Deciphering the Cultural Code: Perceptual Congruence, Behavioral Conformity, and the Interpersonal Transmission of Culture

Richard Lu
University of California, Berkeley

Jennifer A. Chatman
University of California, Berkeley

Amir Goldberg
Stanford University

Sameer B. Srivastava
University of California, Berkeley

Why are some people more successful than others at cultural adjustment? Research on organizational culture has mostly focused on value congruence as the core dimension of cultural fit. We develop a novel and complementary conceptualization of cognitive cultural fit—perceptual congruence, or the degree to which a person can decipher the group's cultural code. We demonstrate that these two cognitive measures are associated with different outcomes: perceptual congruence equips people with the capacity to exhibit behavioral conformity, whereas value congruence promotes long-term attachment to the organization. Moreover, all three fit measures—perceptual congruence, value congruence, and behavioral cultural fit—are positively related to individual performance. Finally, we show that behavioral cultural fit and perceptual congruence are both influenced by observations of others' behavior, whereas value congruence is less susceptible to peer influence. Drawing on email and survey data from a mid-sized technology firm, we use the tools of computational linguistics and machine learning to develop longitudinal measures of cognitive and behavioral cultural fit. We also take advantage of a reorganization that produced quasi-exogenous shifts in employees' interlocutors to identify the effects of peer influence on behavioral cultural fit. We discuss implications of these findings for research on cultural assimilation, the interplay of structure and culture, and the pairing of surveys with digital trace data.

Introduction

Whether assimilating to a country or adapting to a new school, people typically seek to fit in culturally with their social groups. The benefits of conformity, as well as the sanctions and penalties that come with failed cultural integration, are particularly stark in contemporary organizations. Indeed, prior work has consistently demonstrated that high levels of individual cultural fit are associated with increased productivity, stronger commitment, and less turnover (Kristof-Brown et al. 2005, Chatman and O'Reilly 2016). Moreover, employers have increasingly emphasized screening, selecting, and socializing new hires on the basis of cultural fit rather than exclusively hiring for skills (Chatman 1991, Meyer et al. 2010, Rivera 2012). At the same time, as the average tenure in firms has declined (Hall 1996), workers must frequently retool themselves culturally as they move from one organization to the next. Yet people vary considerably in their ability to adapt culturally within a given organization (Srivastava et al. 2018). In this paper, we ask: Why are some people more successful than others at cultural adjustment?

We propose that the answer depends critically on one's definition of cultural fit. Prior research, whether specifically focused on organizational culture (Baron et al. 2001, Chatman and O'Reilly 2016) or more broadly concerned with cultural transmission and socialization (Bourdieu and Passeron 1990), has tended to think of cultural fit as the degree to which a member has internalized the group's values, beliefs, and norms. This work has implicitly assumed that individuals who fit into their social environments both think and act in ways that are consistent with their peers' thoughts and behavioral expectations. Yet cultural congruity reflects a complex equilibrium between individuals' private beliefs and their public behaviors (Mobasseri et al. 2019). Even when people feel pressure to fit in, how they think and feel about their social group can often differ substantially from how they behave when interacting with other members. In other words, cultural cognition and behavior are not necessarily aligned.

Prior work on the cognitive dimension of cultural fit has focused on *value congruence*—the match between a person's values and those that prevail and are normatively reinforced in her social group

(Chatman 1989, Alba and Nee 2009). Broadening the theory of person-culture fit by integrating insights from cultural sociology and psychology, we highlight a distinct and largely unexplored dimension of cognitive cultural fit—*perceptual congruence*, which we define as the match between an individual's perceptions of prevailing values and norms and those that prevail in the group. Stated differently, perceptual congruence represents one's ability to decipher the group's cultural code, whereas value congruence reflects the alignment between that code and one's internalized values and beliefs.

Drawing on this distinction, we first propose value congruence and perceptual congruence have differing consequences for one's behavioral cultural fit and long-term attachment to the organization. We propose that perceptual congruence enables people to fit in behaviorally—whether or not their values are congruent with those of the organization—in everyday interactions with colleagues. Perceptual congruence does not, however, factor into people's choices about whether or not to voluntarily exit the organization. In contrast, we suggest that value congruence is less related to contemporaneous behavioral fit but, consistent with prior research, decreases one's likelihood of voluntary exit (Meglino and Ravlin 1998, O'Reilly and Chatman 1986).

Second, we posit that behavioral cultural fit and the two forms of cognitive cultural fit, value congruence and perceptual congruence, can each fuel individual performance—albeit through different mechanisms. When people behave in ways that conform to group norms, they are better able to coordinate activity and perform interdependent tasks with their peers (Goldberg et al. 2016). Perceptual congruence boosts productivity not only through its effect on behavioral cultural fit but also by helping people define problems and find solutions using approaches that are valued in the culture (Dougherty 1992, Sørensen 2002). Finally, value congruence spurs performance by imbuing people with the motivation to complete tasks in ways that have meaning and value to them and to persist in the face of obstacles (Chatman 1989, Podolny et al. 2005).

Finally, given that culture is learned from others (Herrmann et al. 2013), we advance theory about interpersonal cultural transmission by specifying how exposure to colleagues who vary in behavioral conformity might differentially influence a focal actor's value congruence and perceptual congruence. We argue that values are a relatively inert aspect of cognition, whereas perceptions are more susceptible to social learning. Specifically, we suggest that exposure to culturally compliant (or non-compliant) behavior among one's peers can boost (or dampen) one's own perceptual congruence and, in turn, one's capacity for normative compliance—whether or not one subscribes to those norms. As a consequence, exposure to peers who are normatively compliant: (1) increases perceptual congruence but not necessarily value congruence; and, as a result, (2) enhances one's capacity to behave in normatively compliant ways in routine interactions with colleagues.

To evaluate this more comprehensive theory of cultural fit, we employ a multi-method empirical strategy that draws on survey data, eight years of internal email data, and personnel records from a mid-sized technology firm. We use the Organizational Culture Profile (Chatman 1991), a validated culture survey, in two different ways to measure the value congruence and perceptual congruence dimensions of cultural fit. Following established practice, we assess value congruence by comparing an individual's self-reported preferences to prevailing values reported by her peers. Departing from prior work, we develop a novel measure of perceptual congruence by comparing an individual's reports of widespread values and norms to the ones her peers believe are predominant.

We report results from three kinds of analyses. Cross-sectional analyses demonstrate a positive link between perceptual congruence and a measure of behavioral cultural fit that is based on the similarity of linguistic style in which employees communicate with their colleagues and that has been used in prior research (Goldberg et al. 2016, Doyle et al. 2017, Srivastava et al. 2018). Longitudinal analyses, including an instrumental variable regression that takes advantage of a reorganization that produced quasi-exogenous shifts in employees' peer groups, reveal that a focal actor's behavioral cultural fit is influenced by exposure to peers who vary in their own behavioral cultural fit. Finally, to examine how the three cultural fit measures relate to individual performance and to understand the effects of peer influence on a focal actor's perceptual congruence, we use the tools of computational linguistics and machine learning to transform our cross-sectional measures of cognitive cultural fit into longitudinal measures. Longitudinal models that use *imputed* perceptual congruence and value congruence corroborate our cross-sectional analyses, show a positive link between all three cultural fit measures and performance, and suggest that perceptual congruence is also susceptible to influence from peers' behavioral cultural fit. We conclude by discussing how our findings advance theories of cultural fit in organizations.

Theory and Hypotheses

Cognitive and Behavioral Cultural Fit

Arguments about culture typically make implicit assumptions about underlying cognitive processes (DiMaggio 1997, O'Reilly and Chatman 1996). Organizational sociologists often define culture as "shared understandings," namely, similarities between individuals' beliefs, value systems, and interpretations (Ouchi and Wilkins 1985).[1] In most everyday settings, one's private cognition is, however, unavailable to others. Rather, one observes others' behavior and then draws inferences—with varying degrees of accuracy—about their beliefs, values, and motivations (Kelley and Michela 1980, Schein 2010, Sperber 1996).

Culture, in other words, resides both in the distribution of inner thoughts and observable behaviors across individuals within a social group. Cultural fit, by extension, can be thought of as comprising two related but distinct dimensions: cognitive cultural fit, or the degree of shared understanding between an individual and her peers, and behavioral cultural fit, or the extent to which an individual's behaviors are compliant with the group's normative expectations.[2] Previous research has focused on either cognitive or behavioral cultural fit and implicitly assumed that the two correspond highly to one another (Mobasseri et al. 2019).

In contrast, we begin with the premise that the two broad manifestations of cultural fit are analytically distinct such that one can fit in behaviorally but be cognitively misaligned with one's peers (and vice versa). Indeed, in many cases, people can possess the knowledge needed to successfully interact with one another even when they do not share the same values (Hewlin 2003, Hochschild 2012, Hewlin et al. 2017). To understand how this can occur, it is important to distinguish between two dimensions of cognition: preferences and construals. Whereas preferences define which behaviors are desirable, construals refer to the levels of abstraction and the associated mental representations that a person conjures when making sense of a situation. How an individual construes a social setting affects which of her preferences will be activated and ultimately what action she will pursue (Trope and Liberman 2010). Shared understandings do not necessarily require that all group members hold the same preferences. Rather, to share understandings is, first and foremost, to construe daily experiences through similar interpretative lenses (Goldberg 2011, DiMaggio and Goldberg 2018).

Similar insights derive from symbolic interactionists' studies of interpersonal interaction (Goffman 1959, Garfinkel 1967). As long as group members have a shared understanding of a situation—including the social roles it implies, the behaviors appropriate to those roles, and the implicit meanings these behaviors convey—interactions between members can occur relatively seamlessly. Further, even when the group agrees about how a situation is construed, individual members can still craft their self-presentations in a manner that decouples their behavior from their privately held preferences (Snyder 1979). In the absence of situational agreement, however, interaction breaks down, leading to incompatibilities between one person's expectations and another's behavior. Under such circumstances private cognition is more likely to unintentionally "leak" into public behavior.

Cognitive Cultural Fit: Value Congruence and Perceptual Congruence

Preferences and construals are aspects of individual cognition; however, they become culturally meaningful when we consider an individual in relation to her social group. Value congruence represents the cultural manifestation of preferences in that it reflects the match between what individuals prefer and what prevails in the social group.[3] Perceptual congruence is instead the cultural analogue of construals in that it indicates the degree of alignment between a person's perceptions and those of other group members.

Consistent with the literature on person-culture fit, we anticipate that value congruence will lead people to maintain a more positive self-concept and thus to identify more strongly with their organization and derive greater satisfaction from peer interactions (Chatman and Barsade 1995).

We therefore expect value congruence to be positively related to one's motivation and long-term attachment to the organization—as evidenced by a negative association between value congruence and voluntary exit.

We anticipate, however, that value congruence will be less consequential for a person's behavioral cultural fit. Although people whose values are more congruent with their organization's may be motivated to behave in normatively compliant ways, they may still lack the information needed to do so. It is one thing to prefer, for example, a cooperative work environment and another to understand which behaviors signal cooperativeness in a specific normative context. Moreover, a long history of work in social psychology and cultural sociology suggests that individuals' stated beliefs and motives can be inherently decoupled from the values they have internalized. As a result, there is often a disconnect between what people ideally desire and what they understand as contextually appropriate behaviors (Vaisey 2009, Srivastava and Banaji 2011, Lizardo 2017). Thus, we propose that behavioral cultural fit is more likely to emerge from perceptual congruence than from value congruence.

Perceptual Congruence and Behavioral Cultural Fit

Perceptual congruence describes an individual's ability to decipher the cultural code implicit in others' behaviors. Although organizations often formalize their idealized values into cultural statements, interpreting the local normative environment is a subtle, complex, and ongoing cognitive task. A colleague's cynical joke in a meeting, for example, can be interpreted as a friendly attempt to establish rapport or as a derogatory comment aimed at undercutting others. Correctly construing this behavior requires tacit and layered knowledge that connects behaviors, symbols, and meanings to abstract cultural categories. Possessing this knowledge is essential to knowing how to behave appropriately.

As a concrete illustration, consider the perennially disgruntled employees in Weeks' (2004) ethnography of a British bank. To an outsider observing people habitually complaining, it may have seemed that these employees were fundamentally rejecting the organization and its culture.

As Weeks artfully demonstrates, however, employees were instead partaking in rituals intended to reaffirm their interpersonal bonds and their commitment to the bank. To participate in this ritualistic complaining, bank employees had to complain at the appropriate level: not too much so as to avoid rocking the boat but enough to signal membership and belonging with the group. Consistent with this story, we argue that perceptual congruence will be intimately related to the capacity to exhibit—in routine, real-time interaction—behavior that conforms to the organization's prevailing norms.

