Cultural Transmission & Variation in Organizational Populations: A Formal Model

Anjali Bhatt
Second Year Paper
March 17, 2017

Abstract

What explains the diversity of firm cultures in organizational populations? While research on culture has made significant strides in understanding intra-organizational cultural processes, it has largely taken for granted the existence of variation in organizational culture across firms. In this paper, I develop a formal model to understand cultural variation in populations as a function of cultural transmission both within and between firms. Bridging cultural processes like employee recruitment, socialization, and turnover with labor market mechanisms, the model conceptualizes individual employees as ‘cultural carriers’ that move between firms. Based on agent-based simulations of this model, I find that population-level dynamics like inter-firm mobility have significant and surprising consequences for both cultural variation within and between firms. These dynamics can also interact with and disrupt the intentions of firm-level practices, such as cultural selection in hiring. Importantly, the model validates the significance of and provides a basis for the study of inter-organizational cultural processes.
1 Introduction

Organizational theorists have had a longstanding interest in what determines the level of variation among firms in a population (Hannan & Freeman, 1984). From this interest has stemmed a large literature examining population-level variation in categorical or neatly quantifiable characteristics of firms, such as age, size, structural form, or professionalization of workforce. Culture, while recognized as essential in shaping outcomes and behaviors of organizations, as well as individuals and groups within organizations, has been overlooked in this research on organizational diversity, likely due to the difficulty in measuring culture for population-level analyses (Chatman & O’Reilly, 2016). This leaves a puzzles as to what explains the level of variation in organizational culture in among firms in a population. Why, for example, does it appear that venture capital firms are more culturally heterogeneous than investment banks? Or that biotech firms have more varied organizational cultures than pharmaceutical companies?

Thus far unexplored, cultural variation in organizational populations informs our understanding of both firm culture and the ecology of firms. First, organizational sociologists have long considered culture as a defining attribute of firms that forms the basis for the organizational identity that both employees and firm audiences perceive. Population-level cultural variation may define precisely how distinctive firms can actually be. Second, culture plays an essential role in defining organizational behavior by illuminating the practices and routines that form the basis of an organization (Martin, 2001). As a result, organizational culture can explain many of the otherwise unexplained differences among firms, from positioning in resource space to differential capabilities for innovation (Carroll & Swaminathan, 2000; Saxenian, 1996). The study of organizational diversity, and the ensuing implications for firm competition, survival, and ecosystem vitality, must take into account cultural
variation.

Research on organizational culture has similarly paid little attention to population level cultural dynamics, instead focusing on firm-level differences in cultural content and strength and intra-firm cultural practices (Schein, 1990). An implicit assumption of this literature is that organizational culture is firm-specific and insulated by firm boundaries, and that intra-organizational cultural dynamics sufficiently and comprehensively explain organizational culture and its variation across firms. Specifically, common human resource processes within firms like cultural matching in hiring new employees, and socialization and alienation among existing employees, are considered first-order mechanisms by which organizational culture is maintained. All of these intra-firm mechanisms serve to strengthen firm culture by building consensus among employees as to the norms, values, beliefs that guide organizational behavior.

However, organizational culture may not be as insulated or as distinctive as is often assumed (Martin, Feldman, Hatch, & Sitkin, 1983; Abrahamson & Fombrun, 1994; Chatman & Jehn, 1994). Indeed, as cultural sociologists have pointed out, individuals (and not groups or firms) are the vehicles by which culture is conveyed and enacted (DiMaggio, 1997). Individual employees cumulatively form the cultural forces within organizations. Most importantly, the movement of individuals between organizations provides a plausible mechanism by which culture may actually spread beyond organizational boundaries and in turn be subject to population-level dynamics. Individuals can thus be conceptualized as ‘cultural carriers’ that transmit organizational culture between firms, thus influencing both the cultural strength within firms as well as the cultural variation between firms in a population. While existing accounts of organizational diversity in populations tend to assume macro-level environmental forces, cultural transmission between individuals builds on concrete and well-established micro-processes to provide an emergent explanation of
population-level cultural variation.

In this paper, I construct and simulate a formal model to examine the effects of combining intra-firm cultural processes with inter-firm employee mobility on cultural heterogeneity in organizational populations. The process of cultural transmission within and between groups of individuals is well-suited to a formal modeling approach. Such dynamic models of cultural transmission and evolution are not new (Harrison & Carroll, 1991). Indeed, there is a whole branch of research in evolutionary biology devoted to developing such mathematical models, many of which have spilled over to sociological and anthropological research (Cavalli-Sforza & Feldman, 1981; Sperber, 1985; Boyd & Richerson, 1988). There is much novelty to be gained from the linking of modeling cultural transmission and organizational research, since these models provide a well-formulated basis for modeling horizontal transmission of culture between peer individuals as well as migration between groups (in this case, inter-firm mobility).

Building on the Harrison and Carroll (2006) framework, I formally model individual employees as ‘cultural carriers’ that enable cultural diffusion across firms. Through dynamic simulations of employee recruitment, socialization, turnover, and mobility in a population of firms, I probe how the mobility of cultural carriers affects cultural variation at the level of the organizational population. Based on these simulations, I find that the role of individuals as ‘cultural carriers’ that move between firms in a population plays a dominant role in determining the level of cultural variation both within and between firms. Employee mobility, which would otherwise appear to be a second-order population-level process, actually may outweigh the effects of first-order intra-firm processes that have been the focus of the literature on culture thus far. In other words, a narrow firm-specific focus of the organizational  

\footnote{Such interdisciplinary research is equally illuminating for population biologists, since organizations serve as a unique setting to understand cultural evolution at its extreme, with extraordinarily rapid timescales for migration and transmission (compared, for example, to that of cultural evolution in humans and primates).}
culture research may obscure the significant role that inter-organizational dynamics play in determining culture and its consequences. The initial simulation findings shed light on promising research directions in the study of inter-organizational cultural processes.

The following sections proceed as follows: I first provide an overview of existing research on organizational diversity in populations and how intra-firm cultural mechanisms may inform this literature. I then lay out a formal model of cultural transmission between employees in a population of firms and present the results of simulations of cultural variation. Finally, I discuss the implications of population-level dynamics for research on organizational culture.

2 Theories of Cultural Variation in Populations

What explains the level of cultural heterogeneity in organizational populations? Although few scholars have examined organizational diversity in the context of culture, existing research on organizations offers several theoretical perspectives on this question. A large body of literature has emphasized macro-level environmental forces in explaining population-level variation. These forces refer to mechanisms by which the environmental context as a whole determines the distribution of individual firm traits. Classical ecological perspectives would suggest that organizational diversity is increased through competition and ensuing niche specialization: identical competing organizations cannot coexist, and thus unique specialists are more likely to survive (Hannan & Freeman, 1977). This logic may be implicit in lay theories of cultural distinctiveness: firms that are culturally distinct compete more effectively because they seek out both consumer and labor market niches. Culturally distinct firms may be perceived as being more morally authentic (i.e. true to themselves) to both consumer and labor market audiences (Carroll & Wheaton, 2009), thus accumulating greater rewards in competitive contexts.
On the other hand, there is evidence that firms should be driven towards cultural homogeneity, rather than heterogeneity. Martin et al. (1983) find that organizational culture is not as unique as employees and managers would presume, since it arises from common tensions between societal values and organizational situations. In other words, cultural variation across firms is limited because of environmental forces of institutionalization that constrain variation in organizational routines and societal values. Regulatory, normative, and cognitive pressures on firms might induce them to culturally conform to institutional expectations of what is considered legitimate (DiMaggio & Powell, 1983). Using this logic, Weber (2005) asserts that cultural repertoires of firms in the same field are constrained by what is appropriate given the norms of the field and the social position of the firm, thus limiting cultural variation. Chatman and Jehn (1994) take this one step further, demonstrating that culture is less varied among firms within the same industry than between different industries (arguing that industry context is constraining).

