

# **Do Race, Age, and Gender Differences Affect Manager-Employee Relations?**

## **An Analysis of Quits, Dismissals, and Promotions at a Large Retail Firm**

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## **Abstract**

Using data from a large U.S. retail firm, we examine how differences in race, age, and gender between a manager and a subordinate affect the subordinate's rate of quits, dismissals, and promotions. These differences can have statistically significant and sometimes large effects—especially differences in race and ethnicity. In most cases, these differences produce adverse effects—i.e., higher quit and dismissal rates, and lower promotion rates. But in three cases, where traditionally lower-status managers supervise higher-status employees, differences produce favorable effects. With respect to race, this means having a different-race manager hurts black and Hispanic employees, but helps white employees.

## **I. Introduction**

As both American workers and their managers have grown more diverse in recent decades, demographic differences have become a common feature of the manager-subordinate relationship.<sup>1</sup> Consequently, an important question is how demographic differences between managers and their employees affect the employment relationship.<sup>2</sup> Using daily personnel records from a large U.S. retail firm, this study examines how race, age, and gender differences between a manager and a subordinate affect the subordinate's rate of quits, dismissals, and promotions.

Economists have long studied how race, age, and gender affect employment outcomes. However, because there has been a lack of longitudinal data that matches employees to their managers, it has rarely been possible to examine directly the effects of demographic differences between managers and subordinates on employment outcomes. In fact, we are aware of only one other study that examines the effect of manager-subordinate differences on turnover or promotions, and that study looks only at the effect of gender differences on promotions.<sup>3</sup> Hence the present study addresses an important gap in the literature.<sup>4</sup>

This study analyzes panel data from a large national retailer with hundreds of stores located throughout the United States. The dataset contains the firm's daily personnel records on more than 1,500 store managers and more than 100,000 employees for a 30-month period from 1996 to 1998. Crucially, the dataset identifies the demographic characteristics of both managers and their employees at each store, and it gives the dates and descriptions of all personnel actions regarding each individual. As a result, we can estimate directly how demographic differences between managers and their employees affect employment outcomes.

We look at differences in three dimensions: race, age, and gender.<sup>5</sup> And we estimate the

effect of these differences on three employee outcomes: quits, dismissals, and promotions. We estimate these effects using continuous-time Weibull proportional hazard models. To control for unobserved heterogeneity across local labor markets, we include ZIP-code fixed effects. To account for unobserved heterogeneity across employees, we use models with individual-level frailty.

Our results suggest that demographic differences between manager and employee can have statistically significant and sometimes large effects on employee outcomes. This is especially true of differences in race and ethnicity, which consistently produce significant effects and which produce the largest effects. In general, demographic differences tend to produce adverse effects on employee outcomes (i.e., higher quit and dismissal rates, and lower promotions rates). But in three striking cases, differences produce favorable effects.

Racial differences affect all three employment outcomes. With respect to quits, our analysis has two aspects. Our basic findings suggest that while black employees are no more likely to quit when they have a non-black manager than when they have a black manager, both Hispanics and whites with different-race managers are somewhat more likely to quit.<sup>6</sup> However, further analysis suggests that for one group—white employees—the basic results are only part of the story. We find that the effect of having a non-white manager on quit rates is much larger for white employees who have received new managers than it is for white employees who still have their hiring managers. This suggests that whites who dislike working for non-white managers often avoid working for such managers in the first place.

With respect to both dismissals and promotions, the effects of race differences exhibit a striking contrast between unfavorable effects for black and Hispanic employees vs. favorable effects for white employees. When the manager is a different race, both blacks and Hispanics

are more likely to be fired, and less likely to be promoted. In contrast, when whites have a different-race manager, they are *less* likely to be fired than whites with white managers, and are *more* likely to be promoted.

Age differences do not affect quits or promotions, but they do affect dismissals. Again, the dismissal results display a striking contrast between unfavorable vs. favorable effects. Here the contrast depends on whether the employee is younger or older than the manager. Employees who are at least 20 percent younger than their managers are more likely to be dismissed. But employees who are at least 20 percent older than their managers are *less* likely to be dismissed.

Gender differences affect only quit rates, raising them slightly. But we should note that our gender results may be affected by the fact our sample is relatively youthful and predominantly female.

We also consider the significance of our results. First, we discuss interpretation—why do demographic differences produce the effects we find? We focus especially on how our findings relate to important theories of preferences, discrimination, and social roles. We find strong support for theories maintaining that many people hold preferences for working with similar others, and hence that demographic differences tend to have adverse effects on employment relationships. But we also find support for theories of social roles that predict employees from traditionally higher-status groups will be treated well by managers from traditionally lower-status groups. In all three cases where we find that differences produce favorable effects, traditionally higher-status employees are working for lower-status managers.

Second, we look at the economic significance of our findings. The implied cost of the effects of demographic differences depends on whose perspective is considered. Our results suggest that for the employer, the effects of demographic differences are relatively small—they

account for roughly three percent of all quit-related turnover. At the same time, our results suggest that for black and Hispanic employees, the effects of having a different-race manager can be considerable. This is especially true for blacks, who are 51 percent more likely to be dismissed and 61 percent less likely to be promoted.

## **II. Data**

### **A. The Sample**

The data are the daily personnel records of a large retail employer from February 1, 1996 through July 31, 1998. These records identify the demographic traits of both managers and their employees at each store, and they give the dates and descriptions of all personnel actions for each individual. We analyze a sample of more than 1,500 store managers who were employed at some point during the 30-month sample period, and more than 100,000 frontline employees who were hired during the sample period.<sup>7</sup>

Our sample contains more than 700 stores located throughout the United States. While geographically diverse, these workplaces nevertheless are all very similar: they are all part of a national chain with highly uniform policies and procedures. In a typical store, there is one full-time, overall manager who has the title “store manager”, and there are 25 to 50 mostly part-time employees.

The managers in our analysis are the “store managers”—i.e., the overall manager at each store. The store managers are responsible for all personnel decisions including hiring, dismissals, and promotions.<sup>8</sup> All managers receive a small amount of training in fostering and managing a diverse workforce. The median spell for a manager at a store lasts roughly 13 months; as a result, approximately 80 percent of the stores have at least one change in

management during the 30-month sample period, and roughly 20 percent of all employees get new managers at some point before they leave.<sup>9</sup>

All frontline employees at this company have similar job titles and descriptions. They all rotate through several tasks that involve both dealing with customers and doing support duties. These jobs require only basic skills and employees receive little training. As is common in this sector, employees have very high rates of turnover; the median spell in a store for a frontline employee is 91 days, and roughly 80 percent of employee spells end within a year.<sup>10</sup>

Table 1 summarizes the demographic composition of the managers and employees in our sample. On one side, the managers are predominantly white, relatively young, and largely female. Specifically, the managers are 87 percent white; their mean age is 30, with nearly 70 percent between the ages of 26 and 34; and they are 78 percent female. On the other side, new frontline employees are more racially diverse than their managers: 64 percent are white, 16 percent black, 10 percent Hispanic, and 7 percent Asian.<sup>11</sup> But like their managers, the employees are relatively young (the mean age is 22, with three quarters between the ages of 16 and 23); and they are largely female (70 percent).

Because our data comes from a single employer, it is important to consider how representative our sample is of a larger population. Our sample is from a retail firm, so perhaps it is most useful to look at how our sample compares to the U.S. retail sector as a whole—a sector that accounts for roughly 18 percent of all U.S. jobs. Compared to the retail sector, our sample is typical with respect to its turnover rates and its racial composition.<sup>12</sup> However, both managers and employees are relatively young (with average ages of 22 and 30 vs. national averages of 32 and 39), and this company has a higher share of both female managers (78 vs. 50 percent) and female employees (70 vs. 66 percent).

