Do Race, Gender, and Age 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 employer, we examine how demographic differences between manager and subordinate affect the subordinate's rate of quits, dismissals, and promotions. We distinguish between two effects that demographic differences can produce: (1) the effects of dissimilarity *per se*, and (2) the effects of role breaking where the differences violate traditional social roles and status norms (e.g., non-whites managing whites). Our results suggest that both dissimilarity and role breaking can have statistically significant effects. **Race:** *Dismissals and Promotions:* Blacks and Hispanics with dissimilar managers are much more likely to be fired, and less likely to be promoted. We interpret these as dissimilarity effects. By contrast, white employees with non-white managers are *less* likely to be dismissed than whites with white managers, and *more* likely to be promoted. This suggests role breaking leads non-white managers to defer to white employees. *Quits:* While dissimilarity surprisingly has no effect on black quit rates, it does cause a moderate increase in Hispanic quits. Racial differences also cause a moderate rise in white quit rates. We expected the effect for whites to be larger because it is the sum of dissimilarity and role-breaking effects. Further analysis suggests the effect for whites is suppressed by pre-hire sorting; whites who dislike having non-white managers tend to avoid working for non-whites in the first place. **Age:** Age dissimilarity *per se* does not have effects. However, role breaking does; employees who are at least 20 percent older than their managers are much less likely to be dismissed, and more likely to be promoted. **Gender:** Gender differences have modest, adverse effects on all three employment outcomes.

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I. Introduction

As the workforce in the United States has grown more diverse in recent decades, so has the nation's corps of managers.[1] These parallel trends have altered the demographic relationship between manager and subordinate in two important respects. First, demographic differences have become a common feature of the manager-subordinate relationship. Second, this relationship is increasingly marked by demographic configurations that break with traditional norms and hierarchies. An important question, then, is how the demographic relationship between manager and employee affects the employment relationship.

This study uses daily personnel records from a very large U.S. retail firm to examine how demographic differences between manager and subordinate affect the subordinate's rate of quits, dismissals, and promotions. We look at differences with respect to three demographic dimensions: race, age, and gender. And we distinguish between two types of effects that demographic differences can produce: (1) the effects of dissimilarity *per se*, and (2) the effects of role breaking in cases where the demographic differences violate traditional roles and hierarchies (e.g., when racial minorities supervise whites, or when managers are younger than their subordinates).

While economists have long studied how race, age, and gender affect employment outcomes, few have examined directly the effects of demographic differences.[2] To our knowledge, no previous study has examined the effects of manager-employee differences on exits or promotions. Hence, the present study fills an important gap in the current literature. Also, this is the first study we know of that

[1] Estimates based on the 1984-2004 monthly CPS indicate that in the past 20 years, the share of non-whites and Hispanics in the labor force grew from 17.5 to 28.9 percent, and the share of women grew from 43.8 to 46.8 percent. Moreover, in the same period the share of all managers and supervisors who were either non-white or Hispanic grew from 10 to 18.5 percent, and the share comprised of women grew from 32.6 to 45.4 percent.

[2] With respect to the economics literature, this paper is most closely related to handful of recent papers that focus on the relationship between manager characteristics and the characteristics of those who are hired. These studies suggest that black managers hire black employees at higher rates than do non-black managers (Giuliano, Levine and Leonard, 2005; Stoll, Raphael and Holzer, 2004; Carrington and Troske, 1998a; and Bates, 1994). However, findings regarding gender matching are mixed (Carrington and Troske, 1998b; Giuliano et al., 2005). Related studies have found (1) that racial similarity of police officer to driver reduces vehicle search rates (Antonovics and Knight, 2004); and (2) mixed evidence on the effects of teacher-student gender similarity on test scores (Ehrenberg et al., 1995; Dee, 2001). Finally, a few studies of manager-subordinate similarity are found in the organizational behavior literature (e.g. Wesolowski and Mossholder, 1997; Judge and Ferris, 1993; 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.

distinguishes between two ways that manager-employee differences may matter. First, managers and employees may simply prefer not to work with dissimilar others. Second, sociological theory suggests that behavior can be affected by relationships that break with social roles and status norms.[3]

We examine these issues using thirty consecutive months of personnel data from a large U.S. retail employer with hundreds of stores located throughout the United States. We use hazard models with store "fixed effects" to estimate how the demographic relationship between manager and employee affects an employee's probability of quitting, being fired, and being promoted.[4] We identify the fixed-effects models using within-store variation in manager demographics; our sample contains hundreds of stores that have at least one change in management, and the new managers often have demographics that differ from the managers they replace.

Our results suggest that both dissimilarity *per se* and role breaking can have a statistically significant impact on our three employment outcomes:

Race: The results for dismissals and promotions are straightforward. When the manager is a different race, both blacks and Hispanics are much more likely to be fired, and less likely to be promoted.[5] We interpret these as dissimilarity effects. In contrast, when whites are in the role-breaking situation of having a different-race manager, they are (if anything) *less* likely to be fired than whites with white managers, and are *more* likely to be promoted. These results suggest that role breaking leads non-white managers to be deferential to white employees.

The quits results are less straightforward. First, black employees are no more likely to quit when they have a non-black manager than when they have a black manager. We thus find no dissimilarity effect for black employees. Second, Hispanics with non-Hispanic managers are somewhat more likely to quit. This is due to dissimilarity. Third, whites with non-white managers are also somewhat more likely to quit, but no more so than Hispanics with non-Hispanic managers. We expected race differences to raise the white quit rate more than the Hispanic (or black) quit rate; whereas the minority rates should be

[3] A recent symposium in the *Journal of Economic Perspectives* (Winter 2005) highlighted the importance of incorporating sociological perspectives into economic analysis. (See Gibbons, 2005).
[4] Specifically, we estimate stratified hazard models in which each store has its own baseline hazard function.
[5] We do not report results for Asians in our sample because the estimates generally lack precision.

raised only by a dissimilarity effect, the white rate should be raised by both a dissimilarity effect and by the role-breaking effect associated with being made subordinate to groups traditionally lower in status. Further analysis suggests the overall effect of race differences for whites is suppressed by pre-hire sorting; whites who dislike working for non-white managers tend to avoid working for such managers in the first place.

Age: Manager-employee age dissimilarity *per se* does not affect our employment outcomes. However, role breaking does affect rates of dismissals and promotions. Employees who are at least 20 percent *older* than their managers are less likely to be dismissed, and more likely to be promoted.

Gender: Gender differences have modest, adverse effects on all three outcomes. Employees whose manager is a different sex have slightly higher rates of quits and dismissals, and lower rates of promotions. We should acknowledge two points about our gender results. First, we cannot be sure whether the gender effects are due to dissimilarity, role breaking, or a combination of both. Second, the effects of gender differences may be influenced by the fact that in our sample almost 80 percent of the managers are women.

On the whole, our results suggest that both demographic dissimilarity and role breaking can have measurable effects on our employment outcomes. The implied economic cost of these effects depends on whose perspective is considered. For example, our results suggest that for the employer, the effects of demographic differences are small—they account for only one percent of all quit-related turnover. At the same time, our results suggest that for black and Hispanic employees, the effects of having a dissimilar manager can be substantial. When the manager does not share their race, these two groups are 16-54 percent more likely to be fired, and 12-55 percent less likely to be promoted.

II. Theoretical framework

To explore the effects of demographic differences, we test two sets of hypotheses (Table 1). These hypotheses are grounded in established sociological and psychological theory. The first set is based on "similarity theory", and addresses the consequences of simply being different from one's manager. The second set is based on "social role" theory, and emphasizes the importance of traditional norms and hierarchies.

A. Similarity and Dissimilarity

An old saying goes, "Birds of a feather flock together." Indeed, this truism forms the basis for economic models of labor market discrimination and segregation (Becker, 1957; Arrow, 1958) and for research in organizational demography (Pfeffer, 1983). In brief, these literatures maintain that people prefer to work with members of their own group. To explain such preferences for similarity, social psychologists have produced a growing body of theory; essential here are the similarity-attraction paradigm of Byrne (1971), and the social identity theory of Taijfel and Turner (1986). This body of theory argues, on one hand, that similarity promotes compatibility, interpersonal attraction, and identity reinforcement; and, on the other hand, that dissimilarity creates incompatibility, discord, and alienation.[6]

The implications of such arguments for the three outcomes that we study are straightforward. Specifically, we hypothesize:

> **Hypothesis 1a (Dissimilarity and Quits)**: Quit rates will be higher among employees whose manager is a different race, distinctly different in age, or a different gender.
>
> **Hypothesis 1b (Dissimilarity and Dismissals)**: Dismissal rates will be higher among employees whose manager is a different race, distinctly different in age, or a different gender.
>
> **Hypothesis 1c (Dissimilarity and Promotions)**: Promotion rates will be lower among employees whose manager is a different race, distinctly different in age, or a different gender.

B. Social Roles

The dissimilarity hypotheses above posit that in all cases where there is a demographic difference between manager and subordinate, such a difference will elicit a dissimilarity effect. Our second set of

[6] See also Turner (1987). Several specific "similarity" arguments are also relevant in our setting: (1) managers may communicate more effectively with similar employees (Lang, 1986; Tannen, 1990); (2) demographically similar managers may make better role models and mentors (Thomas, 1990); and (3) because similar individuals are more likely to share social networks, they may enter work relationships with greater levels of mutual trust and cooperation. (On the relationship between homogeneity, social capital and cooperation, see Bernstein, 1992; Greif, 1993; Alesina and La Ferrara, 2000; Costa and Kahn, 2001).

hypotheses, however, suggests that the effects of manager-subordinate differences will also depend on whether the relationship breaks with social norms and traditional hierarchies.