While ecological and institutional perspectives appear to dominate much of the literature on organizational diversity, several micro-level emergent mechanisms have been posited as well. Emergent mechanisms refer to processes by which population-level properties like cultural variation are determined by complex interactions among sub-units (individuals or firms). For example, cultural variation may be explained by the coupling of idiosyncratic managerial choice in individual firms. Founders and CEOs may have arbitrary but interconnected preferences regarding firm culture (for example, the desire to be distinctive from other firms), and thus cultural diversity of firms reflects the coordination of managers. Alternatively (but to a similar effect), under the auspices of rationality, managers may “foolishly” attempt to optimize their cultures to serve performance needs (March, 2006). Because complex firm features like culture are difficult to mimic, firms will effectively innovate (or mutate) culturally, thus creating cultural diversity (Barney, 1986; Levinthal, 1997).
In either case, a managerial perspective would argue that cultural variation in a population of firms is the result of the interdependent preferences of managers. Diffusion processes offer an emergent explanation of cultural homogenization: perhaps culture is less varied among firms within an industry because of cultural diffusion through a common labor market. For example, Phillips (2005) provides support for a diffusion-based explanation of culture in a population of law firms. The study finds that founders transmit cultural norms regarding gender genealogically from their parent firm to their new firm.

Emergent explanations for cultural variation appear especially ripe for examination. While there is little causal evidence of macro-scale environmental forces on cultural variation, many of the micro-level emergent mechanisms for cultural transmission and maintenance are empirically established. I discuss these intra-firm processes in the next section.

3 Cultural Dynamics Within Firms

While much of the established research on organizational culture takes a content-based view of culture, research on the intra-firm dynamics of cultural transmission and maintenance employs a distributive perspective to understanding culture. This distinction is important to clarify before going into detail about the specific cultural processes of interest. Most qualitative studies have focused on analyzing the content of culture; that is, the causes and consequences of the specific norms, values, beliefs, etc. that exist within the organization. For example, researchers might ask questions about whether the cultural value of ‘autonomy’ is beneficial for innovation, or what industries rewards ‘predictability’. Saxenian (1996) describes the cultural content of Silicon Valley firms as encouraging risk-taking and accepting failure. Conversely, most studies on cultural transmission and maintenance, along with many quantitatively focused studies, employ a distributive approach to understand-
ing the level of cultural heterogeneity or disagreement within an organization and between organizations (Harrison & Carroll, 2006). With this approach, the specific cultural attributes are of less relevance than whether these attributes are shared or transmitted between individuals. Cultural heterogeneity within firms, or inversely, the degree of cultural strength or consensus within firms, has been a topic of much study by researchers, since it appears to correspond to the degree of social control firms have over their employees (O’Reilly & Chatman, 1996; Sørensen, 2002). In this paper too, I take a distributive approach to analyzing cultural variation.

Using this distributive approach to culture, scholars have examined cultural transmission and maintenance within firms. These studies build on sociological research establishing that culture resides at the level of the individual as a set of cognitive schemata (DiMaggio, 1997). These schemata constitute a ‘cultural toolkit’ through which situations and interactions are understood (Swidler, 1986). Individuals’ cognitive schemata evolve and adapt according to the social environment, often mirroring the schemata of other proximate individuals. When shared by individuals, these schemata form the basis for efficient communication and for norms, values, and beliefs that guide decision-making. Thus, organizational culture consists of the set of shared cognitive schemata of members; this set can evolve (albeit slowly) over time with the entrance and departures of individuals and their respective (and also evolving) cultural toolkits (Schneider, 1987).

Several well-documented intra-firm practices slow the evolution of firm culture through producing cultural homogeneity among employees. Specifically, firms accumulate cultural strength via three processes: recruitment, socialization, and turnover. In recruiting employees, firms select new hires based on the extent to which they fit with (in other words, share cognitive schemata with) the existing organizational culture (to the extent they can observe candidates’ cultural signals).

---

2This is in contrast to older organizational research in which culture is regarded as an attribute of the group or firm.
Many firms prioritize this cultural matching over other hiring criteria, such as skill-based human capital. For example, Rivera (2012) demonstrates that cultural matching between evaluators and candidates serves as the primary basis for hiring decisions in elite professional service firms. These firms incorporate and prioritize cultural fit as a formal part of candidate evaluation in order to minimize attrition and conspicuousness of time-consuming work. Moreover, like social network-based sorting, cultural sorting in recruitment processes may decrease firm hiring costs by increasing the likelihood of offer acceptance (Sterling, 2014). In this way, existing employees serve as a benchmark for cultural selection of new employees.

Socialization processes within firms that intensify the enculturation of employees also serve to culturally homogenize employees. These processes include ritualistic orientations and social activities, sharing of company narratives, and role modeling or mentoring relationships (Deal & Kennedy, 1982). Firms use these activities as a means to impart both technical and social knowledge; the latter is essentially cultural transmission between employees. According to Louis (1980), transmission occurs because such activities enable sense-making among employees and thus serve to update their beliefs (about the organization) and behaviors to match more closely to employees with greater experience. Socialization activities continue throughout an employee’s tenure at a firm, but with decreasing marginal returns to enculturation (Van Maanen & Schein, 1979). Additionally, socialization can occur in reference to both management ideals as well as to the cultural schemata of immediate peers.

Lastly, organizational cultural homogeneity is maintained through the employee turnover process. Employees who fit culturally within an organization have higher job satisfaction and are more likely to stay with the organization (Chatman, 1991). Conversely, employees who have low cultural fit are more likely to both vol-
untarily and involuntarily leave the organization (Sheridan, 1992). These cultural misfits may either be unable to sufficiently enculturate or may lose interest in fitting in (Srivastava, Goldberg, Manian, & Potts, 2015), leading them to experience negative affect and/or feelings of incompetence (Chan, 2016). Firms can enable retention of cultural matches and attrition of cultural misfits through formal mechanisms like firing and promotion, or through informal mechanisms like culturally alienating misfits to intensify motivation to leave voluntarily. This cultural alienation is produced through culturally conforming employees defining informal boundaries of organizational membership, including who is invited to social events (Gieryn, 1983). The alienation and departure of employees with culturally divergent beliefs thus reduces cultural variation within firms.

These three mechanisms serve to push organizations to become more culturally homogenous through both the selection and adaptation of employees’ cultural schemata. However, the interactions between these employee-level processes are less predictable, creating the potential for unintuitive and emergent dynamics at the organizational. For example, intense alienation forces may obscure the effects of socialization, since remaining employees are only those who are already enculturated into the firm. At the population level, dynamics are even more emergent since the movement of individuals between firms creates additional complexity and interdependence.

4 Individuals as Cultural Carriers

Given the conceptualization of culture as an individual-level cognitive toolkit, it would make sense that employees retain a set of cultural norms prior to entering a firm and after exiting it. Louis (1980) points out that “one critical limitation of studies [of culture]... [is that] usually the process of entering an organization and/or role also involves leaving another one.” As individuals experience mobility between
firms, they might carry and transmit these cultural norms from one firm to another. The question arises, can these individual ‘cultural carriers’ diffuse cultural norms and instill cultural agreement at the inter-organizational level?

Chatman and Jehn (1994) hint at precisely this question in their analysis of industry determinants of organizational culture. They posit that “organizational cultures may become more similar as employees move across firms in the same industries.” Moreover, in many organizational populations, mobility is sufficiently frequent to powerfully affect cultural variation. For example, in her analysis of the economic prosperity of Silicon Valley in the 1970s and 1980s, (Saxenian, 1996, p. 34-37) describes how the high rate of employee mobility may have led to shared organizational cultures:

Silicon Valley was quickly distinguished by unusually high levels of job-hopping. During the 1970s, average annual employee turnover exceeded 35 percent... Engineers shifted between firms so frequently that mobility not only was socially acceptable, it became the norm... [the resulting personal relationships] reinforced a shared technical culture.

While Silicon Valley may represent an extreme level of inter-firm mobility, many organizational fields and populations are likely to exhibit some degree of employee mobility. As a result, individuals may indeed act as influential cultural carriers that enable cultural convergence among firms in a population. I explore this process in the model outlined below.

