time innovation and making it more productive; this, in turn, provides "space" to expand the use of tradition and promote prosocial effort in its diffusion. This reduces the innovation versus tradition trade-off, and yields improvements in firms' adaptability and performance. This finding implies that, contrary to received wisdom, but consistent with some recent efforts (e.g., Gibbons et al. 2021c), cultural strength need not come at the expense of adaptation (cf., Corritore et al. 2020). It also connects organizational culture with the literature on cognition and organizational adaptation (Barr et al. 1992, Tripas and Gavetti 2000, Eggers and Park 2018) and the Carnegie School (March 1991, Puranam 2018, Posen et al. 2018). Furthermore, we find that when *prosocial values increase in intensity*, they improve performance by enhancing the efficiency in the transmission of tradition, which can insulate the organization from shocks. However, by promoting tradition, intense prosocial values "crowd out" innovation and thus diminish the organization's capacity to adapt; we show that if the intensity of

prosocial values is sufficiently high, this second effect dominates, and thus the relation between prosociality and performance takes the shape of an inverted U. We join recent efforts and calls to advance beyond the view that "pro-sociality always improves performance" (Chatman et al. 2019, Hergeux et al. 2021) to study when it can have a detrimental effect on performance.

7. References

Ahuja G, Katila R (2004) Where do resources come from? The role of idiosyncratic situations. *Strategic Management J.* 25:887–907.

Akerlof GA, Kranton RE (2005) Identity and the economics of organizations. *J. Econom. Perspect.* 19(1):9–32.

Argyres NS, Zenger TR (2012) Capabilities, transaction costs, and firm boundaries. *Organ. Sci.* 23(6):1643–1657.

Argote L, Miron-Spektor, E (2011) Organizational learning: From experience to knowledge. *Organ. Sci.* 22(5):1123–1137.

Argote L, Lee S, Park J (2021) Organizational learning processes and outcomes: Major findings and future research directions. *Management Sci.* 67(9):5399–5429.

Barnard, CH (1938) *The Functions of the Executive*. (Harvard University Press, Cambridge, MA).

Barr PS, Stimpert JL, Huff AS (1992) Cognitive change, strategic action, and organizational renewal. *Strategic Management J.* 13(S1):15–36.

Barr PS (1998) Adapting to unfamiliar environmental events: A look at the evolution of interpretation and its role in strategic change. *Organ. Sci.* 9:644–669.

Bauer M, Blattman C, Chytilová J, Henrich J, Miguel E, Mitts T (2016) Can war foster cooperation? *J. Econom. Perspect.* 30(3):249–274.

Benner MJ, Tushman ML (2003) Exploitation, exploration, and process management: The productivity dilemma revisited. *Acad. Manage. Rev.* 28(2):238–256.

Besley TJ, Persson T (2022) Organizational dynamics: Culture, design, and performance. *J. Law. Econ. Organ.* 00:(1-22)

Böhm R, Rockenbach B (2013) The inter-group comparison-intra-group cooperation hypothesis: Comparisons between groups increase efficiency in public goods provision. *PloS One*. 8(2)e56152.

Bolino MC, Grant AM (2016) The bright side of being prosocial at work, and the dark side, too: A review and agenda for research on other-oriented motives, behavior, and impact in organizations. *Acad. Manag. Ann.* 10(1), 599–670.

Bowles S (2009) Did warfare among ancestral hunter-gatherers affect the evolution of human social behaviors? *Science*. 324(5932):1293–1298.

Boyd R (2018) *A Different Kind of Animal: How Culture Transformed Our Species* (Vol. 46). (Princeton University Press, NJ).

Boyd R, Richerson PJ (1985) *Culture and the Evolutionary Process*. (Chicago: University of Chicago Press).

Boyd R, Richerson PJ (2005) *The Origin and Evolution of Cultures*. (Oxford: Oxford University Press).

Brahm F, Poblete J (2021) The evolution of productive organizations. *Nat. Hum. Behav.* 5: 39-48.

Brahm F, Poblete J (2022) Cultural evolution theory and organizations. *Int. J. Organ. Theory Behav*. 3(1):26317877211069141.

Cameron KS, Quinn RE (2011) *Diagnosing and Changing Organizational Culture: Based on the Competing Values Framework*. (John Wiley & Sons, New York).

Cavalli-Sforza LL, Feldman MW (1981) *Cultural Transmission and Evolution: A Quantitative Approach*. (Princeton University Press, Princeton, NJ).

Chakravarthy BS (1982) Adaptation: A promising metaphor for strategic management. *Acad. Manage. Rev.* 7:35–44.

Chatterji AK, Findley M, Jensen NM, Meier S, Nielson D (2016) Field experiments in strategy research. *Strategic Management J.* 37(1):116–132.

Chatman JA, Caldwell DF, O'Reilly CA, Doerr B (2014) Parsing organizational culture: How the norm for adaptability influences the relationship between culture consensus and financial performance in high-technology firms. *J. Organ. Behav.* 35(6):785–808.

Chatman JA, O'Reilly CA (2016) Paradigm lost: Reinvigorating the study of organizational culture. *Res. Organ. Behav.* 36:199–224.

Chatman JA, Srivastava SB (2021) A psychologist and sociologist join strategists for breakfast: Building a framework to understand culture and its relationship to strategy. *Strategy Sci.* 6(2):119–123.

Chatman JA, Greer L, Sherman E, Doerr B (2019) Blurred lines: How the collectivism norm operates through perceived group diversity to boost or harm group performance in Himalayan mountain climbing. *Organ. Sci.* 30(2):235–259.

Cohen MD (2007a) Perspective—Administrative behavior: Laying the foundations for Cyert and March. *Organ. Sci.* 18(3):503–506.

Cohen MD (2007b) Reading Dewey: Reflections on the study of routine. *Organ. Stud.* 28:773– 786, DOI: 10.1177/0170840606077620.

Colla E, Ruiz-Molina ME, Chastenet De Gery C, Schultz M, Deparis M, Lemmet L (2019) Understanding franchisee performance: The role of the franchisee's autonomy, affective commitment to the network and innovativeness. *Int. J. Retail. Distrib.* 47(7):733–751.

Corritore M, Goldberg A, Srivastava SB (2020) Duality in diversity: How intrapersonal and interpersonal cultural heterogeneity relate to firm performance. *Adm. Sci. Q.* 65(2):359–394.

Costanza DP, Blacksmith N, Coats MR, Severt JB, DeCostanza AH (2016) The effect of adaptive organizational culture on long-term survival. *J. Bus. Psychol.* 31(3):361–381.

Crémer J (1993) Corporate culture and shared knowledge. *Ind. Corp. Chang.* 2(3):351–386.

Curry OS, Mullins DA, Whitehouse H (2019) Is it good to cooperate? Testing the theory of morality-as-cooperation in 60 societies. *Curr. Anthropol.* 60(1):47–69.

Cyert RM, March JG (1963) *A Behavioral Theory of the Firm* (Vol. 2, No. 4, pp. 169–187).

Dada O, Watson A, Kirby DA (2012) Toward a model of franchisee entrepreneurship. *Int. Small Bus. J.* 30(5):559–583.

Danneels E (2011) Trying to become a different type of company: Dynamic capability at Smith Corona. *Strategic Management J.* 32(1):1–31.

Dalpiaz E, Di Stefano G (2018) A universe of stories: Mobilizing narrative practices during transformative change. *Strategic Management J.* 39(3):664–696.

Deal TE Kennedy AA (1982) *Corporate Cultures. The Rites and Rituals of Corporate Life*. (Addison-Wesley, Reading, MA).

Denison DR, Mishra AK (1995) Toward a theory of organizational culture and effectiveness. *Organ. Sci.* 6(2):204–223.

Dessein W, Prat A (2022) Organizational capital, corporate leadership, and firm dynamics. *J. Polit. Econ.*, 130(6):1477–1536.

DiMaggio P (1994) Culture and economy. Smelser N, Swedberg R, eds. *The Handbook of Economic Sociology* (Princeton University Press, Princeton, NJ), 27–57.

DiMaggio P (1997) Culture and cognition. *Annu. Rev. Sociol.* 23(1):263–287.

Drucker PF (1994) The theory of the business. *Harvard Bus. Rev.* 72(5):95–104.

Eggers JP, Kaplan S (2009) Cognition and renewal: Comparing CEO and organizational effects on incumbent adaptation to technical change. *Organ. Sci.* 20:461–477.

Eggers JP, Kaplan S (2013) Cognition and capabilities: A multi-level perspective. *Acad. Manag. Ann,* 7(1):295–340.

Eggers JP, Park KF (2018) Incumbent adaptation to technological change: The past, present, and future of research on heterogeneous incumbent response. *Acad. Manag. Ann.* 12:357–389.

Fang C, Lee J, Schilling MA (2010) Balancing exploration and exploitation through structural design: The isolation of subgroups and organizational learning. *Organ. Sci.* 21(3):625–642.

