Distinguishing Round from Square Pegs: Predicting Hiring Based on Pre-hire Language Use

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This article examines how cultural matching relates to a job applicant's likelihood of getting hired into an organization and identifies the components of cultural similarity that matter most for hiring success. Cultural compatibility at the hiring stage can forecast an individual's post-hire productivity but is difficult to reliably measure in the selection process. As a consequence, cultural matching is often subject to various informational and identity-based biases. We develop a language-based model that provides a means for directly assessing job candidates' cultural similarity. Based on variegated data from a mid-sized technology firm—including job applicants' free text responses at the pre-hire stage, applicant characteristics, applicant-interviewer assignments, and hiring outcomes—we find that linguistic similarity with previously hired employees increases a job candidate's chances of being hired, even after controlling for the applicant's human and social capital. We further find that, although all three forms of cultural fit that we assess—fit based on work preferences, lifestyles, and ideology—predict hiring in between-interviewer models, only work preferences fit predicts hiring in within-interviewer models. Supplemental analyses indicate that pre-hire cultural fit is also predictive of successful enculturation in the firm over the first six months of employment. Together, these results indicate that cultural matching leads to sorting on attributes that are both relevant and potentially irrelevant for job success.

Key words: hiring; culture; cultural fit; computational linguistics

1. Introduction

Hiring is a gamble for organizations, akin to purchasing a lottery ticket (Spence 1973). Organizations typically seek to hire the best candidates but lack complete knowledge of which applicants possess the skills and interpersonal characteristics needed for success (Akerlof 1970). This asymmetry frequently places candidates in a favorable position: they can choose what information to divulge and employ self-presentation tactics to make themselves appear more attractive (Barrick et al. 2009, Gilmore and Ferris 1989). Candidates' attempts at impression management only exacerbate the information asymmetry problem, making it harder for organizations to differentiate between high- and low-quality applicants.

Mistakes in the screening and selection of job applicants can impose steep organizational costs. Employees who are poorly matched to a job are more likely to struggle and fall short of meeting performance expectations (Tziner 1987, Downey et al. 1975). They are also more likely to exhibit low job satisfaction and meager organizational commitment, which can be precursors to turnover (Chatman 1991, O'Reilly et al. 1991). Whether voluntary or involuntary, turnover triggers both direct costs and indirect costs stemming from the lost productivity of those who must search for new employees to replace the departed ones (Sheridan 1992). In light of these costs, organizations make sizable investments in screening and evaluating prospective new hires before making them job offers (Huselid 1995).

Although a vast literature has examined how hiring managers rely upon signals of quality in job applicants' educational credentials, past work experiences, and social connections (Hatch and Dyer 2004, Fernandez et al. 2000), a smaller but growing body of work has instead focused on the importance of *cultural matching* (Bourdieu 2011 [1986], Rivera 2012). This perspective assumes that candidates' pre-hire cultural fit will be predictive of difficult-to-observe human and social capital traits that are associated with job success or of cultural traits that are independent of human or social capital yet are still key to individual or group productivity (Kammeyer-Mueller and Wanberg 2003, Kristof 1996, Chatman et al. 1998). Informed by these insights, organizations are increasingly selecting candidates on the basis of their anticipated cultural fit, which they typically infer by assessing—often implicitly—the degree to which candidates appear to be culturally congruent with previously hired employees.

Yet assessments of job candidates' cultural fit based on pre-hire characteristics can often be biased to the point of being unreliable. The biases arise from two main sources. The first is informational: hiring managers' decisions are often swayed by easily observable cultural traits such as the choice of hairstyle or attire, despite the noisiness of these signals and the lack of evidence linking them to relevant skills. The second is identity-based in that hiring managers' preferences for social similarity—for example, favoring candidates with shared sociodemographic traits or common hobbies and lifestyle preferences—can also lead them to overlook culturally dissimilar but otherwise promising candidates (Rivera 2012).

In this article, we examine how access to more direct cultural information at the pre-hire stage informs our understanding of how indirect cultural cues shape hiring outcomes. Building on a growing body of work that uses language as a window into culture (Goldberg et al. 2016, Srivastava et al. 2017, Corritore et al. 2017), we introduce short essay questions into the hiring process of a mid-sized technology firm and develop a language-based model of cultural similarity between job applicants and previously hired employees. Importantly, responses to these questions were not available to job screeners and interviewers at the time they made their evaluations. As a result, we can identify how language use at the pre-hire stage relates to a job candidate's likelihood of being hired independent of the traits that are observable to screeners and interviewers. Using standard natural language processing techniques, we develop an unsupervised method to assess cultural similarity based on responses to the three essay questions.

To preview our results, our pre-hire linguistic similarity measure is predictive of who gets hired, even after accounting for the applicant's human and social capital. Given that the three essay questions provide different cultural information—about job applicants' compatibility of work preferences, similarity of lifestyles, and shared ideological views relative to those of previously hired employees—we then disaggregate the analyses by question to assess the relative importance of each dimension. Although all three fit measures predict hiring in between-interviewer models, only work preferences fit predicts hiring in within-interviewer models. Supplemental analyses indicate that the pre-hire cultural fit of hired applicants also foreshadows their successful enculturation into the firm—as measured by the linguistic similarity of email communication between individuals who are ultimately hired and their interlocutors in the organization—in their first six months of employment. Taken together, our results indicate that job candidates' language contains an identifiable and salient cultural signal that is separate and distinct from the culture proxies on which interviewers typically rely; however, cultural sorting appears to result in the matching of candidates to jobs on attributes that are both relevant and potentially irrelevant for their subsequent productivity.

2. Theory

Organizational theory typically assumes that managers choose whom to hire by trying to match job demands to candidate qualifications (Tilly and Tilly 1998). Although the underlying quality of a candidate is difficult to observe and thus uncertain, hiring managers draw inferences about candidate quality based on factors such as educational credentials, past work experiences, and known social connections to existing employees (Hatch and Dyer 2004, Fernandez et al. 2000). In parallel to work that examines how human and social capital influence hiring outcomes, recent years have seen a surge of interest in the role of culture. In particular, there has been an increasing trend toward examining how the perceived cultural fit of job applicants factors into how they are evaluated and ultimately selected or passed over for jobs (Bourdieu 1984, Koppman 2016, Rivera 2012).