5 Model

Constructing a theory that links population-level variation to aggregated employee-level cultural and mobility processes is essentially a task of dynamically modeling cultural transmission and evolution in a population of firms. The intra-organizational research on culture discussed previously has mostly taken organizational culture to be static, and for appropriate reasons: individual-level mech-
anisms occur on a relatively short time scale during which organizational-level or population-level cultural measures are as good as fixed. However, these individual-level processes interact and unfold on larger time scales, in which firm cultures may evolve to ultimately generate population-level equilibria.

As mentioned before, mathematical models of cultural transmission are commonly used in evolutionary biology and epidemiology. However, with the exception of the work of Harrison and Carroll (2006), there has been little influence of the cultural transmission models on organizational research. While the original mathematical models of cultural transmission were analytically solvable (through the specification of clear differential equations or recursions that relate a cultural measure to its own time-lagged measure), many of the more recent complex questions of cultural transmission have relied on numerical simulation techniques in order to understand interdependent processes that are mathematically intractable (such as those specified here). This paper employs simulation in the form of an agent-based model, frequently used in organizational research (Macy & Willer, 2002). Here, employees serve as individual agents who undergo cultural adaptations based on their interactions over time.

5.1 Representing Culture

I start with the simplest model possible that could describe the dynamics of cultural variation in an organizational population. Specifically, I model culture as a unidimensional, continuous, and unbounded variable $c_{n,f}$, deemed an individual employee $n$’s cultural score in firm $f$. A firm’s cultural score is calculated as the average

---

3It is worth noting, however, that there has been substantial uptake of epidemiological models in the literature on social networks and diffusion of innovations (Rogers, 2010; Burt, 1987; Abrahamson & Rosenkopf, 1997).
cultural score across $N$ employees:

$$\bar{c}_f = \frac{1}{N} \sum_{n=1}^{N} c_{n,f}$$

(1)

This type of measure for culture facilitates interpretation of cultural variation in a population as simply the sample variance of the firm culture measure (where $\bar{c}$ is the average cultural score across $F$ firms):

$$\sigma^2_{\text{between}} = \frac{1}{F-1} \sum_{f=1}^{F} (\bar{c} - \bar{c}_f)^2$$

(2)

A unidimensional measure of culture would appear to be a vast simplification of reality. Organizational scholars have typically conceptualized culture as a multidimensional construct. For example, the commonly used Organizational Culture Profile (OCP) has 54 dimensions along which culture is measured, including ‘predictability’ or ‘autonomy’ (Chatman & O’Reilly, 2016). In simulations, too, culture has been represented as a string of multiple binary variables (March, 1991). However, given the goal of understanding the dynamics of population-level cultural variation, a single dimension both reduces complexity and provides a clear way to understand variation between firms ($\sigma^2_{\text{between}}$). The cultural score $c_{n,f}$ can be interpreted as the extent to which an employee values and behaves according to a single, arbitrary dimension of culture (for example, one of the 54 dimensions in the OCP). A continuous and unbounded measure of culture provides the most general and flexible depiction of culture, imposing no additional constraints.\footnote{As a consequence, the cultural score is an abstracted absolute measure without reference points. This approach is distinct from that used in Harrison and Carroll (2006), in which culture is a bounded construct representing enculturation to a managerial reference point.}

In addition to the cultural variation between firms $\sigma^2_{\text{between}}$, two other measures are of interest at the population level. First, another source of heterogeneity in culture is the average within-firm variation in culture $\sigma^2_{\text{within}}$, measured as the
within-group variability:

\[ \sigma^2_{\text{within}} = \frac{1}{NF-F} \sum_{f=1}^{F} \sum_{n=1}^{N} (\bar{c}_f - c_{n,f})^2 \]  

(3)

This within-firm variation describes the average level of cultural diversity or disagreement within firms (inversely related to a firm’s cultural strength, discussed earlier). Second, an F-test statistic can be used to measure the level of cultural segregation between firms:

\[ F_{\text{stat}} = \frac{N \cdot \sigma^2_{\text{between}}}{\sigma^2_{\text{within}}} \]  

(4)

This is exactly the statistic used in an analysis of variance (ANOVA) to test whether the firms have distinct cultural scores. In other words, \( F_{\text{stat}} \) is a direct measure of whether firms in a population have unique organizational cultures. An illustration of cultural segregation is depicted in Figure 1: on the left side, firms have distinct cultures due to a relatively lower \( \sigma^2_{\text{within}} \). Conversely, on the right side, the firm-specific cultures are not distinguishable from the population-wide average. In all simulations, these three measures (\( \sigma^2_{\text{between}}, \sigma^2_{\text{within}}, \) and \( F_{\text{stat}} \)) are tracked and compared.

5.2 Model Specification

The model of cultural transmission consists of three basic functions that operate in each discrete time period: turnover, socialization, and recruitment (the employee-level cultural mechanisms described previously). These functions determine, through a combination of systematic and stochastic components in each, which employees depart firms, the change in employees’ cultural score, and which employees firms hire. The parameters of the model include the number and size of firms, the alienation and base turnover rates, the socialization intensity and decay rates, and the selectivity in hiring. All parameters in the model (summarized in Table 1...
(a) High $F_{\text{stat}}$ (low $\sigma^2_{\text{within}}$)  
(b) Low $F_{\text{stat}}$ (high $\sigma^2_{\text{within}}$)  

Figure 1: Illustration of possible cultural distribution of five firms. The solid line segments correspond to the within-firm confidence intervals, while the dotted curve corresponds to the between-firm density (which remains constant).

and discussed in more detail below) are specified at the population level, and firms and employees are initialized identically. While some of these parameters are varied to understand their effect, all are calibrated to reasonable values given the time frame.

Each simulation time period $t$ is treated as a single month, and the simulation is iterated over time periods until equilibrium (measured by stability in cultural variation $\sigma^2_{\text{between}}$) or until $t = 500$ months, whichever is sooner.\(^5\) The model is initialized with a collection of $F$ firms, each of size $N$ employees (both set to 30 in the simulations). Firms are indistinguishable (e.g., in status and quality) with the exception of their cultural scores (and employees are similarly identical except for cultural score, employer, tenure, and number of prior employments). Firms remain of size $N$ in each of the subsequent time periods. To begin with, each firm’s cultural

---

\(^5\) I use $\sigma^2_{\text{between}}$, rather than $\sigma^2_{\text{within}}$ or $F_{\text{stat}}$, to determine equilibrium because this is the primary outcome of interest. I choose $t = 500$ as a maximum number of iterations because this corresponds to just over 40 years, which is the maximum interval over which cultural dynamics in organizations is of relevance (since 40 years is a reasonable upper bound for the range of observed employee tenure.
Table 1: Table of parameters in model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Meaning</th>
<th>Value(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F$</td>
<td>Number of firms</td>
<td>30</td>
</tr>
<tr>
<td>$N$</td>
<td>Number of employees per firm</td>
<td>30</td>
</tr>
<tr>
<td>$s$</td>
<td>Selection bandwidth for hiring</td>
<td>${0.1, 0.3, 0.6, 1, 3, 6, 10}$</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>Noise term for hiring and socialization</td>
<td>0.1</td>
</tr>
<tr>
<td>$r_0$</td>
<td>Base rate of turnover</td>
<td>${0.006, 0.01, 0.03, 0.06, 0.1}$</td>
</tr>
<tr>
<td>$r_1$</td>
<td>Cultural alienation bandwidth for turnover</td>
<td>${0.1, 0.3, 0.6, 1, 3, 6, 10}$</td>
</tr>
<tr>
<td>$r_2$</td>
<td>Maximum rate of turnover</td>
<td>0.3</td>
</tr>
<tr>
<td>$b_0$</td>
<td>Asymptotic rate of socialization</td>
<td>0.02</td>
</tr>
<tr>
<td>$b_1$</td>
<td>Initial socialization susceptibility</td>
<td>${0.3, 0.6, 1.0, 1.3, 1.6, 2}$</td>
</tr>
<tr>
<td>$b_2$</td>
<td>Socialization decay due to tenure</td>
<td>0.3</td>
</tr>
<tr>
<td>$b_3$</td>
<td>Socialization decay due to prior employments</td>
<td>0.1</td>
</tr>
</tbody>
</table>

score is randomly drawn from a standard normal distribution:

$$\bar{c}_{f,t=0} \sim \mathcal{N}(0, 1)$$ (5)

