A Dynamic Multilevel Model of Demographic Diversity and Misfit Effects

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In this study, the authors proposed and evaluated the linkages of a dynamic multilevel model of demographic diversity and misfit effects in a large sample of quick-service restaurants. Using a cross-level approach, the authors studied an employee’s demographic misfit in relation to coworkers’ demographics as a predictor of turnover risk over time. At the business-unit level, they studied changes in restaurant demographic diversity in relation to changes in profitability over time and unit turnover rates in relation to profitability. The authors also studied the impact of the match between the racial compositions of the restaurants and their communities on profitability. The results supported linkages between demographic misfit and turnover and partially supported a negative association between racial diversity and changes in profitability.

Organizations are interested in achieving demographic diversity for a variety of social, legal, competitive or strategic reasons, and at least in some organizations, diversity is valued for its own sake (e.g., Thomas & Clark, 2003). In addition, “many . . . employers declare diversity to be the pot of gold for business organizations” (Perloff & Bryant, 2000, p. 102), and others suggest that organizations often assume that this is the case (Bowl, 2001; Elby & Thomas, 2001; Howard & Brakefield, 2001; Kochan et al., 2003; Richard & Kirby, 1999). This belief is not limited to management practitioners: Two thirds of surveyed members of the Society for Industrial/Organizational Psychology agreed with the statement that “diversity in the workforce gives organizations competitive advantage” (Murphy, Cronin, & Tam, 2003, Table 2). A related point is that organizations believe the match between the racial composition of the workforce and the communities they serve is an important determinant of organizational success (Kochan et al., 2003; Murphy, 1998).

These considerations, in combination with the fact that the American population is becoming increasingly diverse, suggest that increasing levels of diversity are inevitable in organizations (Ilgen & Pulakos, 1999). As a consequence, regardless of one’s value judgments regarding diversity, it is critical to understand its impact both on individuals within organizations and on organizations themselves. Although there have been many studies on the correlates of diversity, virtually no published research has simultaneously examined concrete individual- and organizational-level outcomes within an integrated multilevel context. Toward this end, we introduce and evaluate a dynamic multilevel model examining two key outcomes (organizational financial performance and turnover) putatively associated with diversity and demographic misfit.

A dynamic multilevel approach has a number of key benefits. First, it brings a much-needed multilevel conceptualization to the issue of diversity. Second, examining these issues longitudinally, and directly modeling the effects of time, may further clarify the nature of the putative diversity effects and allow for clearer conclusions of causality to be drawn as compared with cross-sectional studies. Third, there has been little research examining the relationship between diversity and organizational financial performance; greater understanding of this potential relationship would go a long way toward educating people about a key outcome that might be associated with diversity. This is critical because the effects of diversity have important social, policy, and legal implications (Crosby, Iyer, Clayton, & Downing, 2003).

This article is organized as follows. First, we provide the broad theoretical background underlying much of the research on demographic diversity and misfit. The particular demographic variables studied here were age, race, and sex, because they are probably the most salient in organizations as they are generally readily detectable (Jackson, May, & Whitney, 1995; Milliken & Martins, 1996). Second, we introduce a dynamic multilevel model of demographic diversity and misfit. Third, after describing the sample and measures used in this research, we introduce and apply cross-domain latent growth curve modeling and multilevel survival analysis (hierarchical nonlinear modeling) to evaluate the linkages of the proposed model. In the research we report here, we extend the extant literature by adding a multilevel focus and by theoretically and empirically addressing these issues over time.

Theoretical Background

Pfeffer’s (1983) seminal work introducing the term organizational demography has shaped much of the current thinking in the empirical literature on diversity. Pfeffer argued that the distribution of demographics within an organizational unit (e.g., an organization, department, or workgroup) impacts the amount of conflict within that unit. This conflict, in turn, was said to impact performance, innovation, turnover, and power distributions. Researchers have subsequently examined the effects of diversity with
regard to a wide array of demographic variables, including race, age, sex, job tenure, and functional background on outcome and process variables such as unit performance, turnover, social integration, social network strength, and conflict (e.g., O’Reilly, Williams, & Barsade, 1998).

In relational demography theory (Tsui, Egan, & O’Reilly, 1992; Tsui & O’Reilly, 1989) demographic similarity is examined at the individual level, suggesting that it positively impacts the social relationships between individuals. Conversely, demographic dissimilarity is thought to disrupt social relationships between individuals. These putative effects are thought to negatively impact affect and attitudes, which, in turn, are hypothesized to impact turnover. Despite the focus on work units and individuals, respectively, the underlying processes and theoretical rationales for both organizational and relational demography are very similar and are described below.

Several major theories in social psychology support the notion that demographic diversity or dissimilarity between individuals impacts the outcomes described above. First, the similarity-attraction paradigm (Berscheid & Walster, 1978; Byrne, 1971) states that perceived similarity leads to liking and attraction, leading to a host of positive outcomes. Two theories that speak to this point are social categorization (Tajfel, 1981; Turner, 1987) and social identity theories (Turner, 1982). A key premise of the former is that to maintain high self-esteem, people categorize others according to salient characteristics, including race, sex, and group membership (and thus maximize perceived differences between groups). The result, which has received extensive empirical support, is that individuals react more positively to interactions with people in the same group, even when group distinctions are arbitrary (Sherif, Harvey, White, Hood, & Sherif, 1961).

Other perspectives in organizational psychology also broadly support the notion that demographic diversity should be associated with negative outcomes at work. First, the notion of supplemental person–organization fit (Muchinsky & Monahan, 1987) states that similarity between an employee and his or her work environment (e.g., as created by coworkers) is associated with positive outcomes at work (Kristof, 1996). To the extent that demographic characteristics of groups create salient work environments, those who do not fit into those environments should experience negative outcomes. Likewise, Schneider’s (1987) attraction-selection-attrition theory suggests that organizations have a natural tendency toward establishing homogeneity because those who do not fit are not attracted to, selected for, or retained on the job. Having discussed this supporting theory, we now turn to a description of our proposed model.

A Dynamic Multilevel Model of Demographic Diversity and Misfit Effects

Figure 1, which loosely resembles a multilevel selection model proposed by Schneider, Smith, and Sipe (2000), depicts our dynamic multilevel model of demographic diversity and misfit effects. The model incorporates considerations from three different levels of analysis (individual, business unit, and community) and shows that the relationship between the two individual-level variables is expected to be jointly dependent on the demographic composition of the business unit and time. Time is also represented at the business-unit level, as the relationship between demographic composition and financial performance is thought to unfold over time. The second mechanism impacting profitability is turnover, providing an indirect pathway for the demographic misfit–financial performance relationship. Finally, the demographic composition of the community is thought to moderate the relationship between business-unit composition and financial performance. In the following sections, we discuss each link.

![Figure 1. Dynamic multilevel model of diversity and demographic misfit effects.](image-url)
The Relationship Between Individual-Level Demographics and Business-Unit Demographic Composition

Link A specifies an association between individual-level demographics and the demographic composition of the business unit. Demographics are properties of individuals rather than business units; however, complexities arise from the fact that there are multiple ways in which lower level phenomena can compose higher level phenomena (Chan, 1998b; Kozlowski & Klein, 2000). It is important to note that no single conceptualization is correct; rather, substantive concerns should drive one's choice of a composition model. Here, we conceptualize business-unit demographic composition as roughly analogous to Kozlowski and Klein's variance model (Chan's dispersion model).

The Relationship Among Business-Unit Demographic Composition, Individual Demographics, and Turnover

Moving left to right and bottom to top in the model, the first set of links (A, B, and C) pertains to the relationship among business-unit demographic composition, individual demographics, and turnover. These linkages, as several others that we discuss later in the introduction to this article, are based on the idea that the overall demographic composition of a unit (e.g., team, group, or business unit) creates a "context of general social relationships" (Webber & Donahue, 2001, p. 143) in which each individual employee exists (Riordan, 2000). Here we represent the entire collective by examining the effects of the group proportions within a unit. Thus, composition refers to proportions of various racial groups, the proportion of women, and the average age of employees within each business unit because we wish to describe the characteristics of the group as a whole by considering each of its constituent members. Research and theory from a variety of fields suggests that the composition of a group, be it demographic, attitudinal, or otherwise, is an important construct worthy of empirical study (e.g., McGrath, 1998). Just as the fit between people and other types of contexts influences important attitudes and behavior (Kristof, 1996), so should employees' fit within the context created by the demographic composition of their business units.

The similarity-attraction paradigm suggests that an employee embedded in a context in which he or she is dissimilar to most of the employees should be substantially less attracted to the other employees. This, in turn, should cause the employee to be less socially integrated, with weaker interpersonal bonds and greater levels of conflict between him- or herself and the others. Alternatively, demographic similarity should facilitate friendships. As a consequence, turnover should result from a lack of demographic fit to the extent that having close bonds and the associated social relationships with coworkers facilitates retention (Feeley & Barnett, 1997; McPherson, Popielarz, & Drobnic, 1992; O'Reilly, Caldwell, & Barnett, 1989). Likewise, friends (who are more likely to be demographically similar than those who are not friends) may refer one another to employers (Holzer, 1988).

Research on demographic dissimilarity has been broadly consistent with these ideas. For instance, a number of researchers have reported that precursors to turnover (e.g., psychological commitment) and turnover itself are related to dissimilarity with regard to age, race, or sex (Jackson et al., 1991; Kirchmeyer, 1995; O'Reilly et al., 1989; Tsui et al., 1992; Wiersema & Bird, 1993). In these studies, the most common approach has been to calculate a Euclidean distance (D) score at the individual level to represent the average dissimilarity between a group member and the other members of the group. A limitation of this measure is that it intermingles constructs at two levels of analysis, which may cloud inference (Sacco, Scheu, Ryan, & Schmitt, 2003). This approach is problematic statistically because the individual-level sample size overestimates the number of units, which can lead to Type I errors. Second, it also has conceptual limitations because it suggests that the effect in question solely occurs at the individual level, underemphasizing the potential for group-level effects or moderators. Third, it collapses across racial groups by treating individuals as either the same or different. Fourth, including explicit composition models allows other researchers to formulate future work from a common theoretical framework. It is important to note, however, that much of the existing research in this area predates the awareness of the potential of multilevel statistical models. Now, given their widespread availability (e.g., Raudenbush & Bryk, 2002), a more precise treatment might simultaneously model the group- and individual-level effects.

Our perspective on this issue is consistent with that of Riordan (2000), who suggested that the mixed findings in relational demography studies might be a function of the different measures used. This is consistent with research indicating that different operationalizations of similarity yield different results (Clark & Ostroff, 2003; Riordan, 1997; Sacco et al., 2003). This is not merely a statistical issue; rather, a levels-of-analysis perspective would clarify important conceptual issues in relational demography research (i.e., the levels at which focal constructs exist and allowing for further development of nomological networks). Likewise, operationalizations of demographic similarity should be closely linked to the level at which the focal constructs are hypothesized to exist. This, in turn, will lead to the use of appropriate composition theories as well as analytical approaches that do not suffer from the limitations described in the first section of the introduction. At least two studies have been consistent with this perspective (Leonard & Levine, 2003b; Sørensen, 2003). On the basis of the theory discussed immediately above, we propose the following hypotheses:

Hypothesis 1a: The sex-based fit of the individual within an organizational unit will predict individual turnover risk such that misfit is associated with a higher turnover risk.

