High-Fidelity Social Learning

Abstract

Social learning has been shown to be more prevalent within organizations rather than across. To explain this regularity, prior research points mostly to structural conditions often found inside organizations, such as proximity or organization-specific language. We complement these explanations with an individual-based view: people display a behavioral disposition for *high-fidelity* social learning (i.e., copying with high accuracy from others) when learning from members of their own organization (and not from outside sources). First, we use a simple formal model from cultural evolution to justify why this behavioral disposition would have evolved to become a part of our norms and/or psychology. Then, we use a pre-registered field experiment to provide empirical support for this individual-level disposition. In our experiment, we document a significant increase in social learning when doing so from fellow organizational members, of which 75% can be attributed to *high-fidelity* social learning. This effect trumps prestige-biased social learning and, consistent with a behavioral predisposition, it seems to operate through sentiments and not reason.

Key Words: Organizational learning, Knowledge transfer, Social learning, Cultural evolution, Theory of the firm, Field experiment.
JEL Classification: D83, L23, M14, Z13

1 Introduction

Social learning—learning from others—allows people to access a wider pool of information, knowledge, and behaviors that the individual may not be able to learn on their own (Bandura, 1977; Boyd and Richerson, 1985; Argote, 2012). Social learning is referred to as vicarious learning, knowledge transfer, or knowledge spillover in the organizational learning literature (Argote, 2024; Argote et al., 2021; Park and Puranam, 2023). Social learning is one of the two processes, the other being experiential learning (where individuals learn from their own experience), that allows individuals or units to accumulate knowledge over time and travel the so-called 'learning curve' (Darr et al., 1995; Levitt et al., 2013; Argote and Epple, 1990; Balasubramanian and Lieberman, 2010), although this can be elusive (Maula et al., 2023).

Prior literature has shown that social learning is more prevalent and effective when performed within an organization (i.e., individuals or units of the same organization learning from other individuals or units) rather than across organizations (Darr et al., 1995; Baum and Ingram, 1998; Sorenson and Sørensen, 2001; Argote et al., 2000; Atalay et al., 2014; Bloom et al., 2013, 2020; Giroud et al., 2024). For example, the classic study by Darr et al. (1995) analyses 36 pizza stores franchised by the same corporation to 10 different franchisees, and find that "knowledge is found to transfer across stores owned by the same franchisee but not across stores owned by different franchisees" (p. 1750). This knowledge transmission advantage can provide a competitive advantage to firms (Argote et al., 2000) and is at a core element of the knowledge-based theories of the firm (Demsetz, 1988; Garicano, 2000; Grant, 1996; Kogut and Zander, 1996; Nickerson and Zenger, 2004; Brahm and Poblete, 2021).

A key question then is where does this organizational advantage for social learning comes from. The literature has mostly focused on the unique structural conditions that organizations have that facilitate social learning (see Argote (2024) for an overview). Some examples are: Nickerson and Zenger (2004) focuses on the role of authority and consensus to promote knowledge transfer within firms; Cremer et al. (2007) focuses on the role of organization-specific languages; and Ren and Argote (2011) focuses on the transactive memory that organizations develop (i.e., systems that track and store "who knows what"). Notwithstanding this progress, much less attention has been placed on individual-level drivers, that is, to the disposition (or preference/bias) that individuals may have for learning socially within organizations compared to outside organizations. Given the array of dispositions documented for social learning in the cultural evolution literature (see Kendal et al. (2018) for a review), such a behavioral disposition

is plausible.

In this paper, we propose and provide evidence of a *behavioural disposition for high-fidelity social learning when doing so within organizations, not across*. Fidelity in social learning is defined as "the accuracy with which learned information passes between individuals" (Laland (2017); p. 151). Recent research has found that individuals display an in-group bias when learning from others (Montrey and Shultz, 2022; Zou and Xu, 2023), which would support a higher frequency of social learning inside organizations. Smaldino and Velilla (2024) uses a formal model to explain the evolution of this bias. We complement these three papers by showing that a behavioral disposition also occurs at the fidelity of knowledge transmission—how accurately the information passes between individuals. High fidelity in social learning has been studied in the field of cultural evolution (Boyd and Richerson, 2005; Laland, 2017; Henrich, 2015), documenting its prevalence in humans as compared to other species (Dean et al., 2012; Herrmann et al., 2007), showing why it has evolved (Laland, 2017; Montrey and Shultz, 2020; Miu et al., 2024), and arguing that fidelity is a more important factor in knowledge accumulation than other sources of learning such as experiential learning and radical innovation (Lewis and Laland, 2012; Miu et al., 2024). The notion of high-fidelity social learning we introduce answers the recent calls in the organizational learning literature for unpacking the determinants of deep, thorough knowledge transfer (Argote, 2024; Myers, 2018).

We proceed as follows. First, we review prior literature and argue that social learning is a central and ancient property of organizations (Brahm and Poblete, 2021). This has been documented, for example, in modern firms (Darr et al., 1995), medieval guilds (De la Croix et al., 2018), Srenis—a guild-like organization in 400 BC India—(Khanna, 2005), and organized apprenticeship systems in forager societies (Sterelny, 2012). This ancient property will provide a basis for the predictions of our model, as explained below.

Second, we develop a simple evolutionary formal model inspired by cultural evolution (Boyd and Richerson, 2005, 1985; Lewis and Laland, 2012) to support the proposal of an evolved behavioural disposition. In the model, a population of agents needs to acquire knowledge by learning from their own experience or by means of social learning. Social learning can have different levels of fidelity. The model shows first that, *when social learning is prevalent*: i) high fidelity is favored by selection, ii) improvement in fidelity is more beneficial to accumulate knowledge than improvements in experiential learning. Given that the prevalence of social learning is an ancient property of organizations (as documented in our literature review), these propositions suggest that high-fidelity social learning within organizations is likely to have

evolved in our lineage. Such evolutionary pressures would be reflected in structural aspects of organizations—which have been documented by extant literature(Argote, 2024)—but *also in individual-level dispositions*, rooted in an evolved psychology (if organizations are sufficiently old) or in the internalization of evolved norms that regulate organizational life.

Third, to provide empirical evidence of the disposition for high-fidelity social learning within organizations, we use a pre-registered framed field experiment (Harrison and List, 2004) in the context of a real-world job.[1] A well-known charity in Chile hired 400 workers to evaluate the ability of its sales executives to persuade pedestrians to become permanent donors. The job took place in an online platform, where workers listen to audio files of conversations between executives and pedestrians and then provide a quantitative measure of the executive likelihood of success.[2] Following the canon of social learning experiments in cultural evolution (Derex et al., 2015; Mesoudi, 2008; Kendal et al., 2018), the charity allowed us to experimentally send messages to the focal worker containing information about *other* workers' evaluations, and then the focal worker could change/update their baseline evaluation of the likelihood of success. Crucially, the quantitative and continuous nature of our measure (a likelihood) allows us to study whether each worker displays high-fidelity learning, that is, whether they fully replace their baseline likelihood prediction with that of the other workers instead of adjusting the likelihood only partially.

To test the within-organization predisposition for high-fidelity social learning, our experiment leverages workers' affiliations to their higher-education institutions. In four given audio files (that all workers evaluate as part of their job), we randomize four messages with the evaluations of other people from different higher-education institutions. In the "Own organization" treatment, the message informs workers of the average prediction of other people from their own higher-education institutions.[3] This is our main treatment, whose effect on social learning we compare to that of three controls. In the first two, we leverage another well-known bias in the literature—prestige-bias (Henrich and Gil-White, 2001). Workers receive a message from other

[1]Workers were only debriefed that they were part of an experiment at the end of the job. Following IRB requirements, the informed consent allowed them not to grant their permission to be part of the study.

[2]Workers fill up an 18-item questionnaire about the executives' soft skills. We use the last question in this questionnaire to implement our experimental variations.

[3]Using workers' higher-education institutions provides a measure of organizational affiliation that works through organizational identification (Mael and Ashforth, 1992) and that: i) mitigates the selection and multiple-identification confounds that are prevalent if other mainstream real-world organizations were to be used (e.g., firms, corporations), ii) provides more realism than using a minimal group paradigm method (Tajfel, 1982), and iii) avoids the weak organizational identification that plague virtual/temporary organizations that the researcher may create(Wiesenfeld et al., 2001; Bartel et al., 2012; Koene and van Riemsdijk, 2005)).

higher-education institutions of varying prestige: in the "High-Prestige" and "Low-Prestige" controls, workers receive a message informing them of the average prediction of other workers from a top and a low-rank high-education institution, respectively. In a third "None" control, workers receive a message with an average prediction of all other workers' evaluations with no reference to an institution. In this within-subjects design, where messages are randomized at the audio file level, the differences in social learning between "Own" and the three controls can be attributed to the importance of organizational affiliation in social learning.

The results document the existence of a higher prevalence of social learning when copying from people with the same organizational membership, of which around 75% corresponds to high-fidelity social learning (i.e., copying exactly the behaviour of other workers from your own institution). Compared to the "None" control, workers are 17pp more likely to change their evaluation and follow the information in the treatment message whenever this information comes from people from their own organization. Of these, 13pp correspond to workers who completely forego their prediction of the executive's success and perfectly conform to the prediction shown in the message. The conditions of "high prestige" and "low prestige" fail to significantly increase social learning and high-fidelity learning, as compared to the "None" control. Further, using a battery of tests, we find that, consistent with the notion of an individual predisposition (or a preference/bias), our result seems to operate through sentiments and not rationality.

We offer three main contributions. First, we contribute to organizational learning literature (Argote et al., 2021), in particular, its knowledge transfer strand (Argote, 2024), by theoretically proposing and empirically documenting a bias in the disposition of human beings for high fidelity social learning when this social learning takes place inside the organization (rather than across). This provides an additional explanatory layer to the well-documented fact of better social learning within firm boundaries than across (Darr et al., 1995; Atalay et al., 2014)—usually explained using "structural" features of organizations—, and complements recent efforts to expand our understanding of thorough knowledge transfer (Myers, 2018; Argote, 2024).

Second, our paper contributes to highlight the importance of organizations in the field of cultural evolution. In particular, we show that high-fidelity social learning, a crucial idea in the field of cultural evolution (Laland, 2017; Lewis and Laland, 2012; Tomasello et al., 1993), might be, at its core, an organizational phenomenon. This joins recent efforts that have documented the importance of organizations for societies' success and progress (Brahm and Poblete, 2021, 2022).

Third, we contribute to the literature that studies how social network structures impact learning (Fang et al. (2010), Miller et al. (2006), Chang et al. (2023), Miller et al. (2006)), the diffusion of ideas (Balachandran and Hernandez (2018), Cattani and Ferriani (2008) and imitation (Posen et al. (2020)), by showing that the fidelity of knowledge transfer is different depending on the type of link in the network. Concretely, we show that if two people are linked and belong to the same organization, we observe high fidelity transmission, while if they belong to different organizations, information transmission depicts low fidelity.

2 Prior literature

This section has the following aims. First, we place this paper within the broader perspective of the organizational learning literature. Second, we discuss how the prevalence of social learning within rather than across organizations is an ancient feature, which is crucial for our argument. Third, we introduce and describe high-fidelity social learning.

2.1 Organizational learning and knowledge transfer

The organizational learning literature has developed a rich and detailed understanding of how knowledge accumulates and improves in organizations (some prominent examples are Darr et al. (1995), Argote and Epple (1990), and Levitt et al. (2013); see the reviews by Argote (2024), Argote et al. (2021), and Argote and Miron-Spektor (2011)). Learning by organizations is reflected in "learning curves," the well-established pattern that organizations reduce their production costs and improve their quality as they accumulate experience (ibid). There is variance in the rate of learning that organizations display (Argote et al., 2000; Dutton and Thomas, 1984; Balasubramanian and Lieberman, 2010; Maula et al., 2023), which is determined by the effectiveness of the three processes underlying organizational learning (Argote et al., 2021; Argote, 2012): knowledge creation, knowledge retention, and knowledge transfer. Knowledge transfer is also called vicarious learning, knowledge spillover, or social learning. We use the latter, but we treat these terms as largely interchangeable.