Then, for firm $f$, each employee’s cultural score is randomly drawn from a normal distribution centered at the cultural score of firm $f$, with standard deviation $s$ denoting the selection bandwidth for hiring.

$$c_{n,f,t=0} \sim \mathcal{N}(\bar{c}_{f,t=0}, s)$$ (6)

The selection bandwidth $s$ describes the range of cultural scores a firm will hire from (based on distance from the firm cultural score $\bar{c}_f$. A higher value of $s$ corresponds to a wider range of acceptable cultural scores, while a lower $s$ corresponds to greater selectivity. Since firms are initialized from a standard normal distribution with a standard deviation of 1 (see Equation 5), and $s$ is the standard deviation of the normal distribution from which firms are initialized, $s$ effectively initializes the ratio of within-firm to between-firm variance. In other words, $s$ is inversely proportional to the initial value for $F_{stat}$. In addition, $s$ serves as a cultural distance threshold for firm hiring decisions in subsequent time periods (described below).
Finally, employee tenure \( u \) is drawn from a lognormal distribution with a mean of 2.5 and variance of 1 for the underlying normal. This corresponds to a median tenure of 12 months:

\[
u_{n,f,t=0} \sim \ln\mathcal{N}(2.5, 1)
\]

In each time period, employee tenure \( u \) is incremented by 1 month and firm culture is recalculated as the average of its’ employees cultural scores (see Equation 1). Then, the three basic functions occur in the following sequence: turnover, socialization, and hiring. The general flow of employees in each time period, described in more detail below, is outlined in Figure 2. First, employees depart firms based on the turnover function. After the remaining employees are socialized, firms draw new hires from the pool of unemployed candidates as well as random candidates from outside the existing pool of employees. Once firms have returned to their capacity of \( N \) employees, any remaining unemployed candidates exit the existing labor market.

### 5.2.1 Turnover Function

Employees leave organizations for many reasons, some of which are related to cultural fit (as described in the theoretical background). The more culturally distant employees are from their firm’s cultural score, the more likely they are to feel alienated, leading to either voluntary or involuntary departure. The extent of cultural alienation within a firm is represented by the alienation bandwidth \( r_1 \), which describes how steeply alienation increases with cultural distance from the firm: the larger \( r_1 \), the more gradual the rise of alienation with cultural distance, and the more accepting the firm is of retaining cultural misfits.\(^6\) All non-cultural reasons

\(^6\)Note that both \( r_1 \) and \( s \) describe cultural distance bandwidths (of employee exit and entry, respectively), so in most firms the two parameters are likely to take on comparable values. However, this does not necessarily have to be the case; one could imagine a firm with a low selection bandwidth (hiring only strong cultural matches) but a high alienation bandwidth (once an employee is hired,
Figure 2: Illustration of employee flow in each time period: from left to right, the sequential panels depict the beginning of a given time period, after turnover, and after hiring.

for departure (such as relocation or performance-based firing) are subsumed under a base rate of departure \( r_0 \).

Employees stochastically leave firms with a negative Gaussian-shaped probability conditional on their cultural distance from their firm cultural score (varying by period) as well as base rate of turnover \( r_0 \), alienation bandwidth \( r_1 \), and maximum rate of turnover \( r_2 \) (with \( r_0 \) and \( r_2 \) bounded between \([0,1]\)). A Gaussian shape is chosen, both because it intuitively represents the symmetric increased likelihood of turnover with distance from the firm cultural score, as well to be consistent with the random hiring function and other specifications (all probabilities and distributions there is less need to demonstrate fit). Conversely, a typical up-or-out firm might have more relaxed cultural criteria for hiring (high \( s \)) but stronger cultural expectations for retention (low \( r_1 \)). As a result, the two parameters are kept independent in simulations.
Figure 3: Illustration of the stochastic rate employee departure as a function of cultural distance between employee and firm \( r_0 = 0.01, r_1 = s = 1, r_2 = 0.3 \) are modeled as Gaussian for consistency.\(^7\)

\[
P(\text{departure} \mid \bar{c}_{f,t} - c_{n,f,t}) = r_2 - (r_2 - r_0) \cdot e^{\left(\frac{-(\bar{c}_{f,t} - c_{n,f,t})^2}{2r_1^2}\right)} \tag{8}
\]

The turnover probability for a base rate \( r_0 = 0.01, r_1 = s = 1 \), and maximum rate \( r_2 = 0.3 \) is illustrated in Figure 3.\(^8\)

### 5.2.2 Socialization Function

Employees experience socialization through a range of activities and from a variety of sources, including management and peers in one’s immediate workgroup (Schein, 1990). However, no hierarchy or organizational structure is assumed in this model (so as to remain as simple and general as possible), so only a single, group source is assumed.

\(^7\)While the essential intuition of this function is similar to that described in Harrison and Carroll (2006), there are some differences in the interpretation. For example, note that the base rate of turnover is not additive in such a specification.

\(^8\)Defining turnover as a conditional probability requires that its form satisfies several criteria: namely, that it is bounded by \([0, 1]\) and that it integrates to something also bounded by \([0, 1]\). See Appendix C for details.
of socialization is considered. Thus, following turnover, remaining employees are enculturated in the direction of the firm cultural score plus a stochastic noise term \( \epsilon \sim N(0, 0.1) \). Prior literature on socialization suggests that susceptibility to socialization decays both over tenure within an organization (Van Maanen & Schein, 1979) as well as with greater prior work experience (Dokko, Wilk, & Rothbard, 2009). Thus, susceptibility to socialization is modeled with an initial socialization susceptibility of \( b_1 \) at entry, an asymptotic base rate of socialization \( b_0 \), and two decay rates \( b_2 \) and \( b_3 \) corresponding to tenure \( u \) and number of prior employments \( v \). Note that due to the exponential decay form, initial socialization intensity decreases with increasing \( b_1 \). This model builds on the basic model of horizontal cultural transmission in groups articulated by Cavalli-Sforza and Feldman (1981) by building in two sources of decay in efficacy of transmission.

In each time period, the cultural score of employed individuals is updated according to the following equation:

\[
    c_{n,f,t+1} = c_{n,f,t} + (\bar{c}_{f,t} - c_{n,f,t} + \epsilon)(b_0 + e^{-b_1 - b_2 u_{n,f,t} - b_3 v_{n,t}})
\]

(9)

5.2.3 Recruitment Function

Following turnover and socialization, firms rehire precisely the number of employees that have departed in order that \( N \) remains fixed at the beginning and end of each time period (so as to hold organizational size constant). While economists have derived various optimal solutions for this problem of labor market clearing, most of the two-sided algorithms (e.g., Gale-Shapley) assume perfect information about matching or entail sequential search by one side based on additional constructs, like firm or employee status. Many of the assumed processes in these models, such as the ability for job seekers to serially evaluate offers, are less realistic in traditional labor markets (Sterling, 2014).
Therefore, I choose to model the hiring process as a randomly ordered sequence of firm decisions (whose offers are immediately accepted by employees). A random ordering of firms is appropriate given no additional basis for ordering firms, and it also provides a more generalized demand side of the labor market. Moreover, since the model seeks to explore outcomes for firms and populations of firms (and not employee outcomes), it makes sense to allow firms (rather than employees) to be proactive agents in decision-making. However, employee preferences are also reflected because firms choose whom to hire based on mutual cultural fit. In each turn, a single hire is made (so firms making multiple hires are randomized to multiple spots in the ordering).