Hypothesis 1b: The race-based fit of the individual within an organizational unit will predict individual turnover risk such that misfit is associated with a higher turnover risk.

Hypothesis 1c: The age-based fit of the individual within an organizational unit will predict individual turnover risk such that misfit is associated with a higher turnover risk.

Along these lines, the model in Figure 1 contains a cross-level effect (Rousseau, 1985) in that the demographic composition of the business units moderates the individual-level demographics–turnover relationship. This is consistent with the notion that fit is an inherently multilevel construct (Schmitt & Chan, 1998; Werbel & Gilliland, 1999). Thus, our model not only represents a conceptual extension but also implies the use of an analytical approach.
(multilevel survival analysis) that is tightly linked to theory, which, in turn, yields results that are more readily interpretable as compared with some earlier approaches. Moreover, examining individual turnover risk rather than group-level turnover rates allows for the explication of which individuals are more likely to turn over, a nuance lost at the group level. This also allows us to examine the effects of individual-level variables such as tenure (i.e., time, discussed in the next section along with other individual-level variables). We note, however, that a number of researchers have examined various types of demographic similarity and turnover-like outcomes using more traditional approaches (e.g., Jackson et al., 1991; Kirchmeyer, 1995; Tsui et al., 1992; Wagner, Pfeffer, & O’Reilly, 1984; Wiersema & Bird, 1993). In this study, we extend previous research by overlaying a levels-of-analysis perspective.

The Moderating Effect of Time on the Relationship Among Business-Unit Demographic Composition, Individual Demographics, and Turnover

Link C suggests that the cross-level interaction between individual-level demographics and business-unit demographic composition will vary as a function of time. Two studies suggest this may be true. First, Harrison, Price, and Bell (1998) found that time moderated the relationship between sex (though neither race nor age) diversity and group social integration such that diversity’s negative effects faded over time. Likewise, Flynn, Chatman, and Spataro (2001) found that extraversion mitigated the negative impressions of demographically dissimilar coworkers. The common theme among these studies is that time and extraversion were thought to facilitate more meaningful interactions among people that might dispel any negative impressions that may have been due to demographic dissimilarity.

Despite the compelling rationale and the findings of these studies, there is room for conceptual and analytical extensions. First, Harrison et al. (1998) examined a group-level outcome and thus did not directly test predictions concerning specific individuals. Conversely, Flynn et al. (2001) examined this issue entirely at the individual level; however, we treat the effects as though they are multilevel in nature. We extend these earlier studies by specifying that individuals who do not fit within a demographic composition are more likely to turn over, and that this will be more likely to occur earlier in their tenure. That is, taking a multilevel perspective, time is understood precisely with regard to the tenure of individual employees within the broader context of an already existing business-unit demographic composition, and the impact on specific individuals (i.e., those who do not fit demographically) is specified. Second, Harrison and colleagues examined newly formed workgroups; however, the entry and exit of individual employees into a broader organizational unit is likely more representative across situations at work. Likewise, because their study focuses on only a single level of analysis, time is only treated at the group level. Third, we extend the work of Flynn et al. by studying turnover as the relevant outcome and by using analytical techniques that are tied to the multilevel theory underlying the predictions. Fourth, we extend both studies by examining the business-unit composition as a dynamic, rather than static, predictor. We present these hypotheses related to time below:

**Hypothesis 2a:** The impact of sex-based demographic misfit on turnover risk will be stronger earlier in employees’ tenure.

**Hypothesis 2b:** The impact of race-based demographic misfit on turnover risk will be stronger earlier in employees’ tenure.

**Hypothesis 2c:** The impact of age-based demographic misfit on turnover risk will be stronger earlier in employees’ tenure.

The Relationship Between Business-Unit Demographic Diversity and Financial Performance

Link E proposes that business-unit demographic diversity is related to financial performance, a relationship that unfolds over time. Diversity is conceptualized as the variance model of Kozlowski and Klein (2000) and Chan’s (1998b) dispersion model. That is, we define diversity as the variability within each business unit with regard to employee demographics. This approach derives from the common use of the term, as well as the meaning attached to it by authors cited throughout this article.

A number of studies have suggested that a relationship between demographic diversity and organizational financial performance exists, and yet few researchers have studied this issue. This represents a large void in the empirical literature because the outcomes associated with diversity are immensely important from a practical perspective (Crosby et al., 2003). The similarity-attraction paradigm and supplemental theories of fit suggest that diversity should impact important group-level outcomes because of the attitudinal and affective consequences of diversity discussed earlier. Diversity has been linked to a host of group processes and outcomes such as group cohesion and performance, social integration, conflict, cooperation, coordination, communication, turnover, climate strength, and absence (e.g., Colquitt, Noe, & Jackson, 2002; Pelled, Eisenhardt, & Xin, 1999; Timmerman, 2000; Tsui et al., 1992; Zenger & Lawrence, 1989; see Riordan, 2000, and Williams & O’Reilly, 1998, for reviews). These disruptions, in turn, should impact the performance of groups, and thus may also distract the attention and energies of managers who are in charge of directing and monitoring group performance and focusing it toward financial outcomes. Despite the relative consensus among researchers concerning the conceptual support for the effects of demographic diversity, the empirical results have largely been “mixed . . . and contradictory” (Riordan, 2000, p. 152). For instance, although there are numerous studies suggesting that demographic diversity has negative consequences at work, a recent meta-analysis by Webber and Donahue (2001) suggested that demographic diversity was unrelated to group cohesion or performance. An important caveat, however, is that only 233 and 622 teams were available for the analyses, respectively, suggesting that more large-sample primary studies are needed.

Conceptually, the linkage to the financial performance of organizational units represents the next logical outcome in the theoretical chain of diversity effects. We agree with the anonymous reviewer who suggested that there is an imperfect association between the performance of collectives and the financial outcomes associated with that performance (Campbell, Gasser, & Oswald, 1996; Ilgen & Pulakos, 1999). To be specific, the former refers to the quality of a work product, whereas the latter is a socially constructed outcome not under the group’s direct control; how-
ever, it is possible to alleviate many of the extraneous forces that can impact financial performance using longitudinal methods.

We have been able to locate only two published quantitative studies of diversity and firm financial performance (Richard, 2000; Richard, McMillan, Chadwick, & Dwyer, 2003). Both studies reported a null main effect for racial diversity on financial performance and suggested that “the effects and their direction could be more precisely assessed through longitudinal studies” (Richard et al., 2003, p. 122). These null results are consistent with those reported by Leonard and Levine (2003a). Given the results that contradict theory and other research, it appears that additional research is needed, especially longitudinal studies. On the basis of the broader theory and research, we formulated the following hypotheses, acknowledging that the studies discussed above make them somewhat more tentative than the earlier hypotheses:

Hypothesis 3a: Race diversity will be negatively related to the profitability of organizational units.

Hypothesis 3b: Age diversity will be negatively related to the profitability of organizational units.

Hypothesis 3c: Sex diversity will be negatively related to the profitability of organizational units.

The Relationship Between Turnover and Business-Unit Financial Performance

Link D connects individual turnover and organizational financial performance. Turnover truly occurs at the individual level of analysis; however, to test the linkage, one must aggregate turnover to the business-unit level (i.e., calculate turnover rates). Aggregating data in this way is conceptually meaningful because it allows one to describe the overall stability of the workforce within a given business unit vis-à-vis the frequency with which employees leave the organization.

It is likely that the instability implied by a high turnover rate disrupts the informal relationships among employee groups that develop over time and facilitate unit performance. These types of effects have been documented in the organizational literature since the Hawthorn studies in the 1920s (see Roethlisberger, 1980). We are aware of no empirical literature, however, directly linking turnover and performance via this particular process explanation.

A related notion is that turnover might be related to individual-level job performance both directly and indirectly through job satisfaction (Griffeth, Hom, & Gaertner, 2000). As a consequence, one would expect business-unit performance to suffer to the extent that turnover is indicative of low levels of individual-level job performance.

Moving from the social to the task side of effectiveness, high turnover rates may disrupt the task functioning within the unit, because skilled employees exit the organization, and less experienced labor must be deployed. Even in simple jobs, it is easy to imagine how inexperienced workers would perform their jobs more poorly or slowly, even in the presence of additional staff. On the basis of this research and theory, we hypothesized that:

Hypothesis 4: Business-unit turnover rates will be negatively related to the profitability of organizational units.

The Match of Workforce and Community Racial Composition and Profitability

Link F suggests that there are community-level influences on the composition–financial performance relationship. This proposition is based on supporting theory as well as on urgings by levels-of-analysis theorists that higher level contextual factors be considered in multilevel models (e.g., Kozlowski & Klein, 2000).

Here, we adapt some of the key ideas outlined by Leonard and Levine (2003a) to support this linkage. First, these authors pointed out that employees with social connections to the community will often generate increased customer traffic through these relationships. Second, they suggested that intergroup communication suffers because different groups use different colloquialisms, such as slang. Perhaps such differences in communication highlight differences between groups and thus have the potential to make customers who do not fit with the composition of the employees feel uncomfortable and less likely to return in the future.

Leonard and Levine (2003a) summarized several studies indicating mixed support for this idea. Much of the evidence is indirect, such as studies indicating relationships between the similarity of athletes and their fan base. Further, the few researchers who have examined this issue more directly have found conflicting results, though small samples were generally used. One exception to this is Leonard and Levine’s article, in which they reported null results that were perhaps due to economic factors that served to mask, or otherwise bias, the results in a direction opposite from that which was predicted. As a consequence, we used per capita income in the community as a key economic variable that might clarify the true relationships of interest. As before, we formulated a hypothesis on the basis of strong supporting theory but with some caution based on the results of other studies. We studied only racial match because race has received the most attention in this regard, and also because we think it is most salient:

Hypothesis 5: The racial similarity between the workforce and the community will be positively associated with the profitability of organizational units.

Method

Sample

The initial sample consisted of 255,630 crew members from 3,454 quick-service restaurants across the United States. The organization defined a crew member as any restaurant employee who was not a manager or a member of the security staff. We obtained a census of all of the crew members employed over a span of 70 weeks. Racial groups that accounted for more than 1.0% of the total sample were: White (46.6%), Black (30.5%), Asian/Pacific Islander (2.8%), Hispanic (18.2%), and Native American (2.0%). 51.3% of the participants were women, and the average age of the participants was 19 years; the age of the employees was severely

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1 It is clear that it is also true that there are administrative costs associated with hiring that must occur to replace employees who have turned over. We do not emphasize these costs in our conceptual analysis of the relationship between turnover and organizational financial performance, however, because it is psychologically uninteresting despite its practical importance. In the Method section, we explain how our profitability measure is not sensitive to such costs.
skewed in that approximately two thirds of the participants were between 16 and 23 years old.