In this paper, we focus on social learning, defined as the process by which units of the organization—workers, teams, divisions—learn from the knowledge that other units have gathered from their experience (i.e., knowledge creation)[4]. A vast literature has explored the deter-

[4]Knowledge creation is the process in which units create new knowledge by learning from their own expe-

minants of social learning. In Argote (2024)'s literature review and associated framework, social learning is determined by five interacting elements: 1) characteristics of the experience/knowledge—for example, ambiguous knowledge is harder to transfer (Szulanski, 1996), 2) mechanisms of transfer—usually of three types i) direct interaction between units, ii) movement of individuals, routines or tools/machines, and iii) mediation via the organizational structure/features (e.g., a common boss, a central repository), 3) motivation of agents—for example, norms may encourage knowledge transfer (Di Stefano et al., 2014), 4) transfer opportunity—for example, proximity to other units makes a unit aware of opportunities to learn from others (Baum and Ingram, 1998; Sorenson and Sørensen, 2001)—, and 5) depth of consideration—for example, deep interaction between donor and recipient which allows for knowledge to be transferred without loss of its meaning, properties and details (Myers, 2018). Successful social learning is not guaranteed (Argote and Epple, 1990; Galbraith, 1990; Maula et al., 2023), and depends on the effectiveness of these five elements.

Our concept of high-fidelity social learning informs most directly the motivation of agents and depth of consideration (elements 3 and 5 above). On motivation, we propose that individuals are predisposed to high-fidelity copying when learning from others inside the organization but not across. Regarding the depth of consideration, the high-fidelity predisposition we propose directly impacts the capacity for knowledge to be transferred with accuracy, maintaining its meaning and detail. While our concept, being a predisposition, doesn't address the idea of depth of consideration—which involves active engagement between units(Argote, 2024; Myers, 2018)—, it does promote the outcome of transfer integrity and fidelity.

Two strands of organizational learning research are the closest to ours. The first is the work on the replication of routines (Winter and Szulanski, 2001; Szulanski and Jensen, 2006; Winter et al., 2012), which argues and shows that routines should be transferred to a new setting without many adjustments and tinkering, replicating them faithfully, as they were used in the context of origin. Like them, we focus on high-fidelity copying and the advantages of it. We differ from that research in that while they focus on the complexity and subtleties of routines (and the accompanying unintended consequences of adjustments and tinkering) as the reason for high-fidelity replication, we focus on an (evolved) behavioral predisposition at the individual level. The second strand is work that has shown how psychology and norms affect knowledge transfer, such as exploring the role of psychological safety (Tucker et al., 2007), emotional states

rience. Knowledge retention is the process through which knowledge gets stored in the physical mediums (e.g., tools, manuals) and in the memory of organizational members (e.g., transactive memory).

(Levin et al., 2010), and norms (Di Stefano et al., 2014; Quigley et al., 2007). In our work, the behavioural disposition we propose may be rooted in evolved psychology and/or norms.

2.2 Ancient organizational edge in social learning

Several papers document that social learning is more prevalent and effective inside organizations. Darr et al. (1995) shows that pizza stores learn better from other stores if they share a common owner; Sorenson and Sørensen (2001) shows that restaurant chains use franchised establishments to favour experimentation, but that they prefer company-owned establishment to diffuse and enforce knowledge and standards; Chan et al. (2014) shows that social learning among salespersons in the cosmetics area of a department store is favoured by common firm affiliation (i.e., same employer), especially for more difficult-to-sell products; Atalay et al. (2014) shows, using population data of US manufacturing firm, that the main reason for owning suppliers is to facilitate the transference of intangible inputs (e.g., practices); Montrey and Shultz (2022) and Zou and Xu (2023) use lab experiments and the minimal group paradigm to show that social learning has a within group bias, which trumps other important, previously-documented biases such as competence bias; Bloom et al. (2020) shows that management practices flow between plants with the same owner but not between plants with different owners. Using census plant-level data, Giroud et al. (2024) shows that while large industrial plant openings raise the productivity of local plants, it also does so of distant plants hundreds of miles away, but only if they belong to large multi-plant, multi-region firms. All these papers provide supportive evidence for the knowledge-based view of firms, the idea that production and diffusion of knowledge is "raison d'être" of firms (Demsetz, 1988; Garicano, 2000; Grant, 1996; Kogut and Zander, 1996; Nickerson and Zenger, 2004; Brahm and Poblete, 2021; Atalay et al., 2014)

We propose that this organizational "edge" for social learning is very old. The papers of the previous paragraph provide convincing evidence for contemporaneous organizations. If we go back in time, we can find that pre-modern organizations heavily relied on social learning. "Partnerships" were a very important vehicle to conduct economic activity in the early modern period (16^{th} to 18^{th} century), before the advent of modern limited liabilities companies and corporations, and they go back as far as the Roman empire (e.g., the "societas"; see Hansmann et al. (2005)). The main function of partnerships is to facilitate learning among its members (Morrison and Wilhelm Jr, 2004). "Craft guilds" in the Middle Ages were predicated on ap-

prenticeship systems to pass on crafts (e.g., carpentry, blacksmiths) between master and pupil, and therein lay their contribution to society (De la Croix et al., 2018; Epstein, 2008). Archaeological research shows that the pattern of amphorae production in workshops dated 200 BC in the Roman empire matches strong social learning within workshops rather than across them (Coto-Sarmiento et al., 2018). Written records of Srenis—a guild-like organization in 400 BC India—show how similar they were to medieval guilds, with apprenticeship and training at their core (Khanna, 2005). Archaeological research on flint daggers in Scandinavia production during the late neolithic concludes that, given its intricacies, "the craft is interpreted as demanding some form of an institutionalised apprenticeship system" (Apel, 2008) (p. 91). Similar can be said of the production of tools in hunter-gatherer societies (which reflect human societies in late paleolithic), where ethnographic studies have uncovered organized apprenticeship systems similar to guilds (Sterelny, 2012).

All these historical findings are consistent with the theory developed by Brahm and Poblete (2021) where, using a cultural evolution model and supporting evidence from the ethnographic atlas, it is shown that an explanation for the evolution of organizations (e.g., partnerships, guilds, modern firms) is their capacity to promote better social learning within their boundaries (which leads social learning to be prevalent inside organizations). Further, these findings are consistent with the in-group social learning bias documented by Montrey and Shultz (2022) and Zou and Xu (2023), and the associated theory developed by Smaldino and Velilla (2024). Our productive environment has been heavily reliant on guild- and firm-like organizations, and thus selection pressures can plausibly generate a bias rooted in psychology and/or norms to learn socially inside organizations.

2.3 High-fidelity social learning

The concept of fidelity in social learning is defined as "the accuracy with which learned information passes between individuals" ((Laland, 2017); p. 151). If fidelity is low, there is a loss of information/knowledge when the trait is transmitted; for example, research on the game of "Chinese whispers" (or "telephone") documents how information may get distorted as it passes down between individuals (Sprott, 1933). High fidelity means that the transmission of information/knowledge between agents occurs without alteration; for example, inter-generational transmission of information via genes displays high fidelity.

Cultural evolution scholars identify two components of high fidelity social learning, "blind

mimicry" and "prosocial teaching" (Tomasello, 2016; Laland, 2017). On the first, humans have a psychological disposition to *blindly mimic* others' behavior, knowledge, beliefs, values, etc. '*Blindly*' means that the individual doesn't consider or question the belief, motivation, status, etc. of others when copying, and does it "just because others do it" (Boyd (2018), p. 27). "Blind" also means that individuals do not need to causally understand how the trait works (Derex et al., 2015; Boyd, 2018; Henrich, 2015); it simply places "faith" in the usefulness of what others are doing (Henrich, 2015). This doesn't mean that individuals are not sophisticated in how they use social learning more generally, as documented by Henrich (2015) and Kendal et al. (2018). For example, people display a bias to copy the successful or to copy only when needed. However, it does mean that at the core of social learning, there is a baseline tendency to copy "blindly." Other words that have been used to describe this blindness in copying are "credulity" (Miu et al., 2024) and "docility" (Simon, 1993).

By *mimic*, we refer to the disposition to copy in great detail (Tomasello, 2016; Laland, 2017; Henrich, 2015). There is ample evidence comparing human children and great apes (Tomasello, 2016), our closest relatives, that shows that only the former display over-imitation, that is, the tendency to copy both causally necessary actions and perceivable unnecessary actions in relation to a given goal (Hoehl et al., 2019). A related idea to over-imitation is the "ritual stance," which means that "when children do not see a clear goal to an actor's action, they imitate even more precisely than if they do see a goal" (Tomasello (2016); p. 2). A psychological tendency that also supports this tendency to mimic is that humans, as compared to great apes, have a strong conformist bias (Tomasello, 2016; Asch, 1951).

Two papers document blind copying are closely related to ours. Over and Carpenter (2012) shows that children copy (do not copy) mistakes or unnecessary steps when they are learning from the in-group (out-group), suggesting that blind copy, in addition to obtaining useful information/knowledge, is about establishing identity and signaling conformity to the group. In Kane (2010), groups of three students engage in a multi-step origami-building task, and then groups can be demonstrating (copied groups) and other receivers (copiers); the authors show that randomly creating super-ordinate group affiliation among two groups (a "group of groups") significantly increases blind copying and this is driven by the receiver group increasing their attention to the demonstrating group (e.g., asking "How did you do that"?) and "did not increase the amount of discussion, monitoring or training" provided by the demonstrating group (Kane (2010); p. 183).

The second component of high-fidelity is "prosocial teaching." Research has shown that

humans have a predisposition to help one another learn, being prosocial when teaching others, and (pro)actively engaging with the learner (Laland, 2017; Tomasello, 2016; Tomasello et al., 1993; Henrich, 2015). For example, Dean et al. (2012) shows experimentally that children, as compared to great apes, display active pro-social engagement and teaching to fellow children, and that this explains why children and not apes managed to successfully accumulate knowledge in the lab. Sterelny (2012) reviews anthropological, ethnographic, and archaeological evidence to substantiate the proposition that past human societies built scaffolds—organized/structured instances, such as guilds—that enabled the active transmission of knowledge via teaching. Regarding teaching, the literature shows that while present in human societies as a human universal (Tomasello, 2016; Laland, 2017; Sterelny, 2012), it is only sparsely present in other species (Laland, 2017). Teaching is essentially a cooperative act (Laland, 2017), and thus it is not easy to evolve; but in our lineage, teaching has emerged as a primary vehicle to transmit knowledge between generations. In the organizational learning literature, the idea of "co-active vicarious learning" by Myers (2018) falls in this second component of high-fidelity. Myers discusses that, while the vicarious learning literature has emphasized one-way transmission of copiers imitating, what frequently occurs in organizations is a much more engaged, structured, and two-way-street process of knowledge sharing.

3 A simple formal model

We develop a simple cultural evolution model to make two propositions: i) high fidelity and social learning are complementary, and ii) when social learning is prevalent inside organizations, improving fidelity is more valuable for the accumulation of knowledge (i.e., organizational learning) than improvements in experiential learning. Given that social learning has been prevalent inside organizations in our history (see literature review above), the first proposition indicates that high-fidelity transmission has likely co-evolved with social learning to be a prevalent feature inside organizations. The second proposition highlights the importance of high fidelity for organizations' performance and, thus, boosts the likelihood it evolved to be an important organizational feature. Over time, the cultural selection of better-performing organizations would come to be reflected in organizations displaying features that promote high-fidelity social learning (e.g., mentoring, norms), which prior literature has documented, but also in a co-evolved individual predisposition towards high-fidelity, either encoded in our biology (if organizations are ancient) or in norms regulating organizational life that individuals internalize.

In our formal model, we don't differentiate between the two components of high-fidelity (blind imitation and prosocial teaching); in the field experiment, we will focus on the first component, blind imitation.

Learning types. There is a continuum of measure one of long-lived agents who acquire and lose knowledge across periods indexed by t. Knowledge naturally depreciates at an exogenous and constant rate d.

In every period, each agent can acquire knowledge through two mutually exclusive channels: learning from their own experience (i.e., experiential learning) or by learning from others (i.e., social learning). We don't model the choice between these two channels; instead, we assume there are opportunities to learn from others that are preferred (Argote, 2024), and if these do not come up, the agent relies on experiential learning.

