# Race, Gender, and Employee Turnover: Evidence from Mergers and Acquisitions

Rui Dai*

Tingting Liu†

Cong (Roman) Wang‡

November 17, 2024

Using machine learning on over one million LinkedIn profiles, we construct a comprehensive dataset to examine how employees' race and gender affect turnover following takeovers. We find that Black and Hispanic (female) employees experience significantly lower turnover rates compared to White (male) employees. These effects are stronger for same-industry acquisitions but not observed in failed deals. Furthermore, we find that race and gender groups that experience higher turnover rates also experience worse subsequent labor market outcomes. Additionally, higher-earning employees in target firms tend to have higher post-merger turnover. We also find that labor cost savings are significantly associated with takeover premiums and merger synergies. These results emphasize the role of labor cost savings in driving merger synergies and highlight the importance of employee diversity in acquirers' layoff decisions.

**Keywords:** Mergers and Acquisitions, Diversity, Labor restructuring, Race, Gender, Acquisition outcome

**JEL Codes:** G34, J30, J15, J16, M14

*Wharton Research Data Services (WRDS). The Wharton School, University of Pennsylvania; School of Management and Economics - Chinese University of Hong Kong (Shenzhen) and Shenzhen Finance Institute. Email: rdai@wharton.upenn.edu

†Department of Finance, Haslam College of Business, University of Tennessee. Email: tliu22@utk.edu

‡Department of Finance, Rawls College of Business, Texas Tech University. 703 Flint Avenue, Lubbock, TX 79409. Email: roman.wang@ttu.edu

*"...[N]ews of a merger often means layoffs are not far behind, leaving families, and even whole communities, in peril and devastation."*

*Washington Post, October 21, 2021*

# 1 Introduction

Firms are increasingly under social pressure to enhance diversity within their organizations. For example, companies have been urged to increase diversity on their boards, including gender, racial, and skill diversity. Scholars have devoted considerable attention to examining the effects of diversity among board members.[1] However, our understanding of diversity among rank-and-file employees remains limited. In this paper, we address two main questions: (1) Do firms consider diversity in their layoff decisions? (2) What is the relationship between employee diversity and firm performance?

While answers to these questions provide valuable insights for researchers, practitioners, and policymakers, addressing them poses several empirical challenges. First, although employee turnover is observable, distinguishing whether an employee is terminated by the firm or leaves the firm for other reasons is less straightforward. Additionally, even if we can identify instances of layoffs, a comprehensive dataset that reliably captures employee diversity is necessary to examine whether firms consider these factors in their layoff decisions.

In this study, we leverage the mergers and acquisitions (M&As) context to investigate employee turnover in target firms following acquisitions, providing insights into previously

[1] Board diversity has been extensively studied in prior research, including Carter et al. (2003), Adams and Ferreira (2009), Kim and Starks (2016), Giannetti and Zhao (2019), Griffin et al. (2021), Eckbo et al. (2022), Giannetti and Wang (2023), and Gormley et al. (2023) among many others.

challenging questions. We argue that M&As provide a valuable context to investigate our primary questions for several reasons. First, labor costs constitute the largest component of expenses in most corporations. Therefore, reducing these costs by eliminating inefficient or overlapping labor force can be an important motive and a key source of synergies in corporate takeovers (e.g., Bhagat et al., 1990; Dessaint et al., 2017). While turnover in this context may still include some voluntary departures, the M&A setting remains valuable, as a significant portion of turnover can be attributed to acquirer-led layoffs, given that labor cost reduction is often a primary motive for acquisitions.[2] Second, the outcomes of acquisitions, including premiums paid to target firms, market reactions and post-merger performance, are quantifiable, facilitating the study of the relationship between employee diversity and firm performance. Finally, the high stakes and significant impact of acquisitions on firms and their employees make this setting highly relevant for understanding the real-world implications of diversity in corporate decision-making and its effect on organizational outcomes.