Table 2 shows the sample statistics for the key independent variables that describe the demographic relationship between manager and employee. Among all manager-employee pairs in our sample (column 3), 38 percent are mixed-race, the average age difference is 10 years, and 37 percent are mixed-gender. Unfortunately, there are relatively few observations in which Asians are paired with other minorities; as a result, the estimates for Asians are very imprecise and we do not discuss these results. But crucially, our sample does contain large numbers of observations in which black and Hispanic managers are paired with white, black and Hispanic employees.<sup>13</sup>

## **B. Dependent Variables: Quits, Dismissals, and Promotions**

The definition of our dependent variables is based on company codes that classify both personnel actions and the reasons for these actions.

**Exits:** Among the frontline employees hired during our 30-month sample period, we observe well over 50,000 exits. We use the company's coding to classify these exits into one of five categories (Table 3), and our analysis focuses on two of these categories—the job-related quits (54 percent of exits) and dismissals (7 percent of exits). Quits include voluntary exits that occur because an employee is dissatisfied or has found a better job; those who quit without giving a reason; and those who simply stop showing up for work. Dismissals are involuntary exits that result from dishonesty, substandard performance, tardiness, absenteeism, or violation of company policies. We exclude from the main analysis both market-driven layoffs (9.2 percent of exits) and those who leave voluntarily to move or to return to school (20.3 percent of exits).<sup>14,15</sup>

**Promotions:** The variable we use to analyze promotions is the number of days after hire until the first time an employee is promoted to a new job title. To maintain a sufficient sample

size, we pool the 15 different job titles to which an employee may be promoted.<sup>16</sup> In all, we observe roughly 2,500 first-time promotions.

### **III. Model and Estimation Methods**

We use continuous time Weibull proportional hazard models to analyze whether rates of employee quits, dismissals, and promotions are affected by the demographic relationship between manager and employee. In hazard models, two problems can cause biased estimates of the effects of covariates. First, as in any regression model, the estimates will be biased if the model omits variables that are correlated with both the outcome and the covariates of interest. The second problem, unique to hazard models, is that even if omitted variables are *not* correlated with the covariates of interest, they can still cause biased estimates because they can cause sample selection bias.<sup>17</sup>

These two problems are addressed in several ways. Both problems are addressed by restricting the analyzed sample to employees with a single job title at a company that has highly uniform workplaces. This eliminates virtually all variation in job characteristics, which are important determinants of quits, dismissals, and promotions. Also, both problems are addressed with a rich set of control variables: we control for observed individual characteristics, for observed characteristics of the store and its workforce, and for unobserved heterogeneity in labor markets conditions both across locations and over time. Finally, sample selection bias could be caused by unobserved heterogeneity across individuals. To account for this source of selection bias, we employ a “frailty” model.

We should describe more fully both our controls and our frailty model. We control, first, for the race, age, and gender of both the employee and the employee's current manager. These controls account for the effect on turnover and promotions of demographically correlated

differences in skills, effort or preferences. Second, we control for three additional employee characteristics that are proxies for skills and job-attachment: (1) an indicator for previous experience with the company, (2) indicators for part-time or temporary (vs. full-time/permanent) status, and (3) an indicator for marital status.

Third, we control for observed characteristics of the store and the store's workforce. Store variables, which are constructed from our company data, include the store's size and average workplace demographics during the sample period. Fourth, to control for unobserved cross-sectional differences in labor markets, we include dummy variables that identify the stores' five-digit ZIP codes.<sup>18,19</sup> Lastly, to control for time-series variation in labor market conditions, we include a vector of dummy variables representing each of the 30 months in our sample period.

Sample selection bias in our hazard model could be caused unobserved heterogeneity across individuals. To account for this source of selection bias, we employ a "frailty" model. Such a model assumes a distribution for the unobserved individual heterogeneity (known in the hazard model literature as "frailty"; Vaupel et al., 1979; Hougaard, 1986). Specifically, we allow the survival time of each individual to depend on a random effect, which is assumed to have a multiplicative effect on the hazard function.<sup>20</sup>

To estimate our models, we assume that the hazards associated with the various modes of exit (quits, dismissals, etc.) are independent conditional on the covariates in the model. Under this assumption, estimation of the competing risks model is equivalent to estimation of separate models for each risk where exits due to the other risks are treated as censored (van den Berg, 2001).<sup>21</sup> Similarly, when analyzing promotions, all exits are treated as censored.

We begin by estimating a baseline model for each employment outcome that shows

whether the likelihood of each outcome is correlated either with employee demographics or with manager demographics. For each outcome, the hazard function for employee  $i$  in store  $j$  is specified as:

$$(1) \quad h_{ij}(t|v_{ij}) = h_0(t) \cdot \exp(X_{ij} \beta_X + M_{ijt} \beta_M + S_j \beta_S + Z_j \beta_Z + T_i \beta_T) \cdot v_{ij}.$$

Here,  $h_0(t)$  is a baseline hazard function with a Weibull distribution and  $t$  is the number of days that individual  $i$  has been employed at store  $j$ . The regressors in this model include variables characterizing the employee ( $X_{ij}$ ) and variables characterizing the employee's current manager ( $M_{ijt}$ ); variables characterizing the store and its workforce demographics ( $S_j$ ); a vector of ZIP-code dummy variables ( $Z_j$ ); and a vector of dummies indicating the sample month in which the employee was hired ( $T_i$ ). The frailty term for employee  $i$  ( $v_{ij}$ ) is assumed to follow a gamma distribution.<sup>22</sup>

In this equation, the coefficients on the variables describing employee demographics and manager demographics show whether the average hazard rates for a given employee outcome differ either by employee demographic group or by manager demographic group. In the dismissals regression, for example, positive coefficients on the dummy variables indicating that the employee is black, Hispanic, or Asian would imply that on average employees from these demographic groups are more likely than white employees (the baseline group) to be dismissed.

Our central question is how demographic differences between managers and employees affect employee quit, dismissal, and promotion rates. To address this question, we add eight dummy variables to equation (1). Specifically, our estimation equation becomes:

$$(2) \quad h_{ij}(t|v_i) = h_0(t) \cdot \exp(X_{ij} \beta_X + M_{ijt} \beta_M + T_i \beta_T + S_j \beta_S + Z_j \beta_Z + (White_{ij} \times MgrDiffRace_{ijt}) \beta_{DR-W} + (Black_{ij} \times MgrDiffRace_{ijt}) \beta_{DR-B} + (Hispanic_{ij} \times MgrDiffRace_{ijt}) \beta_{DR-H} + (Asian_{ij} \times MgrDiffRace_{ijt}) \beta_{DR-A} + (Other_{ij} \times MgrDiffRace_{ijt}) \beta_{DR-O} + EmpYounger_{ijt} \beta_{Younger} + EmpOlder_{ijt} \beta_{Older} + MgrDiffSex_{ijt} \beta_{DS}) \cdot v_i.$$

Here,  $White_{ij} \times MgrDiffRace_{ijt}$  is equal to one if the employee is white *and* the current manager is

of a different race. We include a similar dummy variable interaction for each of the four additional race groups (black, Hispanic, Asian and other). Further, *EmpYounger* represents a dummy variable indicating that the employee is at least 20 percent younger than the manager, and *EmpOlder* indicates that the employee is at least 20 percent older than the manager. Finally, *MgrDiffSex* is a dummy variable that is equal to one if the manager's gender differs from the employee's.