Knowledge accumulation through experience. When the agent learns from experience, she has an exogenous likelihood to learn, captured by μ, where $0 \leq \mu \leq 1$. When she learns from experience, the agent obtains a knowledge level that we set, with no loss of generality, to 1. If the agent is not successful at learning from experience, the agent's knowledge depreciates at a rate d, where $0 \leq d \leq 1$. This formulation captures the well-established ideas of knowledge creation and knowledge depreciation in organizational learning (Argote et al., 2021).

Let k_t^E denote the knowledge accumulated in period t through learning from experience. From the assumptions above, k_t^E follows the rule of motion,

$$k_{t+1}^E = \mu + (1-\mu)(1-d)k_t^E \tag{1}$$

Knowledge accumulation through social learning. The second channel whereby knowledge accumulates is social learning. Learning from others happens with probability s (and thus, with likelihood $1-s$, agents are not learning socially). This probability can be thought of as the share of agents whose attention in a given period is directed towards learning from others. This occurs because either individuals coming across the opportunity to learn (e.g., they are close to an agent with knowledge) or the organization exerts effort to steer/nudge a percentage of workers to learning opportunities (and this is made possible because the organization has set up systems to identify where knowledge resides). As such, when learning from others, individuals will copy the knowledge from the share μ that was successful in learning from experience, and thus, their knowledge will ramp up to 1.

However, learning from others is not automatic; instead, it has a fidelity level f, meaning that a share $(1-f)$ of knowledge is lost. Whenever f reaches 1, we say agents experienced *high-fidelity learning*, that is, they copied verbatim knowledge that others have acquired from experience without any loss. In our model, the friction in social learning resides not in detecting where the knowledge resides but in the fact that communicating the nuances and details of the knowledge is not simple, and thus transmission can be inaccurate.

Let k_t be the average knowledge of people in the group in period t. The expected knowledge of an agent using social learning in a period is given by the following expression,

$$k_{t+1}^{S} = f \tag{2}$$

Total knowledge accumulation. We now combine the types of knowledge accumulation processes. From the assumptions above, the total level of knowledge k_t follows the rule of motion:

$$k_{t+1} = sf + (1-s)(\mu + (1-\mu)(1-d)k_t) \tag{3}$$

Agents learn socially with likelihood s and obtain knowledge $f \times 1$. A share $1-s$ resorts instead to individual learning and is successful with likelihood μ in obtaining knowledge 1; those that are not successful experience a depreciation d of their knowledge.

The long-term unconditional expected level of knowledge can be approximated by

$$\overline{K} = \frac{sf + (1-s)\mu}{\mu + s - su + d - ds - du + dsu} \tag{4}$$

The organization's problem. Agents' behavior in our model is simple: unless a social learning opportunity comes, they default to experiential learning. In contrast, we assume that the organization can influence the parameters that determine knowledge accumulation. We focus on how they can influence μ, s, and f. The organization can influence the success in experiential learning μ through many means, such as selecting abler subjects, requiring and enforcing higher effort in experiential learning from agents, providing agents with time to innovate, and formally compensating innovation. The organization can also influence s (the probability of learning socially) through many means, such as promoting interactions, establishing formal guidelines/systems that direct agents towards learning opportunities, or compensating social learners. The same applies to transmission fidelity f. The organization can generate a culture of knowledge sharing, promote teaching effort by the knowledgeable individuals who are shar-

ing their knowledge, develop mentorship/apprenticeship systems, and insist on the benefits of copying with high-fidelity rather than tinkering/adapting knowledge (Winter and Szulanski, 2001).

The organization's performance can be expressed as follows:

$$\pi(\mu, s, f) = \overline{K}(\mu, s, f) - C_s(s) - C_f(f) - C_\mu(\mu) \tag{5}$$

where C_s, C_μ and C_f are the cost functions related to the rate of social learning, the rate of success in experiential learning, and the level of fidelity in social learning. We don't assume the organization has the foresight to optimally choose the parameters. Instead, organizations try different configurations and cultural evolution through group selection processes (Boyd and Richerson, 2005), cull out over time those with higher performance.

We advance the following proposition.

Proposition 1: **(Social learning and fidelity are complements)** *When there is more social learning, it is more profitable to increase fidelity, and when fidelity is higher, it is more profitable to increase social learning.*

Proof: It follows directly from noticing that $\frac{\partial^2 \overline{K}}{\partial f \partial s} > 0$ which means the function is supermodular, then by (Topkis, 1998) in any maximization problem $f^* = \arg\max(\overline{K}(\mu, s, f))$ is increasing in s and $s^* = \arg\max(\overline{K}(\mu, f, s))$ is increasing in f □

A corollary of proposition 1 is that if increasing social learning and fidelity improves the organization's performance[5] we should observe that social learning and high-fidelity co-evolved in organizations, and thus observed organizations throughout history would tend to display that combination.

Proposition 1 also makes clear that organizations, understood as institutions reliant on knowledge learning (**?**Grant, 1996; Nickerson and Zenger, 2004), may not evolve. To understand this, look at the dynamics of a population of agents that starts at $K_1 = 0$. In the first period, without social learning, it will get to $K_2 = \mu$ while with social learning, it will go to $K_2 = (1 - s)\mu + sf$. If $f < \mu$, the population will accumulate more knowledge without promoting/allowing social learning, thus obtaining μ. One can venture that this population

[5]This would be true if, for example, the cost of increasing fidelity f, social learning s, and μ are linear. In this case there exists a threshold level of social learning s such that for organizations in which social learning is above the threshold, improving high fidelity is more adaptive than improving the success rate of individual learning μ. For groups in which social learning is below this threshold the opposite holds.

would not be an organization at all and, instead, would become an unstructured "market-like" group in which agents learn individually through experience. In contrast, if $f > \mu$, the group will accumulate more knowledge by promoting social learning, and it will have incentives to invest in fidelity as well. This group will find convenient to become a formal organization, geared towards social learning (Brahm and Poblete, 2021). This analysis suggests that when social learning occurred outside organizations, to the extent it did, incentives for enhancing its fidelity were low and thus high-fidelity wouldn't evolve. *This fidelity difference between social learning within and outside organizations is a central prediction that comes out of proposition 1, one that we test with our field experiment.*

Observe that for knowledge to accumulate, you need either to have some success in experiential learning (a positive μ), a positive fidelity level f or both. So how important is the success in experiential learning compared to fidelity in accumulating knowledge? The answer again is that it depends on the frequency of social learning and is stated in our second proposition.

Proposition 2: (Relative importance of high-fidelity) *If social learning is more prevalent than experiential learning, f affects accumulated knowledge more than μ.*

Proof: Let $N = sf + (1-s)\mu$ and $D = \mu + s + d - ds - s\mu + d - ds - du + dsu$. Observe that $\frac{\partial \overline{K}}{\partial f} = \frac{s}{D^2}$ while $\frac{\partial \overline{K}}{\partial \mu} = \frac{(1-s)}{D^2} - \frac{N(1-s-d+ds)}{D^2}$. Observe that $1-s-d+ds = (1-d)(1-s) > 0$, so clearly if $s > 1/2$, $\frac{\partial \overline{K}}{\partial f} > \frac{\partial \overline{K}}{\partial \mu}$ □

While proposition 1 indicates that social learning and high-fidelity transmission would tend to co-evolve inside organizations, that proposition cannot provide certainty about be the evolutionary outcome, as improving μ might still be a better option than pushing for improvement in f (and thus favoured by cultural evolution). Proposition 2 establishes that under a well-documented condition (prevalence of social learning inside organizations, i.e., $s > 1/2$; see the literature review above), evolution will favour the improvement of fidelity (and social learning, per proposition 1), rather than experiential learning.

This proposition is consistent with prior research in cultural evolution, which shows the importance of high-fidelity to explain our species' capacity for knowledge accumulation, as opposed to other animals (which have technological tradition, but fleeting and non-cumulative) (Miu et al., 2024; Laland, 2017; Tomasello, 2016). Cultural evolution discards that the answer is related to a superior intelligence (which might enhance our capacity to innovate and learn from experience) (Herrmann et al. (2007); Boyd (2018); Henrich (2015); see also Simon (1993)[6],

[6]Herrmann et al. (2007) shows that across several cognitive abilities, children only beat great apes in social

and instead has convincingly argued that the answer lies in our unique capacity for high-fidelity social learning.[7] Our paper suggests that this benefit of fidelity may be particularly channeled via organizations.

In sum, *our model predicts that high fidelity should be more prevalent when social learning occurs inside organizations and not outside.* This presence of high-fidelity inside organizations should be reflected both in the presence of "prosocial teaching", usually motivated by "structural features" that the organizations puts in place (e.g., incentives, mentorship, knowledge sharing culture), but also in organizational members having a disposition to "blindly mimic" other organizational members. This psychological disposition could be rooted in our biology, if organizations were old enough to allow evolution to encode it in our genes, or in a culturally evolved norm or belief (e.g., "when copying from other members, mimic") that is internalized by individuals.

3.1 Evidence from the ethnographic atlas consistent with the model

Given the well documented ancient social learning edge of organizations, our model proposes that fidelity would have evolved in these ancient organizations due to its performance benefits (and this, in turn, would be reflected in an evolved behavioural predisposition which we document below). Here we provide evidence from Brahm and Poblete (2021) supportive of these benefits. That paper argues that an explanation for the evolution of organizations (e.g., partnerships, guilds, modern firms) is their capacity to promote better social learning within their boundaries. They provide supportive evidence for their theory using the Ethnographic

learning abilities. Henrich (2015) and Boyd (2018) show how European explorers' big brains were useless when they got stranded in the wild, and the only ones that survived are those who befriended local aboriginal people and learned from them. The cultural brain hypothesis proposes that our big brains co-evolved with the increase in culture, and are required to download the massive amount of information from our forebearers (Laland, 2017; Henrich, 2015; Muthukrishna et al., 2018). Simon (1993) acknowledges that given our bounded rationality, our success as a species has to come from our capacity to learn from one another and build adaptive traditions.

[7] A set of formal models supports the primal importance of high-fidelity social learning for cumulative culture. Enquist et al. (2010) shows that fidelity is crucial for traits to persist and thus enable the ratcheting process to take-off. Lewis and Laland (2012) uses an agent-based model in which agents can resort to incremental innovation, radical innovation (invention), recombination, and social learning (in which fidelity varies). They find that high-fidelity social learning contributes substantially more than the other drivers to the accumulation of knowledge and culture. Miu et al. (2024) uses a social learning strategies tournament—inspired in the earlier tournament of Rendell et al. (2010)—, in which several dozens of submitted learning strategies by contestants (each using unique combinations for incremental innovation, invention, and social learning of varying fidelity) are pitted against one another. They conclude that while invention and incremental innovation are necessary for the build-up of culture, once the culture is complex, evolution "favors conformity, blind imitation, and hyper-credulity" (ibid; p. 1).

Atlas: they show that the presence of organizations that are intensive in social learning increases the fitness of societies (mostly pre-modern societies surveyed by Anthropologists in late 19^{th} and early 20^{th} centuries). Importantly for our purposes, they show in their supplementary information that: i) this impact is boosted when the society also possesses institutions that improve the fidelity in social learning, namely formalized apprenticeship systems and teaching, and ii) the impact of these high-fidelity institutions without the presence of the organizations is negligible, and thus, fidelity matters only when paired with– or used within– organizations.

4 Field experiment

While in our model we focused on both elements of high-fidelity, "prosocial teaching" and "blind mimicry," in the field experiment, we focus on the latter.

4.1 Experimental design

We embed our experiment in a real job implemented in collaboration with a charity in Chile.

(1) *The job.* The charity hired 400 workers to evaluate the performance of their sales executives. The executives' job is to persuade pedestrians to become permanent donors. The charity records conversations as part of its normal operations. In an online platform, workers in our field experiment listen to audio files of these conversations. The job consists of listening to audio files and then filling out a per-audio questionnaire about the executive's soft skills. Workers are paid a fixed wage of CLP 20,000 to listen to and evaluate the audio files. At the time of implementation (July 2023), this payment corresponds to the market wage for a half-day blue-collar type job in Chile.[8]

(2) *Workers' recruitment.* The job recruits workers on social media pages that advertise part-time jobs. To apply, candidates must send their CVs with their credentials. To work, they must be older than 18, have the means to work online (computer and internet connection), and be current students or alumni of a Chilean high-education institution (this information will be crucial to test our theory, as we describe below).