Since a closed labor market pool is both unrealistic and uninteresting dynamically, the model allows for semi-stochastic introduction of new employees. The ‘pool’ refers to existing unemployed candidates in the labor market (that are not employed by the focal firm in the prior period). For each hiring decision, firms choose between hiring the best cultural match in the ‘pool’ and hiring a new employee drawn randomly in a similar fashion to the initial setup. If there exists an unemployed individual whose cultural distance (measured with noise $\epsilon \sim \mathcal{N}(0,0.1)$) from the hiring firm is less than $2s$ (corresponding to 95% coverage of the underlying distribution for random hiring), then the unemployed individual with the minimum cultural distance is assigned to the focal firm. If no such unemployed individual exists, then the focal firm draws a new employee from outside the existing pool. This new employee starts with zero tenure and a culture drawn from a normal distribution around the firm’s cultural score with standard deviation $s$ (as in the initialization).

\[
\text{Hired}_{f,t} = \begin{cases} 
\arg\min_{\text{pool}} |\bar{c}_{f,t} - c_{\text{pool},t}|, & \text{for } \min |\bar{c}_{f,t} - c_{\text{pool},t}| < 2s(1+\epsilon) \\
\text{new draw } c_{n,f,t} \sim \mathcal{N}(\bar{c}_{f,t}, s), & \text{for } \min |\bar{c}_{f,t} - c_{\text{pool},t}| \geq 2s(1+\epsilon)
\end{cases}
\]

Once all hires have been made, any unemployed individual who has remained unas-
signed to a firm is dropped from the pool of potential employees. The hiring algorithm used effectively prioritizes existing candidates in the pool over new candidates, thus modeling a labor market in which employee mobility between firms is normal (this is the case, for example, among technology firms in Silicon Valley). Since the model precisely seeks to explore the effects of such mobility, it makes sense to emphasize rehiring.

These three functions (turnover, socialization, and recruitment), which make up a single time period, are schematically depicted from the perspective of the employee in Figure 4. An individual enters the simulation via assignment to a firm; in each period the individual either stays and enculturates or departs, with the possibility of being hired into a new firm or exiting the simulation.

5.3 Simulation Methods

The model described above is simulated in R; a flowchart of the code is depicted in Appendix A. The simulation stops at equilibrium (or $t = 500$), as measured by relative stability (less than 0.01 fluctuation) in cultural variation $\sigma^2_{\text{between}}$ for at least 50 periods (an overestimate of the time to equilibrium). The system almost always reaches equilibrium (99.99% of simulations).

Figure 4: Schematic of cultural transmission in each simulation time period
As outlined in Table 1, the number of firms $F$ and employees per firm $N$ are set at 30, corresponding to a sufficiently large sample to illustrate dynamics at scale. Several of the socialization parameters are held constant in the simulations ($b_0 = 0.02$, $b_2 = 0.30$, and $b_3 = 0.10$), along with $r_2 = 0.3$ and $\epsilon = 0.1$. The other four parameters ($s$, $r_1$, $r_0$, and $b_1$) are varied, giving a total of 1470 parameter combinations. For each set of parameters, 100 simulations are run.

For each simulation run, several measures of interest are collected at both the initial and equilibrium states, in addition to the time to equilibrium. These statistics include the three cultural variables of interest described above (between-firm cultural variation $\sigma^2_{\text{between}}$, within-firm cultural variation $\sigma^2_{\text{within}}$, and the F-statistic describing cultural segregation between firms $F_{\text{stat}}$). In addition, the mean and variance of all employees’ cultural scores are recorded, in order to understand the extent of cultural drift. Lastly, the average fraction of employees that depart and the average fraction of departures that are rehired are also captured (both initially, over the first 25, and at equilibrium, over the last 25 time periods). From these two measures, the level of mobility between firms and the level of random entry into firms are calculated (since both may mediate the extent of cultural variation).

6 Predictions

Although the unidimensional cultural transmission model is a significant simplification of real-world processes, it still remains complex enough for relationships between variables not to be obvious. Indeed, this is precisely the reason for using simulation methods. However, it is useful to consider the intuition behind the three functions of cultural transmission and articulate expectations regarding key relationships prior to sharing results. As discussed in the theoretical background, all three functions of recruitment, socialization, and turnover serve to increase cultural homogeneity.

\footnote{The values for $b_0$ and $b_2$ are directly borrowed from Harrison and Carroll (2006).}
among employees within a firm. So measures of variance are interpreted on a relative scale: specifically, $\sigma^2_{\text{within}}$ and $\sigma^2_{\text{between}}$ are reported as a ratio of final to initial values. A value of $\sigma^2_{\text{within}} = 0.5$ would mean that the dynamic processes modeled led to a halving of the within-firm cultural variance.

Perhaps the most important prediction of this line of research is the expectation that increasing inter-firm mobility will result in cultural convergence (or lower cultural variation) between firms and less cultural distinctiveness ($F_{\text{stat}}$) for each firm. Although inter-firm mobility is not an independent parameter (since in reality it is not directly controllable by firms), it is expected to be a strong mediator for the parameter-outcome relationships discussed below.

One would expect within-firm cultural variation $\sigma^2_{\text{within}}$ (cultural diversity or disagreement) to have a straightforward relationship with most of the varying parameters. A narrower selection bandwidth $s$, narrower alienation bandwidth $r_1$, and greater initial socialization (lower $b_1$) should all lead to narrower within-firm variance $\sigma^2_{\text{within}}$, since these mechanisms all serve to homogenize firm employees. Thus, $\sigma^2_{\text{within}}$ should increase with $s$, $r_1$, and $b_1$. Based on the findings of Harrison and Carroll (1991), a higher base turnover rate $r_0$ should have little or no effect on within-firm cultural strength (or inversely diversity).

Between-firm cultural variation $\sigma^2_{\text{between}}$ (the initial motivation of this research) is slightly more difficult to intuit. Firms culturally converge through a moderate combination of socialization within firms and mobility between firms, because the two processes work in conjunction to mix and homogenize firms. But both processes must occur; one might predict that too rapid mobility would prevent the time required for socialization, and too rapid socialization would limit the amount of employee attrition required for mobility. This balance of mobility and socialization required for cultural convergence (low between-firm cultural variation) seems possible for moderate (but not extreme) levels of all four varying parame-
ters. Specifically, both \( r_0 \) and \( r_1 \) directly control turnover, so moderate mobility is achieved through moderate levels of these parameters. Selection bandwidth \( s \) affects the level of mobility, since a higher bandwidth means more likelihood of rehiring, so again moderate mobility is achieved through moderate \( s \). And initial socialization susceptibility \( b_1 \) directly affects the level of socialization, so moderate socialization is achieved through moderate \( b_1 \). Thus, one would expect a U-shaped relationship between these parameters and between-firm cultural variation \( \sigma_{between}^2 \).

The \( F_{stat} \) is directly computed from the within- and between-firm cultural variation measures, but the relative magnitudes of variances are difficult to predict. It may be more appropriate to directly consider the effect of parameters on the level of cultural segregation between firms. Since lower values of \( s, r_1, \) and \( b_1 \) all serve to make firms more culturally distinct, through intra-organizational cultural homogenization and filtering of cultural misfits, one would expect an negative correlation: lower values of these parameters to lead to higher values of \( F_{stat} \). Since the base rate of turnover \( r_0 \) serves as an inter-organizational homogenizing force, a higher base rate would lead to less cultural segregation, or lower values of \( F_{stat} \) (so also a negative correlation). Therefore, all four varying parameters would be predicted to have an inverse relationship with \( F_{stat} \).

7 Findings

To get an intuition for the simulation processes themselves, it is useful to visualize the distribution of firm cultures over time. Obviously, because of the stochasticity of the simulations, these dynamics look slightly different in every simulation run. Figure 5 provides a few snapshots, in which firm cultural scores are plotted over time from initialization to equilibrium. For example, different selection bandwidths alter the types of dynamics, with lower values for \( s \) resulting in more cultural variation and segregation (for reasons discussed below). Notice how for \( s = 0.1 \), a subset of
firms persistently clusters together around a lower cultural score than the mean. This sort of clustering and segregation happens sporadically, but it is more common under certain conditions.

Table 2 presents descriptive statistics of the simulation data (a complete correlation matrix is available in Table 5 in Appendix B). All variance measures (\(\sigma\)) are presented as ratios of final equilibrium to initial values. Recall that the processes modeled are all convergent forces, so the variance always decreases over time, resulting in the ratios of final to initial variance always being less than 1. Due to the various stochastic and noisy processes built into the simulation, many of these outcome variables exhibit a wide range of possible values, even holding simulation parameters constant. As a result, it is interesting to examine trends in this range, as well as the mean or median outcome value: this means exploring what parameter values enable more uncertainty in the distribution of culture.