In sum, we argue that one dimension of cognitive cultural fit—perceptual congruence—is closely linked to an individual's capacity for behavioral cultural fit but not to voluntary exit, whereas the other dimension—value congruence—is more related to self-identification and long term attachment to the organization than to contemporaneous behavioral cultural fit. Thus, we propose:

Hypothesis 1 (H1): *(1a) Perceptual congruence is positively related to contemporaneous behavioral cultural fit, whereas (1b) value congruence is positively related to long-term attachment to the organization.*

Cultural Fit and Individual Performance

Next we consider the implications of behavioral cultural fit and the two forms of cognitive cultural fit for individual performance. We propose that all three cultural fit measures are positively related to performance. We posit that behavioral cultural fit enhances performance by enabling people to better coordinate activity and perform interdependent tasks. For example, Weber and Camerer (2003) use laboratory studies to demonstrate that performance on an interdependent task declines when group members operate through the use of divergent cultural conventions. Similarly, Goldberg et al. (2016) and Srivastava et al. (2018) show that a behavioral (language-based) measure of cultural fit is positively related to individual career attainment (e.g., favorable performance ratings and time-to-promotion).

Next, we propose that perceptual congruence improves performance not only through its positive association with behavioral cultural fit (Argote et al. 2018) but also through a more direct channel.

To develop the latter argument, we draw on Dougherty (1992), who describes the interpretive barriers that tend to splinter complex organizations into divergent "departmental thought worlds." As a result of this fragmentation, people in one part of the organization often struggle to understand the values, norms, and beliefs in other areas, which in turn impairs their ability to synthesize knowledge, identify cross-cutting problems, and develop novel solutions. Because perceptually congruent individuals have more accurate mental representations of their organization's culture, we propose that they are more likely to overcome such interpretive barriers and produce outputs that will be more highly valued in the overall organizational culture. In other words, perceptual congruence affects performance not only by changing *how* people coordinate with others but also *what* ideas they choose to focus on developing. In particular, perceptually congruent individuals are more likely to synthesize cross-functional insights and produce valuable knowledge.

Finally, we suggest that value congruent individuals are more likely to naturally exhibit behavior that is appreciated and rewarded by the organization (Chatman 1991). Moreover, such individuals are likely to have greater motivation and commitment to perform tasks at a high level and to persist in the face of obstacles (O'Reilly and Chatman 1986, Elfenbein and O'Reilly 2007, Morrison 2002). Putting together the three sets of arguments, we therefore predict that:

Hypothesis 2 (H2). *Value congruence, perceptual congruence, and behavioral cultural fit will all be positively related to individual performance.*

Cultural Fit and the Interpersonal Transmission of Culture

We turn next to the question of why some people exhibit a greater capacity than others to assimilate into their organizational cultures. Previous work has approached this question from two different and seemingly irreconcilable angles. A prominent line of work has conceptualized cultural fit as a fundamental compatibility between individuals and organizations—a match between the "personalities" of the individual and the group (Schneider 1987, Cable and Judge 1996, Baron et al. 2001). Those who fit in culturally are therefore those who are innately compatible with the organizations' culture. A parallel stream of work on organizational culture emphasizes cultural fit as a dynamic process. This work demonstrates that individuals are capable of adapting their behavior to the prevailing norms in an organization through (direct and indirect) processes of socialization (Van Maanen and Schein 1979, Chatman 1991, Van Maanen 1975, Ashforth and Saks 1996).

The distinction between value congruence and perceptual congruence, we contend, explains why cultural fit can be simultaneously fixed and dynamic. Values are, by definition, deeply held and enduring beliefs about what is desirable and appropriate. Given that individuals' values are encoded in implicit cognition and thus slower to change (Meglino and Ravlin 1998, Vaisey 2009, Srivastava and Banaji 2011), value congruence is likely to remain relatively stable throughout an employee's tenure in an organization. Indeed, as Vaisey and Lizardo (2016) demonstrate, values and moral attitudes are surprisingly durable throughout people's adult lifetimes (see also Dawis and Lofquist [1984]). In other words, cultural change is mostly attributable to generational differences and not to period effects.

Perceptual congruence is, in contrast, organization-, and even subgroup-, specific and therefore more malleable. Employees joining a new organization are required, by virtue of each group's idiosyncratic style, to learn the group's specific cultural code. Recent work demonstrates that individuals exhibit great variability in their ability to adjust their behavioral cultural fit over time. Whereas some gradually adapt their behaviors to meet their peers' expectations, others fail to do so, thereby lowering their chances of promotion and their likelihood of receiving a favorable performance rating (Chatman and Spataro 2005, Srivastava et al. 2018).

What factors lead some people to increase their behavioral cultural fit over time, while others remain stagnant? One line of work attributes such variance to psychological differences between individuals. For example, a robust literature in social psychology has focused on self-monitoring orientation—a sensitivity and responsiveness to social cues of situational appropriateness (Snyder 1979, Kilduff and Day 1994, Sasovova et al. 2010). High self-monitors tend to regulate their behavior given their read of what is expected of them, whereas low self-monitors hew to their sense of self, irrespective of the situation. Self-monitoring is also related to a capacity for deep-acting, the ability to adapt emotions to organizational expectations, leading to more genuine displays of cultural congruence (Grandey 2000, Scott et al. 2012). High self-monitors, in other words, are more motivated to read the cultural code, adjust their behavior to fit with it, and be perceived as authentic when they do.

Yet perceptual congruence is also a matter of context, not just of intrinsic ability. Humans are innately motivated to be attuned to the cultural code prevalent in their immediate social environments (Liebal et al. 2013). Consequently, we argue that perceptual congruence is dependent not only on inherent differences between people's cultural attentiveness but also on the social context in which they are embedded. Adjusting to the cultural code of a group is, by definition, a process of social learning. The quality of this learning depends not only on the student but also on the peers from whom she learns.

We therefore expect that the composition of a person's network has a significant impact on her ability to correctly decipher the cultural code and to adapt her behaviors accordingly. Experimental research in young children, for example, demonstrates that exposure to multiple and consistent behaviors increases the fidelity and speed of cultural transmission (Herrmann et al. 2013). Similarly, in the workplace, employees' ability to learn and their susceptibility to being influenced by others is related to the kinds of colleagues with whom they interact (Chan et al. 2014, Liu and Srivastava 2015). In particular, having colleagues who themselves have a more accurate read of the cultural environment can help correct one's own misperceptions, thereby improving one's own perceptual congruence (Balkundi and Kilduff 2006).

Importantly, people primarily have access to their peers' behaviors rather than their cognition. It is through observing these behaviors that they develop their own perceptions of the cultural environment. We therefore anticipate that peers' behavior—as opposed to their private values or perceptions—will influence the focal individual's own thoughts and behavior. Moreover, because we argue that the ability to behave compliantly is primarily dependent on perceptual congruence, we also expect that individuals' perceptual congruence will be influenced through their observations of their colleagues. In contrast, we expect value congruence to remain more impermeable to peer influence.

In support of these expectations, extensive research has shown that individuals' attitudes can change as a direct consequence of exposure to and interaction with their network contacts (Friedkin and Johnsen 1990, Marsden and Friedkin 1993, Baldassarri and Bearman 2007); however, exposure to peers whose deeply held values and beliefs run counter to one's own can also activate biases in information processing such that discordant information is discounted or even rejected (Lord et al. 1979, Dandekar et al. 2013, Liu and Srivastava 2015, Bail et al. 2018). In contrast, expectations of normatively appropriate behavior are strongly shaped by *shared perceptions* that arise through interaction and observation (Friedkin 2001, Chatman et al. 2014). Taken together, these findings lead to the prediction that a person's perceptions of the cultural order will be more susceptible to social influence than will her deeply rooted values. Overall, we expect:

Hypothesis 3 (H3). *Perceptual congruence and behavioral cultural fit will be susceptible to peer influence. Specifically, as one's peers behave in more (less) normatively compliant ways, one's own perceptual congruence will increase (decrease) and one's behavioral cultural fit will concomitantly increase (decrease).*

Method

Testing our theory requires examining value congruence, perceptual congruence, and behavioral cultural fit over time, as well as quasi-exogenous variation in the set of peers to which a focal actor is exposed. Previous work on cultural fit in organizations has usually relied on self-reports to assess both cultural and behavioral variables. In addition to the challenges of common method bias, self-reports can be limited in that what people report on a survey may not correspond to how they actually behave. Moreover, surveys provide static snapshots but are not well-suited to measuring subtle changes on a granular timescale. Thus, self-reports on their own would be inadequate for testing our theory.

To address these issues, we employ a multi-method approach that draws on a survey and longitudinal email communication data from a mid-sized technology firm and that uses machine learning techniques to impute time-varying measures from cross-sectional data. Moreover, we use an instrumental variables methodology, which takes advantage of a reorganization event within the organization that produced quasi-exogenous shifts in employees' peer groups, to move closer to a causal estimate of interpersonal cultural transmission. We detail these methodological choices in this section. First, we explain how we use email and survey data to measure, respectively, behavioral cultural fit and the two cognitive dimensions of cultural fit: value congruence and perceptual congruence. Second, we provide descriptions of the data and variables, including an explanation of how we use machine learning to transform the one-time survey into imputed, time-varying variables. (As we explain below, we also estimate models in the cross-section—i.e., without any imputed variables—and obtain comparable results to the models that rely on imputed variables.) Finally, we provide an overview of our analytical strategy, with a focus on the instrumental variable approach.

Measuring Behavioral and Cognitive Cultural Fit

Studies of culture often focus on its content, namely, on specific beliefs, interpretations and normative behaviors. In contrast, our approach is distributive (Harrison and Carroll 2006, Corritore et al. 2019). Rather than asking how specific cultural elements relate to one another and to other variables of interest, we characterize individuals on the basis of their cultural similarity to their groups both behaviorally and cognitively. We define each individual's reference group as her email interlocutors in a given month, weighted by volume of interaction. Given that subcultures in organizations do not necessarily conform to the contours of formal subunits, this choice of reference group allows us to identify a person's fit in an empirically grounded manner, without having to make assumptions about subcultural boundaries.

Behavioral Cultural Fit—We operationalize behavioral cultural fit as the similarity between an individual's language and her reference group's, using the Interactional Language Use Model

(ILUM) (Goldberg et al. 2016, Srivastava et al. 2018). Although language is not the only means through which culture is enacted—for example, culture also manifests in dress and various forms of nonverbal communication—it is a dominant medium through which cultural information is exchanged. Given that linguistic similarity can sometimes reflect alignment for non-cultural reasons—for example, two people coordinating on a shared task might use similar language even when they are culturally incompatible (Brugnoli et al. 2019)—we focus on the similarity of *linguistic style* between an individual and her reference group. Drawing on previous sociological work on culture (Bail et al. 2017, Doyle et al. 2017), ILUM uses the well-established and widely used Linguistic Inquiry and Word Count (LIWC) lexicon (Pennebaker et al. 2007) to measure linguistic style. LIWC is a semantic dictionary that maps words into 64 high-level emotional, cognitive, and structural categories. A comprehensive body of work demonstrates that the linguistic units identified by LIWC relate to a wide and universal array of meaningful psychological categories (Tausczik and Pennebaker 2010).

Using LIWC allows us to focus on expressions that are inherently cultural, while downplaying linguistic exchange that is organization- or context-specific or primarily related to functional coordination between organizational members. Imagine, for example, an organization with an aggressive and competitive culture. Such a culture might manifest linguistically in expressions of certainty, negation, and the use of swear words and other forms of non-deferential language. Contrast such a normative environment with one characterized by politeness and the use of tentative and inclusive language, indicating a collaborative and non-confrontational culture. LIWC is specifically designed to capture such culturally meaningful dimensions.

Cognitive Cultural Fit—To assess the two dimensions of cognitive cultural fit, we implemented the widely used Organizational Culture Profile (OCP) (Chatman et al. 2014). The OCP uses a comprehensive set of cultural elements that have been applied to and validated in a wide variety of organizations. It consists of 54 value statements (e.g., fast moving, being precise) that emerged from a review of academic and practitioner-oriented writings on culture (O'Reilly et al. 1991).