(3) *Prediction.* To measure social learning, we leverage one particular question in the evaluation

[8]Workers listened to audio files to fill up evaluations for four hours.

questionnaire, which we refer to as "the prediction question". In this question, workers guess how many pedestrians, out of 100, they think the executive would be able to persuade to become a donor. Figure 1 shows the question screenshot.

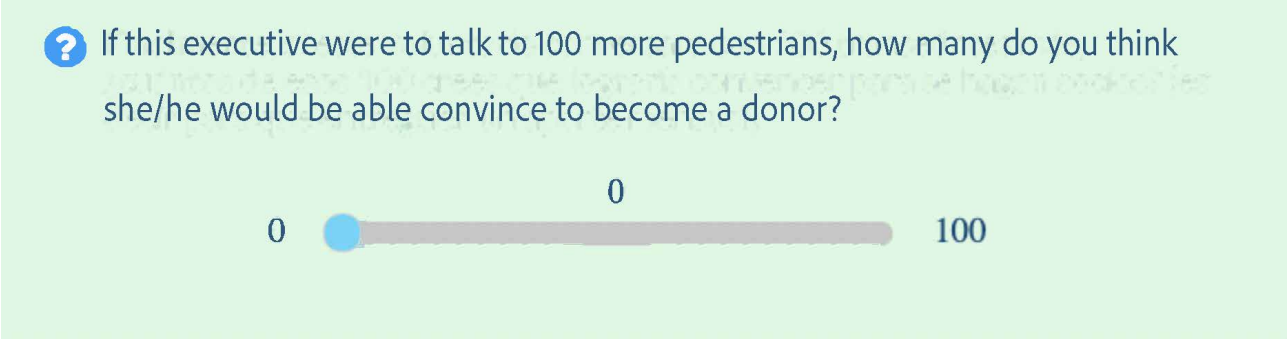


Figure 1: The prediction question.

This prediction will allow us to precisely measure social learning. Intuitively, social learning is captured by how much the worker's prediction changes after being informed of other workers' predictions. In (4), we show how we experimentally manipulate the information on other workers' predictions, and in (5), we describe our measure of social learning and high fidelity.

(4) *Treatment and controls.* Our experiment takes place in the evaluation of four given audio files from three particular executives. For each of these four audio files, workers perform their prediction, and then they receive a message that displays information about other workers' predictions. Then, we offer them the chance to re-evaluate their prediction.

We manipulate the source of other workers' predictions by using a within-subject experimental design in which we randomly assign the content of the message the worker receives in each of the four experimental audios. The message contains the average prediction of other workers who had previously evaluated audios from the same executive.[9] In one audio, the message contains the average prediction of other workers who belong to the worker's own high-education institution ("Own treatment"); in two other audios, the message contains the average prediction of people from a high-prestige high-education institution ("High-prestige" control), and a low-prestige high-education institution ("Low-prestige" control). Finally, one audio contains a message with an average prediction of all other workers but with no reference to an institution ("None" control). The "Own" treatment captures organizational affiliation and is

[9]From the whole set of available conversations, we randomly chose four audios of short length to implement our treatments. These four audios belong to three particular executives for whom we have a large enough number of conversations to have an accurate calculation of their success rate.

the treatment of interest. The two prestige controls allow us to study how social learning and its fidelity prompted by the treatment fares compares the social learning and fidelity that is prompted by learning from other institutions of varying prestige. Prestige bias is well documented in cultural evolution(Henrich and Gil-White, 2001; Jiménez and Mesoudi, 2019), and thus serves as a stringent control. The last control, "None", represents a very basic form of unbiased social learning.

The four messages are randomly assigned to the four treatment audios. The order of the four treatment audios is also randomized for each worker. Figure 3 to Figure 4 show the exact message in the treatment and the three controls.

An important concern in this setting is the degree to which using university affiliation, either as a current student or an alumnus, qualifies as a good proxy for the construct we care about, namely, organizational affiliation. We argue that alternative methods to manipulate organizational affiliation have pros and cons and that university affiliation provides a nice balance across these pros and cons. A first alternative method would be using affiliation to a real organization, say a firm, and then randomizing messages within this firm (e.g., message to employees with information drawn from your own firm versus drawn from other firms). While providing realism, we argue that this has two important problems. First, using firms generates sorting problems. Given that workers self-select and firms put in place multiple and detailed recruitment and hiring procedures, homogeneity in firms is high (Bradley-Geist and Landis, 2012), and thus, workers might react to the "own" treatment due to a homophily-bias in social learning (Smaldino and Velilla, 2024), which is different than the bias/predisposition we propose. Second, workers within a given firm can have competing affiliations, such at the department or occupation level, a multiplicity that can blur the feeling of an overall organization affiliation ((Mael and Ashforth, 1992)). On the opposite end of the spectrum, one could use a lab experiment in which affiliation to groups (and thus an "organization") could be manipulated via the minimal group paradigm (Tajfel, 1982). While this eliminates sorting/selection concerns, it suffers from the lack of realism, something that is particularly important for claims about organizations instead of groups. Finally, we could have created a sense of organization in our online job (i.e., separating the 400 workers into "mini virtual organizations"). While this allows for identification and a touch of realism, prior research shows that affiliation and identification to virtual/temporary organizations is very low (Bartel et al., 2012), threatening our ability to identify any effects. Given all this, we believe that measuring organization by using common affiliation to a university provides a good balance across all these trade-offs: affiliation and iden-

tification to the alma mater is significant and meaningful (more than virtual organizations), it provides realism (that minimal group paradigm cannot provide), and it doesn't have extensive issues of self-selection into multiple affiliations (that plagues more focused and less open organizations such as firms).[10] Further, a foundational study in organizational identification—that is, the organizational affiliation defines "who" the person is—uses university alumni, arguing that alumni are a good group in which to test models of organizational identification (Mael and Ashforth, 1992).

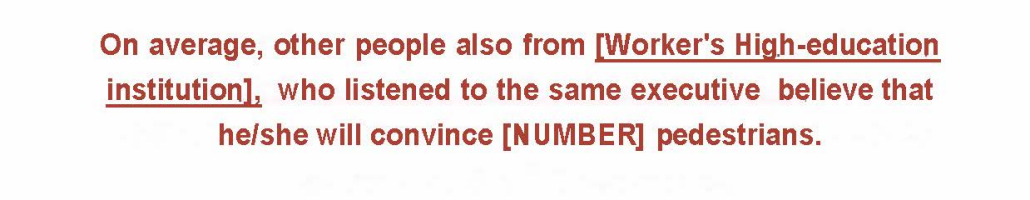


Figure 2: Message in the "Own" treatment.

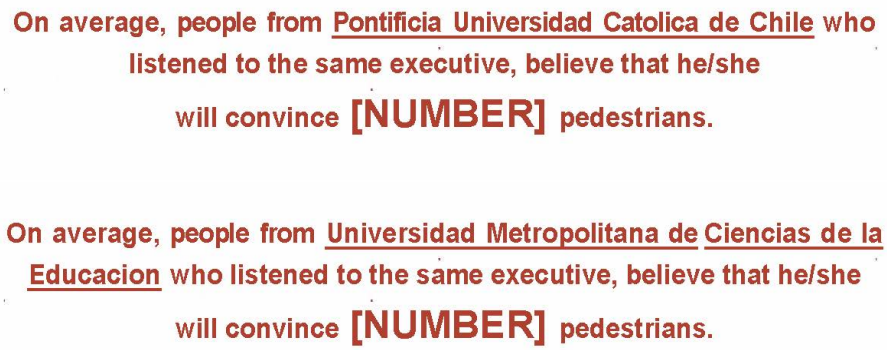


Figure 3: Message in the "High-Prestige" and "Low-Prestige" controls.

Figure 4: Message in the "None" control.

[10] To evaluate the sorting issue, in the online appendix, Appendix Table A1, we computed the share of variance in traits of workers (collected via survey, see below) that is explained by university affiliation. In general, this share of variance is small, around 20% or less. The trait of "sentimentality"—the only personality trait we collected—has 13% and is half the size of the share of personality traits that the literature has attributed to organizations, and equivalent to the share attributable to occupations (Bradley-Geist and Landis, 2012). While this doesn't eliminate the sorting problem, it reduces the concern.

We chose the high and low-prestige institutions as follows. For the high prestige, we used the Webometrics ranking, an objective ranking of universities around the world.[11] The institutions in the low-prestige control required more consideration as Chile has three types of high-education institutions: Universities, Professional, and Technical institutions (CFT and IP). Since we suspected that even the lowest-ranked university would have a higher prestige than the best vocational institution, we decided to vary the institution by subject by choosing a low-ranking institution of the subject's own institutional type.

The messages in the experimental conditions were constructed using a secondary database. The charity had previously hired 400 different workers from varying high-education institutions to perform a very similar job.[12] The messages in the "Own" treatment are calculated using all those workers in the secondary database affiliated with the same high-education institution as the worker in our experiment. The messages in the "High" and "Low-prestige" controls are the average of workers in the secondary database affiliated with the higher/lower ranking institutions. The message in the "None" control is the average prediction of all subjects in the secondary data.[13*14]

Figure 5 shows the timing of the treatment implementation for each of the four audios. Workers first listen to the audio. Then, they do the prediction. Then, they receive one of the four random messages. Then, they receive the prediction question for a second time. Workers can repeat their previous answer, skip the question (which is equivalent to keeping their original answer), or submit a new answer.[15]

(5) *Social Learning Index.* Our pre-registered index of social learning in treatment j captures

[11] https://www.webometrics.info/en/world. Following the ranking, there were two top universities in Chile: Universidad Catolica and Universidad de Chile. All workers received Universidad Catolica in the High-prestige control, and those workers who were students or alumni of Universidad Catolica got a prediction for Universidad de Chile.

[12] In this previous job, workers listened and evaluated three of the four audios we used in our experimental design. Then, they executed a related task.

[13] In the rare case an applicant to the current job was affiliated to an institution for which we had no observations in the secondary data, they were not considered for our study (but still performed the job for the charity).

[14] When we picked the institutions in the Low-Prestige treatment, we deliberately picked institutions (among many low-rank institutions according to the Webometrics ranking) whose average prediction across audios was the same as in the High-Prestige and No-Institution controls. This ensures that any potential effect of the High-prestige control is not due to people from more prestigious institutions being more accurate in their predictions. This common average prediction of the executive's success was around 28% (i.e., 28 pedestrians out of 100 would be convinced to become donors

[15] The exact wording of the second-time prediction question is "You just answered that the executive would convince [answer to previous prediction question] people out of 100. Now that you have read the information in this message, if you want to re-evaluate your answer, you can do it here. If you do not want to reevaluate your answer, you can move to the next page." To answer, the page would display exactly the same bar in Figure 1.

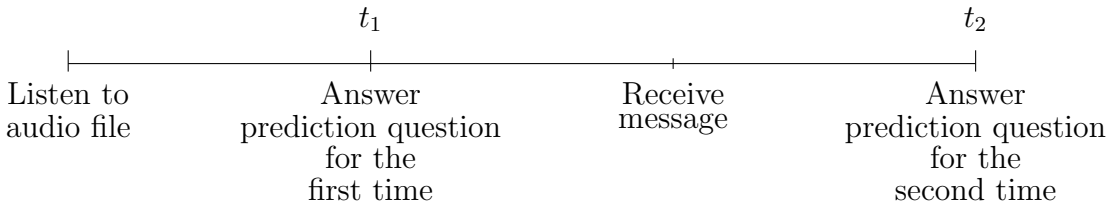


Figure 5: Timing of the message in the four experimental audios.

the % of the gap between the first-time prediction and the message that is closed in the second-time prediction:

$$\mathcal{SL}_j = \frac{(p_{t1} - m^j) - (p_{t2} - m^j)}{(p_{t1} - m^j)}$$

where p_{t1} is the first-time prediction (before the message), p_{t2} is the second-time prediction (after the message), and m_j is the prediction displayed in the message in treatment $j = Own$, *High*, *Low*, *None*.