Our M&A sample involves U.S. public targets and acquirers from 1990 to 2022. We merge the M&A sample with Revelio Labs to construct a novel dataset that tracks target firm employees from three years before the merger to one year after the acquisition announcement. Despite having a broader dataset overall, for our baseline regression, we focus on a sample comprising over 440,000 U.S. domiciled employees across 1,195 completed deals. Our main empirical tests employ a difference-in-differences estimation to identify whether and how

[2]Supporting this argument, prior studies show significant labor restructuring and reduction in target firm employment following acquisitions. For example, Maksimovic et al. (2011) report that 19% of acquired plants are closed and a further 27% are sold off in the three years following a merger. Moreover, Gehrke et al. (2021) document that after the acquisition, target firms experience a 50% drop in employment within two years after acquisitions.

race and gender are related to post-acquisition employee turnover. This focus aligns with the existing literature that centers on racial and gender diversity. (e.g., Carter et al., 2003; Giannetti and Zhao, 2019; Bernile et al., 2018; Griffin et al., 2021; Giannetti and Wang, 2023).

Although Revelio Labs offers data on employees' race and gender by analyzing names and estimating likelihoods based on data from the Social Security Administration, recent studies have raised concerns about the accuracy of these classifications, particularly with regard to individuals' ethnicity (Cook et al., 2022; Berry et al., 2024). We address the limitations of name-based estimation by utilizing LinkedIn profile pictures and DeepFace, a facial attribute analysis package that uses advanced models to examine facial characteristics such as gender, emotion, and race. We construct a supervised classification model, Random Forest Classifier, that combines features estimated from employee profile pictures and names. While names alone are insufficient predictors, we find that they provide incremental information that enhances estimation accuracy. Our model outperforms conventional classification models, such as logistic regression, achieving 96% accuracy for ethnicity groups and 99% accuracy for gender groups in our annotated sample.

With our unique dataset, we first document a significantly higher turnover rate for target employees following the acquisition. Compared to the pre-merger turnover rate of 19.7%, the post-merger turnover rate increases to 28.9%, a 9.2 percentage point increase, or a 47% increase in the likelihood of turnover. Moreover, the increase in turnover varies significantly based on employee race. While White and Asian Pacific Islander (API) employees experience a similar increase of around 10%, Hispanic employees experience an 8.6% increase, and

Black employees experience the least increase at 6.6%. We also find some effect on gender with female employees experiencing a smaller turnover increase post-acquisition. These results provide preliminary evidence on the effects of race and gender on turnover rates after acquisitions.

Next, we employ a difference-in-differences (DID) design to explore the effect of race and gender on post-acquisition turnovers, controlling for deal fixed effects and other employee characteristics such as salary, education, and work experience. Consistent with the univariate tests, the regression results show statistically significant and economically large effects of race and gender on post-acquisition employee turnover. For example, we find that Black and Hispanic employees experience a lower increase in turnover rate, compared to White employees. Similarly, female employees experience a lower increase in turnover rate, compared to their male counterparts. However, we do not find any significant different in the increase in turnover rate between API and White employees. When we further explore the interaction effects of race and gender, we find that post-acquisition, Black female employees experience the lowest turnovers, while White male and API employees — regardless of gender — experience the highest turnovers. These findings provide novel evidence on how both race and gender influence employee turnover.

While post-acquisition turnover is often driven by acquirers' layoff decisions, we recognize that voluntary departures also play a role. To better understand whether the observed race and gender effects are due to acquirers' layoff decisions or employee voluntary departures, we conduct several tests. First, we turn to withdrawn deals. When an acquisition is withdrawn, employee turnover should not be attributed to acquirers' downsizing or restructuring decisions. Any race and gender effects observed in this context would likely reflect voluntary departures. By comparing turnover between completed and withdrawn deals, we can better distinguish between the effects of acquirers' layoff decisions and voluntary departures. Empirically, we find no abnormal turnover following deal withdrawals. Moreover, the racial and gender effects observed in completed deals are not present in these withdrawn deals, suggesting that voluntary departures are unlikely to drive our main results.