Using the Q-sort methodology (Block 1961), respondents are asked to array these 54 statements into nine categories, with a specified number of statements in each category. The required distribution of statements across categories is 2-4-6-9-12-9-6-4-2, so that, for example, respondents rating the current culture of their organization would place two value statements each in the "most characteristic" and "most uncharacteristic" categories, respectively, four value statements each in the "quite characteristic" and "quite uncharacteristic" categories respectively, and 6 statements each in the "fairly characteristic" and "fairly uncharacteristic" categories respectively, and so on, until all 54 value statements were categorized. Unlike a Likert-format scoring scheme in which many or all items can be rated as high or low, or a ranking process, which, with 54 value statements to rank, would be unwieldy for human raters, this semi-idiographic approach forces respondents to choose cultural value statements that are most and least characteristic of their organization. This exercise is completed twice—once with respect to a respondent's perception of the prevailing culture and once with respect to a respondent's own desired culture (Caldwell et al. 2008). Ipsative scores are particularly useful to address the response bias likely to arise in Likert-type responses (van Eijnatten et al. 2015) such as a lack of discrimination among items (e.g., scoring all the items on a 1-7 Likert-type scale as a "4"). Lee and Yu (2004) note that this ipsative approach "avoid[s] imposing researcher generated typologies on respondents"(p. 343). Employing our distributive approach, we can use this cultural profile to estimate each individual's distance from her reference group, as we detail below.

Data and Variables

Our empirical setting is a mid-sized technology firm, from which we obtained three types of data:

Personnel Records—We received monthly extracts from the firm's human resource information system. These extracts included demographic information such as age and gender, organizational status such as departmental affiliation and start date, and information about individual outcomes such as monthly bonus received, date of exit, and reason for exit (voluntary or involuntary).

Email Data—We collected eight years of email data from the organization, including not only metadata (i.e., who sent messages to whom and when) but also raw message content. Given our focus on cultural dynamics within the organization, we excluded emails exchanged between employees and the outside world. We also eliminated automatically generated messages and, per instructions from the company's in-house lawyers, messages sent from or to members of the (small) legal department. The resulting data set included over five million unique emails.

Organizational Culture Profile—All employees completed the OCP survey describing the organization's current culture and a randomly selected half of employees completed the survey of their own personally desired cultural characteristics.[4] Overall, we received 440 completed surveys about the current organizational culture and 238 completed surveys about the personally desired culture.

Archived email data and personnel records were collected in multiple batches starting in 2015 and concluding toward the end of 2016. The OCP was implemented in October of 2016, and a major reorganization, which we use for our instrumental variables analysis, took place in mid-2015. Once we matched the raw email data to personnel records and removed identifying information, the resulting data set consisted of 29,255 person-month observations, spanning the period from 2008 to 2016.

Dependent Variables: Behavioral Cultural Fit Hypothesis 1a and 3 focus on behavioral cultural fit as the outcome variable. We operationalized this construct using ILUM, as applied to internal email communication (Goldberg et al. 2016, Srivastava et al. 2018). To derive this measure, we first translated raw emails into LIWC category counts. We then aggregated each individual's incoming and outgoing emails into monthly time periods and represented each person-month observation as two probability distributions of outgoing and incoming communication over LIWC categories. We used the Jensen-Shannon divergence metric (inverse and log-transformed) between these two probability distributions as the measure of behavioral cultural fit. We discuss the technical details of this measure in Appendix A.

Intuitively, when the outgoing and incoming distributions are nearly identical, the divergence approaches zero, suggesting high behavioral cultural fit; conversely, greater deviation between the probabilities of usage of LIWC categories translates to greater divergence and thus implies lower behavioral cultural fit. Thus, the more an employee's use of cognitive, emotional, and structural terms in sent emails matches the use of those terms in received emails, the greater her behavioral cultural fit in a given month. For example, an individual using a relatively high proportion of negations in her outgoing communication but who receives a far smaller proportion of negations in her incoming messages would be characterized as having low behavioral cultural fit (at least with respect to this LIWC category). Such an individual would be expressing disagreement, whereas her peers would be refraining from doing so.

Although ILUM has been used in previous work to measure cultural fit, it is still a fairly new methodology. To further validate our measure of behavioral cultural fit we conducted two supplemental analyses. The first demonstrates that LIWC categories reflect culturally meaningful content—for example, that individuals who espouse an innovative culture tend to use more future-tense language. The second shows that, even if we assume that certain LIWC categories are culturally meaningless, our measure is still robust to the removal of these categories. These additional analyses are reported in Appendix A.

Dependent Variables: Voluntary Exit Hypothesis 1b considers voluntary exit as the outcome variable. We obtained data on employees' hire dates, as well as their exit dates. Importantly, the personnel records also included the reason for exit: voluntary or involuntary. Thus, we could estimate competing risks hazard models in which the potential outcomes were remaining employed in the organization, exiting voluntarily, or exiting involuntarily.

Dependent Variables: Bonus We used monthly bonus payments as the measure of individual performance to evaluate Hypothesis 2. For people in job roles such as sales or operations in which productivity could be objectively assessed, the company established a formula that linked specific productivity indicators—for example, a sales person's conversion of leads into revenue—to monthly bonus payments. Given that the distribution of bonuses was skewed, we logged this measure in the analyses reported below.

Cognitive Cultural Fit: Perceptual Congruence and Value Congruence We operationalized the two cognitive cultural fit measures—perceptual congruence and value congruence—based on employee responses to the OCP (Chatman et al. 2014). To derive these measures of fit, we calculated the correlation between different culture profiles. We configured the OCP to yield two separate culture profiles for each respondent: a profile based on her assessment of the current organizational culture and one based on her preferences for each value statement. For the former, we asked: "To what extent do the value statements characterize the organization as a whole?" For the latter, we asked: "To what extent do the value statements characterize your personally desired values, that is, the values you desire in an organization?" Our two measures of cognitive cultural fit are based on the correlation between individual i's cultural profile and their relevant reference group's aggregated cultural profile.

To make these measures comparable to our measure of behavioral cultural fit, we chose the same reference group—i.e., the set of colleagues a person had email contact with in a given month weighted by communication volume. We defined *perceptual congruence* as the match between an individual's current culture profile and the reference group's current culture profile. Similarly, we defined *value congruence* as the correspondence between an individual's personal culture profile (what she prefers) and the reference group's current culture profile (the culture that actually exists in the organization). Note that the reference group profile is identical in both cases. The difference between the two measures stems from the choice of individual culture profile: current culture for perceptual congruence and personal culture for value congruence.[5]

Imputing Cognitive Cultural Fit Over Time The procedure above creates cross-sectional cognitive cultural fit measures of perceptual congruence and value congruence. These measures allow us to estimate between-person models of behavioral cultural fit on perceptual congruence and a set of control variables as a first step in testing Hypothesis 1a. Yet such models cannot account for time-invariant, unobserved heterogeneity. For example, people might vary on stable personality traits such as agreeableness or self-monitoring orientation that might be associated with the tendency to exhibit behavioral cultural fit or on conscientiousness or social skill that might influence their job performance. Cross-sectional models cannot account for these unobserved differences, whereas longitudinal models with fixed effects can. Similarly, with cross-sectional measures of perceptual congruence and value congruence, we can examine how exposure to peers who vary in behavioral cultural fit might relate to a focal actor's own behavioral cultural fit, but we cannot assess how perceptual congruence or value congruence might influence this relationship. For both of these reasons, we therefore followed a procedure to transform the two cross-sectional cognitive cultural fit measures into longitudinal measures. Taking inspiration from Salganik's (2017) notion of *amplified asking*—that is, combining surveys with digital trace data to infer responses for people who cannot be feasibly surveyed or whose responses are missing—we undertook a procedure based on machine learning techniques to identify from raw email content (rather than the higher-level LIWC categories used to derive our measure of behavioral cultural fit) the "linguistic signature" of perceptual congruence and value congruence (see also Bail, 2017).

We assumed that, if language reflects internal processes of cognition (Pinker 2007), then there should be an identifiable relationship between email communication and the two dimensions of cognitive cultural fit. If this relationship can be discerned through machine learning, then it should be possible to impute perceptual congruence and value congruence measures for all employees, including those who departed before the OCP was implemented and those who were employed but chose not to participate. Moreover, assuming a relatively stable underlying relationship between language use and cognition, these measures can be imputed for individuals at all points in time for which they exchanged email messages with colleagues. In other words, this procedure allowed us to transform our two cross-sectional measures of cognitive cultural fit into longitudinal ones.

We used a random forest model to help uncover this underlying link between language and cognition (Ho 1995, Friedman et al. 2001). Random forest models have several beneficial characteristics for this task: they can detect arbitrary, nonlinear relationships; they typically require fewer observations than do other machine learning methods to produce comparable results; and they are inherently robust to overfitting, or incorrectly inferring signal from idiosyncratic noise in the data. Figure 1 provides a conceptual overview of this procedure. Further procedural details are provided in the Appendix B; evaluative analyses regarding model fit are provided in Appendix C.

[FIGURE 1 ABOUT HERE]

Peer Cultural Fit After imputing perceptual congruence and value congruence, we turned next to identifying the distribution of these measures in the network of email contacts surrounding a focal individual as a means to test Hypothesis 3. To do this, we first identified an individual i's communication partners J for each month T. Then, using our time-varying measures of cognitive cultural fit, as well as our time-varying measure of behavioral cultural fit, we took the mean cultural fit for all communication partners J, weighted by the volume of incoming communication received from each interlocutor, to generate i's peer cultural fit for month T. We did this for each cultural fit measure, yielding network-based measures that we refer to as peer perceptual congruence, peer value congruence, and peer behavioral cultural fit.

Control Variables We estimated both within-person and between-person models for our analyses. In within-person models, time-invariant effects (e.g., the role of diffuse status characteristics such as gender and ethnicity) are subsumed by individual fixed effects; however, we included three time-varying controls that prior research suggests are relevant to the study of cultural conformity. First, we included (lagged) managerial status since employees may be more likely to accommodate the behaviors, and specifically the language use, of interlocutors who possess greater structural power (Mayer et al. 2009). Next, we included tenure since those who have worked in the organization longer are likely to be exposed to more information about the culture, regardless of the perceptions, values, and behaviors of their peer group. Finally, we included departmental affiliation since departments vary in relative centrality and power, which may in turn influence the degree to which their members are motivated to conform to behavioral norms (Thompson 1967, Salancik and Pfeffer 1974).[6] For our between-person models, we included additional control variables for age and gender.

Analytical Approach

We tested Hypothesis 1a, which posits that perceptual congruence will be positively related to behavioral cultural fit, using OLS regressions based on cross-sectional data, as well as fixed effect regressions based on longitudinal data (including imputed measures of perceptual congruence and value congruence). We standardized all variables in the regression models reported below. We use lagged predictors in longitudinal models to address (though not fully resolve) reverse causality.

To test Hypothesis 1b, which considers the link between value congruence and voluntary exit, we estimated competing risks Cox proportional hazard models. In our case, involuntary exit is the competing risk.[7]

For Hypothesis 2, we estimated ordinary least squares regressions of each focal individual's bonus on the three cultural fit measures. These models included both department and individual fixed effects.

Finally, to test Hypothesis 3, which suggests that perceptual congruence and behavioral cultural fit will be susceptible to peer influence, we identified the effect of changes in peer composition on the focal individual's cultural fit measures. We began by estimating the following basic OLS model, with individual, department and year fixed effects:

$$CF_{idt} = \beta_0 + \beta_1 \langle PeerCF \rangle_{idt-1} + \beta_2 |Peer|_{idt-1} + \eta X_{idt-1} + \beta_3 Year_t + \beta_4 Dept_d + \beta_5 Ind._i + \epsilon_{idt} \quad (1)$$

where CF_{idt} is the relevant cultural fit measure (behavioral cultural fit, perceptual congruence or value congruence) for individual i in department d at time t, $\langle PeerCF \rangle_{idt-1}$ is the mean peer cultural fit at time $t-1$ weighted by number of incoming messages, $|Peer|_{idt-1}$ is the number of peers at time $t-1$, and X are time-varying individual attributes. The inclusion of individual fixed effects accounts for stable variation between individuals, such as differences in innate psychological traits, experience, and preferences. Department and year fixed effects account, respectively, for differences between departments (e.g., different demographic compositions) and periods (e.g. variation in turnover rates) that might systematically affect cultural fit.

We lag mean peer cultural fit and number of peers to ensure appropriate temporal ordering. Yet even with individual fixed effects and lagged predictors, this modeling approach does not yield causal estimates. It could be the case, for example, that individuals with high cultural fit seek to interact with equally culturally integrated individuals. In other words, this modeling approach cannot separate the effects of homophily from those that arise through peer influence.