If the worker does not change her prediction after receiving the message, this index takes value zero; if the worker's second-time prediction gets closer to the message, it takes value $\in (0, 1)$; if the worker does perfect mimicry, it takes value 1 which captures "high-fidelity learning".[16]

This social learning index and the measurement of high fidelity learning as $\mathcal{SL} = 1$ have already been used in the literature. Studying how the choice of the focal individual changes before and after information from others is the standard in the cultural evolution literature (McElreath et al., 2005; Mesoudi, 2008; Muthukrishna et al., 2016). Furthermore, comparing how much the change over time of the individual (i.e., $p_{t1} - p_{t2}$) reflects the distance to the source (i.e., $p_{t1} - m^j$) is the usual way in which the extent of social learning is measured (Mesoudi, 2008; Derex et al., 2015) Further, high-fidelity social learning has been measured by the extent to which the individual does exactly the same as the model (i.e., $\mathcal{SL} = 1$) (Atkinson et al., 2021; Dindo et al., 2010; Watson-Jones et al., 2016).

(6) *Monetary incentives.* We randomize a small monetary bonus that depends on participants' accuracy in their prediction. In two of the four treated audios, workers could earn CLP 1.000 (around 1.2 US dollars) if their prediction matches the actual success rate of the executive in the

[16] Workers can also overreact to the message, i.e., they can increase (decrease) their prediction beyond (below) the message. In this case, the index takes a value greater than one. Finally, workers can also under-react to the message, i.e., they can make a second-time prediction in the opposition direction the message prescribes. In this case, the index takes a negative value. Adding this information doesn't alter our findings.

audio and CLP 500 if their prediction is three percentage points above or below the truth. The incentive is randomized either in the first and third audio/message or the second and fourth. See Figure 6 for the incentive message displayed in the evaluation platform. This incentive treatment allows us to study whether reason and calculation underlie the responses to our treatments: as we explain in detail in the "mechanisms" section below, we should expect that if the "Own" treatment is triggering psychological/emotional dispositions, incentives shouldn't affect its impact on social learning and high-fidelity; instead, incentives may be prone to affect the impact of the prestige treatments.

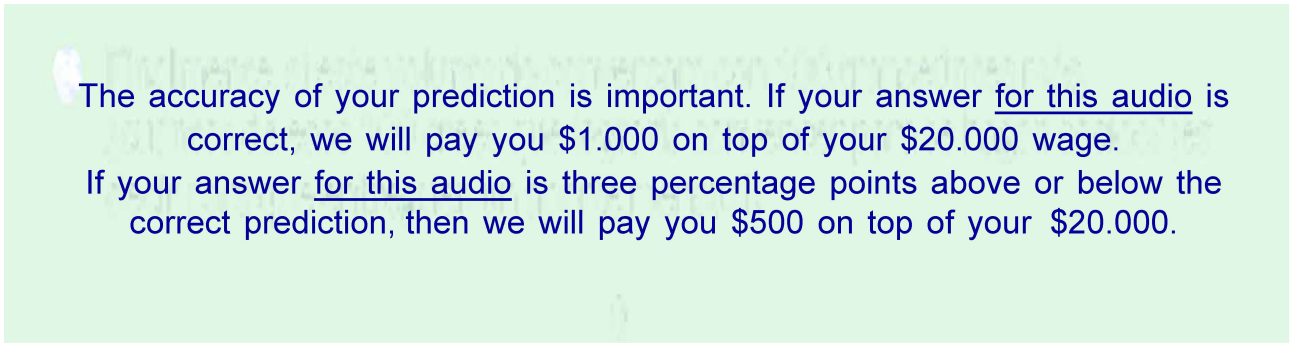


Figure 6: Message in audios that received a monetary incentive

(7) *Exit survey.* Once workers finished their mandated work time, they filled out an exit survey containing the informed consent to participate in this academic article. The survey asked questions to measure perceived prestige, perceived organizational identification, and sentimentality, as follows. To corroborate that workers' prestige perceptions are aligned with the objective high-education institution rankings, the survey asked workers their subjective perceptions of the three institutions in the *Own* treatment, and *High-Prestige*, and *Low-Prestige* controls using a 1 to 7 Likert scale.[17] We measured workers' perception of closeness to their own high-education institution using the overlapping circles' methodology from (Bergami and Bagozzi, 2000).[18] Finally, following (Mael and Ashforth, 1992), we asked workers how "sentimental" they perceived themselves using a 1 to 7 Likert scale.[19]

[17]The exact question in the survey is "People in my community have an excellent impression of [INSTITUTION]." Please rank how much you agree with this claim from 1 (low) to 7 (high)). This measure is from (Mael and Ashforth, 1992).

[18]In this question, the participant must choose between seven pairs of circles ranging from disjoint to perfect overlap. Other authors have also proposed similar methods. See (Shamir and Kark, 2004) and a review of these measures in (Lee et al., 2015).

[19]The exact question in the survey is "I consider myself a sentimental person". Please rank how much you agree with the claim from 1 (low) to 7 (high).

(8) *Preregistration and IRB.* The design was preregistered in the AEA RCT platform (# AEARCTR-0011534). The preregistration was uploaded once the data collection had already started. Despite this, none of the three authors ever downloaded the data before this preregistration was complete. Workers were debriefed once they finished their four-hour job. As IRB requires, they could opt in or out of the scientific study. Only those who agreed to participate in the study will be considered for analysis.[20]

4.2 Results

4.2.1 Descriptive statistics

Before turning into the main result, Table 1 briefly shows the descriptive statistics of our experimental subjects (column 1), their affiliated high-education institutions (column (2)), and the social learning index (column 3).

Workers (1)		Institutions (2)		Social Learning Index ($\mathcal{SL}$) (3)	
N	400	N	62	Obs.	1566
Woman	72%	University	87%	% with $\mathcal{SL}$=0	31.67%
Working	87%			% with $\mathcal{SL} \in (0,1)$	40.36%
Age	31			% with $\mathcal{SL} = 1$	5.56%

Table 1: Summary statistics

Of the total number of recruited workers, exactly 400 agreed to participate in the study after reading and agreeing to the informed consent.[21] Our workers are students or alumni of 62 different high-education institutions, most of them (87%) being universities rather than vocational institutions (13%). They are predominantly women, and the average age is 31 years old. Eighty-seven percent of them declare being full-time workers (the other 13% declare studying and working at the same time). Column (3) shows the raw statistics of the social learning index. Of the total 1600 observations (four observations per worker), 1566 are valid and constitute our final sample size for the social learning index.[22]

[20] We dropped from the data those who did not accept before performing any analysis.

[21] Recall that the informed consent was only signed when workers finished their job and were informed that their work was also part of scientific study.

[22] We cannot calculate the Social Learning index for 34 observations because, by random chance, the message was equal to the initial prediction, creating a division by zero in the social learning index.

4.2.2 Main Result

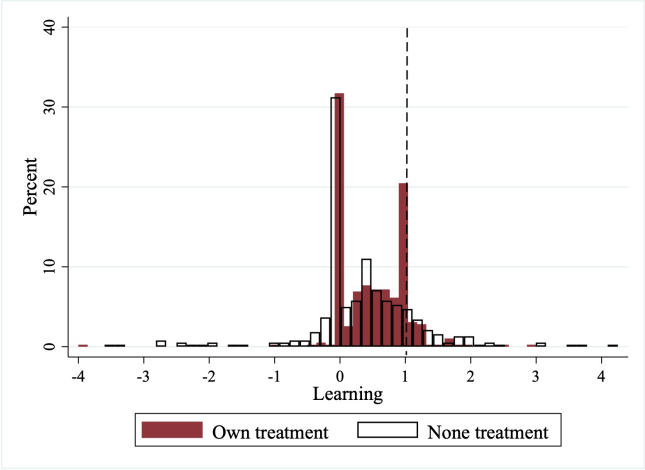
This section shows evidence of high-fidelity social learning whenever workers learn from people in their own organizations. Figure 7 start showing the histogram of the social learning index for the "Own Institution" treatment (panel (a)), the "High-Prestige" control (panel (b)), and the "Low-Prestige" control (panel (c)) relative to the "None" control. We use the non-parametric Mann-Whitney Test (or Wilcoxon Rank Sum Test) to compare the statistical difference between these distributions. The p-value of the test is computed under the null hypothesis that the social learning index generated by each treatment is drawn from the same population as the "None" control. The p-value for the comparison between the "Own" and "None" treatments is 0.0002, thus rejecting the null hypothesis that the two distributions come from the same data-generating process. In contrast, the p-value for the comparison between the "High-Prestige" and "None" controls is 0.8301, and the p-value for the comparison between the "Low-Prestige" and "None" controls is 0.5818, indicating that the null hypothesis cannot be rejected in these cases. This suggests that providing information from other people affects social learning only if the information source shares the worker's organization.

A closer look at Figure 7, panel (a), reveals that the main difference between the distribution of the social learning index in the "Own" treatment and that in the "None" controls lies in the share of observations with a social learning index equal to 1, i.e., in the likelihood of workers experiencing high-fidelity social learning. Indeed, the share of workers who do not learn anything from the message (i.e., $\mathcal{SL} = 0$) is similar across distributions (30.95 and 29.19 in the "Own" and "None", respectively). The share of workers who learn socially but with imperfect fidelity (i.e., $\mathcal{SL} \in (0, 1)$) is slightly bigger in the "Own" treatment (42.46 and 38.58 in the "Own" and "None", respectively). The share of workers displaying high fidelity social learning $\mathcal{SL} = 1$, however, largely increases from 2.79% to 15.60% from the "None" to the "Own" conditions.

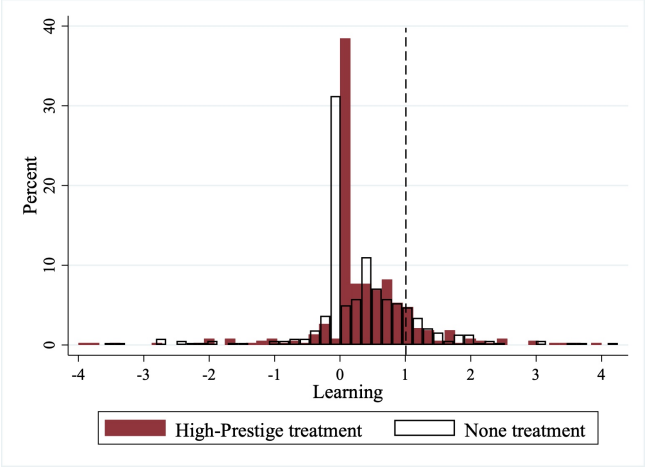
To explore the statistical significance of this result, Table 2 shows the average treatment effect in a regression framework. Following the within-subjects design, standard errors are clustered at the subject level.

Column (1) shows the average treatment effects of the "Own" treatment, "High-Prestige", and "Low-Prestige" controls, relative to the "None" control for all fidelity levels. The dependent variable is a dummy taking value one if the subject learned from the information in the message, i.e., if her second-time prediction is closer to the message relative to the first-time

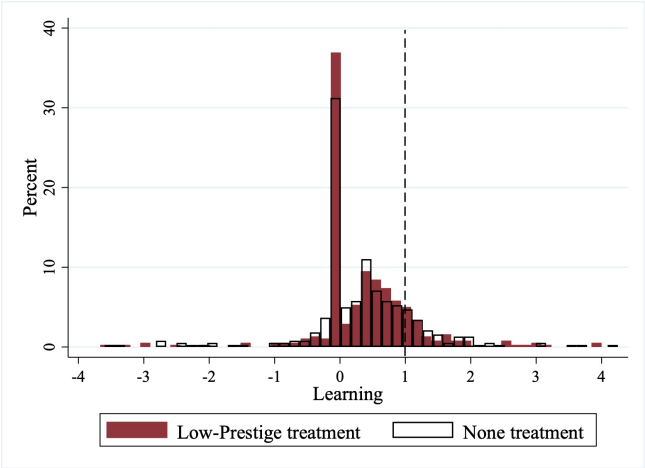
Figure 7: Histograms of the Social Learning Index Across Treatments.



(a) P-value of the Mann-Whitney test = 0.0002.