Second, we conduct subsample tests based on same-industry versus different-industry acquisitions. Prior studies suggest that the acquirer has a greater ability to lay off target employees and reduce labor costs in same-industry acquisitions (e.g., O'Shaughnessy and Flanagan, 1998; Lee et al., 2018; Tate and Yang, 2024). As a result, turnover following same-industry acquisitions is more likely to be driven by post-acquisition labor restructuring rather than voluntary departures. If the race and gender effect we document reflects acquirers' layoff decisions, we would expect stronger effects for same-industry deals. Our results first confirm substantially higher turnover rates — 2.3 times higher — for same-industry acquisitions. More importantly, the racial effects observed in our baseline results remain highly significant and exhibit a larger economic magnitude in the subsample of same-industry acquisitions.

Third, to gain further insight into how acquirers achieve gains through labor restructuring, we examine the impact of labor costs on post-acquisition turnover and explore the interaction effects between wages and employee diversity on turnover rates. High-salary employees make up a significant portion of a company's labor costs, and acquirers may prioritize restructuring these higher-cost positions to reduce expenses and achieve immediate cost savings. Our findings provide strong evidence that higher-wage target employees experience increased turnover following the acquisition, supporting the idea that acquirers use labor restructuring as a key lever to enhance synergies and maximize acquisition value. However, we do not find robust differential effects of race or gender on the turnover rates of higher-wage employees.

Next, we investigate post-turnover labor outcomes, focusing on employees who leave within one year after the acquisition announcement. This analysis is useful because it allows us to examine the longer-term effects of turnover on the careers of departing employees, particularly in terms of their subsequent employment outcomes. Our findings show that Black, Hispanic, and female employees have a significantly higher probability of remaining unemployed in the years following their departure. Moreover, among those who do find new employment, these employees are more likely to experience demotions and less likely to receive promotions. Collectively, our evidence suggests that post-acquisition turnover is, on average, driven by acquirers' labor restructuring decisions.

The last part of our paper explores the relation between labor cost saving and acquisition performance. We find that the estimated labor cost savings are positively and significantly associated with acquirer announcement returns, merger synergies, and takeover premiums. The results are both statistically significant and economically meaningful. Specifically, a 1% increase in annual labor cost saving corresponds to a 0.86% to 1.01% increase in acquirer abnormal returns, a 1.6% to 2.1% increase in combined returns, and a 1.9% higher takeover premium. These findings further corroborate the notion that labor cost reduction is a crucial source of synergy in acquisitions, benefiting both acquirer and target shareholders through effective post-acquisition labor restructuring.

Our paper contributes to the growing literature on labor economics and finance. Despite the importance of corporate DEI practices, the empirical literature still lacks a deep understanding of how diversity affects corporate layoff decisions due to data limitations and difficulties in measurement. The existing evidence often relies on a very small number of firms. For example, using data from one financial firm, Elvira and Zatzick (2002) find that White employees are less likely to be laid off than Non-White employees and that, among Non-White employees, API employees are less likely to be laid off than Black employees or Hispanic employees. Similarly, focusing on layoffs at two companies, Meta and SpaceX, Berry et al. (2024) find some evidence that Black, Hispanic, and female employees experienced higher layoff rates at Meta. While these event studies offer valuable insights into specific cases, generalizing their findings to a broader context is challenging. To the best of our knowledge, our paper is the first to utilize a large sample of acquired firms and systematically document the effect of diversity on employee turnover.

Our paper also makes a contribution to the literature on labor and takeovers. Although cost reductions aimed at achieving economies of scale are widely recognized as significant drivers of synergies (e.g., Houston et al., 2001), empirical evidence linking labor cost savings to takeover premiums and merger gains is limited (e.g., Kaplan, 1989; Bhagat et al., 1990). More recent studies suggest that employee protection generally reduces the likelihood of a firm being acquired and that an acquirer's ability to restructure the target firm's labor force impacts merger outcomes (e.g., Maksimovic et al., 2011; Li, 2013; John et al., 2015; Dessaint et al., 2017; Tian and Wang, 2021). Our paper extends this literature by connecting labor cost savings to deal premiums and merger gains, and by exploring how employee diversity influences acquirers' labor restructuring decisions.

Finally, our findings add to the literature on diversity and firm performance, which has predominantly focused on the effects of board diversity on firm governance and performance.[3] However, the relationship between employee diversity and firm performance remains under-explored, with mixed findings in the literature. For example, Richard (2000) shows that diversity adds firm value in the banking industry, whereas Parrotta et al. (2014) reports a negative relation between ethnic diversity and firm productivity.[4] Our paper adds to this literature by offering new insights into how employee diversity affects merger gains.