Fehr E (2018) Behavioral foundations of corporate culture. University of Zurich, UBS International Center of Economics in Society, Public Paper, (7).

Felin T, Zenger TR (2017) The theory-based view: Economic actors as theorists. *Strategy Sci.* 2(4):258–271.

Francois P, Fujiwara T, Van Ypersele T (2018) The origins of human prosociality: Cultural group selection in the workplace and the laboratory. *Sci. Adv.* 4(9):eaat2201.

Friedkin NE (1999) Choice shift and group polarization. *Am. Sociol. Rev.* 856–875.

Gelfand MJ, Raver JL, Nishii L, Leslie LM, Lun J, Lim BC, … Yamaguchi, S. (2011) Differences between tight and loose cultures: A 33-nation study. *Science*. 332(6033):1100–1104.

Gibbons R, Henderson R (2013) What do managers do?: Exploring persistent performance differences among seemingly similar enterprises. Book chapter in the *Handbook of Organizational Economics*, Eds. John Roberts and Robert Gibbons.

Gibbons R, Licalzi M, Warglien M (2021a) What situation is this? shared frames and collective performance. *Strategy Sci.*

Gibbons R, Siegel J, Weber RA (2021b) Strategy meets culture (for breakfast): Understanding the relationship and highlighting its potential. *Strategy Sci.* 6(2):111–118.

Gibbons RS, Grieder M, Herz H, Zehnder C (2021c) Building an equilibrium: Rules versus principles in relational contracts. *Organ. Sci.* Articles in Advance.

Gibson CB, Birkinshaw J (2004) The antecedents, consequences, and mediating role of organizational ambidexterity. *Acad. Manage. J.* 47:209–226.

Giorgi S, Lockwood C, Glynn MA (2015) The many faces of culture: Making sense of 30 years of research on culture in organization studies. *Acad. Manag. Ann.* 9(1):1–54.

Gorton GB, Grennan J, Zentefis AK (2022) Corporate culture (No. w29322). National Bureau of Economic Research.

Graham J, Grennan J, Campbell H, Shivaram R (2022) Corporate culture: Evidence from the field. *J. Financ. Econ.* forthcoming.

Grant RM (1996) Toward a knowledge-based theory of the firm. *Strategic Management J.* 17(S2):109–122.

Grennan J (2020) Communicating culture consistently: Evidence from banks. Available at SSRN 3350645.

Grennan J (2022) "A Corporate Culture Channel: How Increased Shareholder Governance Reduces Firm Value". Available at SSRN: https://ssrn.com/abstract=2345384

Grennan J, Li K (2022) Corporate culture: A review and directions for future research. Available at SSRN: https://ssrn.com/abstract=4095565

Groysberg B, Lee J, Price J, Cheng J (2018) The leader's guide to corporate culture. *Harv. Bus. Rev.* 96(1):44–52.

Hannan MT, Le Mens G, Hsu G, Kovács B, Negro G, Pólos L, ... Sharkey AJ (2019) *Concepts and Categories: Foundations for Sociological and Cultural Analysis*. (Columbia University Press, New York).

Hartnell CA, Ou AY, Kinicki A (2011) Organizational culture and organizational effectiveness: A meta-analytic investigation of the competing values framework's theoretical suppositions. *J. Appl. Psychol.* 96(4):677.

Hartnell CA, Ou AY, Kinicki AJ, Choi D, Karam EP (2019) A meta-analytic test of organizational culture's association with elements of an organization's system and its relative predictive validity on organizational outcomes. *J. Appl. Psychol.* 104(6):832.

Helfat CE, Martin, JA (2015) Dynamic managerial capabilities: Review and assessment of managerial impact on strategic change. *J. Manage.* 41:1281–1312.

Helfat CE, Peteraf MA (2015) Managerial cognitive capabilities and the microfoundations of dynamic capabilities. *Strategic Management J.* 36:831–850.

Henrich J, (2016) *The Secret of Our Success: How Culture is Driving Human Evolution, Domesticating our Species, and Making us Smarter.* (Princeton University Press, NJ).

Henrich J, (2020) *The Weirdest People in the World: How the West Became Psychologically Peculiar and Particularly Prosperous.* (Farrar, Straus and Giroux, New York).

Henrich J, Muthukrishna M (2021) The origins and psychology of human cooperation. *Annu. Rev. Psychol.* 72:207–240.

Hergueux J, Henry E, Benkler Y, Algan Y (2021) Social exchange and the reciprocity roller coaster: evidence from the life and death of virtual teams. *Organ. Sci.* (Articles in advance).

Hermalin BE (2012) Leadership and corporate culture. *Handbook of Organizational Economics* (Princeton University Press, NJ), 432–78.

Howard-Grenville J, Lahneman B, Pek S (2020) Organizational culture as a tool for change. Stanford Social Innovation Review, Summer.

Janis IL (2008) Groupthink. *IEEE Eng. Manag. Rev.* 36(1):36.

Kendal RL, Boogert NJ, Rendell L, Laland KN, Webster M, Jones PL (2018) Social learning strategies: Bridge-building between fields. *Trends Cogn. Sci.* 22(7):651–665.

Koçak Ö, Puranam, P (2023) Decoding culture: A tool for behavioral strategists. *Strat. Sci.* (Ahead of print).

Kogut B, Zander U (1996) What firms do? Coordination, identity, and learning. *Organ. Sci.* 7(5):502–518.

Kreps DM (1990) Corporate culture and economic theory. *Perspectives on Positive Political Economy*, 90(109–110):8.

Lavie D, Stettner U, Tushman ML (2010) Exploration and exploitation within and across organizations. *Acad. Manag. Ann.* 4(1):109–155.

Lawrence P, Lorsch J (1969) Organization and Environment. Homewood, Ill.: Richard D. Irwin

Levinthal DA (1997) Adaptation on rugged landscapes. *Management Sci.* 43(7):934–950.

Li K, Liu X, Mai F, Zhang T (2021) The role of corporate culture in bad times: Evidence from the COVID-19 pandemic. *J. Financial Quant. Anal.* 56(7):2545–2583.

Liao H, Su R, Ptashnik T, Nielsen J (2022) Feeling good, doing good, and getting ahead: A meta-analytic investigation of the outcomes of prosocial motivation at work. *Psychol. Bull.* 148(3-4):158.

Lix K, Goldberg A, Srivastava SB, Valentine MA (2022) Aligning differences: Discursive diversity and team performance. *Management Sci.*

March, JG (1991) Exploration and exploitation in organizational learning. *Organ. Sci.* 2(1):71–87.

March JG, Simon HA (1958) *Organizations*. (John Wiley & Sons, New York).

Marchetti A (2019*) Firms of a Feather Merge Together: The Coordination Benefits of Compatible Cultures.* Available at SSRN 3712838

Marchetti A, Puranam P (2020) The cultural attributes of "less hierarchical" forms of organization, Working paper.

Maynard-Smith J (1982) *Evolution and the Theory of Games*. (Cambridge University Press).

Mesoudi A (2011) *Cultural evolution: How Darwinian Theory can Explain Human Culture and Synthesize the Social Sciences*. (University of Chicago Press).

Morrison AD, Wilhelm WJ Jr (2004) Partnership firms, reputation, and human capital. *Am. Econ. Rev.* 94(5):1682–1692.

Nowak MA, Sigmund K (2005) Evolution of indirect reciprocity. *Nature*, 437:1291.

O'Reilly CA III, Tushman ML (2013) Organizational ambidexterity: Past, present, and future. *Acad. Manag. Perspect.* 27(4):324–338.

Organ DW, Podsakoff PM, MacKenzie SB (2005) Organizational citizenship behavior: Its nature, antecedents, and consequences. (Sage Publications).

Posen HE, Keil T, Kim S, Meissner FD (2018) Renewing research on problemistic search – A review and research agenda. *Acad. Manag. Ann.* 12(1):208–251.

Puranam P, Stieglitz N, Osman M, Pillutla MM (2015) Modelling bounded rationality in organizations: Progress and prospects. *Acad. Manag. Ann.* 9(1):337–392.

Puranam P (2018) *The Microstructure of Organizations*. (Oxford University Press).

Rand DG, Nowak MA (2013) Human cooperation. *Trends Cogn. Sci.* 17, 413–425

Randle DK, Pisano GP (2021) The evolutionary nature of breakthrough innovation: An empirical investigation of firm search strategies. *Strategy Sci.* 6(4):290–304.

Sandvik JJ, Saouma RE, Seegert NT, Stanton CT (2020) Workplace knowledge flows. *Q. J. Econ.* 135(3):1635–1680.

Sarta A, Durand R, Vergne JP (2021) Organizational adaptation. *J. Manage.* 47(1):43–75.

Schein E (2010) *Organizational Culture and Leadership*. (John Wiley & Sons; 4th edition).