(b) P-value of the Mann-Whitney test = 0.8301.



(c) P-value of the Mann-Whitney test = 0.5818.

Notes. Histograms do not include the 1% and 99% percentiles for clarity. The null hypothesis of the non-parametric Mann-Whitney test is that both samples are drawn from the same distribution. P-values are calculated using all data.

Table 2: Treatment Effects on Social Learning.

	OLS estimates of dummy taking value one if:					
	$\mathcal{SL} \in (0,1]$	$\mathcal{SL} \in (0,1]$	$\mathcal{SL}=1$	$\mathcal{SL}=1$	$\mathcal{SL} \in (0,1)$	$\mathcal{SL} \in (0,1)$
	(1)	(2)	(3)	(4)	(5)	(6)
Own	0.167	0.168	0.128	0.128	0.039	0.040
	(0.033)***	(0.032)***	(0.019)***	(0.019)***	(0.033)	(0.033)
High	0.007	0.009	-0.005	-0.005	0.012	0.014
	(0.034)	(0.034)	(0.011)	(0.012)	(0.034)	(0.034)
Low	0.008	0.009	-0.013	-0.012	0.021	0.021
	(0.035)	(0.035)	(0.010)	(0.010)	(0.035)	(0.035)
Incentives		0.007		0.010		-0.003
		(0.024)		(0.011)		(0.024)
Woman		0.015		-0.013		0.028
		(0.034)		(0.013)		(0.033)
Age		-0.002		-0.001		-0.001
		(0.002)		(0.001)*		(0.002)
University		0.084		0.011		0.073
		(0.038)**		(0.015)		(0.037)**
Constant	0.414	0.357	0.028	0.054	0.386	0.303
	(0.025)***	(0.080)***	(0.008)***	(0.030)*	(0.025)***	(0.077)***
R^2	0.02	0.03	0.06	0.08	0.00	0.01
N	1,566	1,566	1,566	1,566	1,566	1,566
Controls		✓		✓		✓

Notes. Standard errors clustered at the subject level (four observations per subject from the within-subjects design). Estimates consider the full sample of 1566 observations (34 observations had a first-time prediction equal to the message, and thus, the dependent variable is undefined). Controls are audio and order fixed effects and the three survey variables: perceived prestige of own institution, perceived closeness to own institution, and self-perception of sentimentality.

prediction ($\mathcal{SL} \in (0, 1]$). The estimates show that receiving a message from other workers from their own higher-education institution increases the likelihood of learning by 17pp, a statistically significant increase (p-value < 0.001). Contrarily, receiving a message with the average prediction of other workers from a higher or lower prestige institution does not lead to increased social learning: The point estimates for the High and Low treatments are small (0.7% and 0.8%, respectively) and not significant (p-values 0.843 and 0.813, respectively). Column (2) shows that these results are robust to including control variables.

Columns (3) and (5) decompose the overall effect of learning from workers of your own

organization into high-fidelity and partial social learning. Column (3) shows the OLS estimates when the dependent variable is a dummy taking value one if the subject perfectly mimicked the information in the message, i.e., if her second-time prediction is exactly equal to the message ($\mathcal{SL} = 1$). Column (5) shows the same OLS estimates but for those who copied partially from the message ($\mathcal{SL} \in (0, 1)$). Column (3) shows that from a total of 17pp of learning (as shown in column (1)), 13pp corresponds to high-fidelity learning. Column (5) shows that the other 4pp corresponds to partial social learning (or low-fidelity social learning). In both columns (3) and (5), the point estimates for the High and Low-prestige controls are small and insignificant. Columns (4) and (6) show that all of these results are robust to adding the standard set of control variables.

4.2.3 Mechanism

According to our theory, the finding is driven by a psychological predisposition/bias, and not a rational calculation. To support this mechanism, we perform four analyses. First, we randomize a small monetary incentive for prediction accuracy. As we explain in detail below, we expect that if high-fidelity learning arises from a psychological bias, monetary incentives would have a small role in causing it (but would affect the prestige treatments). Second, we use the exit survey detailed in Section 4.1 and explore whether our main treatment effect depends on how sentimental the subject declares to be. We expect that the impact of having access to information from someone from the same organization should be stronger if the participants are more sentimental, i.e., according to the Cambridge Dictionary, a "person that is strongly influenced by emotional feelings, especially about happy memories of past events or relationships with other people, rather than by careful thought and judgment based on facts".[23] Third, given that we document the "blind mimicry" aspect of high-fidelity, prior literature would suggest that our findings should be impervious to the status of and closeness to the university. Fourth, using information on the true success rate of sales executives, we measure the accuracy of our workers' predictions and we find that workers seem not to pay attention to the inaccuracy of the treatment messages, which suggests that workers believe them at face-value (instead of critically assessing their accuracy before copying). We detail these four analyses below.

It is well established in the cognitive science literature that the presence of monetary incentives increases cognitive control (Locke and Braver, 2008; Padmala and Pessoa, 2011; Chiew

[23] https://dictionary.cambridge.org/dictionary/english/sentimental; in Spanish, "sentimental" has the same meaning.

and Braver, 2014; Ličen et al., 2016; Fröber and Dreisbach, 2014). Cognitive control "denotes the ability to manage one's own cognitive processes, is related to a number of processes such as working memory, reasoning, problem-solving, task flexibility, planning, and execution, [...] enables the regulation of thoughts and actions in pursuit of behavioral goals, [and] is essential in directing attention to a stimulus and inhibiting more automatic or habitual response tendencies" (Ličen et al. (2016); p. 2). In short, monetary incentives increase the top-down grip of "reason" on behavior. While this definition suggests that heightened cognitive control might potentially reduce the role that psychological dispositions play (e.g., affect, biases, and emotions), and thus, monetary incentives crowd out emotional responses, Farrell et al. (2014) argues and shows that while the role of emotions in decision making is present both with and without monetary incentives, reason exerts its presence mostly when monetary incentives are present. Therefore, we would expect that "own" treatment would not be affected by monetary incentives (and thus not driven by reason); and the "high prestige" treatment, a useful information when reason is considering accuracy, is positively moderated by monetary incentives. We find evidence aligned with this conjecture. Table 3 displays the same regressions in our main result (Table 2) but includes the interaction term between the treatment dummies and the dummy taking value one for those predictions where workers received the monetary incentive. Column (1) shows that overall learning remains almost unchanged relative to our main result: receiving information from people from your own institution increases the likelihood of learning by 15pp. (p-value = 0.002). The interaction terms of all three treatment dummies with the incentive dummy are not statistically significant. Adding the standard set of controls does not change these results (column (2)). Columns (3) and (4) show that incentives increase the likelihood that workers perfectly mimic the message whenever information comes from a high-prestige source. In column (3), the interaction term between the High-Prestige control and the incentive dummy is small (5pp.), but it is significant (p-value = 0.027), while column (4) shows that this result is robust to including the standard set of control variables. Columns (5) and (6) show non-statistically significant results when analyzing partial, low-fidelity social learning. Overall, these results show that a monetary incentive has no statistically discernible effect on "own" treatment, but it increases high-fidelity learning for the "high-prestige" treatment.

Our second moderation analysis explores whether workers who self-declare as sentimental are more likely to engage in high-fidelity social learning. We define workers as being sentimental if they agree with the assertion "I am a sentimental person" above or equal to the median of

Table 3: Treatment Effects on Social Learning By Incentives.

	OLS estimates of dummy taking value one if:					
	$\mathcal{SL} \in (0,1]$	$\mathcal{SL} \in (0,1]$	$\mathcal{SL}=1$	$\mathcal{SL}=1$	$\mathcal{SL} \in (0,1)$	$\mathcal{SL} \in (0,1)$
	(1)	(2)	(3)	(4)	(5)	(6)
Own	0.146	0.151	0.110	0.111	0.035	0.041
	(0.047)***	(0.047)***	(0.029)***	(0.030)***	(0.048)	(0.048)
High	-0.047	-0.046	-0.030	-0.032	-0.017	-0.014
	(0.050)	(0.050)	(0.014)**	(0.015)**	(0.050)	(0.050)
Low	-0.011	-0.010	-0.021	-0.021	0.010	0.010
	(0.048)	(0.048)	(0.015)	(0.015)	(0.048)	(0.048)
Incentives	-0.043	-0.039	-0.014	-0.016	-0.029	-0.023
	(0.050)	(0.050)	(0.017)	(0.017)	(0.049)	(0.049)
Own x Incentives	0.043	0.035	0.035	0.035	0.008	-0.000
	(0.068)	(0.068)	(0.040)	(0.041)	(0.068)	(0.068)
High x Incentives	0.105	0.109	0.049	0.054	0.057	0.055
	(0.073)	(0.073)	(0.022)**	(0.023)**	(0.073)	(0.074)
Low x Incentives	0.039	0.040	0.017	0.017	0.023	0.022
	(0.070)	(0.071)	(0.021)	(0.021)	(0.068)	(0.068)
Constant	0.435	0.376	0.035	0.065	0.400	0.311
	(0.035)***	(0.082)***	(0.013)***	(0.031)**	(0.035)***	(0.080)***
R^2	0.02	0.03	0.07	0.08	0.00	0.01
N	1,566	1,566	1,566	1,566	1,566	1,566
Controls		✓		✓		✓

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes. Standard errors clustered at the subject level (four observations per subject from the within-subjects design). Incentives is a dummy variable taking value one if the prediction was incentivized using a small monetary incentive as described in Section 4.1. Estimates consider the full sample. Controls correspond to the standard set: audio and order fixed effects, the demographic variables (gender, age, and a dummy for university), as well as dummies for the other three pre-registered perception questions (perceived sentimentality, perceived prestige of own institution, and perceived closeness to own institution).

five on a one to seven Likert scale.[24]Table 4 shows that the main result of high-fidelity learning within organizations is driven by workers who declare themselves as high on the sentimentality scale. To this end, we repeat the interaction analysis, this time using a dummy taking value one for those workers who score five or up on the Likert scale. Columns (1) and (2) show that social learning is not affected by sentimentality, as the interaction between the sentimentality dummy

[24]See Section 4.1, part *(7)*, describing the Exit survey. The mean response to this question is 5.085, while the median is five.

and the treatment dummies is never significant. Column (3) shows, however, that those who score high on sentimentality drive high-fidelity learning within institutions. The interaction between the own treatment and the high-sentimentality dummy is large (13pp) and significant (p-value = 0.001), and this effect does not change with controls (column (4)). Columns (5) and (6) show that sentimentality does not drive social learning with lower fidelity as the parameter associated with sentimentality, nor its interactions with the treatment dummies are significant.

Table 4: Treatment Effects on Social Learning By Sentimentality

	OLS estimates of dummy taking value one if:					
	$\mathcal{SL} \in (0,1]$	$\mathcal{SL} \in (0,1]$	$\mathcal{SL}=1$	$\mathcal{SL}=1$	$\mathcal{SL} \in (0,1)$	$\mathcal{SL} \in (0,1)$
	(1)	(2)	(3)	(4)	(5)	(6)
Own	0.145	0.146	0.040	0.043	0.105	0.104
	(0.058)**	(0.058)**	(0.027)	(0.027)	(0.060)*	(0.060)*
High	0.016	0.021	-0.032	-0.031	0.048	0.052
	(0.058)	(0.058)	(0.023)	(0.023)	(0.059)	(0.059)
Low	0.008	0.013	-0.040	-0.040	0.048	0.053
	(0.061)	(0.061)	(0.021)*	(0.021)*	(0.063)	(0.063)
Sentimental	0.051	0.045	-0.030	-0.028	0.080	0.074
	(0.053)	(0.053)	(0.021)	(0.021)	(0.052)	(0.052)
Own x Sentimental	0.032	0.032	0.128	0.125	-0.096	-0.093
	(0.070)	(0.070)	(0.037)***	(0.037)***	(0.072)	(0.072)
High x Sentimental	-0.013	-0.017	0.040	0.038	-0.053	-0.055
	(0.072)	(0.072)	(0.026)	(0.027)	(0.073)	(0.073)
Low x Sentimental	0.001	-0.005	0.041	0.040	-0.040	-0.046
	(0.074)	(0.074)	(0.024)*	(0.024)*	(0.076)	(0.076)
Constant	0.379	0.337	0.048	0.082	0.331	0.254
	(0.044)***	(0.083)***	(0.019)**	(0.032)**	(0.042)***	(0.080)***
R^2	0.02	0.03	0.08	0.08	0.00	0.01
N	1,566	1,566	1,566	1,566	1,566	1,566
Controls		✓		✓		✓

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes. Standard errors clustered at the subject level (four observations per subject from the within-subjects design). Estimates consider the full sample. Sentimental is a dummy taking value one if the workers answered five or higher (on a Likert scale from one to seven) to the exit-survey question "I am a sentimental person". Controls correspond to the standard set: audio and order fixed effects, the demographic variables (gender, age, and a dummy for university), a dummy for incentives, as well as dummies for the other two pre-registered perception questions (sentimentality and perceived prestige of own institution).