# 2 Data and Methodology

## 2.1 Data sources

We obtain M&A transactions from the Securities Data Company (SDC) database for the period from January 1, 1990 to December 31, 2022. We require that both the acquirer and the target firms be public firms. We also require that the deal value reported by SDC be $1 million or more and that the form of the deal is either a merger, acquisition, acquisition of assets, or acquisition of majority interests. We further require that the bidder owns 100% of that target after acquisition.[5] We merge SDC data with the Center for Research in Securities Prices (CRSP) and Compustat data to obtain stock market and fundamentals

[3] E.g., Carter et al. (2003); Adams and Ferreira (2009); Ahern and Dittmar (2012); Kim and Starks (2016); Giannetti and Zhao (2019); Ewens and Townsend (2020); Griffin et al. (2021); Eckbo et al. (2022); Ferrari et al. (2022); Cook et al. (2022); Cassel et al. (2023), among others.

[4] More recently, Garel et al. (2024) finds no relation between employee diversity and firm performance, while Zhang (2023) suggests that although diversity is unrelated to short-run financial performance, it is positively related to long-run stock returns.

[5] We relax this requirement when examining withdrawn deals.

data. We obtain 3,172 M&A deals after applying these standard filters.

We then merge the M&A sample with Revelio Labs, a third-party data provider that collects and aggregates workforce data from publicly available professional profiles such as LinkedIn and job postings. Revelio Labs offers detailed information on employee career paths, including employer, job title, start and end dates, location, seniority, and salary, along with personal details such as education, skills, gender, and ethnicity. Our main variables of interest are gender and race. Revelio determines individuals' gender based on their first names by estimating probabilities using data from the Social Security Administration. For example, if 70% of the people named Lauren are female and 30% are male, the model assigns probabilities of 0.7 for females and 0.3 for males. Similarly, the database identifies individuals' ethnicity using first names, last names, and locations based on US census data. Merging with Revelio reduces the M&A sample to 1,195 deals.

## 2.2 Measuring race and gender

### 2.2.1 Assessing Revelio accuracy

While Revelio's gender and ethnicity metrics could accurately reflect the distribution of the total labor force, they may not accurately represent our M&A sample. Previous literature has documented significant biases created by name-based algorithms among race and gender groups in the analysis of public firms (e.g, Cook et al., 2022; Berry et al., 2024).

To assess the accuracy of Revelio's gender and race data, we manually checked a random sample of 24,000 employees' LinkedIn profile pictures. Despite our efforts to minimize errors, we recognize that human annotators also exhibit biases in determining ethnicity and gender based on photographs. For instance, annotators with a Latin-American background might occasionally misclassify South Asian individuals as Hispanic, whereas East Asian annotators might mistake individuals of Indian descent as African-American. To mitigate these biases, we also utilize ChatGPT 4.0 Vision to cross-check and resolve instances of discrepancies.[6] We end up with 22,345 randomly selected profile pictures, where our human annotators and ChatGPT agree on gender and ethnicity.

Panel A of Table A2 of the Appendix reports Revelio's race estimates across its four prevalent categories within our randomly selected sample. Our findings indicate that Revelio estimates have a weighted precision below 80%, especially among White and Black employees. A significant proportion of Black employees (37.4%) are erroneously classified as White, while a notable percentage of White employees (14.9%) are inaccurately identified as Black. Revelio's gender estimates also show considerable inaccuracies, especially for female employees. Panel F of Table A2 of the Appendix reveals that 11.4% of females are misclassified as males by Revelio's name-based model, while approximately 4.8% of males are mistakenly identified as females.