Few of the relationships play out as predicted in the simulation data; in fact, only the predictions regarding \(F_{\text{stat}}\) are accurate. This suggests that the mechanisms postulated at the inter-organizational level (regarding mobility and convergence between firms) were stronger determinants than those at the organizational level (regarding cultural homogenization within firms). Table 3 summarizes an OLS regression of both exogenous parameters and endogenous mediators on the cultural variation outcomes of interest; Table 4 provides the regression of mediators on parameters. The directional effects (all statistically significant) are robust to both linear and nonlinear regression specifications. Because \(r_1, s\) and \(b_1\) are all modeled as exponentiated parameters, the natural logarithms are reported in relationships.
Figure 5: Firm cultural scores (gray lines) over time in sample simulations ($\bar{c}$ in blue)

(a) $s = 0.1$  \hspace{2cm} (b) $s = 1$  \hspace{2cm} (c) $s = 10$
Table 2: Descriptive statistics of relevant outcomes over 147,000 simulations (with parameters varying)

<table>
<thead>
<tr>
<th>Statistic</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma^2_{\text{within}}$</td>
<td>147,000</td>
<td>0.021</td>
<td>0.047</td>
<td>0.00000</td>
<td>0.548</td>
</tr>
<tr>
<td>$\sigma^2_{\text{between}}$</td>
<td>147,000</td>
<td>0.010</td>
<td>0.037</td>
<td>0.00000</td>
<td>0.602</td>
</tr>
<tr>
<td>$F_{\text{stat}}$</td>
<td>147,000</td>
<td>203.877</td>
<td>988.759</td>
<td>0.005</td>
<td>35,733.380</td>
</tr>
<tr>
<td>$\bar{c}_{\text{eq}}$</td>
<td>147,000</td>
<td>0.0004</td>
<td>0.256</td>
<td>−1.909</td>
<td>1.685</td>
</tr>
<tr>
<td>Equilibrium Rate of Mobility</td>
<td>147,000</td>
<td>0.079</td>
<td>0.057</td>
<td>0.003</td>
<td>0.282</td>
</tr>
<tr>
<td>Equilibrium Rate of Random Entry</td>
<td>147,000</td>
<td>0.002</td>
<td>0.003</td>
<td>0.0002</td>
<td>0.026</td>
</tr>
<tr>
<td>$t_{\text{eq}}$</td>
<td>147,000</td>
<td>104.818</td>
<td>36.142</td>
<td>58</td>
<td>500</td>
</tr>
</tbody>
</table>

The strength of inter-organizational mechanisms like mobility is clearly seen in its relationship with $\sigma^2_{\text{within}}$ (see Figure 6). Interestingly, the mobility rate has a stronger relationship with $\sigma^2_{\text{within}}$ than $\sigma^2_{\text{between}}$ or $F_{\text{stat}}$, so while part of the story is that firms are culturally converging with each other, there is an even stronger process of within-firm cultural homogenization that results from mobility. The other important mediator of cultural variation is the rate of random entry, that is, the frequency of new hires entering the labor pool through a firm. Because these new hires are randomly drawn from normal distributions (with standard deviation s), they have a non-zero probability of introducing substantial cultural variation by being an extreme outlier. This contribution to cultural variation is most noticeable within firms, because new hires are individual deviants within firms (the effect of these outliers is less noticeable when examining variation between firm means).
Table 3: OLS Regression Results

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>$\sigma^2_{\text{within}}$</th>
<th>$\sigma^2_{\text{between}}$</th>
<th>$F_{\text{stat}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>($r_0$)</td>
<td>$-0.165^{***}$</td>
<td>$-0.178^{***}$</td>
<td>$-2,670.561^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(70.638)</td>
</tr>
<tr>
<td>($\log r_1$)</td>
<td>$0.003^{***}$</td>
<td>$0.001^{***}$</td>
<td>$-21.097^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td>(1.612)</td>
</tr>
<tr>
<td>($\log s$)</td>
<td>$-0.019^{***}$</td>
<td>$-0.006^{***}$</td>
<td>$-166.047^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td>(1.612)</td>
</tr>
<tr>
<td>($\log b_1$)</td>
<td>$0.002^{***}$</td>
<td>$-0.001^{***}$</td>
<td>$-41.618^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td>(3.863)</td>
</tr>
<tr>
<td>Mobility</td>
<td>$-0.186^{***}$</td>
<td>$-0.117^{***}$</td>
<td>$-1,462.673^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(45.073)</td>
</tr>
<tr>
<td>Random Entry</td>
<td>$8.429^{***}$</td>
<td>$2.790^{***}$</td>
<td>$100,788.000^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.030)</td>
<td>(803.576)</td>
</tr>
<tr>
<td>$t_{eq}$</td>
<td>$0.0001^{***}$</td>
<td>$0.00004^{***}$</td>
<td>$1.419^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.00000)</td>
<td>(0.00000)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>Constant</td>
<td>$0.030^{***}$</td>
<td>$0.004^{***}$</td>
<td>$343.327^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0004)</td>
<td>(3.845)</td>
</tr>
</tbody>
</table>

Observations: 147,000 147,000 147,000 147,000 147,000 147,000

$R^2$: 0.410 0.398 0.103 0.097 0.077 0.115

Note: *p<0.1; **p<0.05; ***p<0.01
Table 4: OLS Regression Results, cont’d (Mediators on Parameters)

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Mobility</th>
<th>Random Entry</th>
<th>$t_{eq}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$r_0$</td>
<td>0.835***</td>
<td>0.009***</td>
<td>$-343.620$***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.0002)</td>
<td>(1.945)</td>
</tr>
<tr>
<td>$\log r_1$</td>
<td>$-0.025$***</td>
<td>$-0.001$***</td>
<td>$10.027$***</td>
</tr>
<tr>
<td></td>
<td>(0.00004)</td>
<td>(0.00000)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>$\log s$</td>
<td>0.011***</td>
<td>$-0.002$***</td>
<td>$7.429$***</td>
</tr>
<tr>
<td></td>
<td>(0.00004)</td>
<td>(0.00000)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>$\log b_1$</td>
<td>0.012***</td>
<td>0.0002$^*$</td>
<td>$16.317$***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.00001)</td>
<td>(0.106)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.047$^*$</td>
<td>0.002$^*$</td>
<td>$116.836$***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.00001)</td>
<td>(0.106)</td>
</tr>
</tbody>
</table>

| Observations        | 147,000  | 147,000      | 147,000  |
| R$^2$               | 0.832    | 0.581        | 0.477    |

*Note:* *p<0.1; **p<0.05; ***p<0.01

While the cultural alienation bandwidth $r_1$ and initial socialization susceptibility $b_1$ seem to have minor effects, the directional effect on $\sigma^2_{within}$ is consistent with predictions. Counter to intuition, however, both the base turnover rate $r_0$ and the selection bandwidth $s$ are negatively associated with cultural variation, both within and between firms. For $r_0$, this seems to be entirely mediated by inter-firm mobility: $r_0$ directly influences mobility ($\rho = 0.511$), since a greater fraction of the departing employees are culturally conforming to the firm and population and therefore more likely to be rehired. The negative relationship between $s$ and cultural variation is mediated by both increasing inter-firm mobility and limiting noise from random hires. The selection bandwidth influences mobility by increasing the frequency of rehiring ($\rho = 0.288$); the greater the selection bandwidth, the more acceptable existing unemployed candidates are to firms. Conversely, a greater $s$ also decreases the chance of hiring a new random candidate ($\rho = -0.455$), thus limiting the amount
Figure 6: OLS (red) and 5/50/95 Quantile (blue) fits of cultural variation outcomes versus mobility and random entry
of variance due to randomness (even though if a random candidate were hired, the resulting potential variation would be high). Both $r_0$ and $s$ thus have the effect of decreasing both within- and between-firm cultural variation, as well as the level of cultural segregation (see Figure 7).