Although organizations may take culture into account across a range of decisions they make, two main theories help to explain why they do so in the specific context of hiring. One is signaling theory, which was first introduced in the seminal work of Spence (1973). In that work, Spence demonstrated that in labor markets characterized by information asymmetries, investment in education can serve as a costly (and therefore informative) signal of job candidate quality. Since then, signaling theory has expanded in scope to cover the reduction of information asymmetry between two parties (Spence 2002, Connelly et al. 2011). In the hiring context, signaling theory suggests that applicants' cultural characteristics may be meaningfully related to positive, but difficult to observe, elements of human capital. For example, if a preference for avant-garde music were known to be indicative of creativity, and if it were costly for people to become versed in this genre, then an organization that prizes employees who produce novel ideas might select candidates in part based on their musical tastes.

Yet cultural characteristics can function as more than just a signal of latent human capital. A second line of research sees culture as something that emerges naturally in all organizations and that can serve as a catalyst for individual, group, and organizational productivity (Chatman and O'Reilly 2016). Recent work on the cultural compatibility between individuals and organizations has highlighted the distinction between two different forms of cultural fit: cognitive and behavioral (Mobasseri et al. forthcoming, Srivastava et al. 2017). Cognitive fit refers to the degree of shared understanding between individuals and the group to which they belong, whereas behavioral fit references the extent to which an individuals behaviors are compliant with the group's normative expectations.

Research on organizational culture demonstrates the positive implications of cultural fit along both of these dimensions. An extensive literature has focused primarily on one core component of cognitive fit—value congruence, or the degree of similarity between an individual's own preferred values and those reported by others as being prevalent in the group (Edwards and Cable 2009). Individuals whose values correspond to those that prevail in an organization are more likely to self-identify with the organization (Cable and Judge 1996) and exhibit greater attachment to it (Chatman 1991). Behavioral fit, in turn, matters for individual success because culture serves as a form of tacit knowledge that enables interpersonal coordination, thereby contributing to individual productivity. As a result, behavioral fit—for example, based on linguistic similarity in email communications with colleagues—is positively related to individual attainment (Srivastava et al. 2017). Given these benefits, organizations have strong incentives to hire individuals who are both value congruent and that fit behaviorally.

Even though cultural fit within the organization is associated with many positive outcomes, hiring for cultural similarity is fraught with difficulty and can produce a variety of unintended consequences. Cultural traits tend to provide noisy signals of quality in large part because culture is an abstract construct that has varying interpretations. Most organizations, including those that view culture as a strategic resource and emphasize cultural compatibility in their hiring process, lack standardized approaches for assessing their culture and measuring how existing and prospective new employees fit into it. Thus, assessments of new hires' cultural compatibility are typically based on subjective judgments. Furthermore, because firms lean toward thinking of their cultures as unique, they tend to create a variety of informal means of assessing culture (e.g., company-specific, unstructured "fit" interviews that are especially prone to noise and cognitive bias) (Highhouse 2008, Hoffman et al. 2015).

The absence of reliable measures of cultural fit has an additional negative consequence: it increases the likelihood that employers will instead rely on easily observed, but largely irrelevant, cultural traits. For example, recent work by Rivera (2012) finds that hiring managers at elite law firms often interpret lifestyle choices (e.g., hobbies and leisure activities) and self-presentation styles as markers of underlying cultural compatibility (e.g., a job applicant listing *Star Trek* as a TV favorite might signal fit with the "geeky" culture of a high-technology firm). Yet, as Rivera notes, these markers are often unreliable signals of the underlying qualities they are assumed to represent; instead, they often relate to the applicant's socioeconomic status rather than his or her skills or capacity for cultural alignment. This work hints at a deeper challenge in the hiring process: similarity-attraction bias, or the tendency toward homophily.

Across a variety of contexts, interpersonal similarity has been shown to be tightly connected to judgments of liking. This relationship is robust across many dimensions of similarity including attitudes (Bryne 1971), personality traits (Buss 1984), and physical characteristics (Berscheid et al. 1971). And it carries through to the hiring process: interviewers are apt to give more favorable assessments of candidates when they possess similar surface traits (Goldberg 2005).

Yet this preference for similar others can lead hiring managers to select candidates for reasons that are unrelated to, or even negatively associated with, desirable human capital characteristics. This bias is exacerbated when organizations emphasize cultural fit but fail to provide a structured means of assessing culture in resume screening and interviewing (Campion et al. 1997). Given the lack of objective evaluation criteria and individuals' natural tendency to focus on established and visible cultural markers (Wiesner and Cronshaw 1988, Dipboye 1994), hiring managers often end up choosing candidates based on the schools they attended, the places they previously worked, and the hobbies they engage in—regardless of whether these attributes correlate with productivity on the job.

To assess whether the indirect cultural signals on which job screeners and interviewers rely are relevant or irrelevant to their hiring decisions, we argue for the utility of obtaining direct cultural information about candidates at the pre-hire stage. We focus, in particular, on three types of pre-hire cultural information: ideological fit, work preferences fit, and lifestyle fit. *Ideological fit* refers to the degree of congruence between the job candidate and existing organizational members on the subset of values that are central to the identity of the individual, whereas *work preferences fit* references the degree of correspondence between employees' preferred working style and those held by existing organizational members. Insofar as the preferences of existing organizational members correspond to the beliefs that prevail in the organization, both ideological fit and work preferences fit can be thought of as components of value congruence. And given that value congruence has been linked to successful assimilation into and attachment to the organization (Chatman and O'Reilly 2016), both ideological fit and work preferences fit would appear to be pertinent to the hiring decision.

Lifestyle fit is the extent of similarity between a job candidate and existing organizational members on dimensions of cultural capital such as leisure activities and self-presentation styles. There are reasons to think that lifestyle fit could provide a useful signal of future productivity—for example, if it is predictive of an individual's ability to connect with and forge productive relationships with colleagues. Yet, for the most part, the match between a job candidate's outside-work lifestyle preferences and those of existing organizational members would appear to be largely irrelevant to the hiring decision and more likely to reflect similarity-attraction bias. Rivera (2012: 1019-20), for example, conjectures that "selecting new hires based on extensive devotion to leisure could backfire in the long-term by resulting in a mismatch with the actual demands of the job."