Theories of social roles (Eagly, 1987) argue that society prescribes different roles to members of different groups, and that such roles generally coincide with power and status norms. Further, when work roles break with social roles or traditional hierarchies, this conflict can cause discomfort for both the employee and manager (Kanter, 1977; Eagly 1987).[7] On one hand, when employees from traditionally higher-status groups have managers from lower-status groups, such employees are more likely to resent and to disrespect their managers. On the other hand, lower-status managers may defer to higher-status employees and may refrain from exercising their authority in order to avoid discomfort and disapproval.

In our sample, three demographic relationships break with traditional roles and hierarchies: non-whites managing whites, managers with subordinates older than themselves, and women managing men. Because subordinates may be less comfortable in these role-breaking relationships, we hypothesize that employee quit rates will be higher in these relationships:

> **Hypothesis 2a (Social Roles and Quits)**: Among employees with demographically different managers, quit rates will be higher for white employees (with non-white managers), for employees who are distinctly older than their managers, and for male employees (with female managers).

And because traditionally lower-status managers may behave deferentially toward higher status employees, we hypothesize that dismissal rates will tend to be lower in our role-breaking relationships, and that promotion rates will tend to be higher:

> **Hypothesis 2b (Social Roles and Dismissals)**: Among employees with demographically different managers, dismissal rates will be *lower* for white employees (with non-white managers), for employees who are distinctly older than their managers, and for male employees (with female managers).

[7] This conflict can also be understood in terms of social identity theory (Taijfel and Turner, 1986). Social identity theory suggests not only that discomfort can be caused by interaction with dissimilar others, but also that this discomfort should be stronger when the interaction does not conform to social roles. For example, see Akerlof and Kranton's (2000) discussion of why women find it difficult to enter into high-status occupations such as managers and doctors.

Hypothesis 2c (Social Roles and Promotions): Among employees with dissimilar managers, promotion rates will be *higher* for white employees (with non-white managers), for employees who are distinctly older than their managers, and for male employees (with female managers).

III. Data

A. The Sample

The data are the daily personnel records of a large retail employer from February 1, 1996 through July 31, 1998. 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.[8] This sample is drawn from more than 700 workplaces 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. A typical workplace has a full-time store manager on duty, and 25 to 50 (mostly part-time) employees.

The managers in our analysis are "store managers", and their duties include hiring, training, staff evaluation, and all personnel decisions.[9] These managers receive a small amount of training in fostering and managing a diverse workforce. Managers (like frontline employees) have high rates of turnover; the median employment spell for a manager in a store lasts roughly 13 months.[10] As a result, 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. Importantly for our analysis, new managers are often demographically different from those they replace. Thirty percent of all stores have consecutive managers from different race groups, and 38 percent have both a male and a female

[8] We exclude left-censored employment spells (employees hired before Feb. 1, 1996) because we lack information on the hiring manager for these employees. When analyzing promotions, we restrict the sample to those with no prior company experience.
[9] We ignore assistant managers in our analysis because it is the store manager who makes all personnel decisions. To be sure, there could be attenuation bias in our results if some employees have more contact with assistant managers than with the store manager.
[10] Approximately 60 percent of manager exits involve transfers to other stores.

manager within the sample period. It is this within-store variation in manager demographics that allows us to identify our fixed-effects models.

All frontline employees at this company have similar job titles and descriptions. They all rotate through several tasks in the workplace, dealing with customers and doing support duties. These jobs require only basic skills and employees receive little training. They also have high rates of turnover; the median employment spell for a frontline worker is 91 days, and roughly 80 percent of employment spells end within a year.

Table 2 summarizes the demographic composition of the managers and employees in our sample. With regard to managers, 78 percent are female, and 87 percent are white. The mean age for managers is 30 years, and nearly 70 percent are between the ages of 26 and 34. With regard to new frontline employees, a large majority (70 percent) are women. Further, 64 percent of new employees are white, 16 percent are black, 10 percent are Hispanic, and 7 percent are Asian.[11] Finally, these employees are relatively young; the average age is 22, and roughly three quarters are between the ages of 16 and 23.

Because our data comes from a single retail employer, it is useful to assess how representative our sample is of the retail sector as a whole—a sector that accounts for roughly 18 percent of all U.S. jobs. Compared to that sector, our sample is typical with respect to both its racial composition and its turnover rates.[12] However, this company employs a higher share of women (70 vs. 66 percent) and female managers (78 vs. 50 percent), and both managers and employees are relatively young (with average ages of 22 and 30 vs. 32 and 39).[13]

Table 3 shows the sample statistics for our key independent variables describing the demographic relationship between manager and employee. Among all manager-employee dyads in our sample

[11] The remainder are Native American or "other". These race and ethnicity codes are the company's coding, and they create a set of mutually exclusive and collectively exhaustive categories. Hispanics are classified by ethnicity and not by race. For brevity, we will often refer to these categories simply as "race".
[12] The turnover comparison is based on estimates from the NLSY97. Among those 16-20 year olds who worked in low-wage (≤$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 all individuals with retail-sector jobs in the 1996-1998 monthly CPS. Retail employees were 73 percent white, 13 percent black, 10 percent Hispanic, and 4 percent Asian, and managers were 81 percent white, 7 percent black, 7 percent Hispanic, and 5 percent Asian.
[13] The gender comparison is based on all individuals with retail-sector jobs in the 1996-1998 monthly CPS.

(column 3), 38 percent are mixed-race, the average age difference is 10 years, and 37 percent are mixed-gender. Our sample contains many dyads composed of minority employees with same-race or different-race minority managers. It also contains significant numbers of our three "role-breaking" dyads: white employees with non-white managers, employees whose managers are younger than they are, and male employees with female managers.

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 4), 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 or absenteeism, or violation of company policies. While 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), we will use the latter as a check on our identification.[14,15]

An important question is whether these classifications truly reflect different motivations for exit, or whether they merely reflect different labels for the same thing—as when an employee quits to avoid being fired. While we believe some misclassification exists, we analyze the quits and dismissals outcomes separately because there are systematic differences between them. Basic differences can be seen by comparing the failure functions for quits and dismissals (figures 1a and 1b). Not only are

[14] As few stores close in our sample period, layoffs are typically due to the end of the holiday shopping season.
[15] The remaining 9.5 percent of employment spell terminations in our sample are due either to within-company transfers or to leaves of absence, and hence 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 that were 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.

dismissal rates much lower than quit rates, they also drop off more quickly as the employee's tenure increases.[16] As we shall see in our regression analysis, there are also systematic differences in the ways that quits and dismissals are affected by the demographic relationship between manager and employee.

Promotions: The variable we use to analyze promotions is the number of days after hire until the first time an employee is promoted a new job title. To maintain a sufficient sample size, we pool the 15 different job titles to which an employee may be promoted.[17] In all, we observe roughly 2,500 first-time promotions.

III. Model and Estimation Methods

A. Cox Proportional Hazard Model

We use continuous time Cox proportional hazard models to analyze whether rates of employee quits, dismissals, and promotions are affected by the demographic relationship between manager and employee (Cox, 1972). We control for several things that could cause a spurious correlation between the employment outcomes and the manager-employee demographic relationship.[18] First, we control for the demographic characteristics (race, age, and gender) of both the employee and the employee's current manager. This eliminates compositional bias that would result if demographic groups differ in skills or other traits that affect our employment outcomes.[19] Second, we control for time-series variation in labor market conditions by including a vector of dummy variables that represents the 30 months in our sample period.

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[16] The failure function is (1-Survival function). Figures 1a-c are Kaplan-Meier estimates of the failure functions, which plot, as a function of the number of days since being hired, the fraction of employees that have already quit, been fired, or been promoted.

[17] The lowest paid of these 15 jobs (which accounts for roughly one third of the promotions in our sample) earns on average 12 percent more than the entry level job. The highest paid of these 15 jobs 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 this relationship.

[18] We have already eliminated virtually all variation in the job characteristics in our analysis by restricting the analyzed sample to employees with a single job title at a single company.

[19] For completeness, we also include three proxies for employee skill and job attachment: (1) an indicator for previous experience with the company, (2) indicators for part-time and temporary (vs. full-time/permanent) status, and (3) an indicator for marital status.

Finally, to control for *all* fixed characteristics of both the local labor market and the workplace, we estimate stratified models in which each store has its own flexible, baseline hazard function. This approach not only avoids imposing assumptions about the form of the baseline hazard function, it also allows us to control for all fixed characteristics of each store without estimating hundreds of additional parameters.[20] We are able to identify the stratified model because we have ample within-store variation in manager demographics.

We assume that the hazards associated with various modes of exit 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). Similarly, when analyzing promotions, all exits are treated as censored. This approach may produce biased estimates if the competing risks are not conditionally independent. However, we present evidence below that any such competing risk bias is likely to be small.

We begin by estimating a baseline model for each employment outcome that shows how average hazard rates vary with the demographics of the employee and the manager. For each employment outcome (quits, dismissals, and promotions), the hazard function for employee *i* in store *j* is specified as:

(1) $h_{ij}(t) = h_j(t) * exp(X_{ij}\,\beta_X + M_{ijt}\,\beta_M + T_t\,\beta_T)$.

Here $h_j(t)$ is the baseline hazard for store *j*, with time (*t*) measured in days; X_{ij} is a set of employee variables; M_{ijt} is a set of variables characterizing the employee's current manager on day *t*, including a dummy indicating whether the manager is new; and T_t is a vector of dummies indicating the sample month in which the employee was hired.