To help address this problem, we exploited a reorganization event that transpired over a period of two months, roughly seven years after the firm's founding. An ideal test would have included a fully exogenous shock that assigned certain individuals to interact with a random set of new peers while others retained their previous network contacts. Such a natural experiment would allow for causal identification of peers' cultural fit on that of the focal individual. In the absence of such an experiment, we relied on this reorganization event, which—although not random—was driven primarily by functional needs arising from rapid growth at the time and which affected all employees to some extent. Moreover, unlike network changes generated by downsizing, the restructuring did not disproportionately affect low-performing or otherwise systematically similar peers.

As such, the reorganization can be thought of as quasi-exogenous in that it introduced significant random variation in employees' network compositions. Recognizing, however, that this event was not a pure natural experiment, we used an extension of an instrumental variable peer effects model first introduced by Waldinger (2012). Using a two-stage least-squares model, we first estimated the random variation in mean peer cultural fit and number of peers introduced by the reorganization, and we then used these estimates to predict subsequent changes in cultural fit.

In typical instrumental variable designs, the instrument is assumed to only affect the endogenous variable. In the present case, however, the reorganization also affected the focal individuals' peers' network compositions. Thus, peers also experienced shifts in their cultural fit, driven by changes in their own peer group after the reorganization and social influence from peers in the month of reorganization. To address this complexity, we follow Waldinger (2012) and use *induced change in peer cultural fit*, $\tilde{\Delta}\langle PeerCF\rangle$, as an instrument. $\tilde{\Delta}\langle PeerCF\rangle$ is the change induced by the reorganization between periods $t-1$ and t, *assuming peer cultural fit had remained fixed at its pre-reorganization level.* Defining the measure in this way allowed us to account for the change in peer exposure stemming from the reorganization, while separating out its downstream effects on peers' cultural fit.

In addition to induced change in mean peer cultural fit, we also measured the magnitude of change in network composition as an instrument. Let I_{it} be a vector of length N (total number of employees) wherein each cell $I_{it}(j)$ corresponds to the number of messages that i received from interlocutor j during month t. We define i's network change at time t as the cosine distance between i's vectors of incoming messages in two consecutive months:

$$NC(I_{it}, I_{it-1}) = \cos(I_{it}, I_{it-1}) \tag{2}$$

where the cosine distance between two vectors p and q is defined as:

$$\cos(p,q) = 1 - \frac{\sum_{j=1}^{N} p(j)q(j)}{\sqrt{\sum_{j=1}^{N} p(j)^2}\sqrt{\sum_{j=1}^{N} q(j)^2}} \tag{3}$$

Because the number of messages is non-negative, this measure is bounded by 0 and 1.

We used these instruments—network change, induced change in mean peer cultural fit, and the interaction between the two—to estimate the model's two endogenous variables, mean peer cultural fit and number of peers. In the first stage we estimated the following regressions:

$$\begin{aligned}\langle PeerCF\rangle'_{idt} = \beta_0 + \beta_1 NC(I_{it}, I_{it-1}) + \beta_2 \tilde{\Delta}\langle PeerCF\rangle_{idt-1} \\ + \beta_3 NC(I_{it}, I_{it-1}) \cdot \tilde{\Delta}\langle PeerCF\rangle_{idt-1} + \beta_4 Ind._i + \epsilon_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}|Peer|'_{idt} = \beta_0 + \beta_1 NC(I_{it}, I_{it-1}) + \beta_2 \tilde{\Delta}\langle PeerCF\rangle_{idt-1} \\ + \beta_3 NC(I_{it}, I_{it-1}) \cdot \tilde{\Delta}\langle PeerCF\rangle_{idt-1} + \beta_4 Ind._i + \epsilon_{it}\end{aligned} \tag{5}$$

In the second stage we estimated cultural fit at time $t+1$ (a month after the reorganization) with instrumented mean peer cultural fit and number of peers as independent variables. These models included individual, department, and year fixed effects. We specified the second stage regression as:

$$CF_{idt+1} = \beta_0 + \beta_1 \langle PeerCF \rangle'_{idt} + \beta_2 |Peer|'_{idt} + \beta_3 Year_t + \beta_4 Dept_d + \beta_5 Ind._i + \eta X_{it} + \epsilon_{idt} \qquad (6)$$

where X_{it} represents time-varying individual controls. We report results from eq. 6 in the tables below.

Our instrumental variables set-up departs from Waldinger's (2012) in at least two fundamental ways. First, whereas Waldinger focuses on how shifts in peer quality and number of peers that arise from exogenous dismissals (of scientists) affect a focal actor's own quality, in our set-up a focal actor experiences shifts in peer cultural fit and number of peers through not only the removal of existing peers but also the addition of new peers in her communication network. For the exclusion restriction to hold, we must assume that the processes by which removals and additions occur are orthogonal to the focal actor's behavioral cultural fit. There are reasons to doubt that this would be the case in a typical reorganization. For example, the architects of the reorganization could have moved people around based on expectations of who would fit better with whom and who would likely increase their fit over time. We partially account for this possibility through a robustness check (described below) that excludes senior employees, whose anticipated fit was more likely to be a factor in architects' specific reorganization choices. Another way in which the exclusion restriction would be violated is if people actively changed their interaction partners during the reorganization, with an eye to anticipated cultural fit in the post-reorganization regime. As we will discuss in greater detail below, our empirical results (see Figure 3) suggest that people do indeed adjust their interaction partners following the reorganization; however, they do so after a lag of over a month. Thus, in the relevant time period for our instrumental variable regressions, it seems less likely that the exclusion restriction is violated because of self-selection into networks.

Second, unlike Waldinger's case where dismissals are unambiguous events, shifts in peer exposure in our setting are more ambiguous because we only observe the peers to which a focal actor is connected in the email communication network. Thus, we have no way of accounting for changes in peer exposure that occur in other communication media (e.g., phone calls, text messages, face-to-face meetings). In sum, we believe that our instrumental variable regressions improve significantly upon our OLS estimates and, with some caveats, move us closer to causal estimates of peer influence.

Results

Preliminary Analyses

Table 1 provides descriptive statistics for our key variables of interest and also includes definitions of our various cultural fit measures. Before turning to our main results, we summarize two preliminary analyses. First, we characterize the culture of the organization we studied using insights from the Organizational Culture Profile. Second, we demonstrate the validity of the two cognitive cultural fit measures that were imputed using the procedure described in Appendix B.

[TABLE 1 ABOUT HERE.]

To provide context on the content of the organization's culture, we began by identifying the eight OCP dimensions developed in Chatman et al. (2014). This analysis revealed that the organization was most focused on Customers (mean=6.30), followed by Results (mean=5.82) and Integrity (mean=5.62). In contrast, it was relatively less focused on Transparency (mean=4.66) and Details (mean=4.95). This dimension-level portrait was comparable to the pattern of results for the relative salience of specific value statements, with the six most highly ranked items being: Customer Oriented (mean=6.75, sd=1.8), Making your Numbers (mean=6.32, sd=2.07), Being Results Oriented (mean=6.18, sd=1.78), Listening to Customers (mean=6.13, sd=1.74), Having High Expectations for Performance (mean=6.11, sd=1.85), Being Market Driven (mean=5.99, sd=1.81), and Fast Moving (mean=5.91, sd=2.04). The lowest ranked (Most Uncharacteristic) six items of the 54 item aggregate current culture profile included the items: Predictability (mean=2.97, s.d.=1.65), Stability (mean=3.07, sd=1.78), Security of Employment (mean=3.13, sd=1.77), High Levels of Conflict (mean=3.56, sd=2.11), Being Reflective (mean=3.88, sd=1.53) and Being Calm (mean=4.00, sd=1.67).

Next, given that we theorized that value congruence is relatively stable over time while perceptual congruence is more malleable, we traced the two imputed measures over a person's tenure in the organization. We restricted this analysis to the first 36 months of employment given that only about 10% of employees had tenure exceeding 36 months during our observation period. We separately estimated OLS and fixed effect regressions of the two cognitive fit variables using indicators for each month (up to month 36 of employment). These results are depicted in Figure 2. According to both models, when employees first enter the organization, they have relatively high value congruence and relatively low perceptual congruence. Through approximately the first year of employment, however, perceptual congruence increases sharply and continues a more gradual ascent thereafter. In contrast, value congruence increases—albeit not as steeply—in the first four months of employment and then remains mostly stable over the remaining months. These results support our contention that value congruence is relatively stable, while perceptual congruence is more malleable.

[FIGURE 2 ABOUT HERE]

Main Results

Table 2 provides a test of Hypothesis 1a. The first three models report results from cross-sectional data in which the cognitive fit measures—perceptual congruence and value congruence—are derived directly from the Organizational Culture Profile (OCP). Both measures are imputed in the three longitudinal models that follow.

Models 1 to 3 report results from cross-sectional data, with behavioral cultural fit averaged over three months preceding the administration of the OCP. In support of Hypotheses 1, perceptual congruence is significantly related to behavioral cultural fit. It is also worth noting that value congruence is not related to behavioral cultural fit. Moreover, these patterns hold whether the two predictors are modeled separately (Models 1 and 2) or together (Model 3).

[TABLE 2 ABOUT HERE.]

Table 2, Models 4 to 6, show the same pattern of results as the cross-sectional analyses using longitudinal specifications that include individual, department, and year fixed effects. The longitudinal results provide further support for Hypotheses 1a given that perceptual congruence is significantly related to behavioral cultural fit. As individuals' perceptual congruence increases, their behavioral cultural fit correspondingly increases. Consistent with our theory, it is also worth noting that value congruence relates to the long-term behavioral choice to remain in the organization or exit voluntarily; however, changes in value congruence are unrelated to changes in behavioral cultural fit as measured by language accommodation.

Of the control variables included in the models, only managerial status and tenure are significant. We conjecture that managers exhibit greater behavioral cultural fit than do individual contributors either because their general tendency toward cultural congruity was conducive to their past promotion into management or because subordinates are more likely to linguistically accommodate their communication style. Consistent with previous work on enculturation (Srivastava et al. 2018), we also find that individuals exhibit significantly lower behavioral cultural fit during their first year in the organization.[8]

Table 3 reports tests related Hypothesis 1b regarding the link between value congruence and voluntary exit. In particular, our competing risks Cox hazard models focus on voluntary exit as a function of value congruence and perceptual congruence (with involuntary exit serving as the competing risk).

As Table 3 indicates, value congruence is associated with a decreased risk of voluntary exit, while perceptual congruence is not. The importance of value congruence in affecting voluntary departures, based on the imputed longitudinal measure, is consistent with prior work based on a cross-sectional measure of value congruence that predicted departure from firms up to two years later (Chatman 1991).[9]

Next, to test Hypothesis 2, the relationship between cultural fit and performance, we conducted OLS regressions with individual, department, and year fixed effects, where the dependent variable is bonus (logged) and independent variables—behavioral cultural fit, perceptual congruence (imputed) and value congruence (imputed)—are lagged. We report these results in Table 4. The fixed effects specification with lagged predictors allows us to estimate the effects of within-person change in cultural fit on subsequent productivity.

Whether modeled independently or together, all three cultural fit measures are significantly positively related to productivity, offering support for Hypothesis 2. Thus we find, consistent with prior work (Chatman 1991, Srivastava et al. 2018), that behavioral cultural congruity, as well as cognitive alignment, are positively related to positive job performance. The coefficients for behavioral cultural fit and perceptual congruence are of similar magnitude. The two variables retain their significance even when included together in Model 4.

The effect of value congruence on bonus is more modest, which is consistent with our expectation that value congruence remains more stable over time. Given that the unwavering component of value congruence is subsumed in the individual fixed effect, it is not surprising that its time-varying component accounts for less of the variance in job performance.

[TABLE 4 ABOUT HERE.]

Table 5 reports the analyses we used to test Hypothesis 3—that being connected to colleagues with higher (lower) behavioral cultural fit will be associated with corresponding increases (decreases) in perceptual congruence and hence behavioral cultural fit for the focal individual. Model 1 presents estimates from the baseline fixed effect models with lagged peer behavioral cultural fit, as specified in equation 1. Individuals exhibit a significant increase in behavioral cultural fit when their peers' mean behavioral cultural fit increases in the preceding month. Importantly, this model includes individual fixed effects and thus accounts for a wide range of time-invariant individual differences—such as self-monitoring or cultural capital—that might also affect a person's capacity for behavioral cultural fit.

[TABLE 5 ABOUT HERE.]