Whether pertinent to hiring or not, how can information about ideological, work preferences, and lifestyle fit be gleaned from job candidates at the pre-hire stage? The "personal" line on candidates' resumes often contains some lifestyle information; however, it is typically incomplete and not available on a consistent basis across all candidates. In phone calls and in-person meetings, candidates also "leak" cultural information about themselves to evaluators in a variety of ways, ranging from nonverbal communication to appearance and dress to self-presentation styles (Huczynski and Buchanan 2010, DeGroot and Motowidlo 1999). Yet, in most cases, it is simply impractical to systematically collect and code all of this paralinguistic and nonverbal information.

In contrast, we contend that the *written* language that job candidates use at the pre-hire stage can provide a meaningful and reliable signal about their likely cultural fit. Language is not only a means of communication but also a window into individuals' social identities and shared assumptions (Hofstede et al. 2010, Ravasi and Schultz 2006). How information is communicated—for example, the use of concrete versus abstract terms or the choice to invoke emotional versus non-emotional language—is often just as important as the content of that communication (Burgoon et al. 1990, Tausczik and Pennebaker 2010). On a broader scale, topics themselves are often associated with different groups of people. For instance, individuals with strong ideological commitment to sustainability are more likely to be heard discussing climate change, environmental policy, and the choices they themselves have made to reduce their carbon footprint. In short, language is one of the most important channels through which culture is transmitted and coordinated across individuals. As such, language functions as a powerful signal by which we make judgments about cultural similarity (Lewis 1969, Labov 2001).

We therefore anticipate that language use at the pre-hire stage can predict who will be viewed as culturally compatible and thus suitable for hire. Specifically, we propose:

Main Hypothesis: Linguistic similarity to previously hired employees is predictive of a job candidate's hiring outcome, even after controlling for the applicant's human and social capital.

Because we have no *a priori* reason to believe that linguistic similarity will occur on the basis of relevant versus irrelevant factors, we do not derive hypotheses related to the three specific forms of cultural information: fit with respect to ideology, work preferences, and lifestyles. We do, however, decompose linguistic similarity into these dimensions in the analyses that follow to shed light on the role of these different forms of cultural matching in the hiring process.

3. Data and Methods

3.1. Sample

Our data come from a mid-sized technology company that agreed to embed short, optional essay questions into its job application process and, for purposes of the research study, to mask responses to these questions from employees tasked with screening and interviewing candidates. We also collected application data, which identified job candidates, the positions for which they applied, whether they made it to the interview stage, and who interviewed them. Separately, we pulled human resource records to identify candidates who were ultimately hired and to discern additional sociodemographic traits of these individuals. We used fuzzy matching of candidate names to merge these two data sources. Finally, for the supplemental analysis of post-hire behavioral fit, we extracted email message content for the subset of employees for whom these data were available.[1]

We followed best practices for the management of confidential data. All personally identifiable data remained on a company server, which we accessed via a secure remote connection. The raw data were cleaned and merged on this server before being assigned anonymous identification codes. Only after all identifying information was removed did we extract the data to our own research servers for subsequent analysis.

We collected responses to the pre-hire essay questions from June 2015 through November 2016. During this period, the company received 79,192 job applications and hired 2,560 new employees. Given that the essay questions were optional, job candidates typically chose to answer either all or

[1] Because of broader turmoil in the industry and a resulting change of control at the company, our research access to the company ended somewhat abruptly. As a result, we were only able to obtain post-hire email data for a relatively small subset of employees.

none of the questions. 17% of candidates chose to respond to at least one question. This provided us with a sub-sample of 13,254 job applications for which we had data on pre-hire language use. However, because cultural fit is an attribute of individuals and not of applications, we further restricted our sample to include only the most recent job application for every individual, yielding an analysis sample of 11,587 individuals, 2,128 of whom were interviewed and 353 of whom were hired. For the interviewed sub-sample, there were 161 distinct interviewers. Each interviewer interviewed between 5 and 344 candidates, with an average of 22 interviews per person.

Table 1 provides the specific wording of the questions. Question 1 focused on work preferences fit, while Question 2 assessed lifestyle fit. Given that the company's core mission and values were focused on sustainability and green technology, Question 3 focused on the the fit with candidates' personal values and ideology as it related to sustainability. Table 2 provides representative examples of responses to these three questions.

3.2. Variables

Our dependent variable was a dichotomous indicator set to 1 for candidates who were ultimately hired. We drew on a variety of data sources to generate control variables: candidates' resumes and cover letters, requisition titles for each application, candidates' self-reported gender, their self-reported hiring source (i.e., how they learned about and entered into the company's hiring process), and a record of who interviewed each candidate (for the candidates that made it to the interview stage). In certain cases, for example, in constructing human capital controls, the data were not neatly structured for us to extract relevant control variables such as the quality or status of universities the applicant attended. In these cases, we had to draw inferences about these variables based on analyses of free text. Details of variable construction are provided below. Table 4 reports summary statistics for the analysis sample.

Managerial Role. We created an indicator variable set to 1 for applicants targeting managerial roles. We did so by using the requisition title of the job for which candidates applied. We considered requisition titles containing key words such as "manager," "vice president," and "director," as managerial positions. We included this variable as a control because we anticipated that candidates would have a lower probability of being hired into a managerial, rather than individual contributor, role since the former tend to be more selective.

Log Word Count. We anticipated that a candidate's choice to answer our optional essay questions would signal her motivation and willingness to expend effort to be hired. Yet we suspected that even the candidates who chose to respond to the essay questions varied in their levels of motivation and effort. To account for these differences, we assessed candidates' total answer length across all three questions. Because this variable was skewed, we took its log and included it as a control.

Gender. Gender is a known source of external hiring biases (Fernandez and Campero 2017, Merluzzi and Dobrev 2015) and is likely to be correlated with cultural characteristics. Self-reported gender was included in the raw job application data; however, only 87% of candidates chose to provide this information. We used historical data from the Social Security Administration to impute the missing values. The imputed gender values were based on candidates' first names and imputed years of birth (see explanation of age variable below). When imputed birth year was available, we assigned candidates the gender associated with the highest percentage for their first name and year. When imputed birth year was unavailable, we assigned candidates the gender associated with the highest percentage for their first name for the average of years 1932 to 2012. For example, imagine a candidate named Taylor. If we know that Taylor was born in 1980, then he or she would be assigned the gender 'Male' because 71% of Taylors born that year were male. However, if we were missing birth year for Taylor, then he or she would be assigned the gender 'Female' because 75% of Taylors born between 1932 and 2012 were female.