Next, to examine whether demographic differences between manager and employee affect average rates of quits, dismissals, and promotions, we add three dummy variables to equation (1):

[20] Here, the likelihood function is formed by first calculating for each duration time *t* the conditional probability that, of all individuals employed at a given store for at least *t* days, a particular individual *i* exits (or is promoted) on day *t*; and by then taking the product of these conditional probabilities (Cox, 1975). We use the Breslow (1974) method for handling ties.

$$(2)\ \ h_{ij}(t) = h_j(t) * exp(X_{ij}\,\beta_X + M_{ijt}\,\beta_M + T_t\,\beta_T + MgrDiffSex_{ijt}\,\beta_{DS} + MgrDiffRace_{ijt}\,\beta_{DR} + AgeDiff_{ijt}\,\beta_{DA}).$$

Here, $MgrDiffSex_{ijt,}$ and $MgrDiffRace_{ijt}$ are dummy variables indicating whether manager's gender and race differ from the employee's, and $AgeDiff_{ijt}$ is the absolute difference between the log of manager age and the log of employee age. Equation (2) constrains the effect of a gender difference to be the same for men and women, the effect of a race difference to be the same for all race groups, and the effect of an age difference to be the same whether the manager is older or younger than the employee. Hence, the coefficients on the three "demographic difference" variables—β_{DS}, β_{DR}, and β_{DA}—tell us whether manager-employee demographic differences affect *average* rates of employee quits, dismissals, and promotions.

It is important to note that because these averages are taken across all employees, the coefficients in equation (2) may capture and conflate the two effects that demographic differences can produce: (i) the effect of dissimilarity *per se* (which may affect all employees), and (ii) the effect of role breaking (which may affect only certain groups). It is also important to note that these two effects may have the same sign, or they may be countervailing. Consider the effect of racial differences on dismissals. For minority employees, having a different-race manager may raise dismissals because of a dissimilarity effect. But for white employees with a different-race manager, a basic dissimilarity effect that raises dismissals may be counteracted by a role-breaking effect that lowers them.

In the cases of race and age (but not in the case of gender), we can distinguish dissimilarity effects from social role effects by estimating a third, more flexible model specification. This specification allows (1) the effect of manager-employee race differences to vary across employees of different race groups, and (2) the effect of being distinctly older than one's manager to differ from the effect of being distinctly younger. Specifically, the equation is:

$$(3)\ h_{ij}(t) = h_j(t) * exp(X_{ij}\,\beta_X + M_{ijt}\,\beta_M + MgrDiffSex_{ijt}\,\beta_{DS} + (Race_{ij}\times MgrDiffRace_{ijt})\,\beta_{DR\text{-}Race} + EmpYounger\,\beta_{DA\text{-}Younger} + EmpOlder\,\beta_{DA\text{-}Older}).$$

Here, $Race_{ij} \times MgrDiffRace_{ijt}$ represents a vector of five dummy variables; each is the interaction of *MgrDiffRace* with an indicator for one of our five employee race groups: white, black, Hispanic, Asian, and other. *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.[21]

To test our hypotheses, we use the equation (3) coefficients as follows. First, we note that the coefficients on certain variables may reflect only the effects of dissimilarity *per se*. These are the variables indicating mixed race relationships that do *not* break with traditional hierarchies, and the variable indicating that the employee is *younger* than the manager. Hence, to identify the dissimilarity effects, we use the coefficients $\beta_{DR\text{-}Black}$, $\beta_{DR\text{-}Hispanic}$, $\beta_{DR\text{-}Asian}$, and $\beta_{DA\text{-}Younger}$. For example, to test the hypothesis that dissimilarity raises dismissal rates, we test the predictions that in the dismissals equation: (1) $\beta_{DR\text{-}Black}$, $\beta_{DR\text{-}Hispanic}$, $\beta_{DR\text{-}Asian}$ are all positive, and (2) $\beta_{DA\text{-}Younger}$ is positive.

Next, we note that in the role breaking cases, the coefficient on $White_{ij} \times MgrDiffRace_{ijt}$ ($\beta_{DR\text{-}White}$) and the coefficient on *EmpOlder* ($\beta_{DA\text{-}Older}$) may still reflect a combination of two effects: dissimilarity and role-breaking effects. Hence, to identify the effect of breaking traditional social roles, we *compare* the effect of having a different-race manager in the role-breaking cases with the effect of having a different-race manager in the traditional cases. If there is a difference in the effects, we interpret this difference as a "role-breaking" effect. For example, to test the hypothesis that "role-breaking" reduces dismissal rates, we test the predictions that: (1) $\beta_{DR\text{-}White}$ is smaller than $\beta_{DR\text{-}Black}$, $\beta_{DR\text{-}Hispanic}$, and $\beta_{DR\text{-}Asian}$, and (2) $\beta_{DA\text{-}Older}$ is smaller than $\beta_{DA\text{-}Younger}$.

While in the analysis of race and age differences we have refined equation (2) by adding an interaction term in equation (3), we cannot do so to refine our analysis of gender differences. This is because there are only two discrete gender categories (male and female); hence the interaction of a dummy for employee gender with *MgrDiffSex* is a linear combination of the three gender related dummy

[21] In this specification, employees whose managers are closer in age serve as the base group.

variables already in equation (2) (employee gender, manager gender, and *MgrDiffSex*). Specifically, the identity relating these variables is:

(4) $\textit{Employee male} \times \textit{MgrDiffSex} \equiv (\textit{MgrDiffSex} + \textit{Employee male} + \textit{Mgr female}).$

In other words, the effect of being in a role-breaking relationship (i.e., being a male with a female manager) cannot be identified separately from the combined effects of (1) being male, (2) having a female manager, and (3) having a different-sex manager.

B. Unobserved Heterogeneity and the Weibull Model with Frailty

In a competing risks hazard model, unobserved heterogeneity is an important concern for two reasons. First, in hazard models, omitted variables can lead to biased estimates even if these variables are *not* correlated with the covariates of interest.[22] Second, in models with competing risks, if omitted variables affect more than one risk (e.g. variables that affect both quits and dismissals), then estimates will be biased and inconsistent.

Because the stratified Cox model restricts comparisons to employees and managers in the same store, it removes all unobserved heterogeneity across stores, locations, and local labor markets. However, the Cox model does not account for unobserved characteristics of individuals (such as skills and preferences) that may affect quits, dismissals and promotions. Therefore, to test the robustness of our results from the stratified Cox model, we estimate a parametric proportional hazard model with "frailty" (unobserved individual heterogeneity).[23] Here, the survival time of individual i is influenced by the individual's frailty term v_i. This term is assumed to have a multiplicative effect on the hazard function and

[22] Omitted variables will result in downward biased estimates of the coefficients on other covariates, and the magnitude of the bias will depend on the magnitude of the effects of the omitted variables (Ridder and Verbakel, 1984; Struthers and Kalbfleisch, 1986).
[23] As in Hougaard (1986).

to be drawn from a particular parametric distribution.[24] In other words, the baseline model (corresponding to equation 1) becomes:

$$(5) \qquad h_{ij}(t|v_i) = h_0(t) * exp(X_{ij}\,\beta_X + M_{ijt}\,\beta_M + T_t\,\beta_T + S_j\,\beta_S) * v_i.$$

Here, $h_0(t)$ is a baseline hazard function that is constrained to be the same across all observations, and v_i is the frailty term for individual i. We assume a Weibull distribution for the baseline hazard function, and we assume that the v_i's follow a gamma distribution.[25]

In the Weibull model, stratifying by store would be computationally unwieldy—requiring separate parameter estimates for each of over 700 stores. Instead, we include control variables (S_j) that account for local population demographics and for differences in store size and location type (mall, street, etc.).[26] We are thus trading the ability of the Cox model to control for all unobserved heterogeneity across stores (without any assumptions on the form of the heterogeneity) for the ability of the Weibull model to adjust our estimates for unobserved heterogeneity across individuals (by imposing additional assumptions on functional form).

V. Results

Results from the Cox models of quits, dismissals, and promotions are reported in Tables 5, 6, and 7. In each of these tables, columns (1)-(3) report the estimates from equations (1)-(3) respectively. The corresponding results from the Weibull model are shown in Appendix Tables A1, A2, and A3. For ease of interpretation, the tables report hazard ratios (exponentiated coefficients) instead of the coefficients

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[24] We maintain the assumption that the hazards associated with the various modes of exits are conditionally independent; hence, we assume that the v_i's for each hazard are independent of one another. The model also assumes that the v_i's are uncorrelated with any of the independent variables in the model. This is a reasonable assumption if the frailty term embodies something that is unknown when the individual when hired, and which is learned over time—such as how much they like the job or how well they get along with the manager.

[25] Because results in frailty models are often sensitive to the assumptions of the distribution of 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.

[26] Local population statistics are from the 1990 Census, and are based on all Census blocks within two miles of the center of each store's ZIP code.

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.[27]

A. Baseline Model

The first column of each table reports the results from the baseline model showing the differences across demographic groups in average rates of employee quits, dismissals, and promotions. We present here the results of the Cox model; these are generally confirmed by the Weibull model.