The central parameters of interest are the coefficients on the new dummy variables; these coefficients provide our estimates of the effects of being different from one's manager. In the dismissals regression, for example, a positive value for  $\beta_{DR-B}$  (the coefficient on the dummy indicating a black employee with different-race manager) would imply that black employees with nonblack managers have higher dismissal rates than black employees with black managers. Further, by comparing the coefficients  $\beta_{DR-W}$ ,  $\beta_{DR-B}$ , and  $\beta_{DR-H}$ , we can determine whether the effect of having a different-race manager varies by employee race group.

It should be noted that while equation (2) contains the interaction of *MgrDiffRace* with each of five employee race dummies, it is not possible to include the interaction of *MgrDiffSex* with the dummy variable for employee gender. Because there are only two discrete gender categories (male and female), the interaction of employee gender with *MgrDiffSex* is a linear combination of the three gender related dummy variables already in the equation (employee gender, manager gender, and *MgrDiffSex*).<sup>23</sup> Hence the effect of being a female with a male manager, for example, cannot be identified separately from the combined effects of (1) being female, (2) having a male manager, and (3) having a different-sex manager.

#### **IV. Results**

Table 4 reports the main results from our analysis of quits, dismissals, and promotions.

For ease of interpretation, we report hazard ratios (exponentiated coefficients) instead of the coefficients themselves. For example, a hazard ratio of 1.10 for a dummy variable would imply that the daily rate of quits, dismissals, or promotions is 10 percent higher for the indicated group than for the omitted group.<sup>24</sup>

### **A. Baseline Model: Do Demographics Matter?**

Columns (1a), (2a), and (3a) contain the results from the baseline model. These results show that employee outcomes are highly correlated with employee demographics, but are less consistently related to manager demographics.

**Employee Race:** All three outcomes vary significantly and substantially by employee race. Compared to the quit rate of white employees, quit rates are eight percent lower for Hispanics and 27 percent lower for Asians. Compared to whites, dismissal rates are three times higher for blacks, 60 percent higher for Hispanics, and 17 percent higher for Asians. And compared to whites, promotion rates are 60 percent lower for blacks, 28 percent lower for Hispanics, and 48 percent lower for Asians. While these baseline estimates are not the focus of our study, it is striking that career paths diverge across the races so early in these low-skill, entry-level positions.

**Employee Age:** All three outcomes are also correlated with employee age. As employee age increases, rates of quits, dismissals, and promotions all increase at first, and then decrease. Both quit rates and promotion rates are highest among 24-25 year olds, and dismissal rates are highest among 18-19 year olds.

**Employee Gender:** The quit rate of women is eight percent lower than that of men, and the dismissal rate of women is 51 percent lower. However, the promotion rates of men and women do not differ significantly.

**Manager Demographics:** We do not find any significant relationship between manager race and our employment outcomes; but both manager gender and manager age do have effects. We find that under female managers, employees quit more often and are promoted more often. We also find that as the manager's age increases, rates of employee quits and dismissals both increase at first, and then decline.

## **B. Do Demographic Differences Between Managers and Employees Matter?**

Columns (1b), (2b) and (3b) of Table 4 show the estimated effects of manager-employee demographic differences on our three employment outcomes. The results suggest that demographic differences can have statistically significant and sometimes large effects.

Racial and ethnic differences affect all three outcomes. With regard to quits, our analysis has two aspects. The basic results (col. 1b) indicate that black employees are no more likely to quit when they have a non-black manager than when they have a black manager. But for Hispanic and white employees, having a different-race manager raises quit rates by 16 percent and 7 percent, respectively. The estimates for Hispanics and whites are jointly significant at  $p=.03$ , and a Wald test cannot reject equality of the estimates for these two groups.

However, further analysis suggests that for one group—white employees—the basic estimates are only part of the story. We present evidence below showing that the effect of having a non-white manager on quit rates is much larger for white employees who have received new managers than it is for white employees who still have their hiring managers. This strongly suggests that whites who dislike working for non-white managers often avoid working for such managers in the first place. Consequently, it is likely that such self-selection of their managers by white employees significantly reduces the overall effect of race differences on the white quit rate.

With regard to both dismissals (col. 2b) and promotions (col. 3b), the effects of race differences exhibit a striking contrast between unfavorable effects for black and Hispanic employees vs. favorable effects for white employees. On one hand, both blacks and Hispanics are more likely to be fired when the manager is a different race, and they are less likely to be promoted. The estimates suggest especially large effects for black employees, who are 51 percent more likely to be dismissed and 61 percent less likely to be promoted when the manager is not black. The estimates for blacks are both statistically significant at  $p < .05$ . For Hispanics, the estimates suggest that having a non-Hispanic manager raises dismissal rates by 18 percent ( $p = .36$ ) and reduces promotion rates by 54 percent ( $p = .09$ ). Although the coefficients for Hispanics are smaller and have less statistical significance than the coefficients for blacks, Wald tests cannot reject equality of the coefficients for these two groups.

On the other hand, the estimated effects for whites differ significantly and have the opposite sign from those for blacks and Hispanics (see notes for Table 4, columns 2b and 3b). When whites have a different-race manager, they are 20 percent *less* likely to be fired ( $p = .06$ ) than are whites with white managers, and they are 75 percent *more* likely to be promoted ( $p = .08$ ). Hence whereas racial differences hurt both blacks and Hispanics, they improve white dismissal and promotion rates.

Age differences have no effect on promotions or quits, but they do affect dismissals. Again, the dismissal results display a contrast between unfavorable vs. favorable effects. Here the contrast depends on whether the employee is younger or older than the manager. Employees who are at least 20 percent younger than their managers are 18 percent more likely to be dismissed than those who are closer in age to their managers ( $p = .05$ ). In contrast, employees who are at least 20 percent older than their managers are 26 percent less likely to be dismissed

( $p=.09$ ).

Gender differences have no significant effect on dismissals or promotions. However, gender differences do raise quit rates by a modest four percent ( $p=.06$ ). But (as explained above) we should reiterate that we are not able to estimate separate effects of gender differences for males with female managers and for females with male managers.

## **V. Robustness Tests**

### **A. Self-selection at the Hiring Stage: The Role of Heterogeneous Demographic Preferences**

In assessing the implications of our results, an important issue is whether there is self-selection by managers or employees at the time of hiring on the basis of demographic preferences. Managers could be self-selecting employees either by choosing where to work based on workforce demographics or by selecting new hires based on applicant demographics. Likewise, employees could be self-selecting managers by choosing a place of employment based on manager demographics. Pre-hire self-selection on the basis of demographic preferences is an issue because it could affect the magnitude of the effects of demographic differences on post-hire employment outcomes. As a result, the magnitudes of our estimates might not generalize to other settings where managers or employees exercise a different degree of self-selection.<sup>25</sup>

Using our quits data, we can test for self-selection by employees. In our main analysis of quits, all manager-employee pairs are pooled, and the estimated effect of demographic differences on quit rates is an average effect that is taken across two groups of employees—those who still have their hiring managers and those who have received new managers. Our test exploits the fact that there is no self-selection of managers among the group of employees with new managers because employees play no role in the assignment of new managers. As a result,

we can test whether employee self-selection is affecting our quit estimates by comparing the estimates for employees who were able to exercise self-selection (those who still have their hiring managers) with the estimates for employees who were unable to exercise self-selection (those with new managers). If employee self-selection is affecting our quit estimates, then there should be a significant difference in the estimates for these two groups.