Age. Job candidates did not report their age as part of the standard job application. We therefore imputed age based on the dates listed in candidates' resumes. Specifically, we made the assumption that the oldest date listed on a candidate's resume was the date of college graduation. We also assumed that candidates were 22 years old at the time of their college graduation. As is apparent by the maximum age (136) in our sample (see Table 4), this method is not foolproof and introduces some level of measurement error. Rather than arbitrarily excluding individuals with arbitrarily high and likely incorrect imputed ages, we instead retained everyone for whom age could be imputed, even if measured with some error.

Top-tier University and High-status Organization. Similar to our strategy of imputing age from candidates' resumes, we also mined resume content for information on candidates' institutional ties. In particular, we extracted all named organizational entities (i.e., companies, agencies, institutions, etc.) from the resumes using *spaCy* (an open-source NLP library for Python). For our top-tier university indicator, we identified whether a candidate listed any top 20 educational institution (as defined by the 2017 U.S. News rankings) on her resume. While this approach does not distinguish between affiliations based on undergraduate versus graduate study or affiliations based on employment after graduation, it does serve as a proxy for human capital in that the individual was trained or socialized at an elite institution. We followed a similar approach for the high-status organization indicator, which was set to 1 for candidates who listed on their resume one of the organizations on Fortune's "Most Admired Companies" list in 2017.

Sourced through Recruiter or Employee Referral. The application data included candidate source information such as the company career site, university recruiting, and various Internet job sites.[2]

[2] One of these categories was internal hires. We excluded these candidates given our theoretical focus on external hiring.

From the source information, we included as controls two indicator variables, which were set to 1 for candidates sourced through recruiters and employee referrals. We reasoned that candidates sourced through recruiters might have distinctive human capital characteristics because they were in many cases explicitly targeted by the firm or their search firms. The latter set of candidates likely had a social capital advantage in that they had access to a company insider who could inform them about the company's culture and normative expectations during the screening and selection process (Obukhova and Lan 2013, Greenberg and Fernandez 2016).

3.3. Analysis Strategy

3.3.1. Measuring Linguistic Similarity A variety of methods exist for analyzing free-response text, with no single approach emerging as the standard. Researchers must therefore select a language model that best matches the nature of the data being analyzed. For example, with lengthy documents it is often important to reduce the dimensionality of the text into components, which can then be compared for similarities across individuals. In the case of our pre-hire essay questions, their relatively short length (a few sentences on average) and their narrow focus (responding to a direct inquiry) made dimensionality reduction less relevant. Moreover, the pre-hire questions were designed to elicit distinct dimensions of cultural fit, making them theoretically meaningful in their own right. As such, we chose to analyze the responses to these questions using similarities in individual unigram frequencies under the assumption that word choice itself would be informative about culture.

A next step was choosing the appropriate reference group against which to compare each candidate's language use. We opted to focus on the linguistic similarity between applicants and all hired job candidates (excluding the applicant herself when she was subsequently hired). We then assessed whether a higher degree of similarity between an applicant and all hired candidates (excluding the focal applicant) is predictive of the applicant being hired. This approach allowed us to determine whether there is an overall difference in language use between hired and non-hired individuals. It is this difference—in the presence of appropriate control variables—that we interpret as evidence of a cultural signal.

Text Processing. We began pre-processing the raw text by creating four corpora of documents that corresponded to the three question and their combination. We then removed numbers, punctuation, and common English stop words, before stemming the documents. The stemming process allowed us to group common derivations of the same word under a single unigram stem (e.g., creative and creativity would both be converted to the stem "creati"). For examples of these transformations, see Table 3 for the processed versions of the answers shown in Table 2. We then created unigram document-term matrices for each question's corpus and for the corpus of the combined question set. These matrices record the raw frequencies with which each unigram—or term (t)—is present in each document (d), providing the basis of comparisons between the language of different individuals.

TF-IDF. We then transformed the raw frequencies using the term frequency-inverse document frequency (TF-IDF) statistic. This measure aims to capture the importance of a term to a document in a corpus of text. It is often used in text mining and information retrieval to weight terms by their frequency within a document, while controlling for their frequency in the entire corpus. An important consequence of this process is the downplaying of common words; however, TF-IDF also provides a more nuanced ranking of terms at both the top and the bottom end of term frequency.

The TF-IDF statistic is composed of two parts: term frequency and inverse document frequency. Term frequency (TF) is a straightforward measure of the frequency with which a term (t) appears in a document (d). Inverse document frequency (IDF) is a measure of the uniqueness of a term in the corpus (D). It serves to scale up the weights of rare terms and scale down the weights of common terms. Mathematically, it is a logarithmically-scaled measure of the total number of documents divided by the number of documents containing the term—i.e., the inverse relative document frequency. The full TF-IDF statistic itself is simply the product of these two terms.

$$TF(t,d) = f_{t,d}$$

$$IDF(t,D) = log\left(\frac{|D|}{|\{d \in D : t \in d\}|}\right)$$

$$TF - IDF(t,d,D) = TF(t,d) \cdot IDF(t,D)$$

Cosine Similarity Our next step was to compare the word usage across individuals in our sample. To do this, we employed the cosine similarity metric, $cos(\theta)$, which compares the contents of two vectors, A and B.

$$cos(\theta) = \frac{A \cdot B}{||A||\ ||B||}$$

In this case, because we were comparing two documents in a text corpus, vectors A and B were equivalent to the term frequency vectors of the documents. Specifically, these vectors corresponded to the TF-IDF scores contained in the rows of our document term matrices. Therefore, when we calculated the cosine similarity between all rows of the document term matrix—excluding the self comparisons—we were left with an $n * n$ similarity matrix, CS, of cosine values.

$$CS = \begin{bmatrix} 0 & cos(\theta)_{12} & \dots & cos(\theta)_{1n} \\ cos(\theta)_{21} & 0 & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ cos(\theta)_{n1} & \dots & \dots & 0 \end{bmatrix}$$

We then obtained our independent pre-hire fit measure, CS_H, by multiplying the cosine similarity matrix, CS, by a vector of binary hiring outcomes, $h=0,1$. This resulted in a variable measuring the degree to which each individual's language was similar to the language used by the group of hired individuals (excluding himself or herself when appropriate).