First, we see that employee demographics are highly correlated with the likelihood that an employee will quit, be dismissed, or be promoted:

Race: All three outcomes vary significantly by employee race. Compared to the quit rate of white employees, quit rates are five percent higher for blacks, four percent lower for Hispanics, and 17 percent lower for Asians. Compared to whites, dismissal rates are more than twice as high for blacks, and roughly 40 percent higher for Hispanics. Compared to whites, promotion rates are 46 percent lower for blacks, 16 percent lower for Hispanics, and 40 percent lower for Asians.

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.

Gender: Women are seven percent less likely than men to quit, and 40 percent less likely to be dismissed. However, there are no gender differences in promotion rates.

Second, only in certain cases are manager demographics correlated with average rates of employee quits, dismissals, and promotions:

Race & Gender: Neither manager race nor manager gender significantly affects average rates of employee quits and dismissals. However, female managers promote employees at a higher rate than male managers.

Age: Older managers have higher employee quit rates, but lower dismissal rates.

[27] 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).

B. Do demographic differences matter on average?

The estimates from equation (2) are shown in column (2). These estimates show the average effects of manager-employee demographic differences on employment outcomes. Because these averages are taken across all the employees in our sample, the estimates may conflate the two effects that demographic differences can produce: dissimilarity and role-breaking effects. Hence these estimates must be interpreted with caution. For example, a zero or statistically insignificant average effect may mask a positive effect for some demographic groups and a negative effect for other demographic groups.

The results from both the Cox and Weibull models can be summarized as follows:

Race: Holding constant manager and employee race, average quit rates are 4-5 percent higher for employees with a different-race manager. In contrast, average rates of dismissals and promotions are not significantly affected by race differences.[28] However, as we shall see below, these average effects are masking the true effects of race differences for individual race groups.

Age: Average rates of quits and promotions are not significantly affected by age differences. But dismissal rates are affected; for example, a 20 percent difference between manager age and employee age causes roughly a 5-8 percent reduction in average dismissal rates. Again, however, these average effects are masking the true effects of being older than one's manager vs. being younger than one's manager.

Gender: Gender differences between manager and employee have an adverse effect on all three employment outcomes. Employees with different-sex managers have on average 3-5 percent higher quit rates, 3-8 percent higher dismissal rates, and 8-11 percent lower promotion rates.

In the analysis of gender differences, equation (2) is as far as we can go. As explained above, we cannot identify separate dissimilarity and social role effects. Nevertheless, we can determine whether our gender results are consistent with our hypotheses. First, our results are consistent with the dissimilarity hypotheses for all three of our employment outcomes. That is, our results are consistent with the

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[28] In the dismissals regressions, the Cox and Weibull models produce estimates with different signs—making these results inconclusive; and in the promotions regressions, neither the Cox nor Weibull estimate is significantly different from zero.

hypothesis that *for both men and women*, having a different-sex manager results in higher quit rates, higher dismissal rates, and lower promotion rates (the gender versions of hypotheses 1a, 1b, and 1c).

What about our role-breaking hypotheses? Hypotheses 2a-2c predict that all else equal, role breaking will cause male employees with female managers to have higher quit rates, lower dismissal rates, and higher rates of promotion. We can use equation (4) to see what our estimated coefficients could imply about the effect of being a male employee with a female manager. In short, our results are consistent with the role-breaking hypotheses for quits and for promotions, but are not consistent with the role-breaking hypothesis for dismissals (that men are dismissed less often by female managers). With respect to dismissals, the adverse effect of having a different-sex manager is at least as large for men as it is for women. Hence in contrast to our hypothesis, our results strongly suggest that female managers in our firm are comfortable dismissing male employees.

C. Dissimilarity vs. Role-Breaking Effects of Race & Age Differences

The key findings of our study with respect to race and age are the estimates from equation (3), which are shown in column (3). This specification of our model allows the effect of having a different-race manager to vary by race group, and also allows the effect of being older than one's manager to differ from the effect of being younger. The estimates from this specification permit us to identify separate dissimilarity and role-breaking effects.

The results from both the Cox and Weibull models can be summarized as follows:

Race Differences: *Dismissals:* When the manager is a different race, blacks are 20-24 percent more likely to be fired and Hispanics are 16-54 percent more likely to be fired. For whites, on the other hand, having a different-race manager either has no effect (*per* the Cox estimates) or may even *reduce* the probability of being fired by 26 percent (*per* the Weibull estimates).[29]

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[29] The estimates for blacks and Hispanics with different-race managers are jointly significant in both the Cox and Weibull regressions (p=.039 and p=.006 respectively). They also differ significantly from the estimates for whites in both models (p=.103 and p=.0004 respectively). For Asians, the estimates are inconsistent across the Cox and Weibull models and have large standard errors; thus we cannot draw any conclusions about Asians. For similar reasons, we do not report any of the estimates for employees in the "other" race category.

Promotions: When the manager is a different race, blacks are 11-55 percent less likely to be promoted, and Hispanics are 12-16 percent less likely to be promoted. In contrast, whites with different-race managers are 15-55 percent *more* likely to be promoted than whites with white managers.

The results for dismissals and promotions thus have the clear pattern predicted by our hypotheses. When the manager is a different race, blacks and Hispanics have less favorable outcomes. We interpret these as the dissimilarity effects predicted by hypotheses 1b and 1c. But in the role-breaking cases where non-whites manage whites, white employees have (if anything) better outcomes than white employees with white managers. This reflects the role-breaking effects predicted by hypotheses 2b and 2c.

Quits: First, blacks with non-black managers are no more likely to quit than blacks with black managers. Second, Hispanics with a different-race manager are 7-17 percent more likely to quit. Third, whites with non-white managers are only 5-7 percent more likely to quit than whites with white managers.[30]

We thus find the dissimilarity effect for Hispanics predicted by hypothesis 1a, but the quit results for both blacks and whites are apparently inconsistent with our hypotheses. First, there is no dissimilarity effect for blacks as predicted by hypothesis 1a. We leave this intriguing finding as a subject for future research.[31] Second, we expected race differences to raise the white quit rate more than the Hispanic quit rate; whereas the Hispanic rate should be raised only by a dissimilarity effect (hypothesis 1a), the white rate should be raised by both dissimilarity and role-breaking effects (hypotheses 1a and 2a). As we shall see, further analysis suggests the overall effect of race differences for whites is suppressed by pre-hire sorting; whites who dislike working for non-white managers tend to avoid working for such managers in the first place.

[30] The difference between the effect for blacks on the one hand, and for whites and Hispanics on the other hand, is statistically significant in the Weibull model (p=.033). In the Cox model, this difference is significant only at p=.159. The estimates for Asians are again inconsistent across models and not statistically significant in either model.

[31] One possible explanation is suggested by Fryer and Torelli's (2005) finding that blacks who "act white" (e.g. by investing in behaviors characteristic of whites) have fewer black friends. In our setting, it is possible that black employees are no more comfortable with black managers than with white managers because black managers are seen as "acting white".

Age Differences: The results suggest that manager-employee age dissimilarity *per se* does not affect employment outcomes. Employees who are at least 20 percent younger than their managers are just as likely to quit, be dismissed, and be promoted as employees who are closer to their managers in age.

However, breaking the traditional age hierarchy *does* affect rates of dismissals and promotions.

Dismissals: Employees who are at least 20 percent *older* than their managers are 17-28 percent *less* likely to be dismissed. This matches the prediction of hypothesis 2b that managers will behave deferentially toward employees who are distinctly older than they are.

Promotions: While the estimates from the promotions analysis are not statistically significant, they again suggest that employees who are at least 20 percent *older* than their managers receive deferential treatment.[32] Such employees are 19-30 percent *more* likely to be promoted.

VI. Robustness Tests

A. Assessing the bias due to competing risks

Thus far, we have ignored one potential source of bias in our model—the fact that the competing risks of quitting, being fired, and being promoted are not independent of one another. A non-zero effect of demographic differences on the risk of one outcome could cause biased censoring of the sample at risk for the other two outcomes. Hence the estimated effects of demographic differences on the latter two outcomes could be biased. For example, if employees with different-sex managers were more likely to quit than those with same-sex managers, then those with different-sex managers would be less often at risk for being fired or promoted. As a result, the estimated effects of gender differences on dismissal and promotion rates would reflect a negative bias. The size of the bias would depend both on the size of the true effect of gender differences on quits and on the magnitude of the risk of quitting.[33]

A means of assessing the magnitude of the competing risk bias is provided by data on exit decisions that are driven by external forces—such as quits caused by an employee moving or by the beginning of the school year. The decision to move or to return to school should not be influenced by the

[32] p=.090 in the Cox model and p=.474 in the Weibull model.
[33] See Honore and Lleras-Muney (2004) for a discussion of how the magnitude of the censoring bias depends on the size of the risk.

demographic relationship with one's manager. Hence, if the competing risk bias is small, estimates of the effects of dissimilarity and role breaking on the hazard of moving or returning to school should be close to zero.

Table 8 shows the estimates from a Cox model analogous to those above, but with the dependent variable defined as the hazard of moving or returning to school. The estimates are reassuring—none of the coefficients on the demographic difference variables are significantly different from zero. This is what we would expect if the competing risk bias is small.

B. Quits: the effect of being different from one's coworkers

A concern regarding our quits results is that employees may react not only to being different from their managers, but also to being different from their coworkers.[34] Because the demographics of managers and their employees tend to be correlated, our quits results may be driven partly by employees who do not like the prevailing demographics of their coworkers. We examine the possibility that dissimilarity from coworkers could be driving our quits results by including controls for demographic isolation from one's coworkers in our quits regressions. We define "gender isolation" as the share of coworkers who are the opposite sex, and "race isolation" as the share of coworkers who are a different race.