Third, we explored whether the impact of the "Own" treatment varied with two additional variables we collected in the survey: closeness with own institution and perceived status of own institution. As displayed in Table A2 and Table A3 of the appendix, we failed to find any results. This suggests that what matters for triggering social learning and high-fidelity predisposition within organizations is simply being part of an organization, irrespective of its status or firm-worker closeness. This is consistent with the "*blind* mimicry" component of high fidelity, which we focus on. '*Blind*' means that individuals doesn't consider or question the belief, motivation, status, etc. of others when copying, they copy "just because others do it" (Boyd (2018), p. 27).

Finally, another sign that social learning does not seem to emanate from a deliberate, thoughtful process is that workers' predictions become less accurate as a result of the treatments. This suggest that workers, when learning socially, may pay less attention to the precision of the information from others, simply taking it at face value even if it can reduce precision. First, consider that Table 5 shows that, for whatever reason, the predictions underlying the different messages across treatments are inaccurate: while the executives have a true average success rate of 28 out of 100, across messages workers predict around 38 out of 100. Thus, if workers "believe" the messages at face value, then accuracy might tend to go down after the treatments. That is exactly what we find. Appendix Table A4 displays the likelihood of improving the accuracy of the prediction after the message. We define worker's accuracy as $\frac{|p_{t2}-true^j|}{|p_{t1}-true^j|}$ where p_{t1} and p_{t2} are the first and second-time predictions, $true_j$ is the true success rate of the executive in the audio where message j was randomly assigned, and $|\cdot|$ represents the absolute value function. A worker becomes more accurate if this ratio is strictly smaller than one and less accurate if it is strictly larger than one. We define dummy that takes the value of 1 if $\frac{|p_{t2}-true^j|}{|p_{t1}-true^j|} < 1$ and we use it as our dependent variable. Column (1) displays the OLS estimates of this dependent variable on the "Own", "High" and "Low" conditions. The point estimates show that, relative to the "None" control, workers in all these conditions become less likely to improve their accuracy between 10 and 16 pp. Consistent with our argument, the treatment "Own" reduces accuracy the most (but the difference with the other treatment is not statistically significant). Columns (2) to (4) show that effect of incentives, even though never statically significant, goes in the right direction (see the argument above on incentives triggering cognitive control): whenever workers are rewarded by accuracy in their predictions, they become between 3% to 7% more accurate.

4.2.4 Robustness

In this section, we address four potential concerns about our experimental design: the fact that messages in the "Own" treatment could be more informative than in the controls; the choice of high- and low-prestige institutions; whether our results could be driven by asking workers to answer the prediction question twice; and that our dependent variable includes both a decision to copy or not ("extensive margin") and a decision of fidelity ("intensive margin").

(1)*Message accuracy.* One could argue that the effect we find when learning from people of your own institution is not due to social learning but because messages in the "Own" treatment are more informative than messages in the control conditions. Table 5 shows this is not the case, as messages across all conditions are equally informative. It displays the average prediction of the messages in each treatment and their differences. Column (1) shows that messages are very similar in accuracy, measured as the distance between the prediction in the message and the true prediction: average accuracy ranges between 9.67 to 10.53.[25]

(2) *Choice of the institutions.* Another possible confound in our experimental design relates to the choice of high- and low-prestige institutions following an objective ranking. It could be the case that this objective ranking departs from the workers' subjective perceptions of a high and low-education institution, perceptions that are relevant for workers' predictions.

Figure 8 shows that this does not seem to be the case. The histogram of the answers to the subjective perception of the prestige of the high-education institutions in the High-Prestige treatment(which we collected in the survey)is to the right to that of the subjective perception of the institutions in the Low-Prestige treatments. Workers' subjective perceptions of prestige are, therefore, aligned with that of the objective ranking of the high-education institution.

(3) *Asking for predictions twice.* A third concern is that the variation in predictions before and after the message shown in Figure 9, panel (a), is due to asking workers for their predictions twice, which could lead to experiential learning. To explore this issue, in two different audios—delivered after the four treatment audios—we made workers execute, as before, a prediction that they could revise, but this time, instead of treating them with a message right after the prediction and before the revision stage, we gave them the message at the start, before the workers make their initial prediction (and in this case the revised prediction is prompted without any message). If the effect we detected before is not due to asking them twice, the

[25]The true prediction or actual success rate of every executive in the audio files was granted by the charity. An average message accuracy of around 10 means that if the average success rate across sellers in our audio is 28%, workers, on average, estimate a success rate of 38%.

Table 5: Average and Differences in Average Message Accuracy

	Average Accuracy	Differences in average accuracy			
		Own	High	Low	None
	(1)	(2)	(3)	(4)	(5)
Own	10.525	x	0.548	0.350	-0.855
	[0.9220]		(0.6800)	(0.7893)	(0.5205)
High	9.978	x	x	-0.198	-0.308
	[0.9540]			(0.8822)	(0.8202)
Low	10.175	x	x	x	-0.505
	[0.9296]				(0.7054)
None	9.670	x	x	x	x
	[0.9586]	x	x	x	x

Notes. Message accuracy is defined as the distance between the prediction in the message and the true prediction for that message, averaged across the N=400 observations for each treatment/control. Column (1) displays the average massage accuracy (standard errors in square brackets below). Columns (2) to (5) display the differences between the average accuracy across treatments in column (1) (p-value of the t-tests for differences in means in parenthesis below).

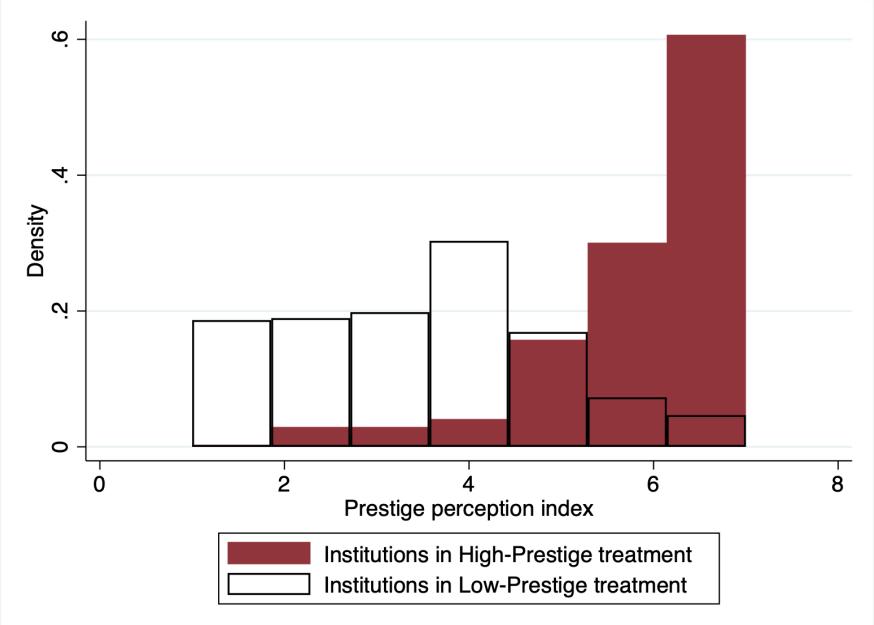
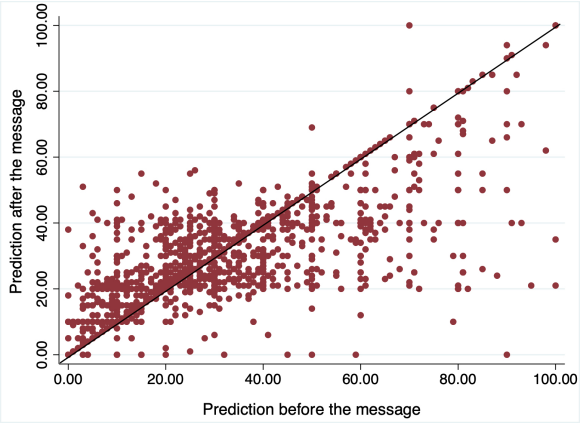


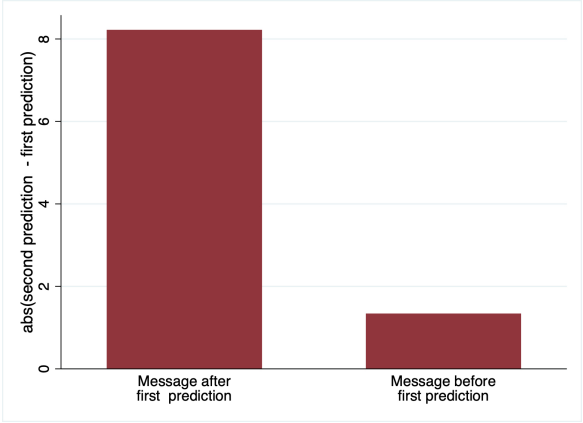
Figure 8: Workers' Prestige Perception of Institutions in the High and Low-Prestige Treatments.

change between the initial and revised predictions when the message is delivered at the start,

Figure 9: First and Second-Time Predictions.



(a) Comparison between the first and second-time predictions pooling across informational treatments.
Average of the absolute change=8.221*** (p-value < 0.001).



(b) Average change in prediction pooling the four informational treatments (first bar) and in control treatments where the message was delivered before the first-time prediction (second bar).
Difference between the two average changes=-6.879*** (p-value < 0.001).

Notes. Standard errors are clustered at the subject level.

i.e., before the initial prediction, should be close to zero.

Figure 9, panel (b), shows the results. The average change in prediction in the Own, High, Low, and None treatments is 8pp (first bar). This average significantly decreases by 7pp in the robustness treatment, where workers are also asked twice for their predictions, but the informational message is delivered before the first prediction. This shows that predicting twice is not driving the results we document.

(4) *The dependent variable.* It could be argued that the dependent variable in Table 2 conflates two choices, which may be consequential for the findings. On the one hand, the decision to learn from others ($\mathcal{SL} > 0$) nor not ($\mathcal{SL} = 0$) (the "extensive margin"), and on the other, the decision of fidelity ($\mathcal{SL} \in (0, 1]$) conditional on learning from others (the "intensive margin"). Our experimental procedure reflects these two choices: workers are told whether they would like to reevaluate their initial prediction (i.e., social learning) or not, in which case they have the chance to skip the task (see footnote 12). In Appendix Table A5 shows that this is not a concern. In that table, as a reference, columns (1) and (2) repeat the analysis in Table 2. In columns (3) to (6), we study the "intensive margin" by using only those workers who decided to learn from others. Columns (3) and (4) show that the likelihood of displaying high-fidelity social learning (conditional on social learning) increases by 18 pp as a result of the

"own" treatment, only 1 pp of difference with columns (1) and (2). Columns (5) and (6) show that lower levels of fidelity among those who learn from others are statistically insignificant for all treatments.

5 Conclusion

In this paper we propose that when learning from others, individuals display a behavioral predisposition to do so with high-fidelity, that is, copying with high-accuracy, but only when learning within the organization (and not across). This proposition is born out of a simple formal model combined with prior evidence. The model that predicts, when social learning is prevalent, high-fidelity would be favoured by evolution. Prior historical and archaeological evidence documents that social learning was prevalent in ancient organizations (Apel, 2008; Brahm and Poblete, 2021; Coto-Sarmiento et al., 2018; Khanna, 2005). Therefore, the conclusion from these premises is that it is likely that a predisposition for high-fidelity social learning within organizations would have evolved, either in our psychology and/or in our norms that regulate organizational life.