$$h=\begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix}, \quad CS_H = CS * h = \begin{bmatrix} 0 & cos(\theta)_{12} & \dots & cos(\theta)_{1n} \\ cos(\theta)_{21} & 0 & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ cos(\theta)_{n1} & \dots & \dots & 0 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix}$$

3.4. Estimation

All of our hiring analyses adhere to the same general logistic model but include a varying matrix of controls, $\boldsymbol{X}$. The dependent variable in these regressions is always a binary measure of hiring, H, and we are primarily concerned with the effect of our measure of linguistic similarity, CS.

$$ln\left(\frac{P(H=1)}{1-P(H=1)}\right) = B_0 + B_1 CS + B_2 \boldsymbol{X}$$

$$OR = e^{B_1}$$

We introduce control variables, $\boldsymbol{X}$, into our model sequentially to eliminate plausible alternative explanations for the link between pre-hire language use and hiring outcomes. Initially, we include only a baseline set of controls aimed at identifying the effects of candidates' effort and desired job role. In subsequent models, we consecutively add controls for demographics, human capital, and social capital, and we end with a model that includes interviewer fixed effects. In presenting the results in this manner, we aim to show that the linguistic signal of culture is distinct from other, well-known sources of variance in hiring outcomes.

4. Results

Table 4 reports summary statistics for our final analysis sample. Tables 5-7 show the results for questions 1-3, respectively. Table 8 shows the same results for the combination of all three questions. Each of these tables include the same five model specifications: Model (1) reports the baseline model, which controls for role and effort; Model (2) adds demographic controls; Model (3) adds human capital controls; Model (4) adds social capital controls; and Model (5) adds interviewer fixed effects. For ease of interpretation, we report hiring odds ratios as opposed to log odds in all tables.

Model (1). In Tables 5-8, Model (1) reports our baseline model, which captures the degree to which we are able to differentiate between the language of hired and not-hired candidates, controlling for their effort and desired role. All four of our measures of cultural similarity are significant, meaning that there are robust differences in the language used by hired and not-hired individuals. For work preferences fit (Table 5), a one standard deviation increase in a candidate's linguistic similarity is associated with a 22% increase in his or her likelihood of being hired. Similarly, for lifestyle fit (Table 6) and ideological fit (Table 7), the effect sizes are 18% and 25%, respectively.

Model (2). In Model (2), we add in demographic controls for gender and age. This reduces our sample size by approximately 22% due to missing data but has a negligible effect on our coefficients of interest. That is, we still see significant effect sizes of 21-29% for a one standard deviation increase in linguistic fit across the three types of cultural fit (Tables 5-7). Thus, it appears that demographics, while related to hiring outcomes overall, are not conveying the same cultural signal as our linguistic measures.

Model (3). In Model (3), which adds human capital controls (i.e., indicators for associations with high-status organizations and top-tier universities, as well as being sourced through a recruiter), we continue to observe the same pattern as models (1) and (2). In this case, both a candidate's association with a top-tier university and being sourced through a recruiter significantly affect the probability that she will be hired, but nonetheless the effects of linguistic similarity remain essentially unchanged. Specifically, one standard deviation increases in work preferences fit (Table 5), lifestyle fit (Table 6), and ideological fit (Table 7) increase the probability of being hired by 26%, 21%, and 29%, respectively. Overall, these results show that the cultural signal we identify in candidates' writing is distinct from their levels of experience and education.

Model (4). Our penultimate model, Model (4), supplements our previous models' controls with an indicator of employee referrals, which we include as a control for candidates' social capital. In these analyses, the effect sizes of our measures of linguistic similarity are reduced, but still mostly remain predictive of hiring. Specifically, one standard deviation increases in work preferences fit (Table 5) and ideological fit (Table 7) now increase the probability of being hired by 21% and 23%, respectively (down from 26% and 29%). However, the effect of lifestyle fit (Table 6) on the probability of being hired declines to 14% and loses statistical significance. This shift in the influence of lifestyle fit is particularly intriguing because it suggests that employee referrals (and, more generally, social connections) are transmitting similar information on candidates' lifestyle match. What is more, if we adhere to the idea that lifestyle fit is less likely to positively influence organizational outcomes, then our evidence seems to suggest that informal ties are one channel through which irrelevant information on cultural capital is transmitted. Finally, although the introduction of social capital controls changes the effects of work preferences fit and ideological fit only marginally, it seems to suggest that at least some proportion of the cultural signal that we capture in our language variables is interchangeable with the signal provided through informal ties.

Model (5). Model (5) controls for time-invariant interviewer idiosyncrasies using a fixed effects specification. Results indicate that interviewers' baseline acceptance rates are correlated with our measures of lifestyle and ideological fit (Tables 6 & 7), but not with work preferences fit (Table 5). As such, introducing interviewer fixed effects reduces the effect sizes of lifestyle and ideological fit (rendering them both insignificant), while leaving the effect size and significance of work preferences fit unchanged.

We see at least three possible interpretations for this pattern of results. First, it may be evidence that lifestyle fit and ideological fit affect the assignment of candidates to interviewers. That is, sorting of candidates at the interview stage is one explanation for the fact that the baseline acceptance rates of some interviewers are highly correlated with the the lifestyle and ideological fit of their interviewees. Second, interviewers may be differentially sensitive to ideological and lifestyle fit, whereas nearly all interviewers pay attention to work preferences fit. Finally, it is also possible that these results are simply representative of a loss of statistical power due to a reduction in degrees of freedom.

4.1. Supplemental Analysis of Post-hire Behavioral Fit

In our discussion of the role played by cultural fit in organizations, we highlighted the many potential benefits of well-fitting employees. In addition, our own analyses have shown a clear relationship between cultural characteristics and hiring outcomes. However, the link between these sets of evidence remains murky. On the one hand, it is possible that hiring for cultural fit leads to better post-hire behavioral fit (e.g., job candidates who are hired because they prefer a team-oriented work environment may thrive in the hiring organization's team-oriented environment). On the other hand, it is also possible that hiring for cultural fit is unrelated to subsequent fit (e.g., job candidates who are hired because of their love of Star Trek may be no more likely to fit in than those who confuse it with Star Wars). Unfortunately, as noted in footnote 1, we have access to only a relatively small sample of post-hire email data that can be used to assess the relationship between pre-hire language use and post-hire behavioral fit—based on a hired employee's conformity with the norms of linguistic style used by her colleagues in email communication.