Smaldino PE (2014) The cultural evolution of emergent group-level traits. *Behav. Brain Sci.* 37(3):243–95.

Sørensen JB (2002) The strength of corporate culture and the reliability of firm performance. *Adm. Sci. Q.* 47(1):70–91.

Srivastava SB, Goldberg A (2017) Language as a window into culture. *Calif. Manage. Rev.* 60(1):56–69.

Swidler A (1986) Culture in action: Symbols and strategies. *Am. Sociol. Rev.* 273–286.

Teece DJ (2007) Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management J.* 28:1319–1350.

Tripsas M, Gavetti G (2000) Capabilities, cognition, and inertia: Evidence from digital imaging. *Strategic Management J.* 21(10-11):1147–1161.

Tripsas M (2009) Technology, identity, and inertia through the lens of "The Digital Photography Company." *Organ. Sci.* 20(2):441–460.

Ulrich D, Allen J, Smallwood N, Brockbank W, Younger J (2009) Building culture from the outside in. *J. Strategic Hum. Resour. Manag.* 8(6):20–27.

Uotila J, Maula M, Keil T, Zahra SA (2009) Exploration, exploitation, and financial performance: Analysis of S&P 500 corporations. *Strategic Management J.* 30(2):221–231.

Vaara E, Sonenshein S, Boje D (2016) Narratives as sources of stability and change in organizations: Approaches and directions for future research. *Acad. Manag. Ann.* 10(1):495–560.

Van den Steen E (2010a) On the origin of shared beliefs (and corporate culture). *Rand J. Econ.* 41(4):617–648.

Van den Steen E (2010b) Culture clash: The costs and benefits of homogeneity. *Management Sci.* 56(10):1718–1738.

Vicinanza, P., Goldberg, A., & Srivastava, S. B. (2023). A deep-learning model of prescient ideas demonstrates that they emerge from the periphery. *PNAS nexus*, 2(1), pgac275Watson A, Senyard J, Dada OL (2020) Acts of hidden franchisee innovation and innovation adoption within franchise systems. *Ind. Mark. Manag.* 89:431–445.

Weber RA, Camerer CF (2003) Cultural conflict and merger failure: An experimental approach. *Management Sci.* 49(4):400–415.

Weber K, Dacin MT (2011) The cultural construction of organizational life: Introduction to the special issue. *Organ. Sci.* 22(2):287–298.

Wilden R, Hohberger J, Devinney TM, Lavie D (2018) Revisiting James March (1991): Whither exploration and exploitation. *Strateg. Organ.* 16(3):352–369.

Zenger T (2013) What is the theory of your firm? *Harvard Bus. Rev.* 91(6):72–78.

Zhu DH (2013) Group polarization on corporate boards: Theory and evidence on board decisions about acquisition premiums. *Strategic Management J.* 34(7):800–822.

8. Figures and table

Figure 1. Trade-off Between Innovation and Help Diffusing Tradition. *Notes:* We graph the ESS equilibrium. We use $c = 0.6$, $C = 0.8$, $\mu = 0.2$, $\lambda = 0.5$, and we vary p between 0.02 and 0.20 using jumps of 0.02, to produce variance in the share of individual learners (innovation) and helping effort. The top-left end of the blue line corresponds to $p = 0.02$ and the bottom-right corresponds to 0.20. Each dot of the graph is the equilibrium value of the share of individual learners and helping effort described by Equations (14), (15), and (16).
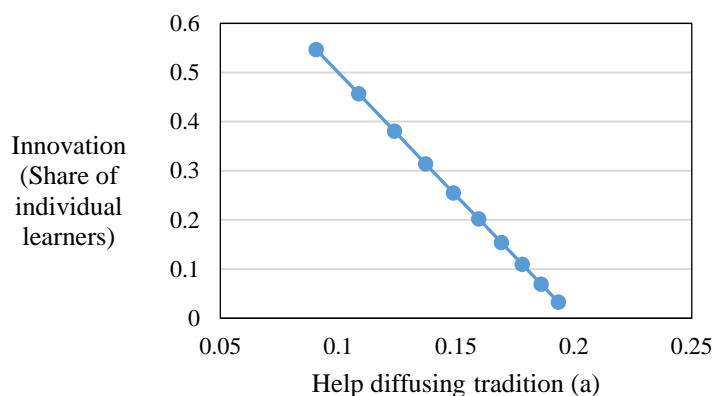
Figure 2. Impact of Improving the Shared Beliefs. *Notes:* We graph the ESS equilibrium. We assume $C = 0.8$, $c = 0.6$, $\mu = 0.2$, and $p = 0.1$.
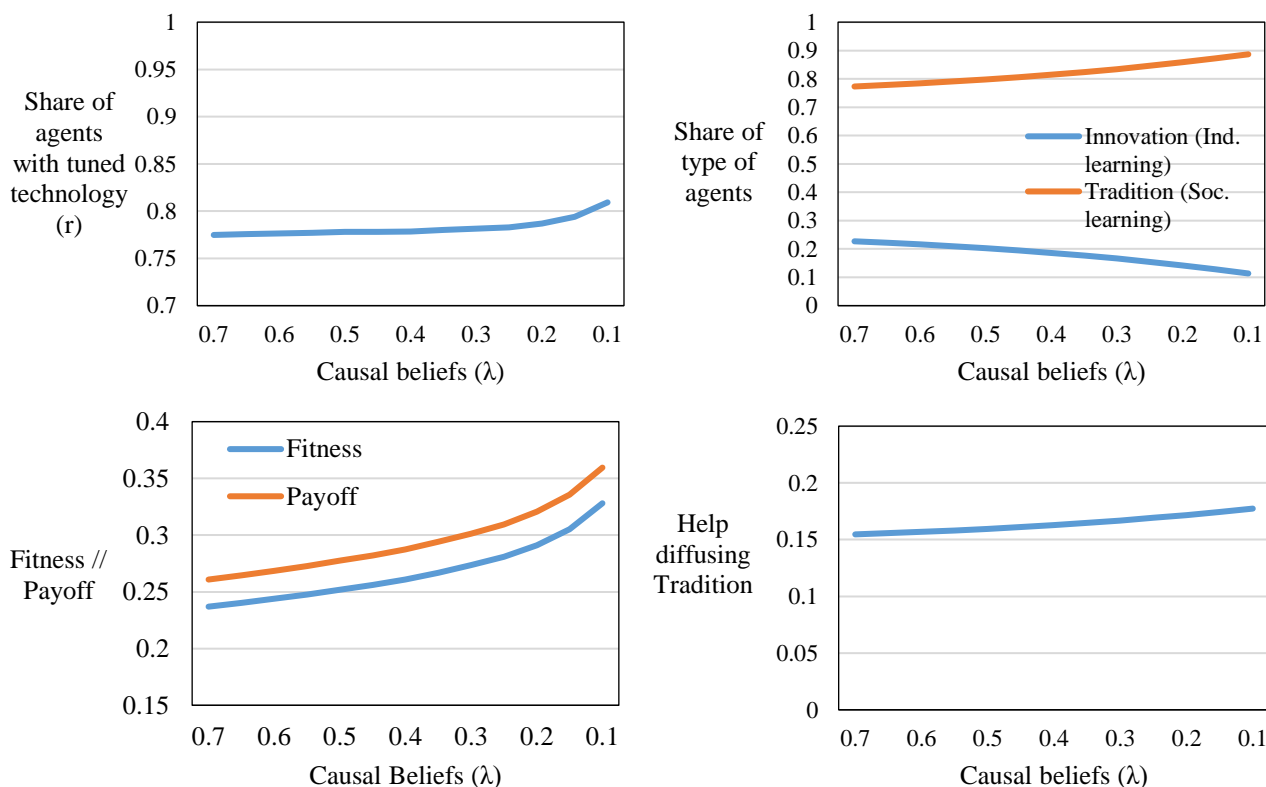
Figure 3. Innovation Efficiency Improves When Beliefs Are More Accurate. *Notes:* We graph the ESS equilibrium. We assume $C = 0.8$, $c = 0.6$, and $p = 0.1$; in the left graph, we assume $\mu = 0.2$, and in the right, $\lambda = 0.5$.