As noted above, the estimates from Model 1 are not causal given that this empirical approach cannot distinguish the effects of homophily, or seeking out similar others, from those of social influence, or modifying one's own behavior to accommodate others' behavior. We therefore turn to our instrumental variable in the remaining models. The primary result is reported in Model 2. The coefficient for peer behavioral cultural fit suggests that those who, as a result of the reorganization, transitioned into a network comprising peers with greater behavioral cultural fit experienced an increase in their own behavioral cultural fit in the following month. The opposite is also true: individuals who, through the reorganization, transitioned into a network of peers with lower behavioral cultural fit experienced a corresponding decline in their own behavioral cultural fit. Interestingly, and likely because reorganizations are disruptive to cultural integration, the majority of employees experienced a decline in peer behavioral cultural fit, and correspondingly, their own behavioral cultural fit during this period.

We illustrate the implications of induced change in peer behavioral cultural fit in Figure 3. The diagram plots the effects of the reorganization on individuals' behavioral cultural fit over time, as estimated by the instrumental variable model. The upper line corresponds to individuals who experienced a half standard deviation positive increase in their peers' behavioral cultural fit, and the lower line corresponds to individuals who experienced a decline of the same magnitude in their peers' behavioral cultural fit. These are substantial changes in peer behavioral cultural fit but not implausible during a period of reorganization. A little over 1% experienced a positive shock at or greater than half a standard deviation, but roughly 35% experienced a decline of that magnitude. Both translate to similarly sized adjustments in the focal individuals' behavioral cultural fit, but in opposite directions. Moreover, both adjustments persisted for roughly two months, after which the effects of the reorganization were no longer apparent and individuals converged toward mean behavioral cultural fit.

Because the reorganization was not a true natural experiment, it is worth noting that changes that occurred after its effects were initially felt could have arisen for a variety of reasons that we do not observe in our data. For example, individuals presumably regained more command over whom they interacted with after the reorganization, which would also reintroduce potentially confounding homophily effects. Hence, the period immediately following the reorganization is the appropriate one to consider for this analysis.

Importantly, the two sets of individuals—positively and negatively "treated"—are indistinguishable in the period preceding the reorganization, suggesting that these adjustments are a result of the imposed change in network composition rather than systematic differences between the two groups. The Kleibergen-Paap F statistic, which is appropriate when using robust standard errors, suggests that the instrument is strong (Kleibergen and Paap 2006, Baum et al. 2007).

Changes in the number of peers had a more modest impact: those who experienced an increase in the size of their network due to the reorganization experienced declines in behavioral cultural fit. Forced network growth, in other words, appears to be disruptive to cultural integration. The difference between these coefficients in the OLS (Model 1) and instrumental variable (Model 2) models is worth noting and suggests that our instrumental variable approach at least partially addresses the endogeneity inherent in our OLS models. During non-turbulent times (Model 1), an increase in number of peers is associated with an increase in behavioral cultural fit. Our results suggest, however, that the increase in network size is driven by improved cultural integration, which facilitates seeking out more contacts in the organization, and not the other way around. When changes are forced, in contrast, attending to a growing number of peers whom the focal individual does not necessarily choose to interact with appears to undermine cultural adjustment (Model 2).

Our models do not speak directly to how precisely this cultural transmission occurs—for example, whether organizational members explicitly reward and penalize their colleagues for culturally compliant or deviant behavior or whether cultural knowledge is transferred tacitly. Models 3 and 4—wherein we estimate the effects of change in peer behavioral cultural fit on the focal individual's perceptual congruence and value congruence, respectively—suggest that behavioral adjustment occurs through changes in perceptual congruence rather than through value congruence. We conjecture that individuals adapt their perceptions, but not their private beliefs, in response to changes in peer composition. Moreover, in Models 5 and 6 we estimate the effects of reorganization-driven changes in peer perceptual congruence and in peer value congruence on the focal individual's perceptual congruence and value congruence, respectively. Neither coefficient is significant, lending further support to our argument that cultural learning occurs through observing peers' behaviors, given that cognition is less directly accessible to others. We suspect that the majority of this cultural transmission happens tacitly. As Models 5 and 6 imply, individuals generally do not have access to their peers' cognitive cultural fit. To the extent that they do, for example, when they explicitly discuss their beliefs, it does not appear to be sufficiently potent to translate into changes in their own cognition. In other words, the cultural transmission we observe appears to be about the diffusion of *perceptions* about the culture rather than the diffusion of *values*.

In Table 6, we report the results of two supplemental analyses designed to assess the robustness of the results of our instrumental variables analysis and test the boundary conditions of our theory. First, given that our measures of cognitive and behavioral cultural fit are all defined with respect to the reference group of an individual's interlocutors in a given month, which people can—to varying degrees—self-select into, we replicated the instrumental variables analysis using behavioral cultural fit and peer behavioral cultural fit measures that were based on the reference group of *all* employees in the organization. Table 6, Model 1, shows that peer behavioral cultural fit, when peers are defined as all other employees in the organization, predicts the focal actor's behavioral cultural fit relative to this same reference group. This result helps mitigate concerns that our main results are an artifact of our choice to define behavioral cultural fit relative to a focal actor's interlocutors in a given month.

Second, our instrumental variable approach is predicated on the assumption that the reorganization produced exogenous shifts in focal actors' peer groups. Yet it is possible that the reorganization was biased toward certain desired shifts in peer groups—for example, distancing leaders and their teams when there was animosity between them or bringing together formal subunits whose heads had compatible management styles. To address such possibilities, we replicated the analyses using a sub-sample of employees who were not in supervisory roles. We reasoned that, insofar as the reorganization was designed in part to change peer groups, such social engineering was targeted to the leadership ranks of the company. For those in individual contributor—rather than supervisory—roles, the reorganization was much more likely to have produced exogenous change in peer networks. As Table 6, Model 2, illustrates, our hypothesized effects hold even for this more restricted sample of employees. By removing individuals with supervisory responsibilities, this analysis also offers insight into whether language accommodation, our measure of behavior fit, is a simple reflection of people aligning to the linguistic style of their most powerful interlocutors. Given the consistency of the findings when supervisors are included or dropped from the analysis, we conclude that this is not likely to be the case.

[TABLE 6 ABOUT HERE.]

Discussion and Conclusion

Adjustments to new and changing cultural environments are a fixture of modern life. People's identities in contemporary society typically intersect many social boundaries—including ethnic, religious, political, occupational, and organizational. This crisscrossing of boundaries requires ongoing cognitive and behavioral effort. The contemporary workplace—with its growing emphasis on culture on the one hand and employees' declining average tenure on the other—is a central arena in which these cultural transitions play out. Navigating the cultural heterogeneity across and within organizations involves maintaining multiple and partial commitments to different cultural orders, which in turn requires cultural awareness and adaptability (Friedland and Alford 1991, Morris et al. 2015, DiMaggio and Goldberg 2018).

Organizational research has tended to approach cultural assimilation through the lens of socialization (e.g., Van Maanen and Schein 1979, Alba and Nee 2009, Ashforth et al. 2007). Such an approach assumes that cultural adaptation entails a gradual internalization of the group's norms and underlying value system. Prior studies have therefore almost exclusively focused on value congruence as the primary dimension of cultural fit, implicitly equating enculturation with value alignment. We offer a more comprehensive model of fit and enculturation which distinguishes deciphering the cultural code—what we term "perceptual congruence"—from its internalization, and we demonstrate how these two mechanisms derive from different sources and relate to different aspects of behavior and individual attainment.

Our theoretical framework and concomitant findings offer three contributions. The first is in advancing person-culture fit theory. Specifically, we demonstrate that the antecedents and behavioral consequences of cultural fit vary by type of cognitive cultural fit—value congruence versus perceptual congruence. Values matter for cultural conformity in the long-run and thus shape outcomes such as the choice to leave an organization. In contrast, perceptions are important for real-time behavioral conformity, here measured in terms of linguistic style similarity. Next, we demonstrate that both cognitive manifestations of cultural fit—value congruence and perceptual congruence—as well as its behavioral form—linguistic conformity with peers—enable people to reap positive career rewards. Indeed, all three of our fit measures are positively linked to individual productivity, as indicated by bonus payments. In contrast to prior theoretical formulations of fit, we also demonstrate that different rewards accrue to different forms of cultural alignment. Those who read the code correctly and behave accordingly benefit from being perceived as true and committed group members, while those who identify with and embrace the code enjoy the psychological well-being that comes with working in an organization that reinforces the values that they already believe to be important. Our findings also relate to the literature on organizational socialization in that we identify ways in which structural factors (i.e., the networks to which members are exposed) affect the capacity to accurately read the organizations cultural code. We depart, however, from prior socialization studies, which tend to focus on intentional socialization practices, by identifying how less intentional factors such as the colleagues one is assigned to work with can also influence cultural learning.

The conceptual separation of cognitive fit into value congruence and perceptual congruence also raises the future research question of how these two dimensions relate to each other dynamically. We speculate, for example, that value congruence may provide a motivational channel through which a person is more or less vigilant in achieving and maintaining perceptual congruence. We similarly conjecture that people with chronically low value congruence may be able to maintain high perceptual congruence for a finite period of time but that doing so may, over time, adversely affect their identity and sense of self-worth (cf. Hochschild 2012). Conversely, even if those with high perceptual congruence and low value congruence do not experience intrapsychic conflict, they may still experience the deleterious effects of being judged by others as inauthentic. Alternatively, we speculate that such individuals may—through self-perception and attribution processes

(Ross 1977)—begin to experience an increase in value congruence. Examining the interrelationships between value congruence and perceptual congruence over time is a fruitful avenue for further developing theories of person-culture fit.

Our second contribution pertains to cultural change and transmission: we identify the factors that cause some people to enculturate more successfully than others and illuminate the role of social networks in cultural transmission. Previous work has often assumed that enculturation is a function of individual differences in endowments. Rivera (2012), for example, demonstrates that labor market matching—at least in the elite firms she investigates—is inherently related to the cultural capital that job applicants possess. Separately, research by organizational psychologists has focused on innate differences in psychological traits, demonstrating that stable dispositions such as self-monitoring and perspective-taking are conducive to cultural adjustment and the benefits it confers (Maddux et al. 2008). In contrast, we use an instrumental variable approach to show that the ability to enculturate is also contextual (cf. Ashforth et al. 2007), accruing to individuals whose peers are themselves successfully enculturated. Cultural adaptation, in other words, is not just a function of the ability to decipher the cultural code but also of the peers from whom this code is learned. In this sense, a person's structural position in an organization is highly consequential regardless of her intrinsic ability to detect the cultural code. If she is connected to peers whose perceptions of the culture are inaccurate and who therefore behave in non-compliant ways, she will find it harder to exhibit normatively compliant behavior herself.

The link we establish between peers' behaviors and those of the focal actor also contributes to our understanding of cultural diffusion. Previous work has argued that some innate aspects of "cultural intelligence" make individuals sensitive to cultural knowledge in others' behaviors (Liebal et al. 2013). The literature on social networks, in contrast, has mostly focused on the structural conditions that enable or impede behavioral diffusion. We combine insights from these otherwise disconnected research domains to make two interrelated contributions. First, we theorize and demonstrate empirically that cultural transmission is a function not only of individuals' attentiveness to cultural knowledge in others' behaviors but also of the structural conditions that lead and expose them to others. Second, our theory offers a novel perspective on how this process of cultural diffusion operates, first and foremost, by primarily affecting perceptions rather than values.

Finally, through this work, we make a methodological contribution that would appear to have wide-ranging application across the social sciences. Building on Salganik's (2017) notion of "amplified asking," we demonstrate an empirical approach that transforms a one-time self-report into a longitudinal data set. Such an approach is of course, selectively appropriate, with requirements that include having a sufficient number of survey observations, access to rich communication content, protocols and safeguards to protect individual privacy and company confidentiality, and significant computational bandwidth. In addition, more work—based on multiple administrations of self-reports alongside contemporaneous communications data—is needed to identify the conditions under which the relationships between language use and the self-reports of interest are (as we assume in this paper) stable over time. Yet, given the ubiquity of digital trace data, the increasing difficulty of collecting survey data (particularly over time and from a large number of organizations), the widespread dissemination of off-the-shelf machine learning tools, and the declining cost of processing capacity, we anticipate that the pairing of self-reports and digital trace data will become increasingly common in social science research (Evans and Aceves 2016, McFarland et al. 2016, Lazer and Radford 2017). We see great potential for such work to more fully illuminate how the cognitive and behavioral arenas of organizational life relate to one another and jointly shape individual careers and the organizational cultures in which they unfold.