Each restaurant was independently operated, though there were highly standardized operating guidelines across the organization. Crew members had responsibility for all of the daily nonmanagerial and nonsupervisory tasks at the restaurants. This included, for instance, preparing and serving food, working the cash register, and cleaning the premises. Because the duties of a crew member on a particular day tended to be narrowly focused (e.g., working the drive-through window), no one crew member could serve a customer without assistance from another crew member. Thus, the restaurant crew required at least a basic level of interdependence, a notion that is supported by the O*NET job analysis database listings for Combined Food Preparation and Serving Workers, Including Fast Food (O*NET, 2003). In particular, a number of team-related work activities received the following scores on importance on a 1–100 scale, where 50 (O*NET, 2003). In particular, a number of team-related work activities received the following scores on importance on a 1–100 scale, where 50 corresponds to the midpoint of the scale: getting information (71); establishing and maintaining interpersonal relationships (67); communicating with supervisors, peers, or subordinates (50); resolving conflicts and negotiating with others (46); and assisting and caring for others (42).

Measures

Demographics

To calculate a racial diversity indicator for each restaurant, we used Blau’s (1977) index of heterogeneity for categorical variables:

\[ RD_j = 1 - \sum_{i=1}^{s} p_i^j \]

where

- \( RD_j \) = racial diversity in restaurant \( j \)
- \( P_i \) = proportion of group members in a racial category
- \( i \) = number of different categories in restaurant \( j \)

This index varies from 0 to 1 asymptotically, and higher values indicate higher heterogeneity. Where the dissimilarity between an employee and the racial composition of the restaurant was the focus, we used two restaurant-level composition variables to indicate the proportions of Blacks, Hispanics, and Whites in a given restaurant. To reduce the number of highly correlated dummy-coded variables in the models, we did not include Asians and Native Americans in these analyses. Because these groups represented such a tiny fraction of the sample, the effect of omitting these groups was likely to be very small. At the individual level, we used dummy codes. We captured restaurant-level composition with regard to sex as the proportion of women. We calculated age as the mean crew member age within a given restaurant. We calculated these demographic composition variables for each of eleven 4-week time periods on the basis of all of the crew members who worked in that restaurant during each time period.

Turnover

We obtained each employee’s hire and termination dates from organizational records. At the business-unit level, we calculated a turnover rate by dividing the number of turnovers by the number of employees for a given period.

Controllable Profit

The organization that provided these data tracks each restaurant’s controllable profit, which is the total revenue from sales minus the cost of food and labor and minus semivariable costs such as utilities and supplies. This last category of expenses is fairly constant over time, though the restaurant general manager (RGM) and crew exert some control over these types of costs. Fixed overhead costs such as rent, administration, and so forth are not included because they are not under the control of the RGM or the crew. Controllable profit is of obvious interest to the organization and is the basis for assessing restaurant performance and that of the RGMs. Thus, to the organization, it represents the most global and important indicator of restaurant performance and served as the restaurant-level outcome in this study. Controllable profit was available for eleven 4-week periods for 2,476 restaurants (which employed a total of 203,766 crew members). The listwise \( N \) for the cross-domain latent growth curve models was 2,373 restaurants.

We have acknowledged that profitability is not a behavioral outcome. Nonetheless, there are several considerations speaking to the appropriateness of this criterion. First, sales revenue exhibited an average same-time-period correlation of .91 with controllable profit; the former is very closely aligned with business-unit level behavioral outcomes because it is a direct function of the number of items sold. This suggests that the impact of expenses, although still under the control of the crew to a certain extent, has a near-zero impact on the rank ordering of restaurants’ controllable profit. Second, focusing on controllable profit rather than on profit per se eliminates many of the concerns associated with traditional (i.e., pure) measures of profitability. Third, by examining changes in controllable profit over time, we largely control any between-restaurant differences that seriously impact restaurant controllable profit. This is especially true for static or relatively static influences such as location, market demand, or product offerings. In sum, changes in restaurant controllable profit are substantially more proximal to overall performance than many other objective measures.

Community Demographics and Per Capita Income

Community demographic diversity served as a control for Hypotheses 3a–3c and as a key predictor in Hypothesis 5. We used data from the 2000 census (U.S. Census Bureau, 2000) for the geographic area defined by each restaurant’s zip code to assess community demographics. In our view, the zip code was large enough to serve as an indicator of the restaurants’ communities but not so large that it would stretch far beyond their bounds. Extending the geographic area considered would have created a host of difficulties, because the next larger geographic area would have often included more than one restaurant and would have varied considerably in size. For Hypothesis 5, we calculated the racial composition of the zip codes using the racial group categories described in the Sample section. For Hypotheses 3a–3c, we used race, sex, and age information, respectively, to calculate zip code diversity on each of these variables. For age, the census reported the number of residents in 12 age ranges rather than the age of each individual person. We created an index of age diversity by calculating the standard deviation across the 10 categories that applied to the ages of the employees studied here (15–19, 20–24, 25–34, 35–44, 45–54, 55–59, 60–64, 65–74, 75–84, and 85 or more years). This index was unrelated to the age diversity of the restaurants; thus, it was not considered further.

We also used the per capita income (PCI) in each zip code as a control variable for Hypothesis 5. Initial analyses indicated that the linear correlation between PCI and controllable profit was less than .01, qualified by a significant negative quadratic association between the two variables after we controlled for the linear component. As a consequence, we included both PCI and PCI^2 as controls.

2 Most of the zip codes contained only one restaurant in our sample (84.3%). When there was more than one restaurant in the sample, the zip code-level data were disaggregated to each restaurant in the zip code. If there were a substantial amount of clustering within each zip code, this would raise levels-of-analysis issues. Because most of the other zip codes that had more than one restaurant only had two (13.5%), we do not think this is a serious problem in these data.
Data Analysis
The Relationship Between Demographic Fit Within a Restaurant and Turnover Risk

Much research has correlated turnover (as a binary outcome) with various predictors; however, this approach has been criticized by a number of authors, because examining turnover for only one time interval is arbitrary (Griffith & Hom, 1994; Morita, Lee, & Mowday, 1989; Peters & Sheridan, 1988; Singer & Willett, 1991), and different results can be obtained depending on the time interval examined (Murnane, Singer, & Willett, 1988). This is especially important here because we studied a high-turnover job over a fairly long time period. Survival analysis (also sometimes called ‘hazard analysis’; Allison, 1984) is designed to overcome these limitations. In survival analysis, one uses a logistic link function to model the instantaneous probability of turnover given that turnover has not yet occurred, taking into account any predictors in the model (Harrison, 2002; Willett & Singer, 1995). Thus, turnover risk is modeled continuously, and employees who are employed at the end of data collection (i.e., cases that are censored) can also be included in the analysis. Censoring can seriously impact the results of more traditional approaches, and yet survival analysis uses information from censored cases (e.g., Harrison, 2002).

The coefficients that result from survival analyses can be used to construct survival functions to predict turnover risk across the time span studied. Separate survival functions can be plotted at different levels of the predictors (e.g., a curve for each demographic group) to graphically depict their effects on turnover risk over time. This allows researchers to examine whether the impact of different variables on turnover risk varies over the time span studied. Models that include interactions with time are called nonproportional, whereas those that do not include such interactions are proportional. Additional detail can be found in the Appendix.

The Relationship Between Demographic Diversity and Controllable Profit

We tested these hypotheses using latent growth curve (LGC) methodology in structural equation modeling (Meredith & Tisak, 1990; Stoolmiller, 1995; Willett & Sayer, 1994). LGC modeling uses a latent intercept and slope representing the starting point and change over time, respectively, of a given variable with repeated measurements. The slope can be linear or a higher order polynomial (e.g., quadratic), depending on the hypothesized or observed pattern of change. Here, we sought to relate intercept and slope parameters across different variables, for example, the starting points and rates of change in restaurant diversity and profitability: cross-domain LGCs (Chan, 1998a). Our intent was to follow a two-step approach: (a) fit separate LGC models for each restaurant-level variable of interest (age, sex, and racial diversity and controllable profit) and (b) combine the demographics and profit models to see whether their slopes and intercepts covary. The controllable profit slope, rather than its intercept, was the main outcome of interest, because associations between intercepts were open to a variety of common cause explanations.

Model specification and model selection. To define the intercept, the factor loadings are fixed at 1. For the slope, the first two loadings are fixed at 0 and 1 to identify the model, whereas the remaining loadings can be fixed to represent other forms of growth (Meredith & Tisak, 1990). For example, a linear growth model for four observation periods would fix the remaining two loadings at 2 and 3, whereas a quadratic pattern would specify an additional latent slope factor in which the third and fourth factor loadings are fixed at 4 and 9 (i.e., $2^2$ and $3^2$, respectively). Alternatively, if no particular change pattern is expected, or if no easily recognizable form is seen in the data, one could freely estimate the final two slope parameters (e.g., Garst, Frese, & Molenar, 2000). We evaluated the relative fit of these freely estimated models, what we call freeform slope models, against linear or quadratic models (Chan, 1998a; Chan, Ramey, Ramey, & Schmitt, 2000); the former have also been called unspecified two-factor models (Chan, 1998a) and linear splines (Meredith & Tisak, 1990).

We used LISREL 8 (Jöreskog & Sörbom, 1993) to estimate the LGC models. We used five practical fit indices to obtain convergent evidence of model fit: the comparative fit index (CFI; Bentler, 1990) root-mean-square error of approximation (RMSEA; Steiger, 1990), normed and nonnormed fit indices (Bentler & Bonnett, 1980), adjusted goodness-of-fit index (Jöreskog & Sörbom, 1989), and standardized root mean residual (Jöreskog & Sörbom, 1986). In addition, we examined modification indices (MIs), standardized residuals, and standardized expected change parameters to determine whether fit might be improved by estimating or constraining specific parameters. We also considered substantive issues such as whether modifying a given parameter was reasonable given the research design and hypotheses. Sex diversity was uncorrelated with controllable profit (average same-time-period $r < .01$; Hypothesis 3c), so to save space, we do not report detailed results for sex diversity here (they are available on request).

To compare alternative LGC models with different slope forms, we considered three issues. First, we examined plots of the diversity and profitability trajectories to see whether there were any readily identifiable functional forms. The observed trajectories were a relatively important consideration, because there is no theoretical reason to expect that the diversity or profit variables should have any a priori form. Second, we examined changes in $\chi^2$ and the practical fit indices. Changes in practical fit indices were considered because changes in $\chi^2$ are sensitive to sample size (Brannick, 1995; Kelloway, 1995); Cheung and Rensvold (2002) suggest that changes in CFI of .02 are practically meaningful. Third, we also strongly considered the general rule that parsimony is better. Because polynomial models add more complexity to the picture, we were reluctant to endorse these models unless they both (a) provided a substantially better fit than alternative models and (b) were clearly consistent with the observed pattern of change in the trajectories.

The relationship between restaurant turnover rates and profitability. Our intent was to test Hypothesis 4 using the LGC methodology; however, there was only a very weak association between turnover rates and profitability, and this preempted the need for this approach.