When we control for gender isolation, the hazard ratio for employees with different-sex managers is reduced only slightly—from 1.028 to 1.026 (Table 9). This stability suggests that our original estimate reflects mainly the effect of being different from one's manager. However, when we control for race isolation, the hazard ratio for white employees with non-white managers falls from 1.050 to 1.026, and the hazard ratio for Hispanic employees with non-Hispanic managers falls from 1.076 to 1.063.[35] These results suggest that our original estimates of the effects of race differences on quit rates were driven partly by employees who did not like working with dissimilar co-workers.

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[34] Sorensen (2003), Levine and Leonard (2004), Jackson, et al. (1991), and O'Reilly, et al. (1989) all find that demographic differences from one's coworkers can affect employee turnover.

[35] The coefficient on whites with non-white managers and the coefficient on Hispanics with non-Hispanic managers remain jointly significant at a 5 percent level.

C. New Manager vs. Hiring Manager Relationships: A Test for Hiring-Stage Sorting

In most employment relationships, both the manager and the employee choose whether to enter the relationship. Hence another issue for interpreting our results is whether people are sorting themselves at the hiring stage on the basis of their demographic preferences. If such sorting occurs, then people who dislike working with dissimilar others or in role-breaking relationships will tend to avoid entering such relationships. As a result, the mixed-demographic and role-breaking relationships in our data would consist disproportionately of people who are most comfortable with these relationships. Such pre-hire sorting would thus reduce the effects of dissimilarity and role-breaking on our three, post-hire employment outcomes.

While we have no clean test for sorting by managers, we can test for sorting by employees.[36] We do so by exploiting the fact that roughly 20 percent of our employees get a new manager at some point. By being selective during the hiring process, employees with strong demographic preferences may avoid being hired by certain types of managers. Once hired, however, employees have no control over the selection of a new manager, and can avoid an unwanted relationship only by quitting. Therefore, if employees do in fact sort themselves based on demographic preferences at the hiring stage, we should find larger effects of dissimilarity and role-breaking on quit rates when the manager in question is new.

While a comparison of "new manager" vs. "hiring manager" dyads does not indicate that employees sort themselves on the basis of age or gender preferences, it does show evidence that one group—white employees—are sorting themselves based on racial preferences.[37] For white employees, the effect of having a non-white manager on quit rates is significantly larger when the manager in question is new. Specifically, among white employees who still have the managers who hired them (i.e., those who chose to work for their current managers), whites with non-white managers are only 4.4

[36] Unlike in the case of employees, the comparison of "hiring manager" vs. "new manager" dyads does not provide a clean test of manager sorting because it is not clear in which of two cases managers have more control over the demographics of their subordinates— when they decide whom to hire or when they decide where to accept a job.
[37] We find some evidence that hiring stage sorting reduces the effects of race dissimilarity on Asian quit rates, but the difference between hiring manager and new manager dyads is significant only at p=.115. We find no evidence of sorting by black and Hispanic employees.

percent more likely to quit than whites with white managers. In contrast, among white employees who have received new managers (i.e., those for whom there is no selection bias), whites who received non-white managers are almost 17 percent more likely to quit than those who received white managers.

As noted above, this result helps address a question about our quits results. Why don't race differences have the relatively large effects on white quit rates that we hypothesized? Our analysis suggests the answer is that white employees who dislike working for non-white managers often avoid working for such managers. When such whites involuntarily find themselves working for a non-white manager, the hypothesized higher quit rate appears.

VII. Discussion: Are the Effects of Demographic Differences Economically Important?

Our analysis suggests that demographic differences between managers and employees can have statistically significant effects on rates of quits, dismissals and promotions. But are these effects economically important? We consider three aspects of this question. First, what are the implications for our employer? Second, what are the implications for our employees? Finally, how might the results from our study generalize to other settings?

To assess the economic implications for our employer, we consider the effects of demographic differences on the company's annual, quit-related turnover. Our estimates suggest these effects are small. For example, the estimates from the Cox model (Table 5) imply that for the company as a whole, the effects of demographic differences can account for only 1 percent of all quit-related turnover. Specifically, if the company could somehow eliminate these effects (e.g., through diversity training), it could reduce annual quit rates from 84.4 percent to 83.5 percent per year.[38] 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

[38] Average annual quit rate is the average number of quits at a store in one year divided by the average number of employees. The effect of demographic differences is a weighted average of quit rates based on the Cox estimates in Table 5 and on the fraction of employees in each demographic group that works for a different-race manager.

extreme case of an all white store, replacing a white manager with a non-white manager would raise average annual quit rates from about 82 percent to 95 percent.

While the economic effects for the employer are not large, the effects for individual employees can be substantial. In particular, black and Hispanic employees who have dissimilar managers are much more likely to be dismissed and less likely to be promoted. A typical black employee has an 18.4 percent probability of being fired within a year by a black manager, but this probability increases to 21.8 percent (i.e., by almost one-fifth) if the manager is not black.[39] For Hispanics, the probability of being fired within a year rises from 14.3 percent to 16.5 percent (i.e., by one-seventh) if the manager is non-Hispanic. Our estimates also imply potentially large effects of manager-employee dissimilarity on black promotion rates. While the probability that a black employee is promoted within a year is between 3.1 percent and 6.4 percent if the manager is black, it is only 2.8 percent if the manager is not black.

For blacks and Hispanics, these dissimilarity effects are obviously important. But a balanced discussion must also consider the question of whose behavior is driving these effects. Clearly, these effects could reflect discrimination by non-black managers against blacks, and by non-Hispanic managers against Hispanics. Still, there are two other possibilities. Such effects could reflect preferential treatment by black managers toward blacks and by Hispanic managers toward Hispanics. Or they could reflect the fact that employees who dislike dissimilar managers may respond with behavior (e.g., reduced effort or increased absenteeism) that raises dismissal rates and reduces promotion rates.

Two points should be made about the possible relationship between discrimination and minority dismissal rates. First, if the dissimilarity effects on black and Hispanic dismissal rates are driven mainly by discrimination, then because there are so few black and Hispanic managers, the implied overall level of discrimination against blacks and Hispanics is substantial. Second, however, we should consider what part discrimination might play in the overall rate of black dismissals. Even if the dissimilarity effects on black dismissal rates were driven entirely by discrimination, the effect of discrimination would still be

[39] These probabilities are calculated based on the estimated dismissal hazard function for blacks and the estimated hazard ratio for blacks with non-black managers from the Cox regression (Table 6). The implied probability of being fired within a year is conditional on not terminating employment at the store for another reason.

small compared to the effects of other unobserved characteristics that are correlated with being black. For whatever reasons, even when the manager is black, blacks are nearly twice as likely as whites to be fired within a year.[40] Hence, our estimates suggest that it is important to identify the other reasons why blacks are fired so often.

Are the effects we find in our sample likely to be larger or smaller than what might be found in other settings? This is a difficult question, and we can only suggest some guidelines for answering it. 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 accounts for 18 percent of all U.S. jobs.

To be sure, the firm in this study is in some ways atypical of the retail sector. First, the relative youth of our workforce could make it more accepting of race and gender differences. Second, due to the high share of women in management, female managers likely enjoy an unusual degree of acceptance. Third, the sample period (1996-1998) was a time of historically low unemployment in the U.S., and during such a period we would expect quits to be more responsive, and dismissals less responsive, to manager-employee differences.

Additional caveats make generalizing to other sectors even more problematic. For example, because of our firm's low wages and its low skill and training requirements, the costs of quitting and firing are small compared to what they are in most other sectors. Thus, even if the underlying preferences among employees and managers are similar in higher-wage sectors, we might expect manager-employee differences to have smaller effects on turnover in those sectors. At the same time, however, the results of our study suggest that race, age, and gender differences would still affect the employment relationship—though perhaps in less quantifiable ways.

VIII. Conclusion

To our knowledge, this is the first study that examines how demographic differences between manager and subordinate affect the subordinate's rate of quits, dismissals and promotions. It is also the

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[40] For blacks, the estimated probability is 18.4 percent; for whites it is 10 percent. These estimates are based on the Cox model, which also shows that white dismissal rates are not affected by the race of the manager.

first study that distinguishes between two types of effects that demographic differences can produce: the effects of dissimilarity *per se* and the effects of breaking with traditional social roles or status norms. Our results suggest that both dissimilarity and role breaking can have measurable effects on all three of our employment outcomes.

First, gender differences have consistently adverse effects on all three outcomes. While these effects are modest, it should be remembered that our company may not the best place to look for gender biases. Second, although age dissimilarity *per se* has no significant effects, role-breaking differences in age have substantial effects on both dismissals and promotions. Employees who are distinctly older than their managers are 17-28 percent *less* likely to be dismissed than other employees, and 19-30 percent *more* likely to be promoted.

Finally, racial differences have marked effects. For black and Hispanic employees, racial dissimilarity *per se* has a negative effect on both dismissals and promotions. Blacks and Hispanics with dissimilar managers are 16-54 percent more likely to be fired, and 12-55 percent less likely to be promoted. But for white employees, role-breaking effects counteract the effects of dissimilarity *per se*, and hence racial differences actually *reduce* dismissals and *increase* promotions. White employees with non-white managers are up to 26 percent less likely to be dismissed than white employees with white managers, and up to 50 percent more likely to be promoted. Lastly, our analysis of quits suggests that even though minority managers defer to white employees, whites still often avoid working for minority managers either by quitting or by not taking jobs in the first place.