Endnotes

[1]The definition of culture as an analytical construct has long been a matter of debate, which we do not attempt to resolve here. "Shared understandings," in our view, is a useful shorthand in that it points to two important properties of culture: that it dwells in the similarities between the

individuals who constitute a group and that these similarities relate to group members' mental representations of the world. Missing from this useful, albeit simple, definition is the idea that such shared understandings emerge through interpersonal interaction.

[2]We acknowledge that not all individuals seek to fit in behaviorally and that some people are more predisposed than others to engaging in non-compliant behavior. Although the need for uniqueness is most likely hard-wired, it is also balanced by the propensity for compliance and assimilation with important social groups (Leonardelli et al. 2010). Moreover, the tendency to conform is mediated by individual endowments: those with high status or who enjoy structural buffering by virtue of being embedded in a tight-knit community may under some circumstances reap the benefits of culturally non-compliant behavior while limiting its adverse consequences (Goldberg et al. 2016). On balance, however, behavioral conformity is generally beneficial such that people are, by and large, motivated to conform to the normative expectations of their social group (Miller and Prentice 2016). Thus, we expect people to be attuned to their cultural environments and to respond to their peers' behaviors in their attempts to fit in.

[3]By "value," we mean enduring beliefs about desired or undesired ways of working and interacting with others (e.g., "I prefer a friendly work environment"), as distinguished from situation-specific preferences (e.g., "I prefer having lunch before noon") (O'Reilly et al. 1991, Vaisey 2009, Miles 2015).

[4]The other half completed a survey of the cultural characteristics needed for the organization to be successful in the future. We shared the results of this latter survey with organizational leaders as a condition of gaining access to the organization as a research site; however, we do not report these results here because they do not pertain to our theory and hypotheses.

[5]For robustness checks reported below, we also produced versions of these measures in which the reference group included all employees in the organization rather than just the focal individual's email interaction partners in a given month.

[6]Managerial status and departmental affiliation can be estimated in fixed effect models because some employees get promoted from individual contributor to managerial roles and because some employees move across departments.

[7]Because including period fixed effects produces unstable estimates in such a model, we instead include the number of employees in the organization as a control. This accounts for time-varying fluctuations in average value congruence due to firm growth or decline. To account for variation in the number of observations per individual (some individuals remain only a handful of months in the organization, whereas others stay for years), we use overall tenure as a sampling weight.

[8]Tenure has a curvilinear relationship with behavioral cultural fit, steadily increasing during the first six to twelve months and gradually stabilizing thereafter. Because individuals vary significantly in their rate of enculturation, we use a binary indicator for early tenure.

[9]Neither perceptual congruence nor value congruence is significant in predicting involuntary exit when we use the same framework with voluntary exit as the competing risk.

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FIGURES

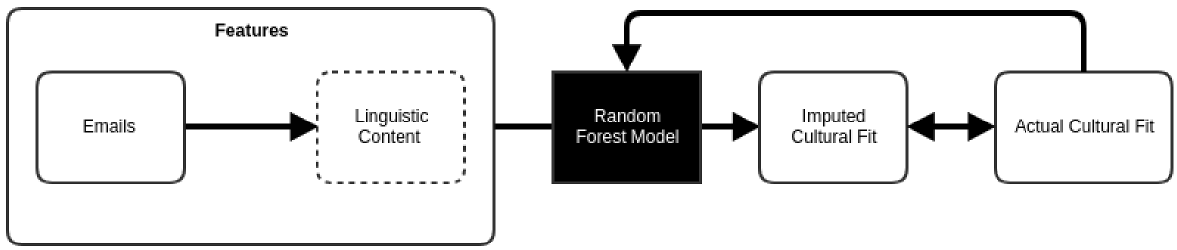

Figure 1 Conceptual Overview of the Machine Learning Process

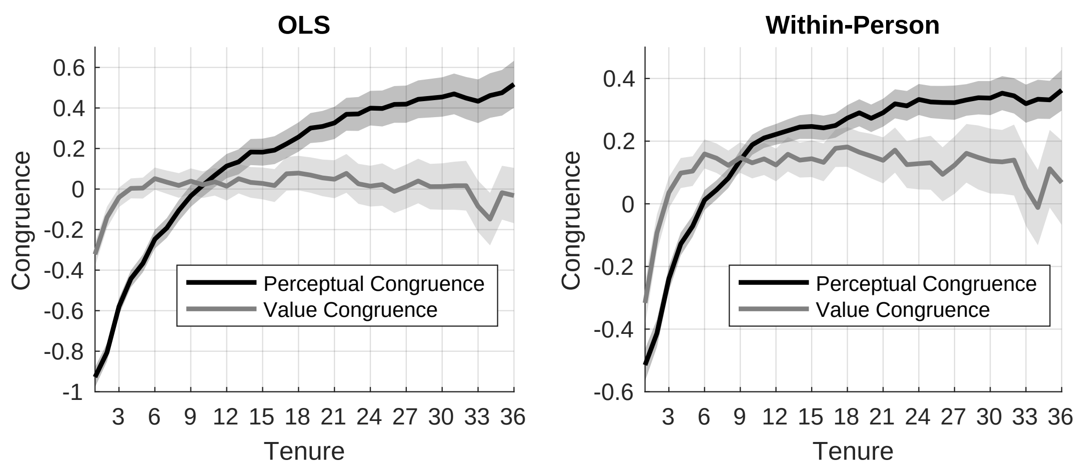

Figure 2 OLS and Person Fixed Effects regressions of perceptual congruence and value congruence, with indicators for each tenure month up to 36 months in the company. Congruence measures are standardized. Shaded areas correspond to 95% confidence intervals.

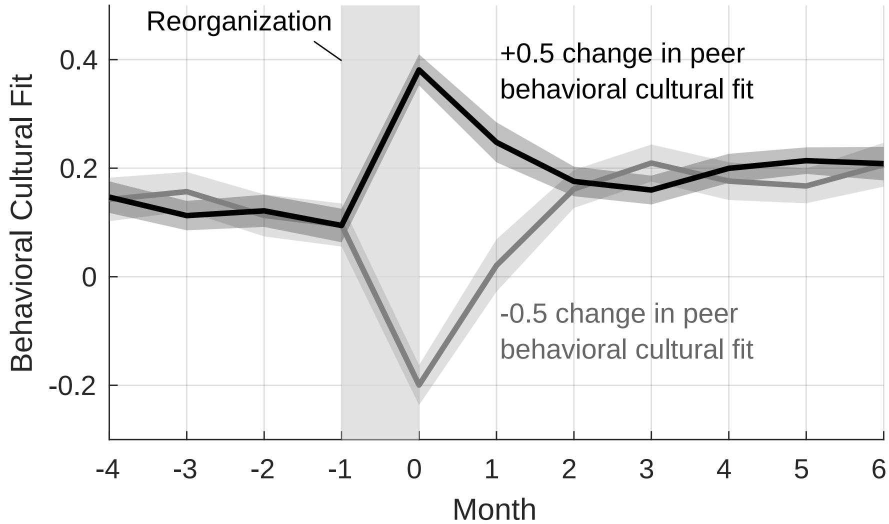

Figure 3 **Marginal effects, estimated by monthly consecutive instrumental variable models, of change in peer behavioral cultural fit on individual behavioral cultural fit. The two lines correspond to individuals who experienced a 0.5 increase (black) or decrease (gray) in peer behavioral cultural fit. Shaded areas correspond to 95% confidence intervals.**

TABLES

Table 1 Variable Definitions and Descriptive Statistics

Statistic	N	Mean	Pctl(25)	Pctl(75)
Behavioral Cultural Fit (standardized) *The Jensen-Shannon divergence (inverse and log-transformed) between the LIWC distributions of an individual's incoming and outgoing emails.*	26,941	0.000	−0.557	0.594
Perceptual Congruence (standardized) *[Cross-Sectional] The correlation between an individual's current culture profile and her reference group's current culture profile, weighted by communication volume.* *[Imputed] The weighted sum of perceptual congruence as predicted by a random forest model, weighted by class probabilities* ($0*$ *probability of class 0* $+1*$ *probability of class 1* $+2*$ *probability of class 2).*	27,984	0.000	−0.755	0.888
Value Congruence (standardized) *[Cross-Sectional] The correlation between an individual's personal culture profile and her reference group's current culture profile, weighted by communication volume.* *[Imputed] The weighted sum of value congruence as predicted by a random forest model, weighted by class probabilities* ($0*$ *probability of class 0* $+1*$ *probability of class 1* $+2*$ *probability of class 2).*	27,984	0.000	−0.699	0.718
Peer Behavioral Cultural Fit (standardized) *The weighted sum of behavioral cultural fit for an individual's communication partners, weighted by incoming communication volume* $(\Sigma_{j\in J} CF_j * \%\_Incoming\_Communication\_Volume_j)$	26,640	0.000	−0.495	0.621
Peer Perceptual Congruence (standardized) *The weighted sum of perceptual congruence for an individual's communication partners, weighted by incoming communication volume* $(\Sigma_{j\in J} PC_j * \%\_Incoming\_Communication\_Volume_j)$	26,118	0.000	−0.463	0.587
Peer Value Congruence (standardized) *The weighted sum of value congruence for an individual's communication partners, weighted by incoming communication volume* $(\Sigma_{j\in J} VC_j * \%\_Incoming\_Communication\_Volume_j)$	26,118	0.000	−0.509	0.525
Manager	29,255	0.136	0	0
Female	29,255	0.316	0	1
Age	28,970	34.157	26.767	39.165

Table 2 Cross-Sectional and Longitudinal Fixed Effects Regressions of Behavioral Cultural Fit

	Cross-Sectional			Longitudinal		
	Model 1†	Model 2†	Model 3†	Model 4	Model 5	Model 6
Perceptual Congruence‡	0.122***		0.149***	0.046**		0.046**
	(3.56)		(3.37)	(2.81)		(2.79)
Value Congruence‡		-0.008	-0.040		0.013	0.012
		(-0.17)	(-0.86)		(1.35)	(1.29)
Manager	0.613***	0.599***	0.555***	0.293***	0.297***	0.292***
	(6.73)	(4.20)	(3.92)	(5.42)	(5.47)	(5.40)
First Year	-0.246**	-0.351***	-0.317**	-0.074*	-0.082**	-0.074*
	(-3.20)	(-3.49)	(-3.13)	(-2.54)	(-2.81)	(-2.53)
Female	0.043	-0.033	-0.065			
	(0.62)	(-0.35)	(-0.68)			
Age	-0.003	-0.002	0.001			
	(-0.84)	(-0.30)	(0.10)			
Constant	0.345*	0.223	0.183	-0.142	-0.145	-0.145
	(2.37)	(1.13)	(0.93)	(-1.14)	(-1.11)	(-1.17)
Individual FE	No	No	No	Yes	Yes	Yes
Department FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes
Observations	386	209	202	24215	24215	24215
R^2	0.275	0.235	0.279	0.107	0.075	0.107

t statistics in parentheses; standard errors clustered by individual when individual fixed effects are used
† Behavioral Cultural Fit is averaged over 3 months, ‡ Imputed and lagged measures in Models 4-6
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 Competing Risks Model of Voluntary (Rather than Involuntary) Exit

	Model 1	Model 2
Perceptual Congruence	1.005	
	(0.07)	
Value Congruence		0.876*
		(-2.30)
Manager	0.833	0.864
	(-0.77)	(-0.62)
Female	1.386*	1.392*
	(2.53)	(2.56)
Age	0.901**	0.902**
	(-3.23)	(-3.23)
Age^2	1.001**	1.001**
	(3.20)	(3.22)
Num. Employees	1.002***	1.002***
	(9.46)	(9.96)
Department Dummies	Yes	Yes
Observations	27467	27467
χ^2	172.161	177.689
Log-Likelihood	-1320.27	-1318.36

Exponentiated coefficients; t statistics in parentheses
Standard errors clustered by individual; Sample weights by tenure
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4 Fixed Effect Regressions of Bonus (logged) on Behavioral Cultural Fit, Perceptual Congruence, and Value Congruence

	Model 1	Model 2	Model 3	Model 4
Behavioral Cultural Fit†	0.131***			0.122***
	(4.45)			(4.14)
Perceptual Congruence†		0.144***		0.122**
		(3.97)		(3.05)
Value Congruence†			0.056**	0.046*
			(3.18)	(2.37)
Manager	-0.194	0.025	0.063	-0.180
	(-1.12)	(0.13)	(0.31)	(-1.02)
Constant	5.642***	5.394***	5.299***	5.666***
	(28.18)	(26.63)	(25.68)	(28.47)
Individual FE	Yes	Yes	Yes	Yes
Department FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4785	6379	6379	4780
Num. Inidividuals	1058	1304	1304	1057
R^2	0.059	0.043	0.040	0.065

t statistics in parentheses; standard errors clustered by individual
† lagged variables, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 OLS and Instrumental Variables Fixed Effects Regressions of Behavioral Cultural Fit on Peer Behavioral and Cognitive Cultural Fit