Measuring Post-hire Behavioral Fit. We measured post-hire behavioral fit using a corpus of email messages—including not only metadata but also message content—that included messages exchanged by a subset of the applicants for whom we had pre-hire language use measures. Following Goldberg et al. (2016) and Srivastava et al. (2017), we used a measure of behavioral cultural fit that was based on the similarity of language categories used in outgoing messages sent to, and incoming messages received by, a focal actor. In other words, a person's fit increases the more she matches the linguistic style of her peers in email communication. Further details of this measurement approach can be found in Srivastava et al. (2017), but we briefly highlight here some salient features. First, these data include monthly observations for all full-time employees, including but not limited to individuals from the hiring analysis who eventually joined the company. Second, to reduce noise in the measure, we excluded employee-months in which an individual exchanged fewer than 20 messages in a given month. Finally, recognizing that cultural fit changes over time through the process of enculturation (Srivastava et al. 2017), we calculated the average fit of individuals in their first six months of employment.

Estimation. For our supplemental analyses, we estimated a basic linear regression model with controls, $\boldsymbol{X}$. Our dependent variable is average post-hire behavioral fit over the first six months of an employee's tenure, CF, and our independent variable is pre-hire linguistic similarity to the group of other hired candidates, CS. Control variables include log word count, gender, and age.

$$CF = B_0 + B_1 CS + B_2 \boldsymbol{X}$$

Results. Table 9 shows the results of the supplemental analyses. Unlike Tables 5-8, model numbers do not correspond to differing sets of controls. Instead, Model (1) shows the results for Question 1 (work preferences fit), Model (2) shows the results for Question 2 (lifestyle fit), Model (3) shows the results for Question 3 (ideological fit), and Model (4) shows the results for all questions combined. Both lifestyle fit and ideological fit are significantly predictive of behavioral (i.e., linguistic) fit, while work preferences fit is of the expected sign but not significant. We view these results as preliminary because of the small sample size; however, we believe they are suggestive of a tantalizing link between pre-hire language use and post-hire behavioral fit.

5. Discussion and Conclusion

The goal of this article has been to identify cultural signals in job candidates' pre-hire language use that predict hiring outcomes and post-hire behavioral fit and that are separate and distinct from observable human and social capital characteristics. We also sought to identify which dimensions of cultural compatibility—ideologies, work preferences, or lifestyles—matter most for hiring outcomes and post-hire behavioral fit. We found that, although all three forms of cultural fit predict hiring in between-interviewer models, only work preferences fit foretells who will be hired in within-interviewer models. Supplemental analyses indicated that ideological fit and lifestyle fit—but not work preferences fit—are predictive of successful enculturation in the firm over the first six months of employment.

5.1. Limitations and Future Directions

This work has a number of limitations, which point to avenues for future research. First, we relied on a bag-of-words approach to measuring linguistic similarity, but this is only one of many available techniques. While our text samples were both short and direct, it would useful in future work to examine longer and more open-ended texts of pre-hire language use. This would open up a wide range of natural language processing methods such as topic modeling and sentiment analysis. Not only would these analyses provide robustness checks of the signals that we identified in the present work, but they could also help pin down the mechanisms that link pre-hire language use to hiring and post-hire enculturation.

In future work, it will also be important to test and compare additional categorizations of cultural fit. We have so far identified three categories—work preferences fit, lifestyle fit, and ideological fit—that, to varying degrees, predict hiring and subsequent enculturation for hired individuals. The salient dimensions of cultural fit are, however, likely to vary across organizational cultures and may even vary across the subcultures that exist in a given organization.

Finally, our analyses of post-hire enculturation were based on a limited sample of employees, and we did not have the data needed to establish a direct link between pre-hire language use and post-hire productivity or attainment. A promising avenue for future research is to draw on more complete data across stages of the hiring process—who gets called back for an interview, how far a candidate makes it through the interview process, who gets and subsequently accepts an offer, and how well a person who joins the organization fits in and ultimately performs on the job—to pin down where and how culture matters and what forms of cultural fit are most consequential at each stage.

5.2. Contributions

In spite of these limitations, findings from this investigation both reinforce and add nuance to our understanding of culture's role in hiring and its potential consequences for inequality (Neckerman and Kirschenman 1991, Rivera 2012, Rivera and Tilcsik 2016, Sharone 2014). Rivera (2012), for example, draws on qualitative evidence that reveals cultural matching between candidates and their evaluators on lifestyle characteristics and links these matching processes to persistent inequalities in the hiring market. Our quantitative analyses complement and reinforce this account. Whether measured qualitatively through interviews or quantitatively using text analysis, lifestyle fit appears to be an influential predictor of who gets hired, including in models that include human capital controls. At the same time, our results paint a more nuanced picture of cultural matching: in models that add social capital controls lifestyle fit no longer predicts hiring, suggesting employee referrals transmit some of the same cultural information as self-reported lifestyle preferences.

That lifestyle preferences are predictive of hiring (in some specifications) and of post-hire behavioral fit also complicates Rivera's contention that hiring managers are often more concerned with reinforcing the prevailing organizational culture than they are with maximizing employee productivity. On one hand, although we do not have direct data on employee productivity, we view it as unlikely that lifestyle preferences—such as the hobbies people engage in outside of work or how they spend time with their families on weekends—would be associated with on-the-job performance. This is especially true for individual contributor roles with low task interdependence (e.g., field sales), which make up a large proportion of our observations. On the other hand, the link between lifestyle preferences and enculturation points to the intriguing possibility that seemingly irrelevant, outside-of-work preferences are nevertheless consequential for a person's ability to conform to colleagues' normative expectations. Prior work has linked this capacity to fit in behaviorally with local cultural norms to productivity-related outcomes such as favorable performance ratings and faster time to promotion (Srivastava et al. 2017).

Next, whereas prior work has focused on cultural matching in the form of lifestyle fit, we identify two other dimensions of cultural matching—work preferences fit and ideological fit—that are also predictive of hiring outcomes. Moreover, work preferences fit significantly predicts whether an applicant will be hired even in within-interviewer models. It remains to be explored whether work preferences fit is predictive of employee productivity post-hire. Although estimated from a small sample, it is also worth noting that work preferences is the only dimension of pre-hire cultural fit that is not significantly related to post-hire enculturation. This finding raises the possibility that hiring managers are selecting candidates on a dimension of cultural fit that is ultimately not related to their capacity to behave in normatively compliant ways.