As mentioned before, parameters and mediators not only influence the expected cultural variation within and between firms, but also the range of possible values this variation takes on. In other words, smaller values for $s$ and $r_0$ (and corresponding lower rates of mobility and higher rates of random entry) result in a wider range of possible values for $\sigma^2_{\text{within}}$ and $\sigma^2_{\text{between}}$. This is clearly visible in the 5/50/95 quantile fits in Figures 6 and 7.

A final set of findings concerns interpreting $F_{\text{stat}}$ as a test statistic of an ANOVA. Given the combination of culturally homogenizing mechanisms, under what conditions do firms culturally converge sufficiently to be culturally indistinguishable? For values of $F_{\text{stat}} \leq 0.61 = f_{29, 870}$, the null of a single cultural distribution for all firms cannot be rejected. A larger selection bandwidth $s$ tends to result in population-wide cultural convergence, measured as more frequent failures to reject the null. This process is different at equilibrium than at initialization (during which $s$ mechanically creates overlapping firm cultural distributions). This seems to be mediated by equilibrium rate of random entry: with higher $s$, less uncertainty is introduced through fewer external hires, and the labor pool is stable enough to allow socialization within and between firms. The distribution of cultural convergence between firms (as measured by failures to reject the null of an ANOVA) is visible in Figure 8.

8 Discussion

The results of simulations based on a formal model of cultural transmission in a population provide a theoretically sound basis for population-level influences on or-
Figure 7: OLS (red) and 5/50/95 Quantile (blue) fits of cultural variation outcomes versus $r_0$ and $s$
ganizational culture. Modeling firm cultures in a population demonstrates how both inter-firm employee mobility and random new entrants can affect the distribution of organizational culture within and between firms. Moreover, specific firm practices like cultural matching in hiring can have unexpected implications for culture when contextualized in an inter-organizational setting.

This observation is perhaps the most surprising and counterintuitive of these findings. Specifically, within-firm cultural variation $\sigma^2_{\text{within}}$ and selection bandwidth $s$ are negatively related. In other words, the more culturally selective a firm is in hiring processes (low $s$), the more cultural disagreement that results in equilibrium.\(^\text{10}\)

This is precisely the opposite of what both scholars of organizational culture as well as organizational development practitioners have emphasized, which is that a more culturally selective hiring process can contribute to stronger organizational cultures and more consensus among employees. But much of this research has been

\(^{10}\)Actually, it is even more striking: since the selection bandwidth is exactly the initial level of within-firm cultural variation ($s$ is the bandwidth used for initialization of employee cultural scores within firms), this trend suggests that lagged within-firm cultural variation is a negative predictor of itself.
focused on dynamics of a single firm, disregarding the population-level dynamics that might play a role. In this case, inter-firm mobility and the uncertainty of random external hires are the dominant population-level mechanisms. These findings suggest that given a population of identically behaving firms (in terms of parameters, not cultures), population-level dynamics may outweigh what are expected to be first-order firm-specific dynamics.

While most theories of organizational culture tend to focus on intra-firm, management-led processes, this model highlights a more emergent process by which culture evolves and is influenced by the external context. In other words, in addition to firms socializing employees, there may be processes by which employees socialize firms as well. By explicitly taking into account the mobility of individuals between firms and conceptualizing individuals as ‘cultural carriers’ between firms, I demonstrate that labor market dynamics can have important influences on organizational culture. It is worth considering the downstream cultural consequences of mobility restrictions in labor markets. For example, does the proliferation of non-compete clauses in certain industries help distinguish and strengthen organizational cultures?

The different inter- and intra-organizational mechanisms for cultural convergence discussed here appear to have a mutually reinforcing effect. This idea has been suggested by Abrahamson and Fombrun (1994), who posit that “interorganizational cooperative and competitive interdependencies [may create] spirals of macrocultural homogenization.” But despite the basis of this model in empirically validated mechanisms for cultural convergence, and the theoretical predictions made in this paper about when cultural convergence occurs, most industries and organizational populations do not seem to demonstrate such complete cultural homogeneity. What allows the maintenance of distinction between organizational cultures? As previously mentioned, competition between firms or idiosyncratic managerial preferences
might drive such differences. In addition, while I chose to model organizations as simple aggregates of employees, the process of cultural transmission would likely look different when accounting for the network structure of individuals within and between firms. In larger firms, for example, internal firm boundaries and hierarchies of communication may constrain the extent of cultural diffusion.

The dynamics of cultural variation have important implications for a wide range of researchers and organizational leaders. There is substantial interest among both scholars and managers to understand the process of cultural development and change in firms. Despite the common perspective that leaders can control culture, the degree of cultural variation in the population may provide a limit on how distinctive these firms can actually be. Greater cultural variation in an organizational population can thus enable more unique and specialized firms. Cultural variation may also explain the level of innovation and economic vitality in a population (Carroll & Hannan, 2000). Because culture constitutes the cognitive toolkit of individuals and groups (Swidler, 1986), larger cultural toolkits that arise from greater cultural variation may increase the level of creativity and divergent thinking, and thus innovation. Finally, cultural variation determines the diversity of careers available to employees, so it has implications for labor market inequality, since employees can more easily find careers matched to their skills and preferences (Hannan, 1988; Sørensen & Sorenson, 2007). On the other hand, cultural diversity among firms may hinder collaboration and knowledge transfer in organizational fields. With such potentially far-reaching consequences, future research must continue to examination of the antecedents of population-level cultural variation.

9 Conclusion

In this paper, I have developed a formal model of cultural variation in organizational populations based on combining intra-firm cultural processes with inter-firm labor
market mobility. I build on established cultural transmission models by representing individuals as ‘cultural carriers’ that migrate between firms. Simulations of this agent-based model suggest that employee mobility and imperfect information in external hiring are competing processes that serve to respectively reduce and increase uncertainty in organizational culture. In addition, human resource practices like culturally selective hiring processes may have unintended consequences contrary to managerial intentions: more intense selection for cultural fit, which would seem to help create strong cultures, can backfire to actually increase the level of cultural disagreement.

These simulations are a first attempt at examining the dynamics of organizational culture at a population level. Importantly, the findings discussed in this paper are theoretical derivations and not real-world data. Such findings, far from being proofs, should be considered as hypotheses for future empirical research. The main takeaway from these simulations is that population-level processes like inter-firm employee mobility may have dramatically different (and perhaps more powerful) consequences relative to intra-firm processes for our understanding of organizational culture. These initial conjectures hint at a fruitful path of inter-organizational research on culture.

The model presented in this paper is the simplest and most general formulation of such dynamics, but it prompts many other interesting and important research questions. For example, what if firms in a population are not behaviorally identical? As a first step towards examining firm heterogeneity, one might consider the equilibrium dynamics of two types of firms that differ significantly on, for example, their selection bandwidth or their initial firm cultural score. In a parallel vein, initial robustness checks demonstrate that non-arbitrary initial cultural arrangements of organizational populations slow cultural convergence and enable the maintenance of cultural segregation.
In addition, given the vast literature on labor market matching, a useful model extension might be examining the effects of different hiring algorithms. The hiring procedure modeled was developed specifically to be disordered and general, but the validity of the findings here depends on how dynamics vary across hiring mechanisms. Similarly, this same model can be applied to examine how specific mobility patterns affect cultural patterns. For example, how does mobility through well-established paths of inter-firm transfer between, say, a large Google-type firm and smaller technology start-ups, affect cultural variation? Lastly, the lack of a force for cultural divergence is one of the clear limitations of this model that can be explored in future research. All of the processes outlined in the model are forces towards cultural homogenization, but processes like competition, firm performance, or managerial choice might illuminate more realistic tensions and dynamics of organizational culture.