Table 5 compares the estimated effects of manager-employee demographic differences on quit rates for employees that still have their hiring managers and employees that have new managers. In most cases, there is no significant difference in the estimates for these two groups; this suggests that in these cases our original estimates are not significantly affected by employee self-selection. However, we do find a significant difference in one case—the effect of race differences on the quit rates of white employees. For white employees, the effect of having a non-white manager on quit rates is significantly larger ( $p = .07$ ) when the manager in question is new.

Specifically, among white employees who still have their hiring managers, whites with non-white managers are only 4.9 percent more likely to quit than whites with white managers. In contrast, among white employees who have received new managers, whites with non-white managers are 34.5 percent more likely to quit than whites with white managers. We believe these results strongly suggest that many white employees who dislike working for non-white managers often avoid working for such managers in the first place. And when such whites involuntarily find themselves working for a non-white manager, their quit rates increase substantially. We thus conclude that the overall effect of race differences on the white quit rate is probably reduced significantly by the fact that many white employees self-select their managers on the basis their racial preferences.<sup>26</sup>

If white employees are self-selecting their managers, it may be that managers are self-selecting their employees. Unfortunately, the comparison of hiring managers vs. new managers does not provide a clean test for the influence of manager self-selection on our estimates. This is because we cannot tell whether managers have more control over the demographics of their employees when they act as “hiring managers” and select whom to hire, or when they become “new managers” and select a new place of employment.

### **B. Dissimilar Managers vs. Dissimilar Coworkers**

Another concern with our analysis is the possibility that employment outcomes are affected not only by demographic differences from one’s manager, but also by demographic differences from one’s coworkers.<sup>27</sup> Because the demographics of managers and their employees tend to be correlated, our estimates might conflate these two effects. For example, in the cases where we find higher quit rates when the manager is dissimilar, the estimates could be driven partly by employees who dislike the prevailing demographics of their coworkers. Similarly, our results regarding dismissals and promotions could reflect the effect that being different from one’s coworkers may have on an employee’s productivity. To address these possibilities, we re-estimate our hazard models with additional controls for “race isolation” (the fraction of an employee’s coworkers who are a different race) and “gender isolation” (the fraction who are the opposite sex).

The results, shown in Table 6, suggest that demographic isolation from one’s coworkers can indeed affect employment outcomes.<sup>28</sup> However, the estimated effects of manager-employee demographic differences change only slightly when the regression controls for such isolation. For example, in the quits regression, the hazard ratios for white and Hispanic employees with different race managers are reduced only slightly—from 1.070 and 1.161 to 1.054 and 1.133,

respectively; and the hazard ratio for employees with different-sex managers is reduced from 1.041 to 1.037. Likewise, the new estimates from the dismissals and promotions regressions are very similar to our original estimates in Table 4. Because the estimates change only slightly with the inclusion of our “demographic isolation” controls, we conclude that our original estimates reflect mainly the effects of being different from one’s manager, and not the effects of being different from one’s coworkers.

## **VI. Discussion**

### **A. Interpretation**

Why do demographic differences produce the effects we find? To explore this question, we first observe that our statistically significant results fall into two basic classes, and we suggest a theoretical explanation for each class. Next, we examine more closely the individual results for each employment outcome.

We can classify our significant results by whether they have unfavorable or favorable effects on our employment outcomes (see summary in Table 7). In most cases, demographic differences between manager and employee hurt the employee. But in three notable cases, dissimilarity helps the employee.

Both economic and psychological theory have long postulated that demographic differences can have generally adverse effects on employment relationships. And both have agreed that the basic cause is “in-group preferences”—i.e., people may hold preferences for working with members of their own group. Indeed, the economic theory of “taste-based” discrimination (Becker, 1957) is predicated on the existence of preferences for members of one’s own group. And social psychologists have produced a large body of theory that attempts to

explain such preferences for similar others (n.b., Byrne, 1971; Tajfel and Turner, 1986). This psychological literature argues that similarity promotes compatibility, interpersonal attraction, and identity reinforcement; and, conversely, that dissimilarity produces incompatibility, discord, and alienation.

But if demographic differences tend to have negative effects, why in three cases do we find that such differences have a favorable effect? Here, social role theory may be helpful (Eagly, 1987). Role theory argues that when work roles break with traditional social roles and workplace hierarchies, this conflict can affect the behavior of both the manager and the employee. For example, when managers from traditionally lower-status groups supervise employees from traditionally higher-status groups, role theory suggests that in order to minimize the conflict and discomfort in the employment relationship, such lower-status managers may behave deferentially toward the higher-status employees. Now, in all three cases where we find that differences have favorable effects for employees, there are role-breaking relationships where lower-status managers are supervising higher-status employees. Hence managerial deference could explain all three cases where we find favorable effects.

We now examine the individual results for each employment outcome. We begin with quits. In the cases where we find significant effects, our estimates all suggest that being different from one's manager leads to higher quit rates. The results suggest that Hispanics and especially whites prefer to work for same-race managers, and that employees prefer to work for managers of the same sex. The quit results thus provide support for the theories of in-group preferences.

Interestingly, race differences do not raise the black quit rate. Indeed, the black quit rate is the only case where race differences may have no effect. The explanation of this intriguing result is likely complex, so we must leave it as a topic for future research. But we mention two

possible explanations to illustrate the complexity. First, because blacks have historically held a lower position in U.S. society and have worked predominantly for non-black managers, it is possible they have become more accustomed to working for dissimilar managers. Second, Fryer and Torelli (2005) find that blacks who “act white” (i.e., by investing in behaviors characteristic of whites) have fewer black friends. Hence it is possible that our black employees are no more comfortable with black managers than with white managers because black managers are seen as “acting white.”

Next, we look at the results for dismissals and promotions. We start with the effects of race differences. Our estimates suggest that race differences have unfavorable effects for black and Hispanic employees, but favorable effects for white employees.

On one hand, when their managers are a different race, both blacks and Hispanics have higher dismissal rates and lower promotion rates. Interpretation here must be cautious. While in-group preferences may be responsible for these adverse effects, this isn't necessarily the case. These effects could simply reflect the fact that same-race managers may be better able to motivate black and Hispanic employees. Furthermore, when considering the role of in-group preferences, we must be mindful that the preferences of a variety of groups could be at work. First, these effects could reflect behavior by black and Hispanic employees; if employees dislike dissimilar managers, they may respond with behavior (e.g., reduced effort or absenteeism) that raises dismissal rates and reduces promotion rates. Second, the effects could reflect preferential treatment by black managers toward blacks and by Hispanic managers toward Hispanics. Finally, these unfavorable effects could reflect discrimination by non-black managers against black employees and by non-Hispanic managers against Hispanic employees.

In contrast to the effects on blacks and Hispanics, we find that race differences have

*favorable* effects on white dismissal and promotion rates. When white employees have non-white managers, they actually have lower dismissal rates and higher promotion rates than when they have white managers. Two factors may help explain this. First, our quit results suggest it is more difficult for non-white managers to retain white employees, and our analysis of employee self-selection suggests it is also more difficult for minority managers to hire white employees. These difficulties could cause minority managers to be especially indulgent toward white employees. Second, role theory maintains that lower-status managers may behave differentially toward higher-status employees. Hence traditionally lower-status minority-race managers may be deferring to traditionally higher-status white employees.<sup>29</sup>

The effects of age differences on dismissals also exhibit a contrast between unfavorable vs. favorable effects. On one hand, we find that for employees who are younger than their managers, age differences have unfavorable effects—i.e., higher dismissal rates. Again, this adverse effect is consistent with the theories of in-group preferences. On the other hand, for employees older than their managers, age differences have favorable effects—i.e., lower dismissal rates. Again, role theory suggests that role-breaking could help explain these favorable effects. In U.S. society, it is traditional for older people to have higher status and to be the managers of younger employees. Hence role-breaking may be leading younger managers to defer to older employees.