49
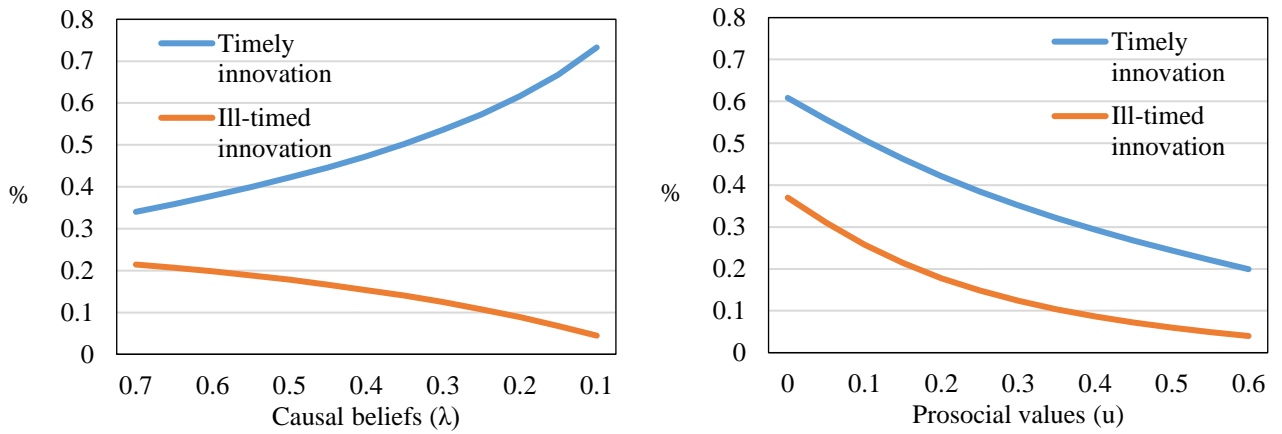
Figure 4. Improving Shared Beliefs Reduces the Trade-off Between Total Innovation and Help in Diffusing Tradition, and Breaks It for "Timely" Innovation. *Notes:* We graph the ESS equilibrium. We assume $C = 0.8$, $c = 0.6$, $\mu = 0.2$, and $p = 0.1$. The graph of the left is equivalent to a weighted average of the graphs in the middle and right, using $p = 0.1$ and $1-p = 0.9$ as weights, respectively.
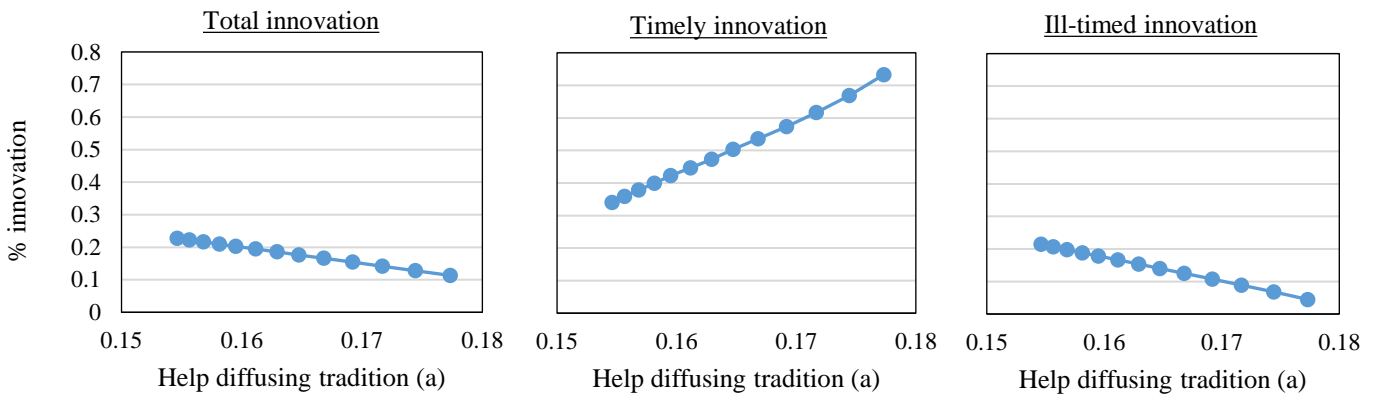

Figure 5. Dynamics of the ESS Equilibrium When Changing Accuracy of Beliefs. *Notes:* In all graphs, we assume $C = 0.8$, $c = 0.6$ and $\mu = 0.2$, and we vary the value of λ. To graph the dynamics of knowledge, we: (i) use Equation (6) at the equilibrium value for d, (ii) seed the simulation with the equilibrium value for r in period 1, and (iii) allow the world to change in period 10 (when $p = 1$) and to remain stable in the other periods (that is $p = 0$). The graph of fitness plugs the changing value of r into the fitness equation. The graphs display how the shared of tuned agents and fitness behaves over time in the ESS.