	OLS	Instrumental Variable				
	Model 1 Behav. Fit	Model 2 Behav. Fit	Model 3 Percep. Accuracy	Model 4 Value Congr.	Model 5 Percep. Accuracy	Model 6 Value Congr.
Peer Behavioral Fit†	0.221***	0.266***	0.068**	-0.020		
	(12.68)	(6.38)	(3.03)	(-0.47)		
Peer Perceptual Congruence†					0.064	
					(0.63)	
Peer Value Congruence†						0.073
						(0.83)
Num. Peers†	0.001**	-0.013*	0.001	0.008*	0.024	-0.004
	(3.11)	(-2.50)	(0.27)	(2.14)	(1.36)	(-0.38)
Manager	0.365***	0.555***	0.042	-0.096	-0.430	0.136
	(7.67)	(4.34)	(0.77)	(-0.95)	(-1.18)	(0.68)
First Year	-0.154***	-0.204***	-0.163***	0.028	-0.013	-0.043
	(-6.72)	(-4.12)	(-6.28)	(0.65)	(-0.12)	(-0.64)
Constant	-0.065	0.648**	0.259**	-0.257	-0.756	0.257
	(-1.23)	(2.67)	(2.67)	(-1.45)	(-0.99)	(0.63)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Department FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	22080	21998	21998	21998	21985	21985
Num. Individuals	1515	1508	1508	1508	1504	1504
R^2	0.28					
Kleibergen-Paap F		8.99	8.99	8.99	0.85	1.79

t statistics in parentheses; standard errors clustered by individual

† lagged variables, instrumented endogenous variables in Models 2-6

** $p < 0.01$, *** $p < 0.001$

Table 6 Robustness Checks—Instrumental Variables Fixed Effect Regressions of Behavioral Cultural Fit on Peer Behavioral Cultural Fit

	Model 1 Organization	Model 2 Non-Managers
Peer Behavioral Cultural Fit†		0.235^{***} (5.78)
Peer Behavioral Cultural Fit (Organization)†	0.158^{***} (5.40)	
Num. Peers †	-0.003 (-1.85)	-0.013^{*} (-2.10)
Manager	0.133^{***} (3.57)	
First Year	-0.034^{*} (-2.27)	-0.150^{**} (-3.25)
Constant	2.154^{***} (26.90)	-0.560 (-1.79)
Individual FE	Yes	Yes
Department FE	Yes	Yes
Year FE	Yes	Yes
N	19938	18097
Num. Individuals	1229	1257
Kleibergen-Paap F	3.03	8.81

t statistics in parentheses; standard errors clustered by individual
† instrumented and lagged endogenous variables
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX A: BEHAVIORAL CULTURAL FIT

The Interactional Language Use Model

We implement the procedure detailed in Goldberg et al. (2016) and Srivastava et al. (2018) to measure behavioral fit. We begin by using LIWC to translate each individual's outgoing and incoming messages in each period t (defined as a calendar month) into probability distributions over the 64 LIWC categories. Specifically, we define $\overrightarrow{m}_{it}$ as each email individual i sends at time t and $\overleftarrow{m}_{it}$ as each email individual i *receives* at time t. We then define the set of LIWC categories as L and the set of all times in any given month as T. Our procedure iterates over all emails sent and received and produces $\overrightarrow{m}^l_{it}$ and $\overleftarrow{m}^l_{it}$ for the count of terms in email $\overrightarrow{m}_{it}$ and $\overleftarrow{m}_{it}$ in LIWC category $l \in L$, respectively. Then, by aggregating all individual email counts $\overrightarrow{m}^l_{it}$ and $\overleftarrow{m}^l_{it}$ for $t \in T$, it produces sent and received LIWC counts in month T, $\overrightarrow{m}^l_{iT}$ and $\overleftarrow{m}^l_{iT}$. We normalize each LIWC count in each month by the total of all LIWC counts in that month to transform the LIWC probability distribution to a standard probability distribution. We use the notation, O^l_{iT} to denote the outgoing normalized probability and I^l_{iT} to denote the incoming normalized probability.

$$O^l_{iT} = \frac{\overrightarrow{m}^l_{iT}}{\sum_{l \in L} \overrightarrow{m}^l_{iT}} \tag{7}$$

$$I^l_{iT} = \frac{\overleftarrow{m}^l_{iT}}{\sum_{l \in L} \overleftarrow{m}^l_{iT}} \tag{8}$$

We define an individual i's behavioral fit in month T as the negative log of the Jensen-Shannon (JS) divergence (Lin 1991) metric between i's outgoing and incoming normalized distributions:

$$BF_{iT} = -log\left(JS(O_{iT} \parallel I_{iT})\right) \tag{9}$$

where the JS-divergence between two probability distributions is defined as a symmetric measure built by first taking the mean probability distribution between the normalized outgoing and incoming distributions, $M_{iT} = \frac{1}{2}(O_{iT} + I_{iT})$, and summing the Kullback-Leibler (KL) divergence (Kullback and Leibler 1951) of the outgoing and incoming distributions from that mean probability distribution.

$$JS(O_{iT} \parallel I_{iT}) = \frac{1}{2} KL\left(O_{iT} \parallel M_{iT}\right) + \frac{1}{2} KL\left(I_{iT} \parallel M_{iT}\right) \tag{10}$$

$$KL(D_{iT} \parallel M_{iT}) = \sum_{l \in L} D^l_{iT} \log_2 \frac{D^l_{iT}}{M^l_{iT}} \tag{11}$$

Validation of Behavioral Cultural Fit

We have argued above that the LIWC lexicon, on which the behavioral cultural fit measure is based, is a useful categorization scheme for measuring culturally meaningful behaviors. Indeed, as previous work demonstrates (e.g. Goldberg et al. 2016, Srivastava et al. 2018), this measure of behavioral fit is effective at predicting individual attainment in an organization. Since this is the first time our measure of behavioral fit has been related to a validated measure of organizational culture, the OCP, we also sought assurances that the LIWC categories contained face valid connections to the existing OCP dimensions. Therefore, we conducted two types of analyses to further establish the behavioral measure's construct validity.

First, we compared respondents' language use to their responses to the OCP survey. Recall that we asked respondents to describe their desired culture (personal culture survey) and their perception of the organizational culture (current culture survey). We expected there to be a systematic relationship between people's desired and perceived cultures on the one hand and their linguistic behaviors on the other. For example, it would seem plausible that a preference for a people-oriented cultural environment would be reflected in greater use of affective words. Thus, we expected to observe a systematic relationship between people's cultural preferences and perceptions, as reflected in their explicit responses to the OCP and their use of language as captured by LIWC.

To examine this, we compared individuals' rankings of the 54 OCP categories with their LIWC category frequencies in outgoing email communication in a 3-month period close to the OCP survey administration. For the personal culture survey, we found 229 significantly correlated ($p < 0.05$) pairs of OCP and LIWC categories (with sample size of 231 individuals). For the current culture survey, we found 583 significant correlations (for 414 individuals). We found an even greater number of significant OCP/LIWC pair correlations when comparing the current culture survey to respondents' incoming email communication, suggesting that—consistent with our hypotheses—individuals' perceptions of the culture are inherently related to the behaviors they observe. We also compared LIWC frequencies to the eight high-level OCP categories (such as collaborative or detail-oriented, see Chatman et al. (2014) for details). For the personal cultural survey we find that 34% of LIWC categories are correlated with at least one high-level dimension, and that 85% of LIWC categories are correlated with at least one high-level dimension in the current culture survey. Together, these analyses indicate that LIWC use significantly and substantially co-varies with desired and perceived culture.

As illustration, we examine the link between language use and a preference for a people orientated culture. We find that respondents who value people orientation tend to include more affect words (e.g., happy, cry, abandon), perceptual process words (e.g., observe, hear, feel), positive emotion words (e.g., love, nice, sweet), and second-person words (e.g., you, your) in their outgoing communication.[10]. We refrain from substantively interpreting these findings, but we view them as qualitative evidence for the cultural meaningfulness of LIWC use and leave a systematic exploration of the complex relationship between stated beliefs and naturally occurring linguistic behaviors to future work.

In our second test of the construct validity of our behavioral fit measure, we recognized that LIWC was originally developed as a means to identify the linguistic signatures of psychological, rather than purely cultural categories. Whereas some linguistic categories contained in the LIWC lexicon, such as swearing, are clearly inherently related to culture, others, such as the use of articles, are more ambiguously cultural. Thus, we sought to understand whether our behavioral fit measure represented a meaningful and relevant set of culturally oriented linguistic categories.

Before discussing these analyses in detail we highlight why we assume that LIWC categories are culturally meaningful. Specifically, while some LIWC categories may initially appear to be unrelated to culture, extensive research by Pennebaker and his colleagues (2013) suggests that the categories are meaningful at both a psychological and sociological level. For example, the use of articles such as *a*, *an* or *the*—each of which seemingly represents a minute technical linguistic decision—actually reflects the speaker's emotional stability, organization, and conservatism (Pennebaker 2013). A group that uses a linguistic style that emphasizes articles might therefore be indicative of a rule-oriented culture that emphasizes attention to detail.

Thus, rather than requiring a typology that distinguishes non-cultural from cultural LIWC categories and that maps the latter to underlying cultural dimensions, we assumed that all LIWC categories are culturally meaningful and that the same category might vary in its cultural meaning across contexts. Our measure of behavioral cultural fit therefore takes all LIWC categories into account and does not privilege certain categories over others.

To test our assumption, we analyzed the measure's robustness to LIWC category inclusion. Let $k < 64$ be the size of a subset of LIWC categories used to generate an alternative measure of behavioral fit, labeled BF_k. We randomly selected k LIWC categories and constructed the measure as we did above (according to equation 9), using only this subset of categories. We repeated this process 1,000 times for each value of k (because $\binom{64}{k}$ is extremely large for most values of k, we could not realistically explore all possible subsets). For each BF_k that we generated, we identified its correlation with the original BF measure based on all 64 categories.

We report the average correlation between BF_k and BF for all 1,000 random samples in Figure A1. As the plot clearly indicates, the behavioral fit measure is robust regardless of whether LIWC categories are removed. The measure remains effectively unchanged even if half of the LIWC categories are removed. We interpret these results as an indication of two properties. First, behavioral fit is not driven by one or a handful of LIWC categories. It is therefore not merely a reflection of a specific linguistic feature or style. Second, the pattern illustrated in Figure A1 indicates that even if certain LIWC categories are culturally irrelevant in this context, their inclusion in the measure construction does not bias its value. In other words, even if we were to conclude that half of the LIWC categories are non-cultural (a conclusion that, for the reasons stated above, we believe is unwarranted) and decide to remove them from the measure, we would still recover near-identical values.

APPENDIX B: MACHINE LEARNING PROCEDURE

Overview

The procedure consisted of five major steps, which are documented at a conceptual level in Figure 1 in the main manuscript and described in greater detail below.

Our first step was to translate the raw email data into a format that is usable by the random forest model. We tokenized and stemmed all words in the body of email messages. Tokenization involves separating the text into distinct terms, for which we used the TwitterTokenizer designed for linguistic analysis Potts (2011). Stemming involves reducing each term to a root form, for which we used the Porter Stemmer from the python nltk package. We removed all characters that could not be encoded into unicode, such as "\x00," and split the text into n-stems, where n is in the set [1,2,3]. Given that language use tends to follow the power law, in which few terms are used frequently and many terms are used infrequently, we then undertook steps to reduce the dimensionality of the data to make it computationally tractable. We retained all n-stems in emails sent from individuals, but only uni-stems in emails sent to individuals. Additionally, we retained only those n-stems that were used by at least 1% of employees in a subsample of emails. Finally, we used principal component analysis (PCA) to further reduce dimensionality, retaining only the top 3,000 PCA components for each type of n-stem. These resulting components served as the feature inputs to our model.

The second step was to transform our measures of cognitive cultural fit into categories that are more conducive to classification given the relatively small number of observations from which we had to fit the model. Recall that perceptual congruence and value congruence were computed as correlations, ranging from 0 to 1. We transformed these continuous measures into three discrete categories–low, medium, and high. Intuitively, this allowed our model to detect distinctive features of belonging to each category, an important characteristic to which we will return when we discuss the testing of our model. For perceptual congruence, we set the cutoffs for low fit at 20% and for high fit at 80%, with everything else considered medium fit. For value congruence, for which we had even fewer observations, we had to set more extreme cutoffs at 10% and 90% to achieve strong model fit.