### 2.2.2 Random Forest Classifier

To mitigate the above limitations of the name-based race and gender classification, we leverage facial features in assessing an individual's race or gender. We first obtain LinkedIn profile pictures and classify the employees' race and gender using DeepFace, a facial attribute analysis package that uses advanced models to examine facial characteristics such as gender,

[6]We upload LinkedIn profile images, along with the individuals' names and countries of work, to ChatGPT and ask it to determine their race and gender. For ethnicities, we focus on the four dominant categories used by Revelio: Black, White, Hispanic, and Asian Pacific Islander.

emotion, and race. We then combine the name-based and picture-based classification using a Random Forest Classifier for its interpretability and reliability. The random forest classifier is a supervised machine learning algorithm used for modeling predictions and is built on decision trees. Unlike traditional decision tree models, the random forest classifier mitigates the high variance problem associated with single decision trees, thereby improving accuracy. Additionally, the random forest classifier does not require parametric assumptions about the functional form among predictors and outcomes. This methodology has been successfully used in various science fields and, recently, in economics and finance (e.g., Frankel et al., 2022; Miric et al., 2023; Guernsey et al., 2022).

Our first step is to randomly divide our random sample of 22,345 observations into three subsets. The first subset, consisting of 80% of the data (18,756 observations), is used for training purposes. The remaining 20% of the data is split into two equal-sized subsets, each containing 2,344 and 2,345 observations, respectively, and is used for validation. We select a random forest model based on the various ethnicity and gender probabilities estimated from both names and pictures for this classification task. The trained random forest algorithm allows us to effectively handle non-linear relationships among picture and name-based features when classifying gender and race, while producing more accurate outcomes compared to other conventional classification models, such as logistic regression and support vector machines.[7]

Panel C of Table A2 of the Appendix shows that our model achieves at least 96.0%

[7] The weighted average F1-score for the random forest model is 94% for ethnicity classification and 98% for gender classification in our out-of-sample tests. In comparison, the same classification evaluation metrics for logistic regression and support vector machines are approximately 92% and 83% for ethnicity prediction and 97% and 97% for gender prediction, respectively.

accuracy for ethnicity groups and 99.5% accuracy for gender groups in our annotated sample. Moreover, Panels D and E of Table A2 of the Appendix demonstrate a minor reduction, though as expected, in prediction accuracy when we apply our random forest model only to two validation samples that were not used in model training. To assess the impact of various probabilities estimated by names and pictures on the accuracy of ethnicity and gender predictions, we plot the feature contributions to our predictive models in Panels A and B of Figure A1 of the Appendix, respectively. Neither the picture-based nor name-based features dominate the other set of features. For instance, the API probability based on the name contributes nearly 25%, while the White and Black probabilities based on the picture contribute 20% and 14%, respectively, to the ethnicity prediction. Similarly, each gender probability from names and pictures contributes at least 20% to the prediction of genders. We then apply our random forest model to all 1,655,098 profile pictures of over 1.4 million professionals for whom we can obtain pictures from LinkedIn, ensuring the accuracy of our estimations.

## 2.3 Summary statistics

Table 1 Panel A details target employee demographics. Approximately 78% of employees at target firms are White, 7% are Asian, 8% are Black, and 7% are Hispanic. Female employees make up 44% of the workforce, while male employees account for 56%.[8] In terms of education, 56% hold a bachelor's degree, about 29% have either a master's or MBA degree, and 5% possess a doctoral degree. The top three occupations—engineering, sales,

[8]Our gender and race statistics largely align with those reported by Tate and Yang (2024), who find that 72% in their target firms are White and 41% are women.

and finance—together account for 75% of the workforce. On average, the annual salary (inflation-adjusted to 2022 dollars) is approximately $113,870, with a median of $102,000.

Panel B of Table 1 presents summary statistics for the sample deals. Variable definitions are in Table A1 of the Appendix. The mean deal size is 2.44 billion, with a median of 0.47 billion. Approximately 53% of the deals are same-industry acquisitions and 19% are tender offers. Consistent with prior literature (see Eckbo, 2009 for a review), the announcement returns for acquirers are small but negative, while the combined returns are small but positive. Specifically, the average one-day (three-day) return for the acquirer is -0.77% (-0.98%), whereas the average one-day (three-day) combined return is 1.44% (1.82%). The average takeover premium is 41%, with a median of 33%.