50
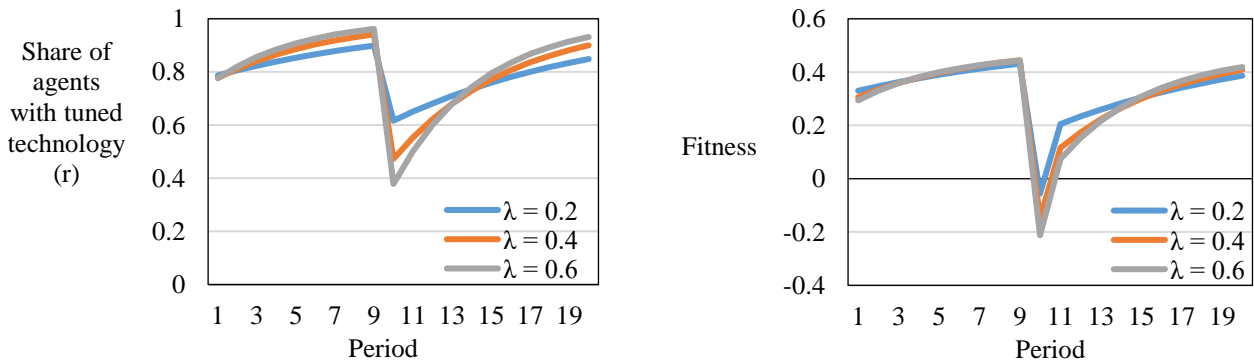
Figure 6. Impact of Increasing the Intensity of Prosocial Values. *Notes:* We graph the ESS equilibrium. We assume $C = 0.8$, $c = 0.6$, $\lambda = 0.5$, and $p = 0.1$.
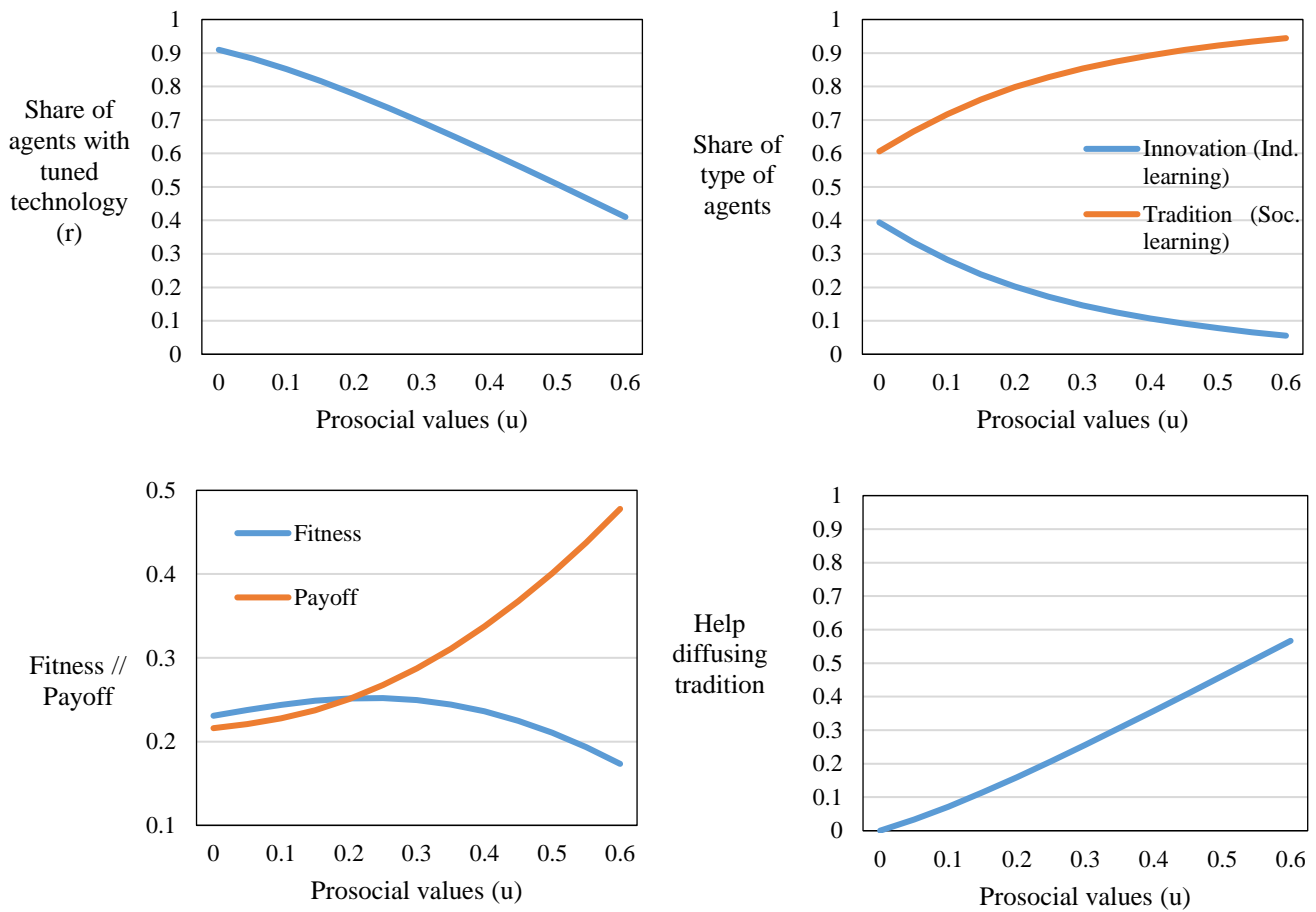
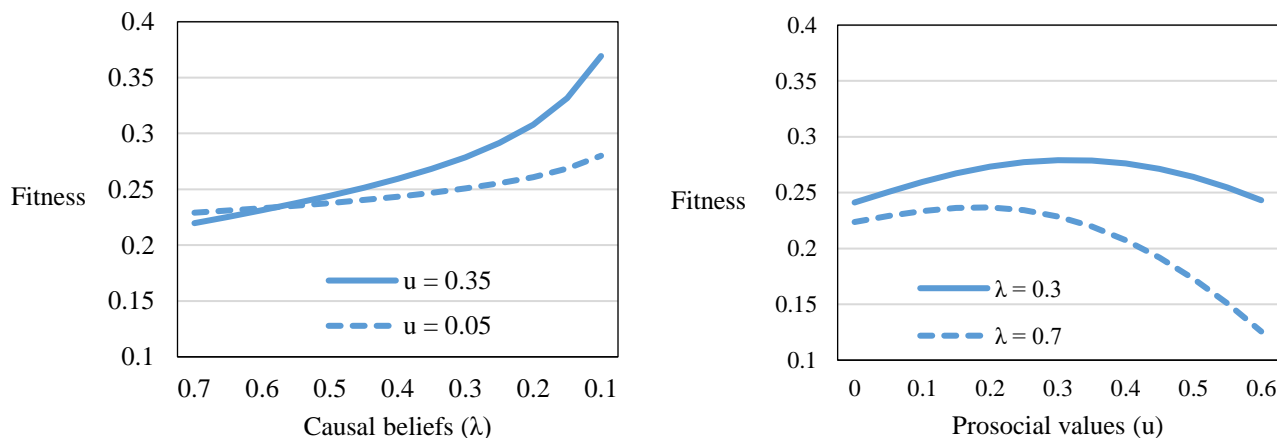
Figure 7. Dynamics of the Equilibrium When Changing Help in Diffusing Tradition. *Note:* In all graphs, we assume $C = 0.8$, $c = 0.6$ and $\lambda = 0.5$, and we vary the value of μ.
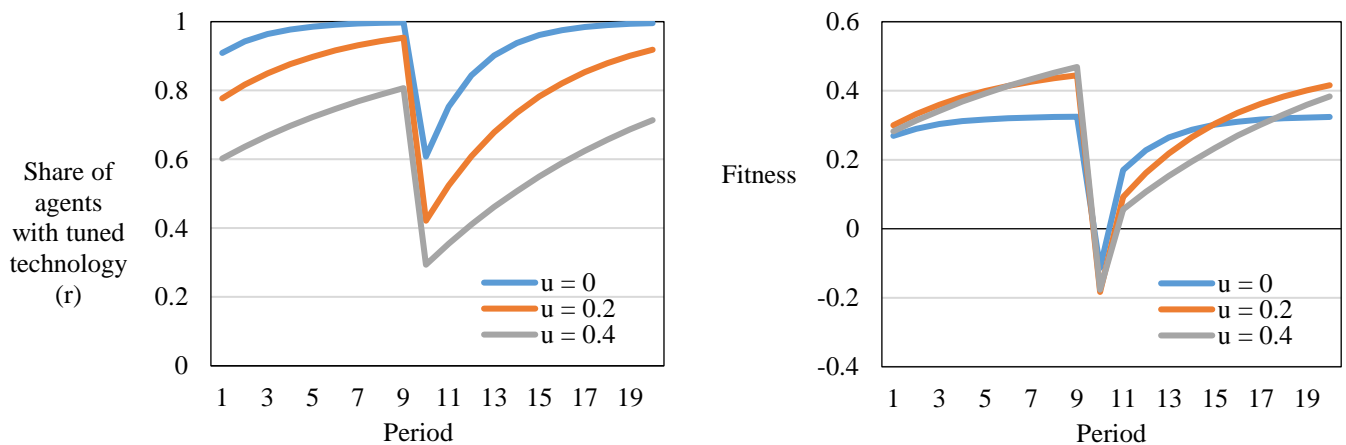
Figure 8. More Intense Prosocial Values Enhance the Trade-off Between Innovation and Help in Diffusing Tradition. *Notes:* We graph the ESS equilibrium. We assume $C = 0.8$, $c = 0.6$, $\lambda = 0.5$, and $p = 0.1$. The graph of the left is equivalent to a weighted average of the graphs in the middle and right, using $p = 0.1$ and $1-p = 0.9$ as weights, respectively.

Total innovation

Timely innovation

Ill-timed innovation
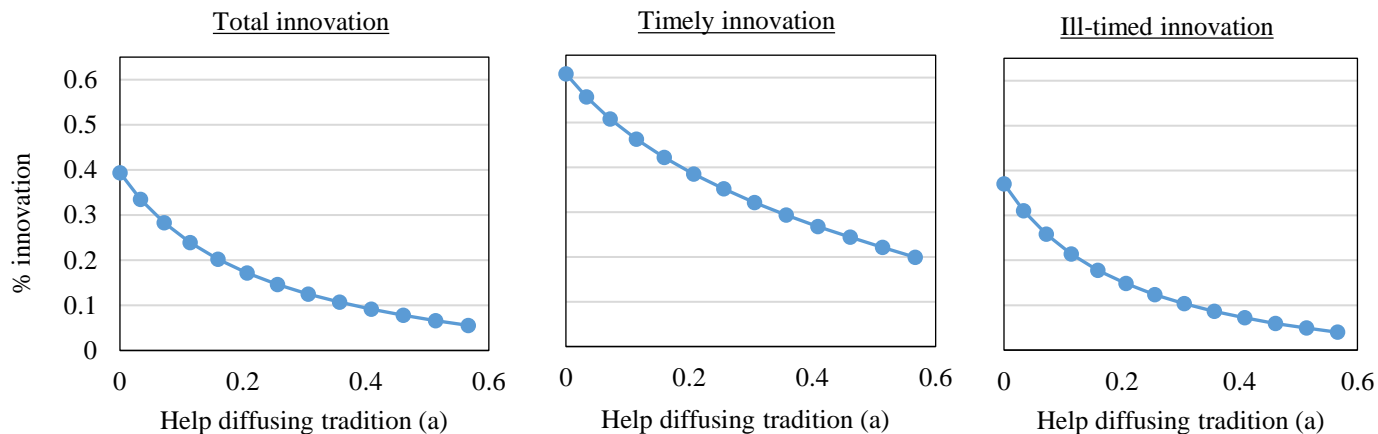
Figure 9. Complementarity Between u and λ. *Notes:* We graph the ESS equilibrium. We assume $C = 0.8$, $c = 0.6$, and $p = 0.1$.