Finally, it is interesting that gender differences do not have a significant effect on dismissals or promotions, and have only a small effect on quit rates. However, the lack of gender bias may be due to the fact that our sample is relatively youthful and predominantly female.<sup>30</sup>

In sum, our results can be seen as consistent with a theoretical framework that makes two

assumptions: first, demographic differences tend to produce adverse effects on employment relationships; but second, the effects of differences also depends on whether the differences violate traditional social roles and workplace hierarchies.

## **B. Are the Effects of Demographic Differences Economically Important?**

Are the effects we find economically important? We consider the implications for our employer and our employees.

To assess the economic implications for our employer, we consider the effects of demographic differences on the company's annual turnover due to quits. Our estimates suggest these effects are small. For example, the estimates from Table 4, column (1b) imply that for the company as a whole, the effects of demographic differences can account for roughly three percent of all quit-related turnover. Specifically, if the company could somehow eliminate the adverse effects of race and gender differences (e.g., through diversity training), it could reduce annual job-related quit rates from about 60 percent to 58 percent per year.<sup>31</sup>

However, our analysis also suggests that the effect on quit rates is small partly because whites who dislike working for non-whites tend to avoid working for non-whites. Hence, demographic trends or policies that increase the presence of minority managers in mostly white stores could be costly for the employer. For example, in the extreme case of an all-white store, replacing a white manager with a non-white manager would raise average annual quit rates from 58 percent to 78 percent.

While the economic effects for the employer are not large, the effects for individual employees can be substantial. This is particularly true for black employees, whose employment outcomes are much better when their manager is black. Our analysis suggests that a typical black employee with a black manager has a 14.9 percent probability of being dismissed within a

year of being hired, and a 6.5 percent probability of being promoted. But for a black employee with a non-black manager, the probability of being dismissed increases by almost one-half to 21.4 percent, and the probability of being promoted falls by almost two-thirds to 2.6 percent.<sup>32</sup>

We can help put these figures for blacks in perspective by asking how much race differences are responsible for the disparities between the employment outcomes of blacks and whites. We saw above that blacks have substantially higher average dismissal rates and lower average promotions rates than white employees with similar observable characteristics. Black employees have a 20.9 percent probability of being dismissed and a 2.9 probability of being promoted within a year, whereas similar white employees have a 7.6 percent probability of being dismissed and a 6.7 percent probability of being promoted. Now, would blacks reach parity with similar whites (most of whom have white managers) if all black employees had black managers? With respect to dismissals, the answer here is no. While having a black manager reduces black dismissal rates substantially (from 20.9 to 14.9 percent), blacks with black managers are still dismissed nearly twice as often as similar white employees. But in the case of promotions, our estimates imply that blacks *do* reach parity with whites when they have black managers. Blacks with black managers have virtually the *same* predicted probability as a similar white employee of being promoted within a year.

Beyond our firm and its employees, how would our findings apply to other settings? Our sample is from a retail firm, and this firm is in most ways typical of other retail firms. Hence our results would generalize best to the retail sector—a sector that accounts for 18 percent of all U.S. jobs.

## **VII. Conclusion**

Historic immigration, an aging population, and continuing occupational advances by

women—all these trends ensure that the American workforce is growing more diverse. Hence it is important to know whether demographic differences affect employment outcomes. To our knowledge, this is the first study that examines directly how demographic differences between manager and subordinate affect the subordinate's rate of quits, dismissals and promotions.

We find that race, age, and gender differences can have statistically significant and sometimes large effects on all three outcomes. This is especially true of differences in race and ethnicity, which consistently produce significant effects and which produce the largest effects. In general, we find that demographic differences tend to have adverse effects on our outcomes. But in three striking cases, where traditionally lower-status managers are supervising traditionally higher-status employees, such differences produce favorable effects.

Three summary points about race differences exemplify our findings. First, it is notable that while being a different race from one's manager hurts black and Hispanic employees, it helps white employees. Second, although minority managers apparently favor white employees, many white employees nevertheless avoid working for such managers—not only by quitting, but also by avoiding jobs under such managers. Finally, black employees suffer the strongest effects of having a different-race manager, their dismissal rate rising by nearly one-half and their promotion rate falling by two-thirds.

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**TABLE 1. SAMPLE STATISTICS: EMPLOYEE AND MANAGER DEMOGRAPHICS**

	<b>Employees</b>	<b>Managers</b>
<b>Gender</b>		
% Female	70.4%	78.4%
% Male	29.6%	21.6%
<b>Race/Ethnicity</b>		
% White	64.4%	87.0%
% Black	16.4%	4.8%
% Hispanic	10.3%	5.5%
% Asian	6.9%	2.4%
% Native American/Other	1.9%	0.3%
<b>Age</b>		
16-17 years	16.5%	0.0%
18-19 years	25.7%	0.1%
20-21 years	21.1%	0.4%
22-23 years	12.4%	4.1%
24-25 years	7.2%	12.9%
26-29 years	7.8%	42.3%
30-34 years	4.1%	26.3%
35-39 years	2.1%	8.8%
40-49 years	2.2%	4.1%
50-64 years	0.7%	8.7%
65 years & older	0.3%	0.0%
% Married	10.1%	
% With prior experience at company	23.8%	
% Part-time when hired	32.7%	
% Temporary when hired	64.4%	

*Notes:* Based on sample of N>100,000 employees hired between February 1, 1996 and July 31, 1998, and N>1,500 managers employed during this period.

**TABLE 2. SAMPLE STATISTICS: DYADS CHARACTERISTICS**

	<i>Hiring managers</i>	<i>New managers</i>	<i>All dyads</i>
<b>Manager is different sex</b>	<b>37.3%</b>	<b>36.9%</b>	<b>37.2%</b>
Female employees with male managers	14.5%	15.7%	14.7%
Male employees with female managers	22.8%	21.2%	22.5%
<b>Manager is different race</b>	<b>38.4%</b>	<b>40.8%</b>	<b>38.9%</b>
White employees with non-white managers	6.3%	7.4%	6.5%
Black employees with non-black managers	15.1%	14.4%	14.9%
Hispanic employees with non-Hispanic managers	8.8%	10.1%	9.1%
Asian employees with non-Asian managers	6.5%	7.0%	6.6%
<b>Average manager-employee age difference (years)</b>	<b>10.04</b>	<b>9.71</b>	<b>9.98</b>
Employees is at least 20% older than manager (average age difference in years)	4.8% (15.00)	7.2% (15.02)	5.2% (15.01)
Employees is at least 20% younger than manager (average age difference in years)	75% (11.68)	69.3% (11.51)	73.9% (11.65)
N >	100,000	20,000	120,000

**TABLE 3. REASONS FOR TERMINATION OF EMPLOYMENT SPELL**

	Share of total
Quit because dissatisfied or found better job . . . . .	54.0%
Quit because returned to school or moved away . . . . .	20.3%
Transferred to another store or took paid leave of absence . . . . .	9.5%
Laid off due to staff reductions or end of seasonal or temp work . . .	9.2%
Fired for substandard performance, absenteeism, dishonesty, or	7.0%

*Note:* Based on sample of N > 50,000 exits.