The relationship between profitability and the demographic similarity of the restaurant and community. Our initial approach was to test this hypothesis using hierarchical linear modeling because both the predictor and outcome at the restaurant level were available at multiple points in time. That is, we formulated these predictions as cross-level interactions in which the demographics of the restaurants’ zip codes moderated the relationship between restaurant demographics and profitability; however, preliminary analyses indicated that the relationship between the proportion of each racial group and profitability did not vary significantly over the 11 time points across the restaurants. Thus, we computed aggregates of the demographic variables and profitability across the 11 time points and performed a traditional moderated regression analysis to test this hypothesis. We summed controllable profit across the time periods, and we computed an indicator variable for each of the four major racial groups in this study (i.e., Asians, Blacks, Hispanics, and Whites). The first step was to sum the total number of days that a member of each of these groups was employed over the 11 time periods. We then divided this by the total.

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3 Chan (1998a, p. 437) describes unspecified two-factor LGC models as “atheoretical.” We broadly agree with this point; however, an examination of the extent to which changes in demographic diversity and profitability are related is the main focus of this research rather than the particular theoretical form of changes in these variables over time. Chan also correctly points out that unspecified models provide a maximal fit to the data. Because, as stated above, the theoretical form of the individual LGC models tested here is not of substantive interest, we rely exclusively on changes in the observed trajectory patterns and, to a lesser extent, the fit indices, in deciding whether one model is preferable to another.
number of days that employees of any of the four groups were employed to arrive at a percentage of days employed for each of the four groups (we refer to these hereinafter as ASIAN©DAYS%, BLACK©DAYS%, HISPANIC©DAYS%, and WHITE©DAYS%). We then used moderated regression to test the expectation that these variables would be more strongly related to total controllable profit when the same race was more heavily represented in the restaurant’s zip code. We refer to the proportions of these groups in a given zip code as ASIANZIP%, BLACKZIP%, HISPANICZIP%, and WHITEZIP%. We also conducted these analyses for minority-majority group status, in which all of the Asian, Black, and Hispanic employees were designated as minorities (MINDAYS% and MINZIP%).

Results

Demographic Fit Within a Restaurant Composition and Turnover Probability With Regard to Sex

Table 1 summarizes the results of the multilevel survival analysis with regard to sex. The first column provides the variable name (and indicates the coding in the case of the dummy and restaurant composition variables) followed by the γ designation and associated random error components (when applicable) and then the parameter estimate (and standard error). Exp(β) represents the relative risk associated with a shift of one unit in the predictor (terms greater than one indicate a higher turnover risk). As can be seen in Column 3, all the substantive parameters of interest were significant predictors of survival probabilities. We calculated a predicted turnover hazard for each time period (a cumulative plot of these predicted values would be called a survival rather than a hazard profile) for men and women working in two different restaurant compositions using an expanded version of the following formula (Tabachnick & Fidell, 1996):

\[ P(\text{Turnover}) = \frac{e^{\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5}}{1 + e^{\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5}} \]

We used this formula in conjunction with the first set of results in Table 1 to calculate the predicted hazard curves (see Figure 2). As can be seen in the figure, being in a restaurant with a higher composition of women reduced the likelihood of turnover for a female employee by 21%. An opposite, though somewhat smaller, effect is seen for men (there was a 15% reduction in turnover risk). Thus, Hypothesis 1a was supported, as increased sex similarity was associated with lower turnover risk. Note that although the differences between the curves on the chart are relatively small, the plotted turnover hazards are not cumulative but, rather, are calculated separately for each time period. Cumulative survival probabilities would reveal larger differences.

The curves in Figure 2 are parallel because this model does not include any interactions with time (i.e., it is a proportional model). Thus, we conducted additional analyses to see whether the Sex × Restaurant Sex Composition interaction might vary as a (linear) function of time (Hypothesis 2a). This analysis included three additional cross-level effects: Sex × Time, Restaurant Sex Composition × Time, and Sex × Time × Restaurant Sex Composition. The last two columns of Table 1 summarize the results (all three interactions were significant). These results are depicted in Figure 3. There is support for the notion that the Sex × Restaurant Sex Composition interaction is initially important, but that this effect fades over time. This is evident after examining the change in the vertical displacement of the two curves for men; at the end of the first 2-week time period (Period 1), a man working in a restaurant composed of 90% women has a predicted hazard rate of 16%, as compared with a predicted hazard of 11% working in a restaurant that is composed of only 10% women. By Period 20, however, the curves cross, and the form of the relationship between sex and restaurant sex composition is reversed. A similar effect is seen for women, except that the curves cross much earlier, indicating that sex similarity effects become a less important predictor of turnover hazard more quickly as compared with that of men. These results support Hypothesis 2a.

Demographic Fit Within a Restaurant Composition and Turnover Probability With Regard to Race

For race, we added one additional variable at each level in the model, because we included three racial groups in these analyses.

Table 1
Results of HnLMs Examining the Effects of Sex Similarity on Turnover Probabilities

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter(s)</th>
<th>Proportional hazards model</th>
<th>Nonproportional hazards model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>B</td>
<td>SE</td>
</tr>
<tr>
<td>Intercept</td>
<td>γ00 + e10k</td>
<td>−2.066*</td>
<td>0.021</td>
</tr>
<tr>
<td>Time</td>
<td>γ10</td>
<td>−0.035*</td>
<td>0.002</td>
</tr>
<tr>
<td>Time²</td>
<td>γ20</td>
<td>0.001*</td>
<td>0.0001</td>
</tr>
<tr>
<td>Female</td>
<td>γ00 + e30k</td>
<td>0.207*</td>
<td>0.02</td>
</tr>
<tr>
<td>Composition of women</td>
<td>γ40</td>
<td>0.422*</td>
<td>0.04</td>
</tr>
<tr>
<td>Women × %Women</td>
<td>γ50</td>
<td>−0.532*</td>
<td>0.04</td>
</tr>
<tr>
<td>Women × Time</td>
<td>γ60</td>
<td>−2.066*</td>
<td>0.021</td>
</tr>
<tr>
<td>%Women × Time</td>
<td>γ70</td>
<td>−0.03*</td>
<td>0.004</td>
</tr>
<tr>
<td>Women × %Women × Time</td>
<td>γ80</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. HnLM = hierarchical nonlinear model; B = logistic regression coefficient; Exp(β) = relative risk associated with a shift of one unit in the predictor. Women = indicator variable for women; %Women = proportion of employees who are women.

* p < .05.
Figure 2. Plots of predicted turnover hazards from proportional multilevel survival analysis examining the effects of sex misfit. A: Female employees; B: Male employees. Circles indicate 90% female employees; triangles indicate 10% female employees.
Figure 3. Plots of predicted turnover hazards from nonproportional multilevel survival analysis examining the effects of sex misfit. A: Female employees; B: Male employees. Circles indicate 90% female employees; triangles indicate 10% female employees.
(Blacks, Hispanics, and Whites). As can be seen in the third column of Table 2, all of the coefficients for the proportional model are significant. Plots of the predicted turnover risk profiles showed support for Hypothesis 1b; however, we do not present these results because they were qualified by significant interactions (see the last two columns of Table 2). We present the results of the nonproportional models (with the nonsignificant coefficients set to zero for calculating the predicted turnover hazard) graphically in Figure 4.

For White employees, there is evidence for Hypothesis 2b, because the interactions among time, the individual-level White dummy variable, and the two restaurant composition variables were significant. Indeed, the figure shows that the difference in predicted turnover hazard among the 80% White, 10% Black, 10% Hispanic, and the other two restaurant compositions for Whites becomes smaller as time goes on. A similar effect is seen for Hispanic employees, though this is seen only in the difference among the 80% Hispanic, 10% Black, and 10% White line and the 80% White, 10% Black, and 10% Hispanic lines. The curves for Black employees are similar in that the protective effects of a predominantly Black restaurant composition on turnover hazard actually reverses its pattern with one of the other compositions at Period 16. These data suggest that the impact of racial misfit on turnover risk is higher earlier in employees’ tenure, supporting Hypothesis 2b.

Demographic Fit Within a Restaurant Composition and Turnover Probability With Regard to Age

Table 3 shows that all three interaction effects in the proportional model were significant. We calculated predicted turnover hazards at approximately the following values: average age (19 years), 10th percentile (16 years), and 90th percentile (31 years). Plots of the predicted turnover risk profiles showed support for Hypothesis 1c; these effects were qualified by significant interactions in the results of the nonproportional analysis (see the last two columns of Table 3) plotted in Figure 5. The plots show that the curve with the steepest slope is that of a 31-year-old in a restaurant with an average employee age of 16 years. Likewise, the differences in the predicted hazard values for a restaurant with an average age of 31 years are largest earlier in time. This supports the notion that these demographic effects are stronger earlier on in employees’ tenure. This analysis supports Hypothesis 2c.

The Relationships Between Demographic Diversity and Profitability

LGC Models for Racial Diversity, Age Diversity, and Controllable Profit

The data in Tables 4, 5, and 6 indicate that the means and standard deviations of race and age diversity and controllable profit were virtually constant over time; however, plots of the restaurants’ trajectories showed substantial variability in the nature of change over time. These plots revealed no readily identifiable function that might explain the changes over time; thus, for each LGC model, the last 9 of the 11 slope parameters were freely estimated (i.e., we estimated freeform models). In addition, we estimated the error covariances of adjacent time periods because the correlations exhibited a simplex pattern (i.e., they were substantially higher as the periods become closer in time). Using the data reported in Tables 4–8, we calculated a series of freeform