Fourth, the fact that lifestyle fit and ideological fit are significant predictors of hiring between interviewers, but not within interviewers, suggests that there may be some sorting of interviewers to candidates on the basis of anticipated similarity on more visible traits. Both lifestyle choices and ideological preferences are easier to signal (e.g., listing specific hobbies in the "personal" line of a resume or noting past leadership roles in groups with a clear ideological bent) than are work preferences. Insofar as our finding reflects this form of sorting and is not simply a reflection of the loss of statistical power in within-interviewer models, it points to another, previously overlooked form of cultural matching—the self-selection or assignment of interviewers to candidates on the basis of anticipated cultural similarity.

Finally, our demonstration that pre-hire language use in the form of responses to short essay questions is predictive of who gets hired and of who successfully enculturates into an organization would appear to have implications for managerial practice—although our findings also raise at least as many questions as they answer. On one hand, for firms seeking to hire for cultural fit, our results point to the potential value of embedding comparable questions to the ones we used in the job application process. Doing so could potentially increase the quality of person-job match and reduce employee turnover, which imposes both direct (e.g., lost productivity) and indirect (e.g., extra effort expended by existing employees to hire replacements) costs on the organization. On the other hand, embedding such questions into the hiring process could produce a variety of unintended consequences. For example, to the extent that job seekers recognize that their essay responses are being used to evaluate cultural fit, how might they try to "game" their responses? In what instances might using language-based measures of cultural fit exacerbate, rather than ameliorate, the biases that creep into hiring decisions? Under what conditions might hiring for anticipated cultural fit lead to the formation of a workforce that is overly homogeneous and thus fails to produce novel ideas or innovations? For what kinds of job roles might it be better to hire cultural misfits rather than those who neatly fit the established cultural mold? We hope that the present study paves the way for investigations into questions such as these.

5.3. Conclusion

In sum, this article underscores the value of using language as a window into person-culture fit. Not only does pre-hire language use predict—above and beyond human and social capital characteristics—who succeeds in gaining entry to an organization, but it also foretells who, among those who are eventually hired, successfully enculturates into the organization. The introduction of language-based measures of anticipated culture fit in the screening and selection of job candidates has great promise but is also likely to create non-trivial complications for managerial practice.

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Table 1 Pre-hire Questions

Question #	Question Text
Q1	In the space below, describe your ideal work environment.
Q2	It has always been our vision at SunCo to have fun. As a team, we strive for greatness and work hard to achieve it. We also have fun in the process. In the space below, tell us about what you like to do for fun.
Q3	In the space below, tell us about how sustainability is a way of life for you personally.

Table 2 Example Pre-hire Question Answers

Question #	Example Answer
Q1	My ideal work environment is collaborative and open, where I can both have a voice in what my team produces, but more importantly learn from my coworkers and consistently evolve.
Q2	I'm a very outgoing person and love people as a whole. I enjoy casual conversation about sports, current events, entertainment and hearing about other peoples lives. For fun I also love being outdoors, playing cards, and anything competitive.
Q3	To me, simplicity and self reliance are key to sustainability. I reuse, I eat locally, I bike and use public transit where possible. I don't outsource jobs that I can do myself and I try to be conscious of how my actions affect the world around me, from resource extraction to product consumption. I like the idea living by example, not by soap box.

Table 3 Example Pre-processed Answers

Question #	Example Answer
Q1	ideal work environ collabor open can voic team produc import learn cowork consist evolv
Q2	im outgo person love peopl whole enjoy casual convers sport current event entertain hear peopl live fun also love outdoor play card anyth competit
Q3	simplic self relianc key sustain reus eat local bike use public transit possibl dont outsourc job can tri conscious action affect world around resourc extract product consumpt like idea live exampl soap box

Table 4 Summary Statistics

Variable Name	N	Mean	St. Dev.	Min	Max
Managerial Role	11,519	0.234	0.423	0	1
Log Word Count	11,519	4.078	0.814	0	6.526
Gender (Female)	11,330	0.335	0.472	0	1
Age	9,176	25.432	5.009	20	136
High-status Organization	11,431	0.116	0.320	0	1
Top-tier University	11,431	0.443	0.497	0	1
Sourced through Recruiter	11,519	0.004	0.061	0	1
Employee Referral	11,519	0.036	0.185	0	1

Table 5 Q1 - Work Preferences Fit

	Hiring Odds Ratio				
	(1)	(2)	(3)	(4)	(5)
Linguistic Similarity	1.217**	1.245**	1.261**	1.209*	1.259*
	(2.997)	(2.905)	(3.050)	(2.435)	(1.975)
Managerial Role	0.254***	0.232***	0.238***	0.252***	0.290*
	(6.420)	(5.927)	(5.813)	(5.547)	(2.135)
Log Word Count	1.162	1.120	1.115	1.084	1.227
	(1.594)	(1.056)	(1.002)	(0.728)	(1.193)
Gender (Female)		0.814	0.833	0.873	1.512
		(1.475)	(1.306)	(0.953)	(1.940)
Age		1.022*	1.021*	1.018	1.017
		(2.553)	(2.514)	(1.882)	(1.210)
High-status Organization			0.835	0.879	1.661
			(0.847)	(0.600)	(1.599)
Top-tier University			0.652**	0.675**	0.744
			(3.152)	(2.860)	(1.422)
Sourced through Recruiter			12.148***	15.027***	1.793
			(5.417)	(5.881)	(0.718)
Employee Referral				8.211***	2.924***
				(12.449)	(3.875)
Constant	0.024***	0.016***	0.019***	0.018***	0.001***
	(13.286)	(10.306)	(9.693)	(9.457)	(10.299)
Interviewer FE	No	No	No	No	Yes
Observations	10,722	8,385	8,385	8,385	8,385
Log Likelihood	−1,397.5	−1,084.5	−1,068.8	−1,011.6	−459.7
Akaike Inf. Crit.	2,803.0	2,181.1	2,155.5	2,043.2	1,249.3