We document this behavioral predisposition using a pre-registered framed field experiment (Harrison and List, 2004) in which we hired 400 workers to perform a task for a real organization. To measure social learning and high fidelity, we fed information about how other workers executed the task; then computed how much workers adjusted their task when given another chance. Crucially, we randomized whether the other workers in the message were part of the same organization, another organization of high or low prestige, or the message provided only the average of other workers, without indicating organizational affiliation. We found that, in comparison to the other conditions, workers displayed more social learning when fed information from fellow organizational members, of which 75 percent is driven by high-fidelity copying. Further analysis showed that, consistent with a behavioral predisposition, this was driven by sentiments, not reason.

We offer several contributions. To the organizational learning literature (Argote et al., 2021), we introduce the notion of a behavioral predisposition for high-fidelity social learning. To date, fidelity has been highlighted in the context of complex routines (Winter and Szulanski, 2001), where tinkering can lead to unexpected consequences. We show that high fidelity is a more general and basic behavioral phenomenon in how individuals learn socially inside organizations. Further, this predisposition provides individual-level micro-foundations to the well-documented

social learning advantage that organizations display Darr et al. (1995); Atalay et al. (2014), which is at the root of the knowledge-based view of organizations Grant (1996); Nickerson and Zenger (2004); Brahm and Poblete (2021), and to date, has been explained mostly by structural features of organizations (Argote, 2024).

More broadly, our study joins recent efforts to bring Cultural Evolution Theory into research in management and organizations Brahm and Poblete (2021, 2022, 2024). This theory is increasingly informing other disciplines, and we believe that it can contribute, among other phenomena, to expand our understanding of how organizations learn and accumulate knowledge. Regarding cultural evolution, our study contributes by showing that organizations are important to consider; we show that high-fidelity social learning, a crucial idea in cultural evolution (Laland, 2017; Lewis and Laland, 2012; Tomasello et al., 1993), can be, at its core, an organizational phenomenon.

Further research could address some of the limitations of our study. First, it is necessary to study whether our findings replicate when manipulating organizational affiliation differently, either via a minimal group paradigm (Tajfel, 1982) or the creation of temporal organizations by the researchers. Clever designs would need to be used to study real world organizations such as firms, in which selection is pervasive and generates confounds. Second, further research could pin down precisely the source of the behavioral predisposition we document, whether it is rooted in psychology or social norms.

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A Appendix Tables

Table A1: Variance in individual traits accounted by universities

Dep. Var	Observations	Change in R^2 (61 dummies)	Change in R^2 (43 dummies)
(1)	(2)	(3)	(4)
Age	400	0.295	0.257
Woman	400	0.179	0.134
Sentimental	400	0.129	0.098
Closeness	400	0.138	0.080
Status Own	400	0.358	0.287
Status High	400	0.144	0.112
Status Low	400	0.130	0.097

Notes. Columns (3) and (4) show the increase in the R^2 in an OLS regression with a dependent variable, as in column (1), from a constant to a full set of university dummies. Since we have 18 Educational institutions with just one worker, column (3) shows the results with the full set of 61 dummies (plus the reference dummy), while column (4) pools all those in the 18 singleton institutions as one dummy (leading to a total of 62-18 dummies including the reference dummy).

Table A2: Treatment Effects on Social Learning By Closeness With Own Institution

	OLS estimates of dummy taking value one if:					
	$\mathcal{SL} \in (0,1]$	$\mathcal{SL} \in (0,1]$	$\mathcal{SL}=1$	$\mathcal{SL}=1$	$\mathcal{SL} \in (0,1)$	$\mathcal{SL} \in (0,1)$
	(1)	(2)	(3)	(4)	(5)	(6)
Own	0.184	0.181	0.165	0.164	0.019	0.017
	(0.051)***	(0.052)***	(0.031)***	(0.031)***	(0.053)	(0.053)
High	0.003	-0.001	0.000	-0.002	0.003	0.001
	(0.056)	(0.056)	(0.016)	(0.016)	(0.058)	(0.058)
Low	0.060	0.061	0.000	-0.001	0.060	0.062
	(0.058)	(0.058)	(0.016)	(0.016)	(0.058)	(0.059)
Closeness	-0.017	-0.022	0.015	0.009	-0.032	-0.030
	(0.051)	(0.051)	(0.016)	(0.017)	(0.050)	(0.051)
Own x Closeness	-0.028	-0.022	-0.061	-0.059	0.033	0.037
	(0.066)	(0.067)	(0.040)	(0.040)	(0.068)	(0.068)
High x Closeness	0.007	0.017	-0.008	-0.005	0.015	0.022
	(0.071)	(0.071)	(0.022)	(0.022)	(0.072)	(0.072)
Low x Closeness	-0.086	-0.086	-0.021	-0.019	-0.065	-0.067
	(0.073)	(0.073)	(0.021)	(0.021)	(0.073)	(0.073)
Constant	0.424	0.344	0.019	0.041	0.405	0.303
	(0.039)***	(0.083)***	(0.011)*	(0.030)	(0.039)***	(0.080)***
R^2	0.02	0.03	0.07	0.08	0.00	0.01
N	1,566	1,566	1,566	1,566	1,566	1,566
Controls		✓		✓		✓

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes. Standard errors clustered at the subject level (four observations per subject from the within-subjects design). Estimates consider the full sample. Closeness is a dummy taking value one if the workers answered three or higher (on a circle scale from one to seven) in the exit-survey question measuring closeness to the worker's high education institution. Three corresponds to the median answer (average is 3.3). Controls correspond to the standard set: audio and order fixed effects, the demographic variables (gender, age, and a dummy for university), a dummy for incentives, as well as dummies for the other two pre-registered perception questions (sentimentality and perceived closeness to own institution).

Table A3: Treatment Effects on Social Learning By Perceived Status of Own Institution

	OLS estimates of dummy taking value one if:					
	$\mathcal{SL} \in (0,1]$	$\mathcal{SL} \in (0,1]$	$\mathcal{SL}=1$	$\mathcal{SL}=1$	$\mathcal{SL} \in (0,1)$	$\mathcal{SL} \in (0,1)$
	(1)	(2)	(3)	(4)	(5)	(6)
Own	0.167	0.170	0.127	0.125	0.039	0.044
	(0.049)***	(0.050)***	(0.027)***	(0.027)***	(0.050)	(0.051)
High	-0.003	0.001	-0.017	-0.017	0.014	0.018
	(0.053)	(0.053)	(0.013)	(0.013)	(0.054)	(0.054)
Low	-0.016	-0.017	-0.011	-0.012	-0.005	-0.005
	(0.054)	(0.053)	(0.014)	(0.014)	(0.054)	(0.054)
Status	-0.016	-0.021	0.009	0.007	-0.026	-0.028
	(0.050)	(0.051)	(0.016)	(0.017)	(0.050)	(0.050)
Own x Status	0.000	-0.002	0.001	0.006	-0.001	-0.008
	(0.066)	(0.066)	(0.039)	(0.039)	(0.067)	(0.067)
High x Status	0.018	0.016	0.022	0.022	-0.004	-0.007
	(0.070)	(0.070)	(0.022)	(0.023)	(0.070)	(0.070)
Low x Status	0.043	0.048	-0.002	0.000	0.046	0.047
	(0.071)	(0.071)	(0.021)	(0.021)	(0.071)	(0.072)
Constant	0.423	0.364	0.023	0.058	0.400	0.306
	(0.037)***	(0.084)***	(0.011)**	(0.031)*	(0.037)***	(0.081)***
R^2	0.02	0.03	0.07	0.08	0.00	0.01
N	1,566	1,566	1,566	1,566	1,566	1,566
Controls		✓		✓		✓

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes. Standard errors clustered at the subject level (four observations per subject from the within-subjects design). Estimates consider the full sample. Status is a dummy taking value one if the workers answered six or higher (on a Likert scale from one to seven) to the exit-survey question "People in my community have an excellent impression of [worker's institution]." Six corresponds to the median answer (average is 5.47). Controls correspond to the standard set: audio and order fixed effects, the demographic variables (gender, age, and a dummy for university), a dummy for incentives, as well as dummies for the other two pre-registered perception questions (perceived prestige of own institution and perceived closeness to own institution).

Table A4: Treatment Effects on Workers' Prediction Accuracy

	OLS estimates of dummy taking value one if workers' predictions become more accurate			
	(1)	(2)	(3)	(4)
Own	-0.155	-0.152	-0.188	-0.165
	(0.034)***	(0.032)***	(0.049)***	(0.048)***
High	-0.096	-0.092	-0.126	-0.114
	(0.034)***	(0.032)***	(0.050)**	(0.049)**
Low	-0.132	-0.131	-0.165	-0.165
	(0.033)***	(0.032)***	(0.048)***	(0.045)***
Incentives		0.030	-0.010	-0.005
		(0.022)	(0.051)	(0.049)
Own x Incentives			0.063	0.027
			(0.071)	(0.070)
High x Incentives			0.059	0.044
			(0.073)	(0.072)
Low x Incentives			0.071	0.070
			(0.071)	(0.069)
Constant	0.523	0.693	0.528	0.709
	(0.025)***	(0.075)***	(0.036)***	(0.078)***
R^2	0.01	0.10	0.02	0.10
N	1,567	1,567	1,567	1,567
Controls		✓		✓

Notes. Standard errors clustered at the subject level (four observations per subject from the within-subjects design). The table shows the change in the likelihood of workers becoming more accurate in their predictions due to the message. Workers become more accurate in their predictions after receiving the message if the index $\frac{|p_{t2}-true^j|}{|p_{t1}-true^j|}$ (where p_{t1} and p_{t2} are the first and second-time predictions and $true^j$ is the true success rate of the executive in the audio where message j was assigned) is strictly less than one. Estimates consider the full sample except those where the index is undefined ($p_{t1} = true^j$).). Controls correspond to the standard set: audio and order fixed effects, the demographic variables (gender, age, and a dummy for university), and dummies for the other three pre-registered perception questions (sentimentality and perceived prestige and closeness to own institution).

Table A5: Treatment Effects on Social Learning Conditional on Learning

Sample:	Full sample		$\mathcal{SL}>0$			
	$\mathcal{L} \in(0,1]$ (1)	$\mathcal{L} \in(0,1]$ (2)	$\mathcal{L}$=1 (3)	$\mathcal{L}$=1 (4)	$\mathcal{L} \in(0,1)$ (5)	$\mathcal{L} \in(0,1)$ (6)
Own	0.167	0.168	0.185	0.183	-0.040	-0.040
	(0.033)***	(0.032)***	(0.029)***	(0.029)***	(0.040)	(0.040)
High	0.007	0.009	-0.008	-0.009	0.032	0.032
	(0.034)	(0.034)	(0.020)	(0.020)	(0.044)	(0.044)
Low	0.008	0.009	-0.022	-0.023	0.047	0.048
	(0.035)	(0.035)	(0.018)	(0.018)	(0.044)	(0.044)
Incentives		0.007		0.022		-0.002
		(0.024)		(0.018)		(0.030)
Woman		0.015		-0.029		-0.020
		(0.034)		(0.022)		(0.039)
Age		-0.002		-0.001		0.002
		(0.002)		(0.001)		(0.002)
Universidad		0.084		0.013		0.070
		(0.038)**		(0.026)		(0.051)
Constant	0.414	0.357	0.049	0.084	0.676	0.509
	(0.025)***	(0.080)***	(0.014)***	(0.050)*	(0.031)***	(0.097)***
R^2	0.02	0.03	0.09	0.11	0.01	0.02
N	1,566	1,566	925	925	925	925
Controls		✓		✓		✓

Notes. Standard errors clustered at the subject level (four observations per subject from the within-subjects design). Estimates consider the full sample. Closeness is a dummy taking value one if the workers answered three or higher (on a circle scale from one to seven) in the exit-survey question measuring closeness to the worker's high education institution. Three corresponds to the median answer (average is 3.3). Controls correspond to the standard set: audio and order fixed effects, the demographic variables (gender, age, and a dummy for university), a dummy for incentives, as well as dummies for the other two pre-registered perception questions (sentimentality and perceived closeness to own institution).