**TABLE 4. ESTIMATES FROM WEIBULL HAZARD MODELS OF QUILTS, DISMISSALS, AND PROMOTIONS**

	QUITS		DISMISSALS		PROMOTIONS	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Employee is Black	1.009 (0.025)	1.080 (0.082)	3.128** (0.170)	2.071** (0.320)	0.395** (0.060)	1.002 (0.505)
Employee is Hispanic	0.922** (0.029)	0.821* (0.073)	1.597** (0.107)	1.319 (0.240)	0.716* (0.115)	1.567 (0.716)
Employee is Asian	0.727** (0.026)	0.841 (0.114)	1.172* (0.094)	0.960 (0.257)	0.521** (0.096)	0.599 (0.437)
Employee age at time of hire	2.606** (0.130)	2.642** (0.143)	1.069 (0.114)	0.995 (0.116)	150.49** (88.30)	137.09** (80.81)
(Employee age) <sup>2</sup>	0.969** (0.002)	0.968** (0.002)	0.997 (0.004)	1.000 (0.005)	0.819** (0.022)	0.823** (0.022)
(Employee age) <sup>3</sup>	1.000** (0.000)	1.000** (0.000)	1.000 (0.000)	1.000 (0.000)	1.003** (0.001)	1.003** (0.001)
(Employee age) <sup>4</sup>	1.000** (0.000)	1.000** (0.000)	1.000 (0.000)	1.000 (0.000)	1.000** (0.000)	1.000** (0.000)
Employee is Female	0.923** (0.017)	0.942** (0.021)	0.494** (0.021)	0.492** (0.024)	1.119 (0.125)	1.049 (0.142)
Employee is married	0.800** (0.031)	0.802** (0.031)	0.697** (0.064)	0.697** (0.064)	1.022 (0.164)	1.015 (0.163)
Employee has firm experience	0.484** (0.012)	0.485** (0.012)	0.397** (0.024)	0.396** (0.024)		
Employee part-time when hired	1.795** (0.115)	1.783** (0.114)	0.637** (0.081)	0.636** (0.081)	0.086** (0.029)	0.087** (0.029)
Employee temp. when hired	2.174** (0.140)	2.173** (0.139)	0.945 (0.119)	0.941 (0.119)	0.058** (0.020)	0.059** (0.020)
Current manager is black	1.069 (0.051)	1.017 (0.064)	1.088 (0.115)	1.393* (0.190)	0.737 (0.218)	0.421* (0.179)
Current manager is Hispanic	0.998 (0.052)	1.001 (0.065)	1.164 (0.136)	1.322* (0.179)	1.529 (0.422)	0.883 (0.342)
Current manager is Asian	0.995 (0.066)	0.941 (0.072)	0.903 (0.130)	1.018 (0.163)	1.121 (0.353)	0.783 (0.316)
Current manager's age	1.056** (0.019)	1.058** (0.020)	1.148** (0.045)	1.129** (0.046)	1.006 (0.110)	0.989 (0.111)
(Current manager's age) <sup>2</sup>	0.999** (0.000)	0.999** (0.000)	0.998** (0.001)	0.998** (0.001)	1.000 (0.002)	1.000 (0.002)
Current manager is female	1.161** (0.029)	1.176** (0.030)	1.026 (0.057)	1.023 (0.057)	1.282 <sup>‡</sup> (0.172)	1.227 (0.177)
Current manager is new (not hiring mgr.)	1.049 (0.033)	1.048 (0.032)	0.739** (0.053)	0.738** (0.052)	1.448** (0.172)	1.449** (0.172)
<b>Employee white, manager not</b>		<b>1.070</b> (0.055)		<b>0.803<sup>‡</sup></b> (0.093)		<b>1.754<sup>‡</sup></b> (0.570)
<b>Employee black, manager not</b>		<b>0.941</b> (0.071)		<b>1.514**</b> (0.229)		<b>0.391*</b> (0.189)
<b>Employee Hispanic, mgr. not</b>		<b>1.161<sup>‡</sup></b> (0.104)		<b>1.180</b> (0.215)		<b>0.462<sup>‡</sup></b> (0.213)
<b>Employee Asian, manager not</b>		<b>0.866</b> (0.118)		<b>1.180</b> (0.319)		<b>0.955</b> (0.698)

(cont'd.)

<b>Empl. ≥ 20% older than mgr.</b>	<b>1.059</b> (0.085)	<b>0.736<sup>‡</sup></b> (0.135)	<b>0.992</b> (0.355)
<b>Empl. ≥ 20% younger than mgr</b>	<b>1.000</b> (0.035)	<b>1.175*</b> (0.096)	<b>1.094</b> (0.184)
<b>Manager is different sex</b>	<b>1.041<sup>‡</sup></b> (0.023)	<b>0.995</b> (0.046)	<b>0.894</b> (0.120)

Notes: Hazard ratios from Weibull proportional hazard model with gamma distributed frailty.

Additional controls (coefficients not shown): average store employment; average share of store’s employees that is black, Hispanic, Asian, other, & female; location type (mall, street); 30 dummies indicating month of hire; and dummies indicating the 5-digit ZIP code where the store is located.

Columns (3a) & (3b) control for city dummies instead of ZIP code dummies, but also include controls for residential population within two miles of store’s ZIP; median household income of local population; fraction of local population that is black, Hispanic, Asian, & other. Number of observations > 100,000 in all estimations. Robust standard errors in parentheses, adjusted for clustering on employee. <sup>‡</sup> significant at 10%; \* significant at 5%; \*\* significant at 1% (based on test that the hazard ratio is different from one).

Tests for joint significance and equality of coefficients across race groups:

- *Quits, Column (1b):* Wald Test could not reject equality of coefficients on “Employee white, manager not white” and “Employee Hispanic, manager not Hispanic” (p=.483), and these two coefficients are jointly significant at p=.034. When whites with non-white managers and Hispanics with non-Hispanic managers are pooled, the coefficient on the indicator for this group differs significantly from the coefficient on “Employee black, manager not black” (p=.052).
- *Dismissals, Column (2b):* Wald Test could not reject equality of coefficients on “Employee black, manager not black” and “Employee Hispanic, manager not Hispanic” (p=.281), and these two coefficients are jointly significant at p=.019. The coefficients on “Employee black, manager not black” and “Employee Hispanic, manager not Hispanic” both differ significantly from the coefficient on “Employee white, manager not white” (p=.005, p=.102, respectively).

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- *Promotions, Column (3b)*: Wald Test could not reject equality of coefficients on “Employee black, manager not black” and “Employee Hispanic, manager not Hispanic” ( $p=.794$ ), and these two coefficients are jointly significant at  $p=.071$ . The coefficients on “Employee black, manager not black” and “Employee Hispanic, manager not Hispanic” both differ significantly from the coefficient on “Employee white, manager not white” ( $p=.034$ ,  $p=.050$ , respectively).