Note: T-statistics in parentheses. *p<0.05; **p<0.01; ***p<0.001

Table 6 Q2 - Lifestyle Fit

	Hiring Odds Ratio				
	(1)	(2)	(3)	(4)	(5)
Linguistic Similarity	1.176**	1.213**	1.211**	1.140	1.083
	(2.818)	(2.947)	(2.892)	(1.933)	(0.822)
Managerial Role	0.255***	0.232***	0.238***	0.250***	0.292*
	(6.398)	(5.917)	(5.799)	(5.577)	(2.148)
Log Word Count	1.259**	1.296**	1.314**	1.269*	1.611**
	(2.816)	(2.746)	(2.871)	(2.424)	(3.184)
Gender (Female)		0.871	0.897	0.937	1.664*
		(0.996)	(0.781)	(0.464)	(2.430)
Age		1.023**	1.023**	1.019*	1.023
		(2.712)	(2.660)	(2.063)	(1.773)
High-status Organization			0.842	0.874	1.581
			(0.810)	(0.623)	(1.468)
Top-tier University			0.629***	0.654**	0.696
			(3.403)	(3.076)	(1.742)
Sourced through Recruiter			12.809***	15.860***	1.829
			(5.445)	(5.917)	(0.732)
Employee Referral				8.076***	2.757***
				(12.216)	(3.643)
Constant	0.018***	0.010***	0.011***	0.010***	0.000***
	(15.471)	(11.950)	(11.396)	(10.975)	(11.866)
Interviewer FE	No	No	No	No	Yes
Observations	10,828	8,477	8,477	8,477	8,477
Log Likelihood	−1,401.4	−1,085.4	−1,068.5	−1,013.2	−468.7
Akaike Inf. Crit.	2,810.8	2,182.9	2,155.1	2,046.5	1,267.3

Note: T-statistics in parentheses. *p<0.05; **p<0.01; ***p<0.001

Table 7 Q3 - Ideological Fit

	Hiring Odds Ratio				
	(1)	(2)	(3)	(4)	(5)
Linguistic Similarity	1.252**	1.285**	1.286**	1.230*	1.174
	(3.279)	(3.200)	(3.183)	(2.575)	(1.341)
Managerial Role	0.246***	0.212***	0.218***	0.228***	0.273*
	(6.306)	(5.934)	(5.820)	(5.619)	(2.195)
Log Word Count	1.178	1.195	1.214	1.203	1.513*
	(1.756)	(1.655)	(1.780)	(1.644)	(2.374)
Gender (Female)		0.873	0.894	0.923	1.749*
		(0.963)	(0.788)	(0.556)	(2.525)
Age		1.027**	1.027**	1.023*	1.026
		(3.164)	(3.108)	(2.376)	(1.761)
High-status Organization			0.874	0.921	1.608
			(0.641)	(0.385)	(1.527)
Top-tier University			0.645**	0.666**	0.724
			(3.165)	(2.886)	(1.524)
Sourced through Recruiter			11.255***	14.005***	1.536
			(4.881)	(5.331)	(0.464)
Employee Referral				8.272***	2.912***
				(12.250)	(3.765)
Constant	0.020***	0.010***	0.011***	0.010***	0.000***
	(11.944)	(10.115)	(9.682)	(9.444)	(10.167)
Interviewer FE	No	No	No	No	Yes
Observations	10,463	8,189	8,189	8,189	8,189
Log Likelihood	−1,341.4	−1,041.8	−1,028.0	−972.7	−449.6
Akaike Inf. Crit.	2,690.7	2,095.6	2,074.0	1,965.3	1,229.2

Note: T-statistics in parentheses. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 8 All Questions

	Hiring Odds Ratio				
	(1)	(2)	(3)	(4)	(5)
Linguistic Similarity	1.468***	1.529***	1.527***	1.412***	1.331*
	(5.000)	(4.845)	(4.795)	(3.847)	(2.206)
Managerial Role	0.249***	0.227***	0.233***	0.241***	0.241*
	(6.512)	(6.017)	(5.892)	(5.723)	(2.449)
Log Word Count	0.955	0.950	0.960	0.962	1.112
	(0.454)	(0.440)	(0.341)	(0.322)	(0.582)
Gender (Female)		0.818	0.839	0.877	1.587*
		(1.469)	(1.278)	(0.941)	(2.237)
Age		1.025**	1.025**	1.021*	1.021
		(3.052)	(2.965)	(2.282)	(1.601)
High-status Organization			0.854	0.895	1.498
			(0.752)	(0.525)	(1.323)
Top-tier University			0.642***	0.668**	0.716
			(3.331)	(2.985)	(1.655)
Sourced through Recruiter			11.592***	14.237***	1.868
			(5.310)	(5.774)	(0.780)
Employee Referral				7.994***	2.830***
				(12.308)	(3.818)
Constant	0.041***	0.024***	0.027***	0.023***	0.001***
	(7.695)	(6.912)	(6.551)	(6.589)	(7.808)
Interviewer FE	No	No	No	No	Yes
Observations	11,519	9,003	9,003	9,003	9,003
Log Likelihood	−1,465.5	−1,128.7	−1,112.6	−1,056.3	−496.4
Akaike Inf. Crit.	2,939.0	2,269.3	2,243.3	2,132.6	1,322.8

Note: T-statistics in parentheses. *p<0.05; **p<0.01; ***p<0.001

Table 9 **Post-hire Behavioral Fit**

	Dependent variable:			
	Average Cultural Fit (Months 1-6)			
	(1)	(2)	(3)	(4)
Linguistic Similarity (Q1)	0.012			
	(1.342)			
Linguistic Similarity (Q2)		0.017^{*}		
		(2.165)		
Linguistic Similarity (Q3)			0.020^{*}	
			(2.143)	
Linguistic Similarity (All)				0.024^{*}
				(2.336)
Log Word Count	−0.003	−0.019	−0.012	-0.029^{*}
	(−0.267)	(−1.960)	(−1.121)	(−2.457)
Gender (Female)	-0.050^{**}	-0.039^{**}	-0.044^{**}	-0.038^{*}
	(−3.311)	(−2.685)	(−2.903)	(−2.620)
Age	0.000	−0.000	0.000	0.000
	(0.005)	(−0.015)	(0.134)	(0.421)
Constant	0.182^{***}	0.234^{***}	0.212^{***}	0.288^{***}
	(4.703)	(6.161)	(4.819)	(5.668)
Observations	90	90	86	92
Log Likelihood	120.8	120.5	115.0	123.7
Akaike Inf. Crit.	−231.5	−231.0	−220.1	−237.5

Note: T-statistics in parentheses. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$