Table 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter(s)</th>
<th>Proportional hazards model</th>
<th>Nonproportional hazards model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$\gamma_0 + e_{0k}$</td>
<td>$-1.846^*$, $0.022$, $0.158$</td>
<td>$-2.019^*$, $0.022$, $0.133$</td>
</tr>
<tr>
<td>Time</td>
<td>$\gamma_1$</td>
<td>$-0.043^*$, $0.003$, $0.958$</td>
<td>$-0.021^*$, $0.003$, $0.979$</td>
</tr>
<tr>
<td>Time$^2$</td>
<td>$\gamma_2$</td>
<td>$0.001^*$, $0.000$, $1.001$</td>
<td>$0.001^*$, $0.000$, $1.001$</td>
</tr>
<tr>
<td>White</td>
<td>$\gamma_{30} + e_{3k}$</td>
<td>$0.254^*$, $0.041$, $1.289$</td>
<td>$0.579^*$, $0.030$, $1.784$</td>
</tr>
<tr>
<td>Hispanic</td>
<td>$\gamma_{40} + e_{4k}$</td>
<td>$0.204^*$, $0.054$, $1.226$</td>
<td>$0.216^*$, $0.053$, $1.241$</td>
</tr>
<tr>
<td>%White</td>
<td>$\gamma_5$</td>
<td>$0.394^*$, $0.030$, $1.482$</td>
<td>$0.414^*$, $0.041$, $1.513$</td>
</tr>
<tr>
<td>%Hispanic</td>
<td>$\gamma_6$</td>
<td>$0.174^*$, $0.053$, $1.190$</td>
<td>$0.202^*$, $0.054$, $1.224$</td>
</tr>
<tr>
<td>White × %White</td>
<td>$\gamma_7$</td>
<td>$-0.678^*$, $0.048$, $0.508$</td>
<td>$-0.926^*$, $0.048$, $0.396$</td>
</tr>
<tr>
<td>White × %Hispanic</td>
<td>$\gamma_8$</td>
<td>$-0.362^*$, $0.063$, $0.696$</td>
<td>$-0.516^*$, $0.063$, $0.597$</td>
</tr>
<tr>
<td>Hispanic × %White</td>
<td>$\gamma_9$</td>
<td>$-0.606^*$, $0.081$, $0.545$</td>
<td>$-0.446^*$, $0.073$, $0.640$</td>
</tr>
<tr>
<td>Hispanic × %Hispanic</td>
<td>$\gamma_{100}$</td>
<td>$-0.373^*$, $0.073$, $0.689$</td>
<td>$-0.651^*$, $0.081$, $0.521$</td>
</tr>
<tr>
<td>White × Time</td>
<td>$\gamma_{110}$</td>
<td>$-0.030^*$, $0.003$, $0.970$</td>
<td>$-0.006^*$, $0.005$, $0.994$</td>
</tr>
<tr>
<td>Hispanic × Time</td>
<td>$\gamma_{120}$</td>
<td>$-0.026^*$, $0.004$, $0.975$</td>
<td>$-0.001$, $0.005$, $0.999$</td>
</tr>
<tr>
<td>%White × Time</td>
<td>$\gamma_{130}$</td>
<td>$-0.026^*$, $0.004$, $0.975$</td>
<td>$-0.001$, $0.005$, $0.999$</td>
</tr>
<tr>
<td>%Hispanic × Time</td>
<td>$\gamma_{140}$</td>
<td>$-0.026^*$, $0.004$, $0.975$</td>
<td>$-0.001$, $0.005$, $0.999$</td>
</tr>
<tr>
<td>White × %White × Time</td>
<td>$\gamma_{150}$</td>
<td>$0.041^*$, $0.005$, $1.041$</td>
<td>$-0.006^*$, $0.005$, $0.994$</td>
</tr>
<tr>
<td>White × %Hispanic × Time</td>
<td>$\gamma_{160}$</td>
<td>$0.025^*$, $0.006$, $1.026$</td>
<td>$-0.006^*$, $0.005$, $0.994$</td>
</tr>
<tr>
<td>Hispanic × %White × Time</td>
<td>$\gamma_{170}$</td>
<td>$0.012^*$, $0.007$, $1.012$</td>
<td>$-0.006^*$, $0.008$, $1.006$</td>
</tr>
<tr>
<td>Hispanic × %Hispanic × Time</td>
<td>$\gamma_{180}$</td>
<td>$0.006$, $0.008$, $1.006$</td>
<td>$-0.006^*$, $0.008$, $1.006$</td>
</tr>
</tbody>
</table>

Note. HnLM = hierarchical nonlinear model; $B =$ logistic regression coefficient; $\text{Exp}(B) =$ relative risk associated with a shift of one unit in the predictor. White and Hispanic = indicator variables for White and Hispanic status at the individual level. %White and %Hispanic = proportion of employees in restaurant belonging to these groups.

* $p < .05$. 

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Figure 4. Plots of predicted turnover hazards from nonproportional multilevel survival analysis examining the effects of racial misfit on Black (A), White (B), and Hispanic (C) employees. Circles indicate 80% White, 10% Hispanic, and 10% Black employees; triangles indicate 10% White, 80% Hispanic, and 10% Black employees; squares indicate 10% White, 10% Hispanic, and 80% Black employees.
LGC models. The fit statistics for Models 1c, 2c, and 3c in Table 9 are based on these freeform models; Models 1a, 1b, 2a, 2b, 3a, and 3b provide fit statistics and model comparisons for the linear and quadratic slope models for the three respective variables. On the basis of the considerations described in the Data Analysis section, we accepted the freeform models for each. The slope factor loadings were consistent with the idea that freeform rather than linear or quadratic models best describe these data. Figures with completely standardized parameter estimates are available from Joshua M. Sacco on request.

Cross-Domain LGC Model for Racial Diversity and Controllable Profit

In Figure 6, we present the completely standardized parameter estimates for the racial diversity–controllable profit cross-domain LGC (4a in Table 9). As can be seen in the figure, the race intercept was significantly associated with the controllable profit slope and intercept ( \( r = .11 \) and \( r = .16 \), respectively; both \( p < .05 \)). This means that at the beginning of data collection, racially diverse restaurants also reported slightly higher profitability; however, the initial level of racial diversity correlated negatively with changes in profit.

To account for the racial diversity of the zip code, we added a single-indicator latent variable (with no disturbance term) to the model (4b in Table 9). The parameter estimates associated with this model are shown in Figure 7. As one would expect, the racial diversity of the area defined by the zip code was strongly related to the restaurant racial diversity intercept ( \( r = .71 \), \( p < .05 \)). In addition, the racial diversity in the zip code was a strong predictor of the controllable profit slope ( \( r = -.66 \), \( p < .05 \)), and the strength of the relationship between the restaurants’ racial diversity intercept and the controllable profit slope increased substantially as compared with the model depicted in Figure 6 ( \( r = -.16 \) and \( -.47 \), respectively, \( p < .05 \)). Thus, Hypothesis 3a was supported. Again, the initial level of racial diversity was associated with declining profitability over time.

To assess the practical impact of these results, we calculated predicted trajectories for different levels of racial diversity. First, using several different theoretical racial diversity compositions, we calculated standardized values of the racial diversity index. Second, we adjusted the trajectory defined by the standardized LISREL slope factor loadings on the basis of the standardized value of the racial diversity index and the correlation between the racial diversity intercept and the controllable profit slope ( \( r = -.47 \)). Third, we summed across each time period in the trajectory and multiplied by 1.18 (i.e., 52 weeks divided by the 44 weeks used in this research). Finally, we added this value to the predicted intercept, which was based on the standardized racial diversity index and the correlation between the racial diversity and controllable profit intercepts ( \( r = .11 \)). These calculations indicated that a 1 SD difference in racial diversity yields a predicted change of $39,821 in controllable profit. Because the racial diversity metric is not one that is likely to be familiar to organizational researchers, we present several hypothetical restaurant racial compositions to more clearly demonstrate the predicted effects over the course of 1 year (see Figure 8).

Each pattern in the charts represents a different racial group, and the smallest slice (e.g., one of the two small slices in Panel 2) represents 1 employee. These charts reinforce the notion that small differences in racial diversity are predicted to make sizable differences in controllable profit. For instance, the difference between Panels 5 and 6 is 2 members from one racial group, and the difference in predicted annual profit between the two compositions is over $12,000. Panel 6 has only 1 member from the nonnumerical majority group in the restaurant, whereas Panel 4 depicts a restaurant in which half of the members are of the same race and in which the remainder is made up of members of three different races. The predicted annual difference in profit for these compositions is $41,269. It is important to note that these values pertain to predicted change for a single restaurant. We note that these figures likely represent slight overestimates of these effects, because the structural parameters used in these calculations correct for the
Figure 5. Plots of predicted turnover hazards from proportional multilevel survival analysis examining the effects of age misfit on 16-year-old (A), 19-year-old (B), and 31-year-old (C) employees. Circles indicate restaurants at which the average employee age is 16 years; triangles indicate restaurants at which the average employee age is 19 years; squares indicate restaurants at which the average employee age is 31 years.
variability in measurements for which the overall latent intercept and slope do not account.4

Cross-Domain LGC Model for Age Diversity and Controllable Profit

Figure 9 provides a representation of this model along with the standardized parameter estimates (Model 5a in Table 9). As can be seen in the figure, the age diversity intercept was positively and significantly associated with the profitability intercept ($r = .18$, $p < .05$), but was negatively associated with controllable profit ($r = .04$, and the average correlation for adjacent time points ($r = .04$), a result that did not change when significance. Thus, Hypothesis 3b was not supported.

The Relationship Between Restaurant Turnover Rates and Profitability

Overall, the intercorrelations among the monthly turnover rates were negative although generally small. To be specific, the average correlation was $r = -.04$, and the average correlation for adjacent time periods was also small ($r = -.05$). This made it impossible to adequately represent the change over time in LGC terms. This was compounded by the null relationships between the turnover rates and controllable profit (average $r = .00$), even at the same time points (average $r = -.01$), a result that did not change when we doubled the length of the time periods or aggregated them across the entire length of the study. Hence, Hypothesis 4 was not supported.

The Relationship Between the Similarity of Restaurant Demographics and Community Demographics With Profitability

In Table 10, we present the means, $SD$s, and intercorrelations for the variables used to test Hypothesis 5. As would be expected, the representation of the four groups in the zip codes was significantly related to the proportion of employment days for which each accounted ($r = .39-.69$, $p < .05$), supporting the appropriateness of these measures. In addition, the proportion of days worked by Hispanic employees was positively associated with controllable profit ($r = .18$, $p < .05$), but was negatively associated with controllable profit for Black employees ($r = -.20$, $p < .05$).

We used only three of the four racial group proportions in the regression analysis, because the fourth is linearly dependent on the first three (i.e., it is the remainder when the sum of the first three are subtracted from 1; see Table 11). PCI and PCI² yielded significant though relatively small predictions of controllable profit ($\Delta R^2 = .003$, $\beta_{PCI} = .148$, $\beta_{PCI^2} = -.158$). In the second step, we entered the three proportions for the days employed at the restaurant level. In the third step, we entered these groups’ representation in the zip code, and we entered the product terms in the final step. Two interaction terms were significant: HISPDAYS% $\times$ ASIANZIP%, and WHITEDAYS% $\times$ WHITEZIP%.

To better understand the interactions, we plotted the results using the coefficients and constant from the final step of the regression. We chose two levels of each of two of the proportions (i.e., zip code and employed days at restaurant): 33% and 66%, whereas the remaining proportions were set to be equal. The pattern of results does not support the notion that profitability is higher when a group has a high representation in both the restaurant’s workforce and the zip code (see Figure 10). The results for the minority–majority analysis are shown in Table 12. The coefficient for the interaction term was negative, indicating that minority representation was negatively associated with profitability in higher minority zip codes. Neither analysis supported Hypothesis 5.

We investigated whether the community racial composition might be an inappropriate measure of the potential customer base because quick service restaurants are often situated near highway exit ramps (i.e., to serve travelers). First, all of the restaurants’ addresses were read into a geographic information systems software package. The software was able to automatically geocode (i.e., locate) 2,313 (93%) of the addresses. Next, we used the software to determine which restaurants had an interstate highway exit located within a 0.5-mile radius ($n = 335$, 14% of the geocoded restaurants). Omitting these restaurants from the regressions reported in Tables 11 and 12 yielded results nearly identical to those reported in the table (details available on request). As a result, we used only the data from the remaining 1,978 restaurants for the analysis.