**TABLE 5. EFFECTS OF DEMOGRAPHIC DIFFERENCES ON QUILTS FOR HIRING VS. NEW MANAGERS**

	<b>Hazard Ratio (std. Error)</b>	<b>Chi<sup>2</sup> (prob&gt;chi<sup>2</sup>)</b>
<b>White Empl. * Manager is different race * Hiring mgr.</b>	<b>1.049</b> (0.058)	<b>3.30<sup>‡</sup></b> (0.069)
<b>White Empl. * Manager is different race * New mgr.</b>	<b>1.345*</b> (0.178)	
<b>Black Empl. * Manager is different race * Hiring mgr.</b>	<b>0.954</b> (0.075)	<b>0.30</b> (0.582)
<b>Black Empl. * Manager is different race * New mgr.</b>	<b>0.834</b> (0.199)	
<b>Hispan Empl. * Manager is different race * Hiring mgr.</b>	<b>1.138</b> (0.102)	<b>0.08</b> (0.779)
<b>Hispan Empl. * Manager is different race * New mgr.</b>	<b>1.174</b> (0.154)	
<b>Asian Empl. * Manager is different race * Hiring mgr.</b>	<b>0.880</b> (0.121)	<b>0.47</b> (0.492)
<b>Asian Empl. * Manager is different race * New mgr.</b>	<b>0.820</b> (0.134)	
<b>Employee Older than Manager * Hiring mgr.</b>	<b>1.073</b> (0.090)	<b>1.54</b> (0.214)
<b>Employee Older than Manager * New mgr.</b>	<b>0.844</b> (0.157)	
<b>Employee Younger than Manager * Hiring mgr.</b>	<b>1.029</b> (0.037)	<b>0.58</b> (0.445)
<b>Employee Younger than Manager * New mgr.</b>	<b>0.956</b> (0.080)	
<b>Manager is different sex * Hiring mgr.</b>	<b>1.040<sup>‡</sup></b> (0.023)	<b>0.07</b> (0.790)
<b>Manager is different sex * New mgr.</b>	<b>1.060</b> (0.068)	
Observations	>100,000	

*Notes:* Hazard ratios from Weibull proportional hazard model with gamma distributed frailty.

Control variables as in Table 4, col. (1b) plus all interactions of manager race, gender and age, and employee race, gender and age indicators with the indicator that the manager is new.

Robust standard errors in parentheses, adjusted for clustering on employee. <sup>‡</sup> significant at 10%; \* significant at 5%; \*\* significant at 1% (based on test that the hazard ratio is different from one). Final column reports Wald test of equality for each pair of hazard ratios.

**TABLE 6. DISSIMILAR MANAGERS VS. DISSIMILAR COWORKERS**

	<b>Quits</b>	<b>Dismissals</b>	<b>Promotions</b>
<u>% Coworkers different race (at time of hire):</u>			
White * % Non-white coworkers	1.502** (0.128)	0.798 (0.159)	1.190 (0.372)
Black * % Non-black coworkers	2.085** (0.321)	1.152 (0.316)	0.195** (0.119)
Hispanic * % Non-Hispanic coworkers	1.108 (0.194)	0.991 (0.349)	0.771 (0.460)
Asian * % Non-Asian coworkers	1.662* (0.391)	2.043 (1.082)	1.244 (1.111)
% Coworkers different sex (at time of hire)	1.132‡ (0.082)	0.670* (0.110)	1.241 (0.352)
<b><u>Manager-Employee Race Differences:</u></b>			
<b>Employee white, manager not white</b>	<b>1.054</b> (0.055)	<b>0.830‡</b> (0.095)	<b>1.639*</b> (0.374)
<b>Employee black, manager not black</b>	<b>0.898</b> (0.068)	<b>1.410*</b> (0.210)	<b>0.451*</b> (0.141)
<b>Employee Hispanic, manager not Hispanic</b>	<b>1.133</b> (0.099)	<b>1.168</b> (0.214)	<b>0.564‡</b> (0.196)
<b>Employee Asian, manager not Asian</b>	<b>0.820</b> (0.112)	<b>1.055</b> (0.286)	<b>1.299</b> (0.784)
<b>Manager is different sex</b>	<b>1.037‡</b> (0.023)	<b>1.016</b> (0.047)	<b>0.976</b> (0.086)
Observations	>100,000	>100,000	>100,000

*Notes:* See Table 5.

**TABLE 7. QUALITATIVE SUMMARY OF RESULTS**

	<b>QUITS</b>	<b>DISMISSALS</b>	<b>PROMOTIONS</b>
<b>Effects of race differences:</b>			
Employee white, manager not white	<b>Unfavorable</b>	<i>Favorable</i>	<i>Favorable</i>
Employee black, manager not black	--	<b>Unfavorable</b>	<b>Unfavorable</b>
Employee Hispanic, manager not Hispanic	<b>Unfavorable</b>	<b>Unfavorable</b>	<b>Unfavorable</b>
<b>Effects of age differences:</b>			
Employee is ≥ 20% older than mgr.	--	<i>Favorable</i>	--
Employee is ≥ 20% younger than mgr.	--	<b>Unfavorable</b>	--
<b>Effects of gender differences:</b>			
	<b>Unfavorable</b>	--	--

## Notes

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<sup>1</sup> Estimates based on the 1984-2005 monthly CPS indicate that in the past two decades, the share of women in the labor force grew from 43.8 percent to 46.8 percent, and the share of nonwhites and Hispanics grew from 17.5 percent to 29.3 percent. Moreover, in the same period the share of all managers and supervisors who were women grew from 32.6 percent to 45.4 percent, and the share that was either nonwhite or Hispanic grew from 10 to 18.5 percent.

<sup>2</sup> Economists and sociologists have long noted that people may prefer to work with similar others, or be biased against dissimilar others; n.b., economic models of labor market discrimination and segregation (Becker, 1971) and theories of organizational demography (Pfeffer, 1983). To explain preferences for similarity, social psychologists have produced a body of theory; n.b., Byrne (1971), Tajfel and Turner (1986), and Turner (1987). For specific economic arguments about how similarity and difference may affect the employment relationship, see Akerlof and Kranton (2005 and 2000), Rothstein (1997), Thomas (1990), Lang (1986).

<sup>3</sup> DeVaro and Blau (2005) find that gender differences between managers and subordinates cannot explain differential promotion rates between men and women.

<sup>4</sup> In the economics literature, this paper is related to—and has learned much from—a handful of recent papers that focus on the relationship between the characteristics of hiring managers and the characteristics of those who are hired. These studies suggest that black managers hire black employees at higher rates than do nonblack managers (Giuliano, Levine and Leonard, 2006; Stoll, Raphael and Holzer, 2004; Carrington and Troske, 1998a; Bates, 1994). However, findings regarding gender matching are mixed (Carrington and Troske, 1998b). In the organizational

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behavior literature, there are a few studies of manager-subordinate similarity (e.g. Wesolowski and Mossholder, 1997; Thomas, 1990; Tsui and O'Reilly, 1989). However, these studies are confined to small-scale surveys and focus on subjective outcomes such as performance evaluations, role ambiguity, and job satisfaction. The findings of these studies are mixed. Finally, recent studies of non-employment outcomes have found (1) that racial similarity of police officer to driver reduces vehicle search rates (Antonovics and Knight, 2004); and (2) that race and gender dissimilarity between students and teachers significantly causes teacher evaluation of students to be more negative (Dee, 2005); and that race dissimilarity between NBA basketball players and officials increases the number of personal fouls called (Price and Wolfers, 2007).

<sup>5</sup> For brevity, we use the term “race” to refer to race *or* ethnicity. In our data, Hispanics are classified by ethnicity rather than by race; hence “Hispanic” is one of our mutually exclusive “race” categories.

<sup>6</sup> We do not report results for Asians because the estimates generally lack precision (see p. 5).

<sup>7</sup> For employees, we exclude left-censored employment spells (those who were hired before Feb. 1, 1996) because we lack dates of hire for these employees. When analyzing promotions, we restrict the sample to those with no prior company experience (i.e., we exclude re-hires).

<sup>8</sup> In some stores, it is possible that some employees have more contact with an assistant manager than they do with the store manager. This could cause some attenuation bias of our results. Nevertheless, we ignore assistant managers in our analysis because it is the store manager who is responsible for all personnel decisions.

<sup>9</sup> Managerial spells at a store are somewhat more likely to end in transfers to other stores rather than in exits from the employer.

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<sup>10</sup> Only 9.5 percent of spell terminations are due either to within-company transfers or to leaves of absence. See section B below for a breakdown of exits by type.