Finally, Panel C of Table 1 presents the distribution of sample deals by year. Although the requirement for Revelio data reduces our M&A sample size, the distribution over time remains consistent with what has been documented in previous literature. For example, there was a high volume of transactions in the late 1990s and early to mid-2000s, followed by an active takeover market in the late 2020s (see Andrade et al., 2001; Harford, 2005; Eaton et al., 2022). Additionally, the average number of target employees varies widely, ranging from a few hundred in the earlier years to several thousand in the later years.

# 3 Racce, Gender, and post-acquisition employee turnover

In this section, we analyze the relationship between race, gender, and employee turnover in target firms following acquisitions, focusing on how these demographic factors influence turnover patterns and the dynamics of workforce composition during the post-acquisition period.

## 3.1 Empirical strategy

To investigate how race and gender are related to target employee turnover after an acquisition, we track the employment of all professionals in each target firm from three years before the acquisition announcement to one year afterward. For each anniversary of the announcement date (from t-3 to t), we determine whether the employee is still affiliated with the target firm to compute employee turnover. It is imperative to incorporate the target firm's pre-merger turnover rate, as it accounts for unobservable firm-level factors that may influence turnover decisions among employees. Specifically, to identify the effects of race and gender on post-acquisition turnover, we estimate the following difference-in-difference regression:

$$\begin{aligned} Turnover_{i,j,t+1} = {} & Post_{j,t} + Race_i + Female_i + Post_{j,t} \times Race_i + Post_{j,t} \times Female_i \\ & + \Gamma Z_{i,j,t} + \text{Fixed Effects} + \epsilon_{i,j,t+1}, \end{aligned} \tag{1}$$

where $i, j, t$ index for person $i$ who is an employee of the target firm in deal $j$ in year $t$. we consider year $t \in [-3, 0]$, where $t = 0$ being the deal announcement year. To predict the turnover decision at year $t + 1$, we require the employee to be employed at year $t$. The dependent variable is $Turnover_{i,j,t+1}$, which is an indicator variable equal to one if the employee leaves the target firm in year $t + 1$, and zero otherwise. Notably, we assign this indicator to zero if the employee is retained by either the acquirer or the target after the merger announcement. The key independent variables are *Race*, is a set of race indicators (i.e., *API*, *Black*, and *Hispanic*) and *Female*, an indicator for female employees. *Post* is an indicator variable that equals one if the year is the deal announcement year (i.e., $t = 0$). $Z_{i,j}$ includes a set of control variables, including *Ln(Salary)*, *Experience*, and *Tenure*. We also include deal, year, job category, seniority, and highest education degree fixed effects, and cluster the standard errors by acquirer industry and year.[9]

To test the impact of race and gender on post-acquisition turnover, we use White employees as the benchmark group. The first-order terms *Black*, *Hispanic*, and *API* capture pre-merger turnover differences between White employees and other racial groups. Our key variables of interest are the coefficients on the interaction terms between *Post* and *Race*, which capture the differences in turnover changes between race groups.

For the effect of gender on turnover, the benchmark group is male employees. The first-order term *Female* captures pre-merger turnover differences between male and female employees, and the coefficient on the interaction term between *Post* and *Female* captures the differences in turnover changes between male and female employees following the acquisition.

## 3.2 Univariate analyses

As a prelude to our main analysis, we conduct univariate analyses on the effect of diversity on post-acquisition employee turnover and report the results in Table 2. Panel A presents the target firm employee turnover rates before and after the acquisition for all target employees. Our results indicate that the annual average turnover rate increases from 19.7% before the merger to 28.9% after the acquisition. This finding aligns with the literature suggesting that

[9] When examining withdrawn deals, we cluster the standard errors by target industry and year.

acquirers reduce labor costs post-merger through workforce reductions within the target firm. This difference is statistically and economically significant.

Panel B of Table 2 presents statistics by employee race. The results show significant variations in turnover rates based on race. White and Asian employees experience similar turnover increases of around 9.9%, Hispanic employees see a 8.6% increase, and Black employees show the smallest increase at 6.6%. These differences are economically significant, as White and Asian employees are more than twice as likely to leave the firm after the merger compared to Black employees.