Table 1. How Our Model Applies to a Sales Force

Object	Definition	Sales force example
p	Likelihood of change in environment Range: [0,1]	Likelihood of change in customers (e.g., change in taste and/or preferences), competitors (e.g., sales strategy, complementary products/services), technology (e.g., online sales, AI), industry (e.g., entry), etc. (common to all salespersons).
r	Share of agents with tuned technology Range: [0,1]	The share of salespersons who have the right "technology/practices/skills" (e.g., sales technique, preparation before a sale, route ordering, discount management) given the state of the environment. There is a "right" technology/practices/skills because the world changes (see p above). This "right" technology provides higher sales level than the "wrong" technology (in our model, this distance is standardized as 1 and 0).
s	Signal obtained from the organization–environment interaction Range: [0,∞)	For each period (e.g., month, quarter, semester) every salesperson receives a signal in the form of sales, customer complaints, sales returns, or non-payment (these can be absolute level or percentage change).
d	This is a threshold against which the signal is compared to decide behavior Range: [0,∞)	Each salesperson has a rule of this type: "If the drop in sales is more than 10%, then I will innovate (e.g.,., try new sales techniques, reroute my day, change the way I handle discounts and promotions); if not, I will follow tradition (i.e., I will use the "technology/practices/skills" that my peers have been using in the past). The rule's threshold varies across salespersons. Innovation is individual learning, and tradition is social learning. Salespersons learn socially, either by directly copying other salespersons—usually those who are more experienced or more prestigious—but also when they learn from the organizational guidelines/handbooks that contain encoded accumulated experience/tradition.
λ	Beliefs about the environment and the role of the organization in it (problem it solves, how it solves it, and the value it creates). These beliefs drive the informativeness of the signal with respect to environmental change. Range: (-∞, 0]	How much a salesperson understands: (i) the environment in and of itself (e.g., customer demand, competitors, technology, industry) and (ii) the role that the organizations performs for customers (or the problem it solves). These beliefs are common to all salespersons. Sales forces have different beliefs about customers: some beliefs are simplistic and less accurate (e.g., "all customers are only driven by price"), which more often than not will lead to signal misinterpretation (such as not recognizing that a drop in sales was caused by customers increasingly value quality); some beliefs are more accurate (e.g., "some customer prioritize price, but others prioritize quality and service"). A salesperson would also have beliefs about the role of the sales force: some simplistic and inaccurate (e.g., "we simply take sales orders"), which will often lead to misinterpret signals (such as sales drop driven by novel service-oriented competitors to be misinterpreted as noisy), or more sophisticated and accurate (e.g., "we provide solutions—a bundle of the right products, the right price, and a great good service—to the customer's problem") which will allow them to recognize a novel service-oriented competitor (a change in the environment) as a probable cause.
μ	Strength of prosocial values in the organization Range: [0,∞)	How much the organization values salespersons helping one another directly. This translates to how much normative emphasis is placed—via informal/symbolic rewards, such as reputation and awards, or prosocial punishment (e.g., reprimands of selfish salespersons)—on salespersons helping their colleagues learn the sales techniques/knowledge they have

		(e.g., how to manage a new SKU, market information about competitors, use IT tools, a novel sales technique).
a	Effort in helping others learn about tradition Range: [0,∞)	Effort exerted by a salesperson so that a colleague who is imitating them better learns the sales techniques/knowledge they have (e.g., how to manage a new SKU, market information about competitors, use IT tools). In others words, effort in helping passing the tradition along to colleagues.
$C, c,$ $m(a)$	Cost of learning and helping effort Range: [0,∞)	Cost in terms of time and effort that the salesperson must bear for learning and helping.
h	Fitness of the agent Range: [-c,∞)	This is the added value that the salesperson generates (i.e., price minus the "opportunity" cost C, c and $m(a)$). Although we don't model value capture for the firm and employee (i.e., salesperson's compensation plan), we can nonetheless assume that part of this added value will be captured by the salesperson in the form of compensation and that this share will increase with added value.
q	Payoff of the agent Range: [-c,∞)	On top of h, salespersons care about the informal benefits they receive from helping others learn the organization's tradition. These benefits can be reputational, symbolic awards (e.g., "salesperson of the month"), or avoiding shame (e.g., the sales supervisor calling you out in public for not helping) or guilt (if the norm is internalized by the salesperson).

A. Online appendix

A.1. Threshold strategy is optimal

Remember that the expected fitness from individual learning is always $1 - C$, whereas from social learning it is $r - c > 1 - C$ if the state does not change and 0 if it does.

Let $f(s|NC)$ and $f(s|C)$ be the distributions of signal s conditional on the state not changing and the state changing respectively. Using Bayes' rule, we can compute the distribution of the state of the world contingent on the signal as follows:

$$P(NC|s) = \frac{f(s|NC)\,P(NC)}{f(s)}$$

$$P(C|s) = \frac{f(s|C)\,P(C)}{f(s)}$$

Conditional on the signal s, the expected payoff of individual learning is $1 - C$, which is constant in s, and the expected payoff of social learning is

$$P(NC|s)(r - c) + P(C|s)(-c)$$

For the threshold strategy to be optimal we need to show that this term is monotonically decreasing in s. Since $P(NC|s) + P(C|s) = 1$ for every s, this occurs iff $\frac{P(C|s)}{P(NC|s)}$ is increasing in s. Notice that from bayes rule $\frac{P(C|s)}{P(NC|s)} = \frac{f(s|C)}{f(s|NC)}\frac{P(C)}{P(NC)}$ which is monotonic if the two distributions $f(s|C)$ and $f(s|NC)$ satisfy the MLRP condition, which states that for any $s1 > s0$, $\frac{f(s1|C)}{f(s1|NC)} > \frac{f(s0|C)}{f(s0|NC)}$.

A.2. Proof of the existence and uniqueness of ESS

We assume that a cannot be negative and that the cost of social learning $c - a$ cannot be negative. Sufficient conditions for a to be an interior solution that satisfies these restrictions are the standard INADA conditions $\lim_{x \to c} m'(x) = \infty$ and $\lim_{x \to c} m'(0) = 0$.

Proof

We show existence and uniqueness of the ESS provided that the cost of helping effort $m(a)$ is sufficiently convex. $m'(a^*) = \mu[(1-p)F_{\lambda=1}(d^*) + p\,F_{\lambda<1}(d^*)]$

An ESS is a triplet (a, d, r) that satisfies Equations (14), (15), and (16) in the main body of the manuscript. First, notice that Equation (14) can be written as

$$a = m'^{-1}(\mu[(1-p)F_{\lambda=1}(d) + p\,F_{\lambda<1}(d)])$$

where a is strictly increasing in d. To save notation, we define the function $a = a^*(d)$.

Analogously, Equation (16) will be defined as $r^*(d)$. Equation $r^*(d)$ is strictly decreasing in d and $r^*(0) = 1$ and $\lim_{x \to \infty} r(x) = 0$.

Replacing both equations, the equilibrium can be characterized by the equation

$$(1-p)f_{\lambda=1}(d^*)(r^*(d) - c + a^*(d) - [1-C]) + p\,f_{\lambda<1}(d^*)(-c + a^*(d) - [1-C]) = 0 \quad \text{(A.1)}$$

To prove existence, notice that evaluated as $d = 0$ we have $a = 0$ and $r = 1$ and, therefore, the left-hand side of Equation (A.1) is $(1-p)(C-c) + pf_{\lambda<1}(C - c - 1)$. Because we have assumed that $C - c > p$, this term is positive.

On the other hand, as we take the limit as $d \to \infty$, we have $r = 0$ and $a \leq c$; therefore, $C - c + a - 1$ is negative and so is the left-hand side of Equation (6), which is equal to $(1-p)[f_{\lambda=1}(d)](C - c + a - 1) + p[f_{\lambda<1}(d)](C - c + a - 1)$. Because Equation (6) is continuous, positive at $d = 0$ and

negative as d→∞ by the intermediate value theorem, there must exist some positive value of d at which the equation becomes 0; this is an ESS.

To show uniqueness, it suffices to show that whenever Equation (6) is 0, its slope is negative because in this case it crosses the axis at most at one.

Differentiating with respect to d, we obtain

$$(1 - p)[f'_{\lambda=1}(d)](C - c + r^*(d) + a^*(d) - 1) + p[f'_{\lambda<1}(d)](C - c + a^*(d) - 1) +$$

$$(1 - p)f_{\lambda=1}(d) \cdot r^{*'}(d) + [(1 - p)f_{\lambda=1}(d) + pf_{\lambda<1}(d)]a^{*'}(d)$$

Considering that the function f_λ corresponds to the density of the exponential distribution, therefore $(\partial f_\lambda(d))/\partial d = -\lambda f_\lambda(d)$. Also notice that we assume that Equation (6) holds, and thus the derivative can be expressed as

$$(1 + \lambda)p[f_{\lambda<1}(d)](C - c + a^*(d) - 1) + (1 - p)f_{\lambda=1}(d) \cdot r^{*'}(d) + [(1 - p)f_{\lambda=1}(d) +$$

$$pf_{\lambda<1}(d)]a^{*'}(d)$$

The first term is negative because $(C - c + a^*(d) - 1)$ must be negative for Equation (6) to hold. The second term is also negative because $r^{*'}(d)$ is negative. The final term, however, is positive because $a^{*'}(d)$ is positive.