While the demographic diversity of our company clearly reflects the changing nature of the American workforce, our results point to the enduring nature of demographic preferences and traditional hierarchies. In particular, our results suggest that racial biases continue to present obstacles for minorities in the workplace, and continue to preserve the privileged position of whites. When minorities have dissimilar managers, they are much more likely to be fired and much less likely to be promoted. And when minorities do obtain managerial positions, they have difficulty hiring, retaining, and exercising authority over whites.

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TABLE 1. HYPOTHESES

	Similarity Theories	Social Role Theories
Quit rates are . . .	***. . . higher when:***	***. . . higher when:***
Gender	Manager and subordinate have different genders	Male subordinate has female manager
	<<The above hypotheses are perfectly collinear>>	
Race	Manager and subordinate have different races/ethnicities	White subordinate has non-white manager
Age	Manager and subordinate ages are very different	Manager is much younger than subordinate
Dismissal rates are . . .	***. . . higher when:***	***. . . lower when:***
Gender	Manager and subordinate have different genders	Male subordinate has female manager
	<<The above hypotheses are perfectly collinear>>	
Race	Manager and subordinate have different races/ethnicities	White subordinate has non-white manager
Age	Manager and subordinate ages are very different	Manager is much younger than subordinate
Promotion rates are. . .	***. . . lower when:***	***. . . higher when:***
Gender	Manager and subordinate have different genders	Male subordinate has female manager
	<<The above hypotheses are perfectly collinear>>	
Race	Manager and subordinate have different races/ethnicities	White subordinate has non-white manager
Age	Manager and subordinate ages are very different	Manager is much younger than subordinate

TABLE 2. SAMPLE STATISTICS: EMPLOYEE AND MANAGER DEMOGRAPHICS

	Employees	Managers
Gender		
% Female	70.4%	78.4%
% Male	29.6%	21.6%
Race/Ethnicity		
% 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%
Age		
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 3. SAMPLE STATISTICS: DYADS CHARACTERISTICS

	Hiring managers	***New managers***	**All dyads**
Manager is different sex	**37.3%**	**36.9%**	**37.2%**
Female employees with male managers	14.5%	15.7%	14.7%
Male employees with female managers	22.8%	21.2%	22.5%
Manager is different race	**38.4%**	**40.8%**	**38.9%**
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%
Average manager-employee age difference (years)	**10.04**	**9.71**	**9.98**
Employees is at least 20% older than manager	4.8%	7.2%	5.2%
(average age difference in years)	(15.00)	(15.02)	(15.01)
Employees is at least 20% younger than manager	75%	69.3%	73.9%
(average age difference in years)	(11.68)	(11.51)	(11.65)
N >	100,000	20,000	120,000

TABLE 4. 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 policy violation. .	7.0%

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

TABLE 5. COX PROPORTIONAL HAZARD ESTIMATES OF QUITS

	(1)	(2)	(3)
Employee is female	0.933**	0.947**	0.947**
	(0.008)	(0.009)	(0.009)
Employee is black	1.039**	1.007	1.055
	(0.011)	(0.016)	(0.044)
Employee is Hispanic	0.962**	0.934**	0.909*
	(0.013)	(0.016)	(0.040)
Employee is Asian	0.830**	0.803**	0.792**
	(0.013)	(0.016)	(0.059)
Employee age at time of hire	1.814**	1.806**	1.816**
	(0.033)	(0.039)	(0.035)
(Employee age)^2	0.980**	0.980**	0.980**
	(0.001)	(0.001)	(0.001)
(Employee age)^3	1.000**	1.000**	1.000**
	(0.000)	(0.000)	(0.000)
(Employee age)^4	1.000**	1.000**	1.000**
	(0.000)	(0.000)	(0.000)
Employee is married	0.879**	0.879**	0.879**
	(0.012)	(0.012)	(0.012)
Employee has prior company experience	0.622**	0.622**	0.622**
	(0.006)	(0.006)	(0.006)
Employee is part-time when hired	1.269**	1.269**	1.268**
	(0.031)	(0.031)	(0.031)
Employee has temp/seasonal status when hired	1.427**	1.427**	1.426**
	(0.035)	(0.035)	(0.035)
Current manager is female	0.995	1.005	1.005
	(0.014)	(0.015)	(0.015)
Current manager is black	1.041	1.032	1.012
	(0.028)	(0.028)	(0.036)
Current manager is Hispanic	1.015	1.005	1.007
	(0.028)	(0.028)	(0.035)
Current manager is Asian	0.981	0.964	0.961
	(0.037)	(0.036)	(0.041)
Current manager's age	1.016	1.017‡	1.015
	(0.010)	(0.010)	(0.010)
(Current manager's age)^2	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)
Current manager is new (not hiring manager)	1.063**	1.063**	1.063**
	(0.013)	(0.013)	(0.013)
Manager is different sex		**1.029****	**1.029****
		(0.010)	(0.010)
Manager is different race		**1.040****	
		(0.015)	
Employee white, manager not white			**1.050**‡
			(0.029)
Employee black, manager not black			**0.990**
			(0.041)
Employee Hispanic, manager not Hispanic			**1.076**‡
			(0.048)
Employee Asian, manager not Asian			**1.057**
			(0.080)
| Log(manager age) – log(employee age)|		**0.984**	
		(0.045)	
Employee is at least 20% older than mgr.			**1.003**
			(0.028)
Employee is at least 20% younger than mgr.			**1.009**
			(0.014)
Observations	> 100,000	> 100,000	> 100,000

Notes: Hazard ratios from Cox proportional hazard model, stratified by store. Robust standard errors in parentheses, adjusted for clustering on employee. Omitted race category is white. Coefficients for 30 month of hire dummies not shown.
‡ significant at 10%; * significant at 5%; ** significant at 1% (based on test that the hazard ratio is different from one).

TABLE 6. COX PROPORTIONAL HAZARD ESTIMATES OF DISMISSALS

	(1)	(2)	(3)
Employee is female	0.604**	0.615**	0.615**
	(0.012)	(0.015)	(0.015)
Employee is black	2.269**	2.139**	1.914**
	(0.060)	(0.079)	(0.173)
Employee is Hispanic	1.423**	1.345**	1.239*
	(0.048)	(0.056)	(0.124)
Employee is Asian	1.071	1.009	0.933
	(0.047)	(0.052)	(0.154)
Employee age at time of hire	1.093‡	1.028	1.048
	(0.053)	(0.064)	(0.057)
(Employee age)^2	0.996*	0.997	0.997
	(0.002)	(0.002)	(0.002)
(Employee age)^3	1.000*	1.000	1.000
	(0.000)	(0.000)	(0.000)
(Employee age)^4	1.000*	1.000	1.000
	(0.000)	(0.000)	(0.000)
Employee is married	0.734**	0.733**	0.733**
	(0.034)	(0.034)	(0.034)
Employee has prior company experience	0.516**	0.517**	0.516**
	(0.016)	(0.016)	(0.016)
Employee is part-time when hired	0.833**	0.833**	0.831**
	(0.052)	(0.052)	(0.052)
Employee has temp/seasonal status when hired	1.043	1.042	1.039
	(0.065)	(0.065)	(0.065)
Current manager is female	0.990	0.994	0.992
	(0.037)	(0.037)	(0.037)
Current manager is black	1.029	1.041	1.128
	(0.071)	(0.071)	(0.097)
Current manager is Hispanic	1.134‡	1.131‡	1.190*
	(0.082)	(0.081)	(0.096)
Current manager is Asian	1.119	1.100	1.155
	(0.101)	(0.099)	(0.114)
Current manager's age	0.972	0.982	0.962
	(0.026)	(0.027)	(0.027)
(Current manager's age)^2	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)
Current manager is new (not hiring manager)	1.016	1.015	1.014
	(0.033)	(0.033)	(0.033)
Manager is different sex		**1.034**	**1.034**
		(0.025)	(0.025)
Manager is different race		**1.078***	
		(0.036)	
Employee white, manager not white			**0.978**
			(0.067)
Employee black, manager not black			**1.198***
			(0.107)
Employee Hispanic, manager not Hispanic			**1.161**
			(0.117)
Employee Asian, manager not Asian			**1.153**
			(0.193)
| Log(manager age) – log(employee age)|		**0.760‡**	
		(0.119)	
Employee is at least 20% older than mgr.			**0.834***
			(0.077)
Employee is at least 20% younger than mgr.			**1.009**
			(0.041)
Observations	> 100,000	> 100,000	> 100,000

Notes: See Table 5.