A final note on methodology: although formal models such as this one remain less mainstream in organizational research, they have been well-received and incredibly fruitful in many fields. For scholars of culture, these models are becoming all the more promising as computational tools are developed to empirically examine large-scale data related to culture. The impact of these flourishing techniques like language and media processing, capable of testing previously intractable hypotheses, will depend on developing well-grounded, quantifiable theory on culture.
Appendices

A Simulation Flow Chart

Figure 9: Flowchart of the simulation code
### B Additional Simulation Results

Table 5: Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>$r_0$</th>
<th>$r_1$</th>
<th>$s$</th>
<th>$b_1$</th>
<th>$\sigma^2_{within}$</th>
<th>$\sigma^2_{between}$</th>
<th>$F_{stat}$</th>
<th>$\bar{c}_{eq}$</th>
<th>Mobility</th>
<th>Random Entry</th>
<th>$t_{eq}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_0$</td>
<td>1</td>
<td>0</td>
<td>-0</td>
<td>0</td>
<td>-0.124</td>
<td>-0.169</td>
<td>-0.095</td>
<td>-0.001</td>
<td>0.511</td>
<td>0.091</td>
<td>-0.333</td>
</tr>
<tr>
<td>$r_1$</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0.056</td>
<td>0.034</td>
<td>-0.021</td>
<td>-0.002</td>
<td>-0.488</td>
<td>-0.203</td>
<td>0.406</td>
</tr>
<tr>
<td>$s$</td>
<td>-0</td>
<td>0</td>
<td>1</td>
<td>-0</td>
<td>-0.346</td>
<td>-0.173</td>
<td>-0.158</td>
<td>0.0002</td>
<td>0.288</td>
<td>-0.455</td>
<td>0.357</td>
</tr>
<tr>
<td>$b_1$</td>
<td>0</td>
<td>0</td>
<td>-0</td>
<td>1</td>
<td>0.033</td>
<td>-0.010</td>
<td>-0.030</td>
<td>-0.001</td>
<td>0.139</td>
<td>0.048</td>
<td>0.316</td>
</tr>
<tr>
<td>$\sigma^2_{within}$</td>
<td>-0.124</td>
<td>0.056</td>
<td>-0.346</td>
<td>0.033</td>
<td>1</td>
<td>0.336</td>
<td>0.248</td>
<td>0.0001</td>
<td>-0.279</td>
<td>0.573</td>
<td>-0.065</td>
</tr>
<tr>
<td>$\sigma^2_{between}$</td>
<td>-0.169</td>
<td>0.034</td>
<td>-0.173</td>
<td>-0.010</td>
<td>0.336</td>
<td>1</td>
<td>0.808</td>
<td>-0.0004</td>
<td>-0.204</td>
<td>0.241</td>
<td>0.005</td>
</tr>
<tr>
<td>$F_{stat}$</td>
<td>-0.095</td>
<td>-0.021</td>
<td>-0.158</td>
<td>-0.030</td>
<td>0.248</td>
<td>0.808</td>
<td>1</td>
<td>0.0001</td>
<td>-0.115</td>
<td>0.321</td>
<td>-0.045</td>
</tr>
<tr>
<td>$\bar{c}_{eq}$</td>
<td>-0.001</td>
<td>-0.002</td>
<td>0.0002</td>
<td>-0.001</td>
<td>0.0001</td>
<td>-0.0004</td>
<td>0.0001</td>
<td>1</td>
<td>0.003</td>
<td>-0.001</td>
<td>-0.006</td>
</tr>
<tr>
<td>Mobility</td>
<td>0.511</td>
<td>-0.488</td>
<td>0.288</td>
<td>0.139</td>
<td>-0.279</td>
<td>-0.204</td>
<td>-0.115</td>
<td>0.003</td>
<td>1</td>
<td>-0.045</td>
<td>-0.302</td>
</tr>
<tr>
<td>Random Entry</td>
<td>0.091</td>
<td>-0.203</td>
<td>-0.455</td>
<td>0.048</td>
<td>0.573</td>
<td>0.241</td>
<td>0.321</td>
<td>-0.001</td>
<td>-0.045</td>
<td>1</td>
<td>-0.365</td>
</tr>
<tr>
<td>$t_{eq}$</td>
<td>-0.333</td>
<td>0.406</td>
<td>0.357</td>
<td>0.316</td>
<td>-0.065</td>
<td>0.005</td>
<td>-0.045</td>
<td>-0.006</td>
<td>-0.302</td>
<td>-0.365</td>
<td>1</td>
</tr>
</tbody>
</table>
C  Proof of Bounded Probability of Departure

In the model’s turnover function, I defined the stochastic rate of employee departure as a conditional probability:

\[
P(\text{departure} \mid \bar{c}_{f,t} - c_{n,f,t}) = r_2 - (r_2 - r_0) \cdot e\left(-\frac{(\bar{c}_{f,t} - c_{n,f,t})^2}{2\sigma^2}\right)
\]

(11)

However, in order for this expression to truly be interpreted as probabilistic, it must satisfy two criteria. First, \(P(\text{departure} \mid \bar{c}_{f,t} - c_{n,f,t})\) must be bounded by \([0, 1]\). Second, because integrating over all cultural distances gives the unconditional expected probability of departure (which is also by definition a probability), this integral must also be bounded by \([0, 1]\). Below I demonstrate that both of these criteria are met by the form specified in Equation 11. For notational ease, let us define the cultural distance \(c = \bar{c}_{f,t} - c_{n,f,t}\).

C.1  Bounded Conditional Probability

The exponential component of a Gaussian form is necessarily bounded:

\[
0 \leq e\left(-\frac{x^2}{2\sigma^2}\right) < 1
\]

\[
0 \leq (r_2 - r_0) \cdot e\left(-\frac{x^2}{2\sigma^2}\right) < r_2 - r_0
\]

\[
r_2 \geq r_2 - (r_2 - r_0) \cdot e\left(-\frac{x^2}{2\sigma^2}\right) > r_0
\]

\[
r_2 \geq P(\text{departure} \mid c) > r_0
\]

Since \(r_0\) and \(r_2\) are bounded by \([0, 1]\) as minimum and maximum rates of turnover respectively, so too is the conditional probability of departure:

\[
0 < P(\text{departure} \mid c) < 1
\]
C.2 Bounded Integral

We are interested in the weighted integral of the conditional probability. The conditional probability is weighted by the initial normal distribution of cultural scores from which new employees are drawn.

\[
\int_{-\infty}^{\infty} P(\text{departure} \mid c) \cdot P(c) \, dc = \int_{-\infty}^{\infty} \left( r_2 - (r_2 - r_0) \cdot e^{-\frac{c^2}{2\sigma_1^2}} \right) \cdot \left( \frac{1}{\sqrt{2\pi\sigma^2}} \right) \cdot e^{-\frac{c^2}{2\sigma^2}} \, dc
\]

\[
= r_2 \int_{-\infty}^{\infty} \left( \frac{r_0 - r_2}{\sqrt{2\pi\sigma^2}} \right) \cdot e^{-\frac{c^2}{2\sigma^2}} \, dc
\]

\[
= r_2 + \int_{-\infty}^{\infty} \left( \frac{r_0 - r_2}{\sqrt{2\pi\sigma^2}} \right) \cdot \frac{r_1 s^2 + r_1^2}{s^2 + r_1^2} \cdot e^{-\frac{c^2}{2\sigma^2}} \, dc
\]

\[
= r_2 + \frac{(r_0 - r_2) \cdot r_1}{\sqrt{s^2 + r_1^2}}
\]

\[
= r_2 \left( 1 - \frac{r_1}{\sqrt{s^2 + r_1^2}} \right) + r_0 \left( \frac{r_1}{\sqrt{s^2 + r_1^2}} \right)
\]

\[
= r_2 (1 - \beta) + r_0 (\beta)
\]

Where \( \beta = \frac{r_1}{\sqrt{s^2 + r_1^2}} \) is a common expression bounded by \((0, 1)\). Since \( r_0 \) and \( r_2 \) are bounded by \([0, 1]\):

\[
r_0 < \int_{-\infty}^{\infty} P(\text{departure} \mid c) \cdot P(c) \, dc < r_2
\]

\[
\therefore \quad 0 < \int_{-\infty}^{\infty} P(\text{departure} \mid c) \cdot P(c) \, dc < 1
\]
References