Finally, notice that using the implicit function theorem, we can compute

$$a^{*'}(d) = \frac{\mu[(1 - p)f_{\lambda=1}(d) + pf_{\lambda<1}(d)]}{m''(a)}$$

This term is bounded above by $\mu/m''(a)$ and, therefore, can be made arbitrarily small if $m''(a)$ is sufficiently large. Therefore, if the function m is sufficiently convex ($m''(a)$ is sufficiently large), the ESS equilibrium is unique. ∎
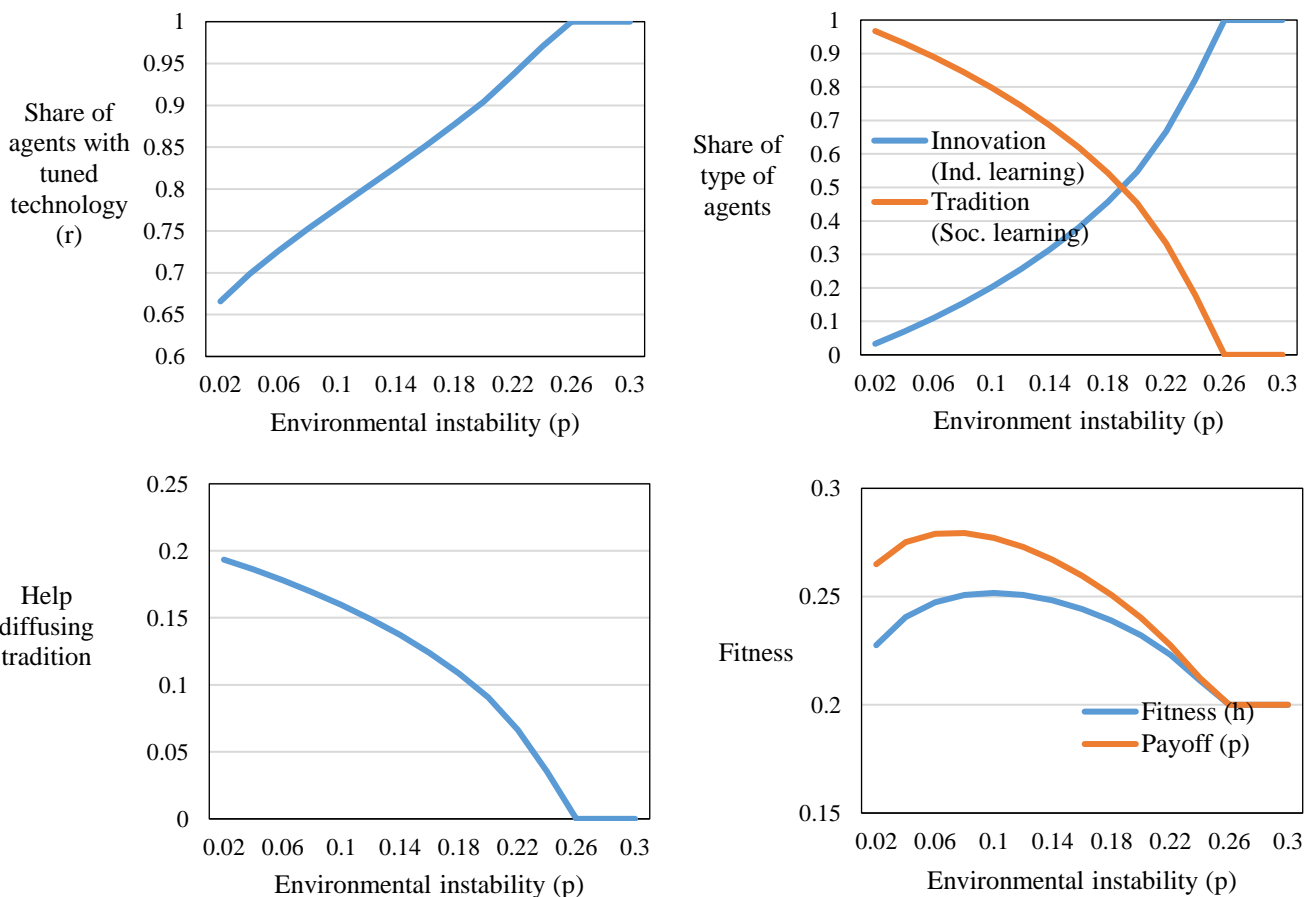
A.3. Impact of changing environmental uncertainty (p).

In Figure A.1 below, we assume $C = 0.8$, $c = 0.6$, $\mu = 0.2$ and $\lambda = 0.5$, and we then graph the impact of modifying p. Increasing p has two intuitive effects that ultimately affect fitness, displayed in the bottom-left graph of Figure A.1. First, it increases the amount of individual learning (top-right graph) which increase the share of agents with tuned technology r (top-left graph). Second, the reduction in social

learning implies that helping effort becomes less attractive, and thus it decreases (bottom-right graph). These two effects—an increase in r and a reduction in a—are slightly concave (particularly cooperation); thus, fitness displays an inverted-U relationship with uncertainty p. Although this inverted U implies that there is a p that maximizes fitness, the fitness reduction on each side of this maximum is approximately one-quarter of the fitness swings that are experienced when modifying other parameters (see other comparative statics below). Thus, one reading of Figure A.1 is that cultural evolution is very good at fine-tuning the parameter d and the extent of innovation versus tradition so that fitness is not sacrificed. Finally, notice in this graph that fitness and payoff are different and may lead to tensions. Payoff is what workers care about, and in this case, they rather have less uncertainty than the firm would prefer.

Figure A.1. Impact of Changes in Environmental Uncertainty. *Notes:* We graph the ESS equilibrium. We assume $C = 0.8$, $c = 0.6$, and $\lambda = 0.5$.

A.3.1. How changing p changes the impact of changing u *and* λ

In Figures A.2 and A.3, we explore how environmental uncertainty affects the impact that modifying u and λ have on the organization. The thick colored lines are the same as in Figures 2 and 6 of the main body of the paper.
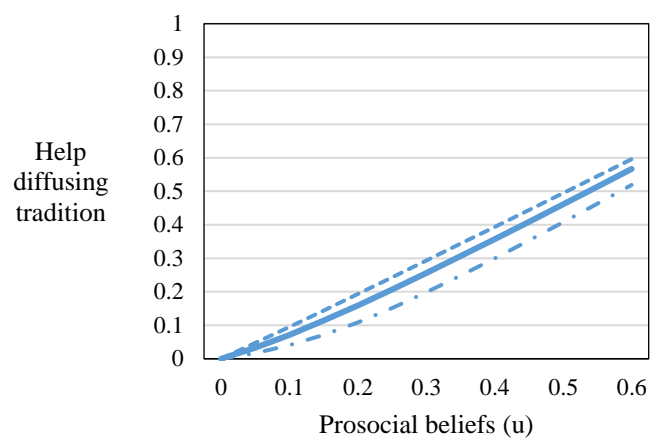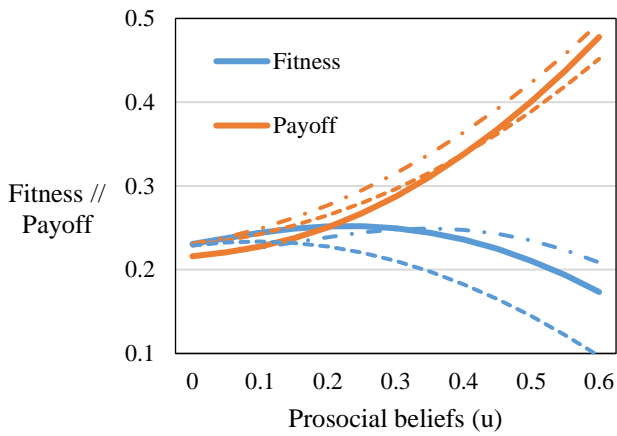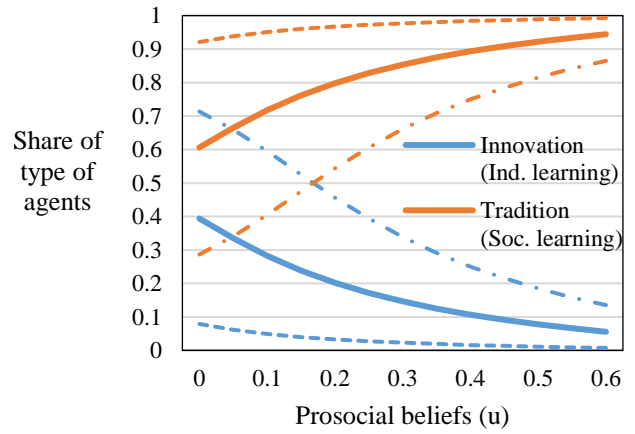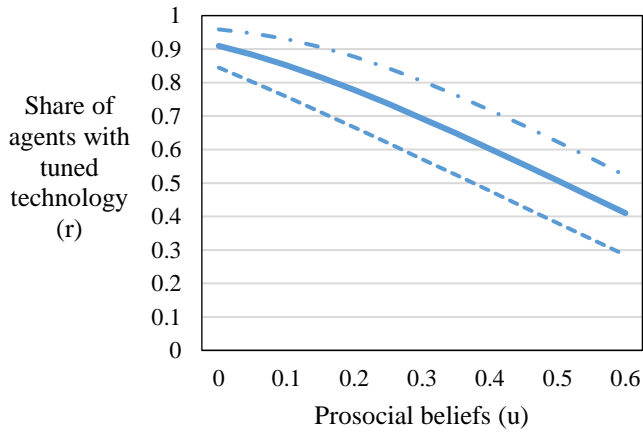
We draw two main insights from these two figures. These insights are part of the main body of the paper. The first insight comes from the bottom left graph in figure A.3 where it is easy to appreciate that the "optimal" level for u—that is, the intensity of u that maximizes organizational performance— is higher (smaller) when p is higher (smaller). We bring this result into the main body of the paper, as a corollary of Proposition 2, which we state as follows: "*The optimal level for the intensity of prosocial values increases with the degree of environmental uncertainty* p."