TABLE 7. COX PROPORTIONAL HAZARD ESTIMATES OF PROMOTIONS

	(1)	(2)	(3)
Employee is female	1.011	0.943	0.942
	(0.057)	(0.063)	(0.063)
Employee is black	0.531**	0.511**	0.604‡
	(0.045)	(0.057)	(0.165)
Employee is Hispanic	0.828*	0.797*	0.953
	(0.073)	(0.089)	(0.286)
Employee is Asian	0.602**	0.576**	0.376‡
	(0.064)	(0.076)	(0.221)
Employee age at time of hire	71.570**	68.997**	74.323**
	(26.695)	(26.185)	(26.372)
(Employee age)^2	0.842**	0.843**	0.842**
	(0.015)	(0.015)	(0.014)
(Employee age)^3	1.003**	1.003**	1.003**
	(0.000)	(0.000)	(0.000)
(Employee age)^4	1.000**	1.000**	1.000**
	(0.000)	(0.000)	(0.000)
Employee is married	0.927	0.925	0.929
	(0.071)	(0.071)	(0.072)
Employee is part-time when hired	0.263**	0.266**	0.264**
	(0.026)	(0.027)	(0.026)
Employee has temp/seasonal status when hired	0.203**	0.205**	0.203**
	(0.019)	(0.020)	(0.019)
Current manager is female	1.225‡	1.166	1.164
	(0.129)	(0.126)	(0.126)
Current manager is black	1.007	0.989	0.902
	(0.191)	(0.189)	(0.218)
Current manager is Hispanic	1.571*	1.542‡	1.384
	(0.357)	(0.354)	(0.391)
Current manager is Asian	1.223	1.194	1.195
	(0.293)	(0.288)	(0.338)
Current manager's age	0.981	0.981	0.979
	(0.065)	(0.065)	(0.066)
(Current manager's age)^2	1.000	1.000	1.000
	(0.001)	(0.001)	(0.001)
Current manager is new (not hiring manager)	1.062	1.060	1.060
	(0.070)	(0.070)	(0.070)
Manager is different sex		**0.884**‡	**0.883**‡
		(0.058)	(0.058)
Manager is different race		**1.052**	
		(0.099)	
Employee white, manager not white			**1.154**
			(0.222)
Employee black, manager not black			**0.885**
			(0.246)
Employee Hispanic, manager not Hispanic			**0.880**
			(0.265)
Employee Asian, manager not Asian			**1.665**
			(0.981)
| Log(manager age) – log(employee age)|		**0.835**	
		(0.214)	
Employee is at least 20% older than mgr.			**1.304**‡
			(0.205)
Employee is at least 20% younger than mgr.			**1.067**
			(0.090)
Observations	> 100,000	> 100,000	> 100,000

Notes: See Table 5.

TABLE 8. COX PROPORTIONAL HAZARD ESTIMATES OF RETURNING TO SCHOOL OR MOVING

	(1)	(2)	(3)
Employee is female	1.155**	1.160**	1.160**
	(0.016)	(0.020)	(0.020)
Employee is black	0.682**	0.699**	0.674**
	(0.015)	(0.020)	(0.054)
Employee is Hispanic	0.608**	0.621**	0.613**
	(0.017)	(0.020)	(0.053)
Employee is Asian	1.033	1.058‡	1.125
	(0.023)	(0.032)	(0.123)
Employee age at time of hire	4.008**	5.952**	4.506**
	(0.292)	(0.512)	(0.305)
(Employee age)^2	0.945**	0.935**	0.942**
	(0.003)	(0.003)	(0.003)
(Employee age)^3	1.001**	1.001**	1.001**
	(0.000)	(0.000)	(0.000)
(Employee age)^4	1.000**	1.000**	1.000**
	(0.000)	(0.000)	(0.000)
Employee is married	0.699**	0.697**	0.702**
	(0.022)	(0.022)	(0.023)
Employee has prior company experience	1.751**	1.743**	1.734**
	(0.024)	(0.024)	(0.024)
Employee is part-time when hired	2.193**	2.171**	2.147**
	(0.129)	(0.128)	(0.126)
Employee has temp/seasonal status when hired	3.499**	3.464**	3.418**
	(0.206)	(0.204)	(0.201)
Current manager is female	0.996	1.001	0.999
	(0.024)	(0.025)	(0.025)
Current manager is black	0.990	0.999	1.014
	(0.045)	(0.047)	(0.061)
Current manager is Hispanic	0.942	0.953	0.956
	(0.047)	(0.049)	(0.059)
Current manager is Asian	0.947	0.955	0.944
	(0.060)	(0.062)	(0.072)
Current manager's age	1.024	0.943**	0.985
	(0.017)	(0.017)	(0.017)
(Current manager's age)^2	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)
Current manager is new (not hiring manager)	1.001	1.000	1.001
	(0.019)	(0.019)	(0.019)
Manager is different sex		**1.010**	**1.010**
		(0.017)	(0.017)
Manager is different race		**0.972**	
		(0.024)	
Employee white, manager not white			**0.969**
			(0.047)
Employee black, manager not black			**1.012**
			(0.081)
Employee Hispanic, manager not Hispanic			**0.982**
			(0.086)
Employee Asian, manager not Asian			**0.908**
			(0.099)
| Log(manager age) – log(employee age)|		**0.987**	
		(0.147)	
Employee is at least 20% older than mgr.			**1.046**
			(0.027)
Employee is at least 20% younger than mgr.			**0.950**
			(0.092)
Observations	> 100,000	> 100,000	> 100,000

Notes: See Table 5.

TABLE 9. DEMOGRAPHIC DIFFERENCES FROM MANAGER VS. COWORKERS
COX PROPORTIONAL HAZARD ESTIMATES OF IMPACT ON QUIT RATES

	Similarity	Social Roles
% Coworkers not my sex (at time of hire)	1.145**	1.143**
	(0.037)	(0.037)
% Coworkers not my race (at time of hire)	1.214**	
	(0.027)	
White * % Non-white coworkers		1.303**
		(0.050)
Black * % Non-black coworkers		1.117
		(0.068)
Hispanic * % Non-Hispanic coworkers		1.023
		(0.076)
Asian * % Non-Asian coworkers		1.336*
		(0.162)
Manager is different sex	**1.026****	**1.025****
	(0.010)	(0.010)
Manager is different race	**1.021***	
	(0.010)	
Employee white, manager not white		**1.026**
		(0.028)
Employee black, manager not black		**0.991**
		(0.041)
Employee Hispanic, manager not Hispanic		**1.063**
		(0.048)
Employee Asian, manager not Asian		**1.004**
		(0.077)
Observations	> 100,000	> 100,000

Notes: Cox proportional hazard estimates, stratified by store. Robust standard errors in parentheses, adjusted for clustering on employee. Additional controls as in Table 7, Columns (2) and (3). * significant at 5%; ** significant at 1% (based on test that the hazard ratio is different from one).

TABLE 10. EFFECTS OF DEMOGRAPHIC DIFFERENCES ON QUITS FOR HIRING VS. NEW MANAGERS

	Coefficient (std. Error)	Chi^2 ($prob>chi^2$)
Manager is different sex * Hiring manager	**1.034****	
	(0.010)	**.078**
Manager is different sex * New manager	**1.017**	(0.377)
	(0.018)	
White Empl * Manager is different race * Hiring manager	**1.044**	
	(0.033)	**3.56**‡
White Empl * Manager is different race * New manager	**1.167****	(0.059)
	(0.064)	
Black Empl * Manager is different race * Hiring manager	**0.988**	
	(0.045)	**0.13**
Black Empl * Manager is different race * New manager	**0.956**	(0.773)
	(0.083)	
Hispan Empl * Manager is different race * Hiring manager	**1.053**	
	(0.048)	**0.18**
Hispan Empl * Manager is different race * New manager	**1.039**	(0.723)
	(0.542)	
Asian Empl * Manager is different race * Hiring manager	**1.033**	
	(0.079)	**2.48**
Asian Empl * Manager is different race * New manager	**1.099**	(0.115)
	(0.091)	
Employee Older than Manager * Hiring manager	**0.968**	
	(0.031)	**2.06**
Employee Older than Manager * New manager	**1.052**	(0.151)
	(0.056)	
Employee Younger than Manager * Hiring manager	**1.013**	
	(0.016)	**0.19**
Employee Younger than Manager * New manager	**0.991**	(0.659)
	(0.031)	
Observations	>200,000	

Notes: Cox proportional hazard estimates, stratified by store. Control variables as in Table 7, column (2), plus all interactions of manager race, gender and age, and employee race, gender and age indicators with an indicator that the manager is new. Robust standard errors in parentheses, adjusted for clustering on employee. ‡ significant at 10%; * significant at 5%; ** significant at 1%. Final column reports chi squared test of equality for each pair of hazard ratios.

TABLE A1. WEIBULL FRAILTY ESTIMATES OF QUITS

	(1)	(2)	(3)
Employee is female	0.891**	0.916**	0.916**
	(0.011)	(0.014)	(0.014)
Employee is black	1.119**	1.072**	1.180**
	(0.018)	(0.025)	(0.074)
Employee is Hispanic	0.983	0.943*	0.858*
	(0.020)	(0.025)	(0.057)
Employee is Asian	0.789**	0.754**	0.823‡
	(0.019)	(0.023)	(0.094)
Employee age at time of hire	2.568**	2.480**	2.530**
	(0.077)	(0.090)	(0.082)
(Employee age)^2	0.968**	0.969**	0.969**
	(0.001)	(0.001)	(0.001)
(Employee age)^3	1.000**	1.000**	1.000**
	(0.000)	(0.000)	(0.000)
(Employee age)^4	1.000**	1.000**	1.000**
	(0.000)	(0.000)	(0.000)
Employee is married	0.804**	0.804**	0.804**
	(0.018)	(0.018)	(0.018)
Employee has prior company experience	0.447**	0.447**	0.447**
	(0.007)	(0.007)	(0.007)
Employee is part-time when hired	1.223**	1.223**	1.222**
	(0.051)	(0.051)	(0.051)
Employee has temp/seasonal status when hired	1.524**	1.524**	1.523**
	(0.064)	(0.064)	(0.064)
Current manager is female	1.018	1.036*	1.037*
	(0.014)	(0.015)	(0.015)
Current manager is black	1.001	0.988	0.951
	(0.026)	(0.026)	(0.041)
Current manager is Hispanic	0.934*	0.920**	0.936‡
	(0.026)	(0.026)	(0.038)
Current manager is Asian	0.970	0.945	0.925
	(0.035)	(0.036)	(0.045)
Current manager's age	1.072**	1.077**	1.069**
	(0.009)	(0.010)	(0.010)
(Current manager's age)^2	0.999**	0.999**	0.999**
	(0.000)	(0.000)	(0.000)
Current manager is new (not hiring manager)	1.070**	1.070**	1.070**
	(0.023)	(0.023)	(0.023)
Manager is different sex		**1.052****	**1.052****
		(0.015)	(0.015)
Manager is different race		**1.055****	
		(0.022)	
Employee white, manager not white			**1.073**‡
			(0.044)
Employee black, manager not black			**0.953**
			(0.059)
Employee Hispanic, manager not Hispanic			**1.174***
			(0.079)
Employee Asian, manager not Asian			**0.965**
			(0.110)
| Log(manager age) – log(employee age)|		**0.878**‡	
		(0.069)	
Employee is at least 20% older than mgr.			**0.945**
			(0.046)
Employee is at least 20% younger than mgr.			**1.016**
			(0.022)
Observations	> 100,000	> 100,000	> 100,000

Notes: Hazard ratios from Weibull proportional hazard model with gamma distributed frailty. Robust standard errors in parentheses, adjusted for clustering on employee. Omitted race category is white. Coefficients for 30 month of hire dummies not shown. Additional controls (coefficients not shown): average store employment; location type (mall, street); 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.
‡ significant at 10%; * significant at 5%; ** significant at 1% (based on test that the hazard ratio is different from one).