Table 4
Descriptive Statistics and Intercorrelations for Restaurant Racial Diversity at the 11 Time Periods and Zip Code Racial Diversity

<table>
<thead>
<tr>
<th>Variable</th>
<th>M</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. RD Time 1</td>
<td>.38</td>
<td>.21</td>
<td>1</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. RD Time 2</td>
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<td>.21</td>
<td>.93</td>
<td>1</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>3. RD Time 3</td>
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<td>.21</td>
<td>.87</td>
<td>.94</td>
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<td>.91</td>
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</tbody>
</table>

Note. RD = racial diversity. All correlations are significant at $p < .05$. N = 2,373 restaurants.

4 We thank David Chan for bringing this point to our attention.

5 We thank David I. Levine for suggesting this analysis.
consequence, our results cannot be easily explained by the fact that some of the restaurants might have served interstate highway travelers rather than the communities in which they were located.

Discussion

In the research reported here, we evaluated the linkages of dynamic multilevel models of demographic diversity and misfit effects. We studied hypothesized linkages with a large number of employees from a national sample of quick service restaurants. There was support for some of the main linkages in the model, but overall, the results were mixed. In the following sections, we discuss the results pertaining to each link in turn. In doing so, we pay close attention to key implications and potential explanations for the observed results, as well as directions for future research. We then discuss the results more broadly in terms of how the model and results further our understanding of diversity in organizations.

Relationship Between Demographic Misfit on Turnover

The relational demography literature reviewed in the introduction to this article suggested that an employee who was demographically dissimilar to his or her coworkers would have a higher turnover risk. There was support for this set of hypotheses for all three demographic variables studied—age, race, and sex. This suggests that being demographically different from one’s work cohort is associated with attitudes about some aspects of the job that may lead to turnover. The results also indicated that demographic mismatch is related to higher turnover risk earlier in an employee’s tenure, and that this effect fades and, in some cases, reverses direction over time.

For instance, socialization interventions that accelerate the process by which employees get to know one another might be helpful. Such interventions may be especially helpful in environments such as those studied here, in which the turnover rate is relatively high.

Table 5

Descriptive Statistics and Intercorrelations for Restaurant Age Diversity at the 11 Time Periods and Zip Code Age Diversity

<table>
<thead>
<tr>
<th>Variable</th>
<th>M</th>
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</table>

Note. AD = age diversity. All correlations greater than .03 are significant at \( p < .05 \). \( N = 2,373 \) restaurants. Age diversity was divided by 100 because LISREL could not calculate starting values with the original large values.

6 Although the effects reverse in direction, so few employees remain on the job by the time most of these reversals occur, the practical impact of these effects is likely to be trivial.
caveats: (a) this relationship could have been caused by a third variable (though we think this is unlikely for the reasons stated above) and (b) the slopes were unrelated, which would have provided stronger support for the hypothesis.

The findings with regard to racial diversity provide some evidence for the relevance of these theories to organizational science, moving beyond studies that examine softer criteria such as communication or attachment to an organization. It is important to note, however, that we did not obtain these results for sex or age diversity. Because of the sample size and nature of the measures used here, these null results cannot be easily ascribed to a lack of power. These results have two important implications. First, the mixed results suggest that relational demography theory may be too broad and that the salience of different types of demographic diversity might vary as a function of the situation and the demographic variable that is considered. Second, they suggest that racial diversity may be associated with something more powerful and organizationally relevant as compared with the other two types of diversity studied here. Though it is tempting to ascribe this to the overall relevance of race to everyday life, future research should seek to identify why this might be the case. On the other hand, it is also possible that our sample was too restricted in terms of age diversity to yield any significant effects. It should be noted, however, that Leonard and Levine (2003a) suggested that such range restriction might yield opposite effects.

A related question is why age and sex misfit was associated with turnover risk, but diversity on these variables was not associated with profitability. The former result suggests that racial diversity might substantially disrupt some aspect of work unit communication or coordination that, in turn, impedes profitability. On the other hand, on the basis of our results, age or sex diversity do not seem to be associated with the same effects, but rather are something that is perhaps more interpersonally- rather than task-based. Although we did not have information on absenteeism available to us, crew members were responsible for finding their own replace-

### Table 6

Descriptive Statistics and Intercorrelations for Restaurant Controllable Profit at the 11 Time Periods and Zip Code, Age, Sex, and Racial Diversity

<table>
<thead>
<tr>
<th>Variable</th>
<th>M</th>
<th>SD</th>
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<th>2</th>
<th>3</th>
<th>4</th>
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</tbody>
</table>

Note. CP = controllable profit; T = time; Zip RD = racial diversity in zip code; Zip %M = percentage of males in zip code; Zip Code AD = zip code age diversity. All correlations are significant at $p < .05$. $N = 2,373$ restaurants.

### Table 8

Intercorrelations Between Restaurant Age and Racial Diversity and Controllable Profit at the 11 Time Periods

<table>
<thead>
<tr>
<th>Controllable profit</th>
<th>Age diversity time period</th>
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<td>Time 9</td>
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</tr>
<tr>
<td>Time 10</td>
<td>.16</td>
</tr>
<tr>
<td>Time 11</td>
<td>.15</td>
</tr>
</tbody>
</table>

Note. All correlations greater than .03 are significant at $p < .05$. $N = 2,373$ restaurants.
ments when they were unable to work on a day they were scheduled to work. Crew members who were demographically dissimilar to their colleagues may have encountered more difficulties in changing their work schedules, or they may have had more unexcused absences. Both outcomes could have led to an increased turnover risk. This provides one possible explanation for the observed differences in the correlations of demographic misfit and diversity; however, the unanswered question that still remains is why the effects of age and sex misfit may have been pervasive enough to impact interpersonal relations with coworkers but not to task work outcomes that likely impact profitability. Given that organizational and relational demography theories make similar predictions about the effects of different types of demographic diversity, future theory and research that addresses this issue would be especially informative.

This is the first large-scale study in the psychological or management literature linking racial diversity to organizational profitability. If this finding can be replicated in other settings, it presents a serious quandary for organizations that seek to become more racially diverse. This is underscored by the fact that the measures of racial diversity, like the other measures in this study, underestimate the true effect sizes because of missing information about how many hours each employee worked at a given restaurant, and more important, which employees actually worked together. Further, because these results were obtained even after controlling for the racial diversity in the community, hiring decisions made for a particular restaurant become very important, because each restaurant is embedded in a community whose demographic composition is a relatively stable environment that is unlikely to quickly change over time.

As a consequence, although there may be political or social reasons to seek racially diverse workforces, results such as these suggest that racial diversity may negatively impact an organization’s bottom line. This is especially true because our data suggest that diversifying in an effort to match the racial composition of one’s workforce to that of the community will not impact profitability. Organizational decision makers are thus potentially faced with a choice between two goals that are mutually exclusive to some extent. This parallels the tension often seen at the individual level between minority representation and average levels of individual-level job performance (DeCorte, 1999; Sackett & Roth, 1996; Silva & Jacobs, 1993), a point that we discuss in more detail later in the discussion. It is important to emphasize, however, that these results speak to the impact of racial diversity per se, rather than to the representation of a particular racial group.7 An additional point of importance is that despite the large sample of individuals and units, this research was still conducted in a single organization with one specific and a very simple type of job. It is entirely possible that future research in other settings might lead to different results.

### The Relationship Between Turnover Rates and Profitability

We expected turnover rates to impact profitability via disruptions they caused. Contrary to expectations, the two vari-

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7 We investigated the possibility that the representation of one particular racial group was driving the overall level of racial diversity in the restaurants by examining the correlations between the number of employees belonging to each racial group and the index of racial diversity for each of the 11 points in time. The vast majority of the same time period correlations ranged from −.30 to .30, indicating that our racial diversity measure was not strongly related to any one group’s representation. We thank Katherine J. Klein for bringing this issue to our attention.

---

Table 9

**Fit Statistics and Model Comparisons for Single-Construct and Cross-Domain Latent Growth Curve Models**

<table>
<thead>
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<th>Model</th>
<th>Description</th>
<th>df</th>
<th>$\chi^2$</th>
<th>Comparison</th>
<th>$\Delta df$</th>
<th>$\Delta \chi^2$</th>
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<th>RMSEA</th>
<th>SRMR</th>
<th>NFI</th>
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<td>RD quadratic</td>
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<td>RD freeform</td>
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<td>593.53*</td>
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<td>134.64*</td>
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<td>3a CP</td>
<td>CP linear</td>
<td>51</td>
<td>4,536.89*</td>
<td></td>
<td></td>
<td>.89</td>
<td>.21</td>
<td>.05</td>
<td>.88</td>
<td>.88</td>
<td>.75</td>
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<tr>
<td>3b CP</td>
<td>CP quadratic</td>
<td>47</td>
<td>2,406.88*</td>
<td></td>
<td></td>
<td>.94</td>
<td>.15</td>
<td>.04</td>
<td>.94</td>
<td>.93</td>
<td>.90</td>
<td>.90</td>
</tr>
<tr>
<td>3c CP</td>
<td>CP freeform</td>
<td>42</td>
<td>643.16*</td>
<td>3b and 3c</td>
<td>5</td>
<td>1,763.72*</td>
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<td>.08</td>
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<td>.98</td>
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<tr>
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<td></td>
<td>3a and 3c</td>
<td>9</td>
<td>3,893.73*</td>
<td></td>
<td></td>
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<tr>
<td>4a RD</td>
<td>RD, CP</td>
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<td>1,178.78*</td>
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<td></td>
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<td>.05</td>
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<td>.95</td>
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<tr>
<td>4b RD</td>
<td>RD, CP, RD Zip</td>
<td>209</td>
<td>5,027.25*</td>
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<td></td>
<td>.95</td>
<td>.08</td>
<td>.03</td>
<td>.95</td>
<td>.94</td>
<td>.94</td>
<td>.94</td>
</tr>
<tr>
<td>5a AD</td>
<td>AD, CP</td>
<td>200</td>
<td>1,336.37*</td>
<td></td>
<td></td>
<td>.98</td>
<td>.05</td>
<td>.05</td>
<td>.98</td>
<td>.98</td>
<td>.98</td>
<td>.98</td>
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</tbody>
</table>

Note. Data for the models are in the following tables: 1a–1c, Table 4; 2a–2c, Table 5; 3a–3c, Table 6; 4a and 4b, Tables 4, 6, and 7; 5a, Tables 5, 6, and 8. Freeform models were used for Models 4a–5a. Models with nonadjacent error covariances estimated: 1a–1c (Tables 3 and 5); 2a–2c (Tables 6 and 8, Tables 4 and 6, Tables 9 and 11); 4a (RD Tables 1 and 3), 4b (RD Tables 1 and 3, RD Tables 8–10). To facilitate estimation, in Models 4a and 4b, we fixed RD factor loadings for Tables 5 and 7 on the basis of LISREL estimates in Model 1c; we did the same for Model 5a on the basis of estimates from Model 2c. CFI = comparative fit index; RMSEA = root-mean-square error of approximation; SRMR = standardized root-mean-square residual; NFI = normed fit index; NNFI = nonnormed fit index; AGFI = adjusted goodness-of-fit index; RD = racial diversity, AD = age diversity, CP = controllable profit.