The second insight is that the impact of λ on increasing the use of social learning (top right graph in Figure A.2) and help others learn better (top right graph in Figure A.2), and thus the "efficiency" of tradition, is much more powerful when the environment is highly unstable ($p = 0.18$), and not at all when the environment is stable ($p = 0.02$) (recall that, as Figure A.1 shows and section A.4.2 below discusses, p cannot be larger than 0.26 if social learning and tradition is to evolve). This result is intuitive as accurate beliefs matter more for innovation to be timely (i.e., focused on periods of change) when uncertainty is high; and it is this "focusing of innovation when it matters" that "frees up" the time of agents to increase the use of social learning in periods of stability (which in turn motivates an increase in helping behavior).

Figure A.2. Impact of Improving Shared Beliefs. *Notes:* We assume $C = 0.8$, $c = 0.6$, and $u = 0.2$. The continuous thick line uses $p = 0.1$; the dashed line uses $p = 0.02$; and the dash-point-dash line uses $p = 0.18$.
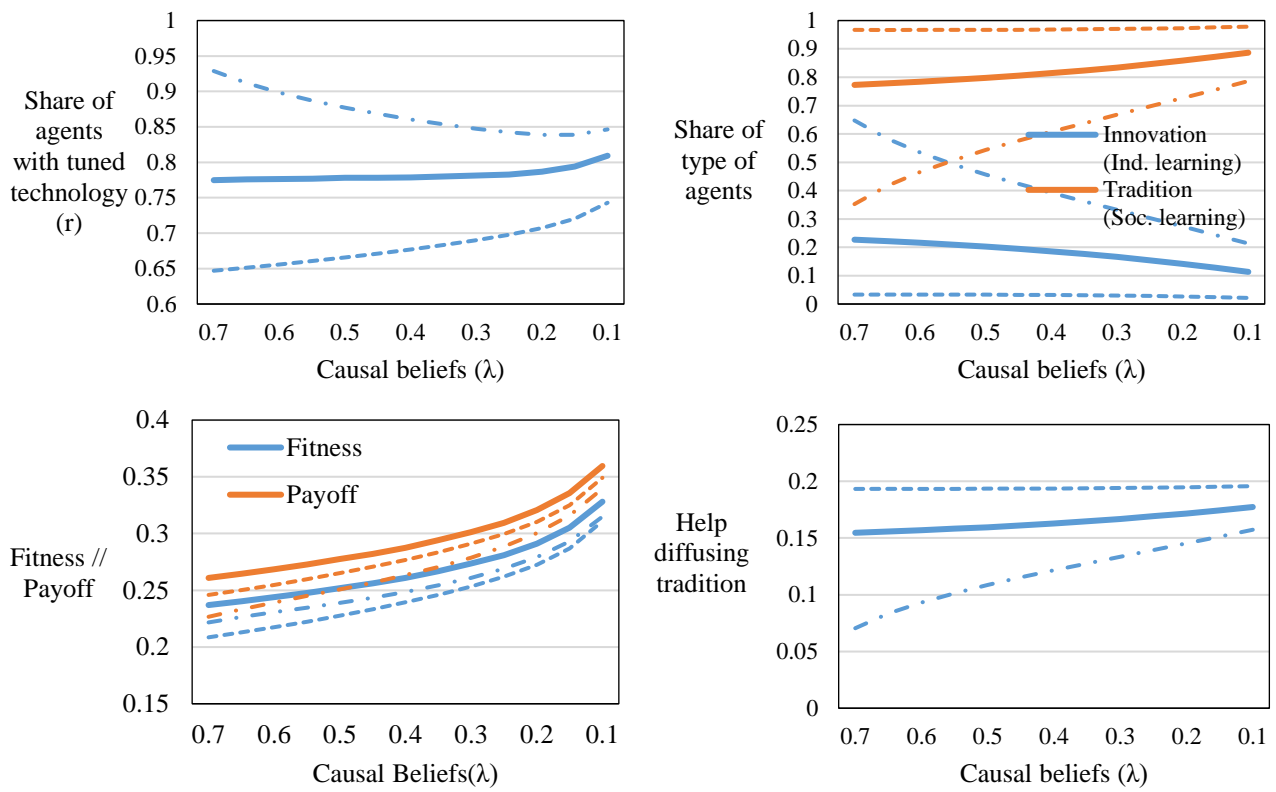
Figure A.3. Impact of Increasing the Intensity of Prosocial Beliefs. *Notes:* We assume $C = 0.8$, $c = 0.6$, and $\lambda = 0.5$. The continuous thick line uses $p = 0.1$; the dashed line uses $p = 0.02$; and the dash-point-dash line uses $p = 0.18$.

Share of agents with tuned technology (r)

1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

0   0.1   0.2   0.3   0.4   0.5   0.6

Prosocial beliefs (u)

Share of type of agents

1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

0   0.1   0.2   0.3   0.4   0.5   0.6

Prosocial beliefs (u)

Innovation (Ind. learning)
Tradition (Soc. learning)

Fitness // Payoff

0.5

0.4

0.3

0.2

0.1

0   0.1   0.2   0.3   0.4   0.5   0.6

Prosocial beliefs (u)

Fitness
Payoff

Help diffusing tradition

1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

0   0.1   0.2   0.3   0.4   0.5   0.6

Prosocial beliefs (u)

A.3.2. *Condition for the evolution of social learning*

In section 3.1, we indicated that $C - c > p$ is a necessary condition for social learning to evolve.

Assuming $\lambda = 1$ when the world changed, Equation (15) dictates that $f_{\lambda=1}(d^*)(-c + a^* - [1 - C]) + (1 - p)f_{\lambda=1}(d^*)\, r = 0$. Assuming that $\mu = 0$, and thus $a^* = 0$, this expression simplifies to $r = \frac{(1-C+c)}{(1-p)}$. Equation (16) dictates that at equilibrium $r = \frac{1 - F_{\lambda=1}(d^*)}{1 - (1-p)F_{\lambda=1}(d^*)}$. Therefore, $\frac{1 - F_{\lambda=1}(d^*)}{1 - (1-p)F_{\lambda=1}(d^*)} = \frac{(1-C+c)}{(1-p)}$. Using the exponential distribution, $\frac{(1-C+c)}{(1-p)} = \frac{e^{-d}}{1 - (1-p)(1 - e^{-d})}$, which after some algebra

becomes $\ln\{(1 - p)(1 - (1 - C + c))\} - \ln\{(1 - C + c)\, p\} = d$. For social learning to have a positive share in equilibrium, $d > 0$, and thus $\ln\{(1 - p)(1 - (1 - C + c))\} - \ln\{(1 - C + c)\, p\} > 0$. This simplifies to $(C - c) > p$.

We just showed that the condition is necessary to have social learning in the limit case when the signal is not more informative during a period of change ($\lambda = 1$) and the prosocial values absent ($\mu =$

0). Intuitively, it is not hard to grasp that the necessary condition for social learning to take place will be less demanding that in this limiting case. As the signal becomes informative, agents engage in social learning only when the signal is below the threshold d, which implies that the expected fitness of social learning is larger with an informative signal. A similar effect occurs as prosocial values become stronger, which reduces the cost of social learning. Thus, the condition $(C - c) > p$ is a sufficient condition for any value $\lambda < 1$ during periods of change and $\mu > 0$.

A closed-form analysis of the condition when $\lambda < 1$ during change and $u > 0$ is cumbersome without much added value. Instead, we revert to simulation.

Figure A.1 above shows that after a certain level of environmental uncertainty, individual learning goes to 100% and social learning goes to 0%. In this figure, we use $C = 0.8$ and $c = 0.6$, and given that $\lambda < 1$ in periods of change and $u > 0$, we find that the point when social learning is selected out is close to $p = 0.26$, larger than the threshold 0.2 (= 0.8 - 0.6), which is the value of p that grants that social learning can evolve any $\lambda < 1$ in period of change and $\mu > 0$.

A.4. Impact of changing learning costs C and c.

The final comparative static we perform is manipulating the costs of learning. In Figure A.2, we change the value of C from 0.7 to 0.9. The results are straightforward: If C increases, then innovation decreases and tradition increases; the share of agents with tuned technology decreases (due to less innovation) and cooperation increases (due to more social learning). The decrease in adaptive knowledge is stronger than the increase in cooperation; thus, fitness undergoes a reduction. If, instead of changing C, we change c, the results would be symmetric, but in opposite directions.

Figure A.4. Impact of Changing the Cost of Individual Learning. *Notes:* We graph the ESS equilibrium. We assume $c = 0.6$, $u = 0.2$, $p = 0.1$; and $\lambda = 0.5$.