Table A2. Weibull Frailty Estimates of Dismissals

	(1)	(2)	(3)
Employee is female	0.481**	0.502**	0.501**
	(0.015)	(0.018)	(0.018)
Employee is black	3.593**	3.713**	2.816**
	(0.135)	(0.197)	(0.372)
Employee is Hispanic	1.773**	1.830**	1.142
	(0.090)	(0.115)	(0.180)
Employee is Asian	1.156*	1.198*	1.454
	(0.074)	(0.090)	(0.349)
Employee age at time of hire	1.108	0.989	1.026
	(0.089)	(0.099)	(0.090)
(Employee age)^2	0.994‡	0.997	0.997
	(0.003)	(0.004)	(0.003)
(Employee age)^3	1.000*	1.000	1.000
	(0.000)	(0.000)	(0.000)
(Employee age)^4	1.000‡	1.000	1.000
	(0.000)	(0.000)	(0.000)
Employee is married	0.634**	0.636**	0.637**
	(0.044)	(0.044)	(0.044)
Employee has prior company experience	0.365**	0.365**	0.365**
	(0.017)	(0.017)	(0.017)
Employee is part-time when hired	0.680**	0.681**	0.681**
	(0.068)	(0.068)	(0.068)
Employee has temp/seasonal status when hired	1.070	1.072	1.072
	(0.106)	(0.107)	(0.106)
Current manager is female	0.961	0.978	0.977
	(0.035)	(0.036)	(0.036)
Current manager is black	1.238**	1.242**	1.526**
	(0.075)	(0.075)	(0.155)
Current manager is Hispanic	1.131‡	1.139‡	1.426**
	(0.077)	(0.078)	(0.131)
Current manager is Asian	1.281**	1.303**	1.436**
	(0.110)	(0.115)	(0.155)
Current manager's age	0.979	0.996	0.961
	(0.023)	(0.025)	(0.024)
(Current manager's age)^2	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)
Current manager is new (not hiring manager)	0.731**	0.731**	0.729**
	(0.040)	(0.040)	(0.040)
Manager is different sex		**1.083***	**1.086***
		(0.039)	(0.039)
Manager is different race		**0.958**	
		(0.046)	
Employee white, manager not white			**0.740****
			(0.073)
Employee black, manager not black			**1.240**
			(0.163)
Employee Hispanic, manager not Hispanic			**1.542****
			(0.244)
Employee Asian, manager not Asian			**0.746**
			(0.181)
| Log(manager age) – log(employee age)|		**0.639**‡	
		(0.147)	
Employee is at least 20% older than mgr.			**0.714***
			(0.101)
Employee is at least 20% younger than mgr.			**1.036**
			(0.062)
Observations	> 100,000	> 100,000	> 100,000

Notes: See Table A1.

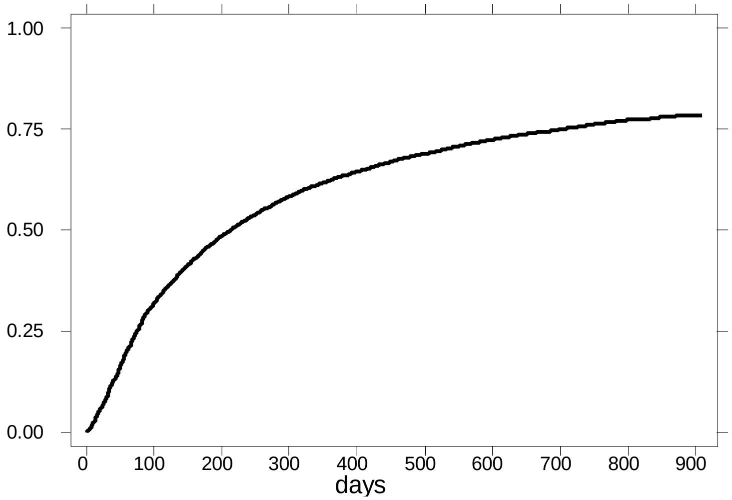
TABLE A3. WEIBULL FRAILTY ESTIMATES OF PROMOTIONS

	(1)	(2)	(3)
Employee is female	1.010	0.963	0.961
	(0.080)	(0.092)	(0.092)
Employee is black	0.443**	0.431**	0.980
	(0.049)	(0.063)	(0.364)
Employee is Hispanic	0.758*	0.741*	0.953
	(0.090)	(0.107)	(0.342)
Employee is Asian	0.465**	0.452**	0.413
	(0.069)	(0.079)	(0.273)
Employee age at time of hire	154.625**	140.089**	158.900**
	(66.770)	(61.324)	(68.548)
(Employee age)^2	0.819**	0.821**	0.819**
	(0.017)	(0.017)	(0.016)
(Employee age)^3	1.003**	1.003**	1.003**
	(0.000)	(0.000)	(0.000)
(Employee age)^4	1.000**	1.000**	1.000**
	(0.000)	(0.000)	(0.000)
Employee is married	0.967	0.965	0.965
	(0.110)	(0.109)	(0.109)
Employee is part-time when hired	0.089**	0.090**	0.089**
	(0.018)	(0.019)	(0.019)
Employee has temp/seasonal status when hired	0.064**	0.064**	0.064**
	(0.013)	(0.013)	(0.013)
Current manager is female	1.201*	1.158	1.161
	(0.102)	(0.109)	(0.109)
Current manager is black	1.022	1.011	0.662
	(0.154)	(0.162)	(0.167)
Current manager is Hispanic	1.202	1.182	0.908
	(0.178)	(0.177)	(0.237)
Current manager is Asian	1.366	1.342	1.044
	(0.262)	(0.268)	(0.290)
Current manager's age	0.916‡	0.926	0.920
	(0.047)	(0.049)	(0.050)
(Current manager's age)^2	1.001	1.001	1.001
	(0.001)	(0.001)	(0.001)
Current manager is new (not hiring manager)	1.281**	1.280**	1.289**
	(0.105)	(0.105)	(0.106)
Manager is different sex		**0.920**	**0.920**
		(0.086)	(0.085)
Manager is different race		**1.033**	
		(0.121)	
Employee white, manager not white			**1.499‡**
			(0.374)
Employee black, manager not black			**0.445***
			(0.167)
Employee Hispanic, manager not Hispanic			**0.843**
			(0.300)
Employee Asian, manager not Asian			**1.206**
			(0.803)
| Log(manager age) – log(employee age)|		**0.620**	
		(0.234)	
Employee is at least 20% older than mgr.			**1.188**
			(0.285)
Employee is at least 20% younger than mgr.			**1.012**
			(0.119)
Observations	> 100,000	> 100,000	> 100,000

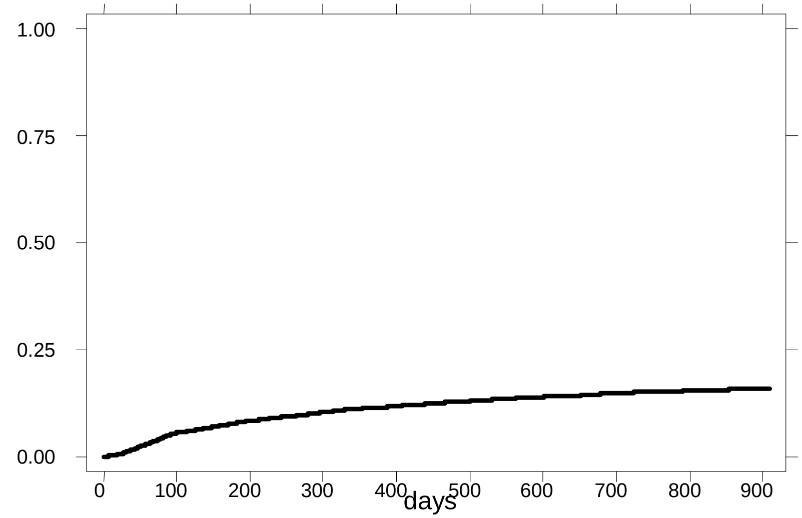
Notes: See Table A1.

FIGURE 1. KAPLAN-MEIER ESTIMATES

A. QUITS



B. DISMISSALS



C. PROMOTIONS