* $p < .05$. 

---

7 We investigated the possibility that the representation of one particular racial group was driving the overall level of racial diversity in the restaurants by examining the correlations between the number of employees belonging to each racial group and the index of racial diversity for each of the 11 points in time. The vast majority of the same time period correlations ranged from −.30 to .30, indicating that our racial diversity measure was not strongly related to any one group’s representation. We thank Katherine J. Klein for bringing this issue to our attention.
ables had no meaningful relationship. It is important to highlight the fact that our dependent variable, controllable profit, is not sensitive to the purely administrative costs associated with turnover. Rather, it is sensitive to additional staffing costs associated with bolstering the performance of an inexperienced crew, costs associated with the additional staff required to provide on-the-job training for new employees, and perhaps indirect effects via the performance of those who might remain on the job. It should be noted, however, that these costs may be relatively low (and thus difficult to detect even with a large sample) due to the simple nature and low pay rates of these jobs. Likewise, a high turnover rate may also be indicative of other more deeply rooted problems that might negatively impact profitability.

Several explanations are possible. First, turnover may not matter very much in these jobs aside from the administrative costs. Given the relatively large sample and relative lack of measurement error, this possibility seems somewhat likely. It is interesting, however, to note that organizations in this industry are very concerned about reducing turnover because of its costs, though it is not entirely clear whether these concerns primarily center on administrative costs. Second, it is possible that identification of various types of turnover (e.g., voluntary, involuntary, and downsizing; McElroy, Morrow, & Rude, 2001) might yield different results. Although we had access to turnover reasons, the data were at least moderately unreliable (which is why we did not use them in this research). Hence, future research might examine this issue in different types of turnover.

Figure 6. Cross-domain latent growth curve model relating restaurant racial diversity (RD) to controllable profit (CP). *p < .05.
The Match of Workforce and Community Racial Composition and Profitability

One of the key principles guiding demographic diversity efforts is that it is especially important to achieve a match between the composition of the workforce and the community it serves. This match, in turn, is frequently hypothesized to impact organizational effectiveness. Though this is consistent with organizational and relational demography theories, and although we found evidence that these theories have important implications in the data studied here, our results yielded no support for this assertion. That is, the similarity between the racial composition of the workforce and the community was unrelated to profitability. The two theories mentioned in the introduction to this article suggest that this similarity would lead to outcomes such as more positive interpersonal relationships between the communities (i.e., the potential customer base) and the workforce, which we would expect to have clear implications for the restaurants’ profitability.

There are a number of possible explanations for this null result. First, the zip code may not have been an appropriate indicator of the community’s demographics. This could have occurred if the zip code represented an area that was either too broad or too narrow to successfully encompass the customer base served by each restaurant. On the basis of the correlations between the representations of various groups in the zip code and the restaurants’ workforce (which centered around .70 for all the groups studied here), however, we believe that the zip code indeed reflected a reasonable geographic area to study.

Figure 7. Cross-domain latent growth curve model relating zip code and restaurant racial diversity (RD) to controllable profit (CP). \( \ast p < .05 \).
Figure 8. Predicted yearly controllable profit based on six hypothetical racial compositions. RD = racial diversity.
Second, it is possible that the match between the racial composition of the workforce and that of the community impacts some aspect of the restaurants’ business performance, but that this does not extend to profitability. Whatever aspect of the restaurants’ performance this would supposedly impact, it would have to be highly circumscribed given that the behavior of an organization’s customers has such a profound effect on its profitability.

Third, there was a high degree of consistency between the racial composition of the communities and that of the workforce. This restricted range in terms of mismatch, in turn, might make it difficult or impossible to detect the effects of interest, even with large sample sizes. One possible approach to this issue is to study multiple business units in the same community who vary in their demographic compositions (Leonard & Levine, 2003a). Though the correlations reported here suggest this may be challenging, future research that can include such design elements is encouraged.

Fourth, the nature of quick-service restaurants might make the match between the demographics of the workforce and the community less important as compared with other businesses. For instance, the customer’s experience in quick-service restaurants is highly product-focused and transaction-based rather than relationship-based, and this, in turn, might eliminate or substantially attenuate any effects organization–community match might have. That is, different results might be obtained in consultative sales or small business environments, where interpersonal interactions and relationships between the customers and employees would presumably be more important. As a consequence, the results reported here may only apply to certain types of organizations, depending on the emphasis placed on interpersonal interactions in the customer’s experience. We see the door swinging

\[ Figure 9. \text{ Cross-domain latent growth curve model relating age diversity (AD) to controllable profit (CP).} \]

\[ *p < .05. \]
both ways, as the limited interactions in quick service environments should make dissimilarity effects especially salient. Thus, a blanket approach to matching the workforce’s demographics to that of the community might be misguided. Future empirical or theoretical work is strongly encouraged.

Table 10
Descriptives and Intercorrelations for Variables Used to Examine Restaurant–Community Racial Similarity and Profitability

<table>
<thead>
<tr>
<th>Variable</th>
<th>M</th>
<th>SD</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. ASIANDAYS%</td>
<td>.04</td>
<td>.08</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>2. HISPDAYS%</td>
<td>.23</td>
<td>.31</td>
<td>.06*</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>3. WHITEDAYS%</td>
<td>.46</td>
<td>.34</td>
<td>.16*</td>
<td>.55*</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>4. BLACKDAYS%</td>
<td>.27</td>
<td>.31</td>
<td>.15*</td>
<td>.39*</td>
<td>.52*</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>5. MINDAYS%</td>
<td>.54</td>
<td>.34</td>
<td>.16*</td>
<td>.55*</td>
<td>.52*</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>6. ASIANZIP%</td>
<td>.04</td>
<td>.06</td>
<td>.38*</td>
<td>.46*</td>
<td>.36*</td>
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<tr>
<td>7. HISPZIP%</td>
<td>.14</td>
<td>.18</td>
<td>.08*</td>
<td>.66*</td>
<td>.44*</td>
<td>.19*</td>
<td>.44*</td>
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<td></td>
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<tr>
<td>8. WHITEZIP%</td>
<td>.70</td>
<td>.25</td>
<td>.09*</td>
<td>.69*</td>
<td>.32*</td>
<td>.71*</td>
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<tr>
<td>9. BLACKZIP%</td>
<td>.12</td>
<td>.17</td>
<td>.09*</td>
<td>.41*</td>
<td>.12*</td>
<td>.09*</td>
<td>.60*</td>
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<td></td>
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<td></td>
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<tr>
<td>10. MINZIP%</td>
<td>.30</td>
<td>.25</td>
<td>.09*</td>
<td>.44*</td>
<td>.69*</td>
<td>.30*</td>
<td>.69*</td>
<td>.32*</td>
<td>.71*</td>
<td>.60*</td>
<td></td>
<td></td>
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<tr>
<td>11. CP</td>
<td>$186.03</td>
<td>$85.21</td>
<td>.19*</td>
<td>.00</td>
<td>.07*</td>
<td>.10*</td>
<td>.01</td>
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<tr>
<td>12. PCI</td>
<td>$22.09</td>
<td>$7.83</td>
<td>.18*</td>
<td>.10*</td>
<td>.03</td>
<td>.10*</td>
<td>.19*</td>
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<td>13. PCI2</td>
<td>$5493</td>
<td>$5040</td>
<td>.13*</td>
<td></td>
<td>.10*</td>
<td>.04*</td>
<td>.19*</td>
<td>.22*</td>
<td>.26*</td>
<td>.95*</td>
<td>1</td>
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</tbody>
</table>

Note. N = 2,476. ASIANDAYS%, HISPDPAYS%, WHITEDAYS%, BLACKDAYS%, and MINDAYS% = the percentage of days worked by Asian, Hispanic, White, Black, and minority employees, respectively; ASIANZIP%, HISPZIP%, WHITEZIP%, BLACKZIP%, and MINZIP% = the proportion of Asians, Hispanics, Whites, Blacks, and minorities represented in the restaurant’s zip code, respectively. CP = controllable profit (in $1,000s). PCI = per capita income (in $1,000s); PCI2 is in $100,000s. *p < .05.

The Relationship Between Minority Representation and Profitability

Though not of conceptual interest here, it is important to comment on the results concerning minority representation and orga-
nizational financial performance (see Table 10). This is of great practical importance and has also been addressed in terms of average levels of individual-level performance (Silva & Jacobs, 1993). The research design used here, however, speaks more directly to what matters from a broad organizational perspective because upper management’s top priority is generally the performance of a group, department, or organization rather than that of an individual employee (Ployhart, 2004).

We think the above statements also apply to aggregated measures of individual performance, as their linkage to overall organizational financial performance can be critical.

Table 12

Results of Moderated Regression Analyses Testing the Hypothesis That the Minority Status Similarity of the Restaurant and Zip Code Jointly Predict Profitability

<table>
<thead>
<tr>
<th>Step and predictors</th>
<th>Statistics for step</th>
<th>Statistics for predictors</th>
</tr>
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<tr>
<td></td>
<td>Constant</td>
<td>$R^2$</td>
</tr>
<tr>
<td>1</td>
<td>$168,131$</td>
<td>.002</td>
</tr>
<tr>
<td>Per capita income</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per capita income$^2$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>$166,312$</td>
<td>.002</td>
</tr>
<tr>
<td>MINORITYDAYS%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>$166,388$</td>
<td>.002</td>
</tr>
<tr>
<td>MINORITYZIP%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>$149,169$</td>
<td>.016</td>
</tr>
<tr>
<td>MINORITYDAYS% × MINORITYZIP%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. MINORITYDAYS% = the percentage of days worked by minority employees; MINORITYZIP% = the proportion of minorities represented in the restaurant’s zip code. $N = 2,476$.

*p < .05.
nizational financial performance is probably indirect and not known. Table 10 shows that the overall association between the proportion of employment days by minorities and controllable profit was nil. At a more granular level, the relationship was also zero for Asians but was positive for Hispanics and negative for Blacks. Thus, grouping all minorities together is misleading, even those who typically score lower on tests of cognitive ability as compared with Whites (i.e., Blacks and Hispanics). These results suggest that the representation of individual racial groups does indeed relate to overall organizational financial performance, an effect that cannot be spuriously attributed to socioeconomic effects that jointly relate to the available labor pool (and hence the business-unit composition) and profitability. That is, subsequent analyses found that neither controlling for PCI and PCI² nor the proportions of each of the racial groups’ representations in the zip code appreciably changed the results. This suggests that neither income nor community racial composition acts as a CCA.