The third step was to use our feature inputs and their now-discrete mappings to cognitive cultural fit to train a random forest model. The random forest model is an ensemble method, which means it aggregates and blends multiple independent decision trees (Ho 1995, Friedman et al. 2001). After several such decisions according to specific features of the input, all of the inputs are sorted into decision leaves. The random forest model then collects those independent trees and their leaves and predicts results for new observations. New observations get sorted into resultant leaves depending on their own features, and their probabilities of being predicted as a certain class depend on the other data points sorted into that leaf in the trained model. In a simplistic model, imagine that the only decision is that PCA1 $> .5$ and that all observations with PCA1 $> .5$ are high in cultural fit. Then, a new observation whose PCA1 $> .5$ would also get sorted into the same leaf and would then be classified as high cultural fit.

The fourth step was to evaluate the trained model. To do so, we assessed the model's predictions compared to the original continuous values. Random forest models produce, along with the classifications of input, probabilities of observations belonging to each class. Conceptually, this means that if an observation has certain characteristics that correspond to a given class, it will have a higher probability of being in that class. For example, if an individual's email communication has indicators of low, medium, and high cognitive cultural fit, but more indicators of high cultural fit than the others, then his or her output from the random forest model might indicate a 0.2 probability of low fit, a 0.3 probability of medium fit, and a 0.5 probability of high fit. We can then take a weighted sum of these probabilities to generate a measure that is conceptually analogous to the original continuous measure. We used a mix of methods to evaluate the model, including the area under the curve of the receiving operating characteristic curve (ROC AUC), precision-recall, and separation between low and high cognitive cultural fit with respect to the original continuous values. As reported in Appendix C, the final models we used performed well on these evaluations.

The final step was to impute perceptual congruence and value congruence using their corresponding random forest models for all individuals in all time periods for which we had corresponding email data. To do this, we followed the first step above to retrieve the input feature vector for each individual over time and used all the linguistic data for each individual up to a certain month to impute perceptual congruence and value congruence for that individual in that month.

There were a total of over five million unique emails. Each email can be sent from an individual and several other individuals (via the to/cc/bcc lines). We included both messages sent to and received from the focal individual in our final model.

Dimensionality Reduction of Features Considering the size of our potential feature vector, we used dimensionality reduction techniques to make our process computational tractable. In particular, we used a discriminative heuristic to determine which n-stems to keep, since there is a tradeoff between keeping frequent and non-frequent terms: frequent terms allow for discrimination to the extent that they are used differently among a large population of people, while non-frequent terms allow for discrimination to the extent that some people use them and others do not. Given this trade-off, we retained those n-stems that were used by at least 99% of all employees, regardless of their objective frequency. To retain as much information from this pared down set of n-stems, we used principal component analysis (PCA). This allowed us to reduce the hundreds of thousands of features to only a few thousand per n-stem, while still retaining a large part of the variance of the original data. Because of the exponential size of the "to" stems compared to the "from" stems, we ended up using the top 3,000 PCA components from the "from" uni-, bi-, and tri-stems, and from the "to" uni-stems.

Random Forest Model Specification We selected the random forest model because of several favorable characteristics. First, random forest models allow for nonlinear relationships between input and output. Decision trees in general, of which random forest is a collection, thus allow for arbitrarily complex relationships, which we would assume govern the relationship between linguistic data and cognitive cultural fit. Second, random forests are ensembles of decision trees, which inherently reduce overfitting and increase robustness. Since there is the potential for a link between linguistic data and cognitive cultural fit to be extremely idiosyncratic (e.g., use of a certain phrase or way of communicating), it greatly helps that we use a more robust method. Third, random forest models do not require as much training data as neural networks. Deep neural networks have the same, if not better, ability to pick up complex relationships, but require far more training data, depending on the depth of the model. As a result, random forest models are simpler and tend to require fewer training data for comparable results.

We split the data into the usual training, development, and testing sets, with 56% of the original data in the training set, 14% in the development set, and 30% in the testing set. Because of the way the random forest algorithm is implemented, it is strongly vulnerable to the "class imbalance" problem. Specifically, if the input to the model from the training set were 10% class 0, 80% class 1, and 10% class 2, then the model would err towards predicting most new observations as class 1. To overcome this, we used a bootstrapping procedure that randomly samples with replacement the lesser classes until they reach the amount of the most populated class. This procedure ensured that, on average, input classes were balanced and therefore class prediction depended more on the splits than on the original balance of the input classes. In addition to searching the hyperparameter space, we also tested varying N for bootstrapped samples.

APPENDIX C: EVALUATING MODEL FIT

Test Set Metrics

Because of the way we constructed our pseudo-continuous imputed cultural fit, we needed to use a set of test metrics that accurately capture what it means to have a "good model." The choice of bounds for the continuous to discrete distribution is forced; it is an educated guess that produces empirically validated results. Therefore, observations that lie just on one side may not differ substantively from observations that lie just on another side. Concretely, observations that are on the high end of the medium cultural fit may be very similar to observations that are on the low end of the high cultural fit, given that we had set the cutoff ourselves. Therefore, our measures should focus less on perfect categorization (i.e., precision, recall), and more on separation of low and high cultural fit and predictive power of imputed results on actual results. As a result, our performance metrics are a mix of the traditional machine learning metrics, as well as novel metrics we developed ourselves.

For the traditional test metrics, we present the pairwise precision and recall measures on the test set. We provide the pairwise precision recall rather than an F score, because we differentially care about the pairwise results. That is, we care the most about the precision recall between the high and the low cultural fits and less about the precision recall between the mid and either high or low cultural fits, as per our previous discussion.

[TABLE C1 ABOUT HERE.]

A better metric might be to directly examine the separation between groups. If we link the original continuous values with the classifications, then we would see a split like in the figure below.

[FIGURE C1 ABOUT HERE.]

We then used the means and standard deviations of each group to see if the classifier successfully split the observations into statistically distinct groups. We find that the models appear to appropriately distinguish between the low and high groups.

[TABLE C2 ABOUT HERE.]

Finally, we used the receiver operating characteristic curve (ROC) that has become popular in machine learning. Since the ROC works with threshold probabilities of classification, mapping the true positive rate versus the false positive rate at different thresholds, it conceptually measures the extent to which the rank-ordering of predicted values is in line with expectations. For a perfect area under the curve (AUC), the rank-ordering would be monotonically increasing such that all actual values of 1 would have higher probabilities of being classified as 1 than all actual values of 0, and vice versa. Since we have three classes versus the regular binary classification, we use the micro-averaged ROC curve, which takes into account this structure. The ROC curves with their AUC's are presented below.

[TABLE C3 ABOUT HERE.]

APPENDIX FIGURES

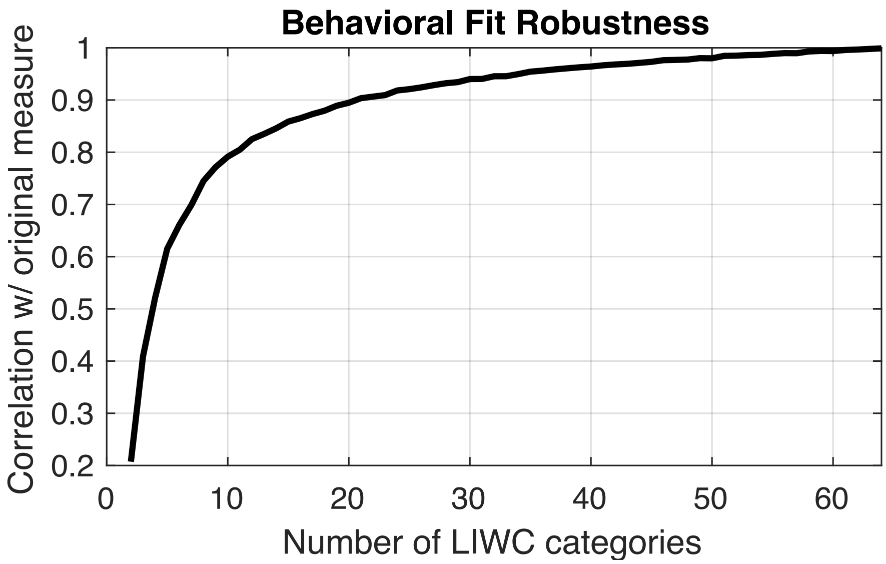

Figure A1 **Robustness of the behavioral fit measure to LIWC category composition**

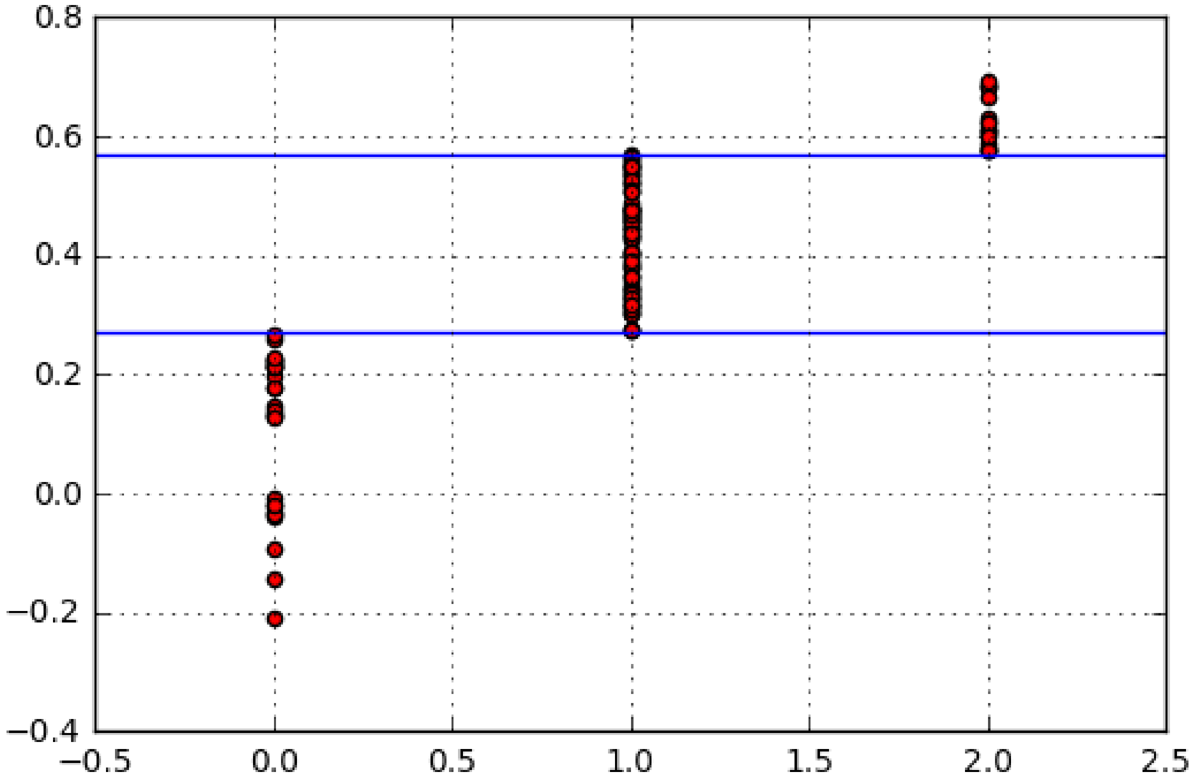

Figure C1 Division of Continuous Cultural Fit into Classes

APPENDIX TABLES

Table C1 Test Set Precision-Recall Metrics for Imputations

	Precision Low-High	Precision Low-Mid	Precision Mid-High	Recall Low-High	Recall Low-Mid	Recall Mid-High
PC-Interloc.	0.857	0.726	0.767	0.267	0.651	0.711
PC-Org.	1	0.875	0.865	0.547	0.867	0.849
VC-Interloc.	1	0.952	0.950	0.667	0.952	0.934
VC-Org.	1	0.923	0.951	0.667	0.923	0.906

Table C2 p-Values for Difference in Means between Low and High

	P-Value
PC-Interloc.	$2.661e{-3}$
PC-Org.	$1.874e{-8}$
VC-Interloc.	$8.500e{-6}$
VC-Org.	$7.157e{-5}$

Table C3 Areas under the ROC Curve

	ROC AUC
PC-Interloc.	0.740
PC-Org.	0.910
VC-Interloc.	0.950
VC-Org.	0.930