<sup>11</sup> The remainder are classified as Native American or “other”. The company’s records classify Hispanics by ethnicity and not by race; hence these categories are mutually exclusive and collectively exhaustive.

<sup>12</sup> The turnover comparison is based on estimates from the NLSY97. Among those 16-20 year olds who worked in low-wage ( $\leq$ \$9.00/hr) retail jobs in 1999, the median employment spell was about 110 days, and 87 percent left their job within a year. The racial composition comparison is based on based on all individuals in the 1996-1998 monthly CPS who had retail jobs. Of retail managers, 81 percent were white, 7 percent black, 7 percent Hispanic, and 5 percent Asian; retail employees were 73 percent white, 13 percent black, 10 percent Hispanic, and 4 percent Asian.

<sup>13</sup> For example, we observe more than 1,000 Hispanic employees with black managers and more than 2,000 black employees with Hispanic managers.

<sup>14</sup> As few stores close in our sample period, layoffs are typically due to the end of the holiday shopping season.

<sup>15</sup> The remaining 9.5 percent of spell terminations are due either to within-company transfers or to leaves of absence, and so are not separations from the employer. We do not analyze transfers because we lack information on the reason for the transfer. For example, we cannot distinguish among transfers requested by the employee due to friction with the manager, those that were tantamount to promotions (e.g. relocations to a more desirable location), and those that resulted simply from a change in the employee’s place of residence.

<sup>16</sup> The lowest paid of these 15 jobs (which accounts for roughly one third of the promotions) earns on average 12 percent more than the entry level job. The highest paid of these 15 jobs

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earns 26 percent more than the lowest. We find no evidence that either the *type* of job code at first promotion or the increase in pay is affected by manager-employee similarity. However, our sample is not large enough to allow precise estimates of these relationships.

<sup>17</sup> Because hazard models are relatively uncommon in economic analysis, we should briefly explain the second problem. If an omitted variable causes some individuals to have a higher risk for a certain outcome, then such individuals will leave the sample over time, and the remaining sample will consist disproportionately of individuals at low-risk for that outcome. Hence failure to control for the omitted variable will lead to biased estimates of both the risk for the outcome and of the effect of covariates on that risk.

Further, in a model like ours with competing risks, the selection bias in the estimates of one risk (e.g., the risk of quitting) may be exacerbated if an omitted variable is also correlated with a competing risk (e.g., the risk of being dismissed). In our model, quitting is a competing risk for being dismissed and vice versa. Further, quitting and being dismissed are both competing risks for the risk of being promoted. However, being promoted is not a competing risk for quitting or for being dismissed because promotion does not remove an individual from the sample at risk for quitting or being dismissed.

<sup>18</sup> In the analysis of promotions, we use city fixed effects instead of ZIP-code fixed effects in order to obtain sufficient variation in our dissimilarity variables. However, in these regressions we also control for observed characteristics of the population residing within two miles of the center of each store's ZIP code. These local population variables are based on the 1990 Census, and they include population density, median household income, and the racial and ethnic composition of the population.

<sup>19</sup> The ZIP-code fixed effects (and city fixed effects) are identified through two sources of

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variation in manager demographics: (1) variation *between* stores with the same five-digit ZIP codes, and (2) variation *within* stores that results from manager turnover.

Because we have substantial within-store variation in manager demographics, it is possible to identify models with store fixed effects (rather than the broader, ZIP-code fixed effects); however, the inclusion of store dummies in the Weibull model with frailty is computationally impractical. To assess the importance of store fixed effects, we estimated semi-parametric Cox (1975) models stratified by store. These models yielded results that were very similar to (but less precise than) both the results from Cox models stratified by ZIP code and the results from (non-frailty) Weibull models with ZIP-code dummies. Hence we conclude that the store fixed effects are not important.

Because the store fixed effects are not crucial, and because the stratified Cox model is incompatible with the individual “frailty” model, we chose the Weibull frailty model over the stratified Cox model. Results from the Cox model are reported in a previous version of this paper and are available from the authors on request.

<sup>20</sup> We must still consider how our estimates would be affected if omitted individual-level variables *are* correlated with the probability of having a dissimilar manager or employee (our covariates of interest). Our main concern here is that if people vary in their demographic preferences, then people who dislike working with dissimilar others may tend to avoid entering such relationships at the hiring stage. In the robustness section below, we discuss the implications of such sorting by employees and by managers for interpreting our results, and we provide evidence that pre-hire sorting does occur among white job-seekers.

<sup>21</sup> For an explanation of the competing risks in our model, see fn. 15.

<sup>22</sup> Because results in frailty models are often sensitive to the assumptions of the distribution of

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the frailty parameter (Heckman and Singer 1984), we also estimated all of the frailty models under the assumption that the  $v_i$ 's follow an inverse-Gaussian distribution. The results were very similar.

<sup>23</sup> Specifically, the identity relating these variables is  $Employee\ female \times MgrDiffSex \equiv \frac{1}{2} (Employee\ female - Manager\ female + MgrDiffSex)$ .

<sup>24</sup> The standard errors reported in the tables are computed using the delta rule; that is, they are the standard errors of the coefficients multiplied by the exponentiated coefficients. The test of significance is a test of whether the hazard ratio differs from 1.00 (which corresponds to a coefficient of zero).

<sup>25</sup> For example, in a sample that has a larger proportion of minority managers than our sample, choosing a same-race manager might be easier for minorities and more difficult for whites; consequently, the effects of race differences on employment outcomes might differ in magnitude from those in our sample.

<sup>26</sup> This finding is consistent with the results of our separate analysis of hiring patterns (reference suppressed), which suggest that (1) replacing a white manager with a black manager in a typical store leads to a four percentage point decline in the share of new hires that is white, and (2) in stores located in highly Hispanic areas, replacing a white manager with a Hispanic manager leads to a ten percentage point decline in the share of new hires that is white.

<sup>27</sup> Leonard and Levine (2005), Sorensen (2003), and O'Reilly, et al. (1989) all find that demographic differences from one's coworkers often increases employee turnover.

<sup>28</sup> Specifically, we find that race and gender isolation both lead to significantly higher quit rates (col. 1), that gender isolation (but not race isolation) significantly reduces dismissal rates (col. 2), and that race isolation significantly reduces the promotion rates of blacks, but not of any other

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group (col. 3). The estimates imply, for example, that a ten percentage point increase in the share of non-white coworkers raises white quit rates by roughly 4 percent, and a ten percentage point increase in the share of non-black coworkers reduces black promotion rates by 15 percent.

<sup>29</sup> Such deference could also reduce the white dismissal rate in another way: non-white managers who dismiss a white employee might be more willing to officially classify that employee's exit as a quit.

<sup>30</sup> We should note that DeVaro and Blau's (2005) analysis of establishments in the Multi-City Study of Urban Inequality also finds that manager-subordinate gender differences have no effect on promotion rates. This suggests that our results regarding gender differences might indeed generalize to other, more representative, settings.

<sup>31</sup> The average annual quit rate is the average number of job-related quits at all stores in one year divided by the average number of employees at all stores. Estimates of the effects of demographic differences on annual quit rates are calculated using: the annual quit rates for each demographic group; the employment shares of each group; the estimated effects of demographic differences from Table 4, column (1b); and the fraction of employees in each demographic group that works for a different-race or different-sex manager.

<sup>32</sup> These probabilities are calculated based on the estimated dismissal and promotion hazard functions for blacks with non-black managers, and on the estimated hazard ratio for blacks with non-black managers (relative to blacks with black managers) from Table 4, column (2b). The predicted probability of being dismissed within a year is conditional on not terminating employment at the store for another reason.