Although it is entirely possible that some other third variable accounts for these effects, we think that these two sets of control variables were those that were most likely to explain the observed effect as a CCA, if one indeed exists. If there is indeed a causal linkage between the two (again, reiterating that there, in fact, may not be), this finding is surprising given that racial differences on average levels of job performance are supposedly caused by differences in cognitive ability, which would be expected to have relatively little impact in the simple jobs studied here. Conceptually, these results also provide some indirect support for the notion that performance across different levels of analysis might indeed relate to overall organizational financial performance, an effect that cannot be spuriously attributed to socioeconomic effects that jointly relate to the available labor pool (and hence the business-unit composition) and profitability. That is, subsequent analyses found that neither controlling for PCI and PCI² nor the proportions of each of the racial groups’ representations in the zip code appreciably changed the results. This suggests that neither income nor community racial composition acts as a CCA.

It is also important to mention the key limitations of this research, to some of which we alluded earlier in this article. First, and most important, despite its large size, the participants in this sample worked in very simple jobs in a single industry. Though we discussed several ways in which some of the results obtained here might generalize to other settings, it is also possible that the results obtained here may not generalize widely. A key benefit of studying standardized work environments, however, is that it largely controls for a host of environmental influences that might impact the key relationships of interest. In this sense, this approach somewhat resembles an experimental design in which demographics vary within constant environments (Leonard & Levine, 2003a). In fact, we think that these findings may generalize to other settings because quick service restaurants are highly structured with relatively little opportunity for individual differences to impact profitability as compared with other industries (Leonard & Levine, 2003a). Thus, the association between racial diversity and profitability might be even stronger in less constrained environments.

A second limitation is that all the study participants came from one organization. Thus, it is also possible that sampling from a different organization, even in the same industry, would yield divergent results. Third, due to the dynamic nature of the employees’ schedules, we were unable to determine which employees actually worked together. Although this gives us greater confidence in the significant results we obtained, it is also possible that some of our null findings might be an artifact resulting from this imprecision. Thus, future research interested in obtaining better estimates of the effect sizes reported here might use samples that are more static. Fourth, restaurant crews are less interdependent than many types of workgroups and teams. As a consequence, it remains to be seen whether the observed effects generalize to team-based work environments.

Finally, studying other outcomes such as customer satisfaction, organizational climate, or employee attitudes might yield different results and would enable a test of mediation effects that were not evaluated here. Taken together, these limitations suggest that additional research is needed to determine whether the results obtained here generalize to other key populations of interest. Likewise, these limitations should also be considered as caveats to the discussion points presented above.

**Broad Implications for Relational and Organizational Demography and Fit Research**

A key lesson from this research is the importance of considering contextual variables such as the attributes of the communities used here. As we mentioned earlier, controlling for community effects substantially strengthened the relationship between racial diversity and controllable profit. In accordance, at least in relational and organizational demography studies, examining contexts such as these may allow key relationships of interest to emerge that would otherwise be obscured by variability in contexts. Approaches such as this might also be used in studies of targeted recruiting and applicant self-selection to see whether community demographic composition effects predict applicant behaviors beyond individual-level effects (e.g., Ryan, Sacco, McFarland, & Kriska, 2000).

More broadly, the results reported here also have implications for how similarity and person–organization fit are related. In particular, we demonstrated how similarity can be conceptualized as fit between an individual and a composition in which that individual is embedded. Similar approaches may help to clarify levels-of-analysis issues in the relational demography literature and also would provide researchers with a powerful approach to the study of the fit between individuals and their work contexts. In addition, the diversity analyses can also be construed as a higher level conceptualization of supplemental misfit. This approach should be pursued in other studies because it enables person–organization fit and other types of fit researchers to broaden the nomological network of variables surrounding the notion of fit.

**Conclusion**

This research represents what is apparently the first effort in the psychological or management literature to empirically evaluate an integrated and dynamic multilevel model of demographic diversity and misfit effects. By incorporating time in both the conceptual model and the derivative analytical techniques we have obtained a clearer picture of the linkages that exist in this sample and can make stronger inferences concerning causality. Along with these innovations comes a key challenge, however, in that traditional analytical techniques are not ideally suited for such complex...
research questions. Nonetheless, we are optimistic that future research taking a similar approach in this substantive domain and others will not only advance our conceptual understanding of behavior in organizations but will also engender more widespread use and refinement of analytical techniques specifically oriented toward addressing the inherent complexities of multilevel organizational research.

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Appendix

Multilevel Survival Analysis

One of the first issues to address in survival analysis is whether to use a discrete or a continuous time model. We used discrete-time survival analysis here because its multilevel extensions are more fully developed compared with those of continuous time models; we also chose a relatively short time interval (2 weeks) to more closely approximate a continuous model. Thus, we arranged our dataset in person–period format (i.e., one record for each time period during which a person was observed; Singer & Willett, 1991). We chose a time interval of 2 weeks because this was a relatively high turnover job and because terminations were generally entered into company databases every 2 weeks (i.e., at the end of a pay period). Further, a short time period such as 2 weeks substantially increases the similarity between the results of a discrete-time model and those of a continuous-time model. Thus, an employee who worked for 20 weeks had 10 records in the dataset. We included the effects of time in the model by adding two variables, time and time², to represent the linear and quadratic effects of time on turnover risk. For the turnover variable, the last record had a value of 1 if the employee turned over at the end of the 20-week period and 0 if the employee was censored (i.e., he or she was still working at the end of data collection). Once the time interval was chosen and the data were restructured into the person–period format, we proceeded with the analysis using logistic regression (Willett & Singer, 1993). Thus, as in logistic regression, one can raise model coefficients to the exponent e to assess their impact on overall risk of incurring the outcome of interest (i.e., turnover). Thus, Exp(B) for coefficient j represents the relative turnover risk associated with a one-unit increase in predictor j. For example, if Exp(B_age) = 1.25 where the B is the coefficient for age, then a one-unit increase in age is associated with a 25% increase in turnover risk.

Because the interest here is on how demographic misfit impacts turnover risk, we applied survival analysis within a multilevel framework (Raudenbush & Bryk, 2002) vis-à-vis hierarchical nonlinear modeling (HnLM). Hierarchical linear models (HLMs) are a class of random coefficient models (e.g., Bliese, 2002) that are designed to handle nested (e.g., multilevel) data structures. HLMs compute a separate regression coefficient for each predictor within each nesting unit (i.e., restaurant). The variability of these coefficients is then modeled as a function of higher level variables (e.g., restaurant demographic composition). In this research, we hypothesized that the variability of within-restaurant association between individuals’ demographics and turnover risk would be predicted by the demographic composition of the restaurant as a whole. That is, the analytical approach was dictated by conceptual considerations, including level-of-analysis issues. We used a nonlinear implementation of these models that accounted for survival analysis issues. We used a nonlinear implementation of these models that specified a survival (i.e., logistic link) function rather than a more common linear function at the individual level.

Survival analysis can also handle time-varying predictors. This is done by entering the appropriate value for the predictor on the record corresponding to the time interval in question (recall that each person has
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multiple records in the person–period format). In this research, the issue is complex, because the time-varying predictor was the restaurants’ demographic compositions (i.e., the same employees do not work in a restaurant at each time point) rather than an individual-level attribute. We thus followed the approach of Barber, Murphy, Axinn, and Maples (2000) by entering this time-varying predictor at the individual level but not allowing it to vary randomly across restaurants. It is important to note that the conceptual model for this analysis is the same as what one would come to expect in a typical hierarchical model; however, entering these Level 2 variables at Level 1 allows for proper estimates of this effect (Barber et al., 2000, provide the statistical details on why this is the case).

As an example, we provide the equations used to test the demographic fit hypotheses with regard to sex (those used to study race and time effects are somewhat more complex due to the use of multiple dummy variables and additional interaction terms):

\[
\text{Logit}(p_{jk}) = \beta_{0k} + \beta_1 \text{Time}_k + \beta_2 \text{Time}_k^2 + \beta_3 \text{Sex}_j + \beta_4 \text{RestaurantSex}_k \text{Sex}_j + \beta_5 \text{RestarntSex}_k \text{Sex}_j \text{Time}_k, \\
\beta_{0k} = \gamma_0 + \epsilon_{0k} \\
\beta_1 = \gamma_10 \\
\beta_2 = \gamma_20 \\
\beta_3 = \gamma_30 + \epsilon_{3k} \\
\beta_4 = \gamma_40 \\
\beta_5 = \gamma_50
\]

where

- \(\beta_{0k}\) = the overall turnover probability in restaurant \(k\)
- \(\beta_1\) = the effects of time on the turnover probability for person \(j\) at time \(t\)
- \(\beta_2\) = the effects of time\(^2\) on the turnover probability for person \(j\) at time \(t\)
- \(\beta_3\) = the sex effect on the turnover probability for person \(j\)
- \(\beta_4\) = the effect of restaurant sex composition on turnover probability for person \(j\), which varies as a function of the restaurant sex composition in restaurant \(k\) at time \(t\), estimated as a fixed effect to allow for proper estimation.
- \(\beta_5\) = the interaction between sex effect on the turnover probability for person \(j\), and the restaurant sex composition effect in restaurant \(k\) at time \(t\), estimated as a fixed effect to allow for proper estimation.

\(\epsilon_{0k}\) = the unobserved random effects error terms (i.e., that vary across \(k\) restaurants).

In the example above, Equation 3 represents the Level 1 (i.e., employee-level) model, whereas the remaining equations are at the restaurant level (i.e., Level 2). Here, each employee’s turnover risk is modeled as a function of the average turnover risk in restaurant \(k\) (\(\beta_{0k}\)), time (\(\beta_1\)), time\(^2\) (\(\beta_2\)), the employee’s sex (\(\beta_3\)), the restaurant’s sex composition (\(\beta_4\)), and the interaction between these last two variables (\(\beta_5\)). Again, following the approach of Barber et al. (2000), the time-varying restaurant sex composition (and its interaction with employee sex) is entered at the individual level, and only the latter is allowed to vary across restaurants (denoted by the error term \(\epsilon_{3k}\) in Equation 7). In this research, we used the statistical significance of the \(\beta_3\) parameter to determine whether the employee’s sex and the restaurant sex composition interact to impact turnover risk. For models with significant interaction terms, we plotted the form of the interaction to see whether it was consistent with the hypotheses and to gauge the size of the effect. For nonproportional models (i.e., those including interactions with time), we added the following terms: (a) Sex \(\times\) Time, (b) Restaurant Sex Composition \(\times\) Time, and (c) Sex \(\times\) Restaurant Sex Composition \(\times\) Time. The third interaction term was of substantive interest here because it indicates whether the effects of employee sex and restaurant sex composition on turnover vary as a function of time (i.e., the employee’s tenure). A number of authors have provided detailed background on HLM (Kreft & de Leeuw, 1998; Raudenbush & Bryk, 2002; Snijders & Bosker, 1999; and see Bliese, 2000, 2002; Hofmann, 1997, for examples in organizational research), and Barber et al. (2000) explained multilevel survival analysis using an example in sociology. Thus, to summarize, multilevel survival analysis offers several key advantages as opposed to other approaches. First, it models turnover risk continuously and thus is well suited for research questions examining the timing of binary outcomes. Second, it is consistent with the conceptual basis of the hypotheses as cross-level effects. Third, it allows for dynamic predictors at the individual level as well as at the group level. This latter strength is particularly useful for longitudinal multilevel research in which compositions change over time, as they did here.

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