Panel C presents the results of turnover rates by gender. Prior to the deal announcement, male and female employees exhibit turnover rates of 19% and 20.7%, respectively. Post-announcement, both male and female employees experience heightened turnover rates. More importantly, the difference between male and female turnover rate increases is statistically significant at the 5% level. This result indicates a meaningful disparity in how male and female employees respond to mergers in terms of their likelihood of leaving the firm.

## 3.3 Regression analysis

Table 3 reports the regression results. For all regressions, we include deal, year, job category, seniority, and highest degree fixed effects. Column (1) includes only our key independent variables. Column (2) – (4) includes *Ln(Salary)*, *Tenure*, and *Experience* as control variables sequentially. Variable definitions are in Table A1 of the Appendix.

Consistent with Table 2, we find that post-acquisition turnover is significantly higher, as the coefficients on *Post* are statistically significant at the 1% level across all models.

Focusing on Column (4), which includes the full set of controls, we find that, prior to the deal announcement, API and Black employees experience higher turnover compared to White employees. Unlike in the univariate analysis, after controlling for various individual and deal characteristics, we find that Hispanic employees experience similar levels of turnover to White employees, while female employees experience lower turnover than male employees before the acquisition. After the deal announcement, all racial and gender groups experience increases in turnover rate. However, there exists large heterogeneity among different racial and gender groups. For example, we find that Black and Hispanic, employees experience less increase in turnover rate, compared to White employees. In contrast, API employees experience an increase in turnover rate that is not statistically different from that of White employees.

Table 4 further examines the joint effects of race and gender on post-acquisition turnover, captured by the triple interaction terms among *Post*, *Race*, and *Female*. The results indicate that the most significant effect on turnover is seen among Black female employees, followed by Black male employees and Hispanic female employees. While Hispanic male and White female employees also show notable effects, the impacts on API male and API female employees are statistically insignificant.

Overall, the results in Tables 2, 3, and 4 offer new evidence from a large sample of target firms, suggesting that layoff decisions vary significantly based on employees' gender and race. Our findings also contrast with prior studies that, based on smaller samples, have suggested a higher likelihood of employer-initiated layoffs for Black or female employees (e.g., Elvira and Zatzick, 2002; Berry et al., 2024).

## 3.4 Analyses of withdrawn deals

The above race and gender effects on employee turnover can be driven by acquirers' layoff decisions or by employee voluntary departures. To distinguish these two channels, we turn our attention to withdrawn deals. Previous literature uses withdrawn deals as an identification strategy to estimate the impact of mergers on acquirers' post-acquisition performance (e.g., Savor and Lu, 2009; Malmendier et al., 2018). In our setting, employee turnover should not be attributed to acquirers' downsizing or restructuring decisions in withdrawn deals. If the above results are mainly driven by voluntary departures, we should expect to observe similar race and gender effects for withdrawn deals. On the other hand, if the acquirers' layoff decisions are the main drivers of the above results, we should expect to observe no significant differences in turnover rates between race and gender groups.

To prevent any confounding effects from subsequent potential acquisitions, we require that each target firm in the sample is not acquired within two years of the withdrawn deal's announcement date. This resulted in 278 withdrawn deals involving 323,347 unique employees. We apply the same methodology for identifying employee race and gender and conduct a similar analysis to that in Table 3.

Table 5 presents the regression results for withdrawn deals. The *Post* dummy is insignificant for all columns. In contrast, the coefficients on *Post* in Table 3 range from 7.2% to 7.6%, and are highly significant across all columns. These findings suggest that employee turnover in completed deals largely reflects labor restructuring following the acquisition. Moreover, the coefficients on the interaction terms: *Black* $\times$ *Post*, *Hispanic* $\times$ *Post*, and *Female* $\times$ *Post* are all statistically insignificant and economically minimal. Overall, these results support our main finding that significantly lower post-acquisition turnover for Black, Hispanic, and female employees reflects acquirers' consideration of diversity in their post-merger layoff decisions.

### 3.5 Cross-sectional analysis

In this section, we identify situations where turnovers are more likely driven by post-acquisition labor restructuring to assess the role of diversity in layoff decisions made by acquirers. The literature indicates that acquirers are better positioned to lay off target employees and reduce labor costs in same-industry acquisitions. This is because there is less need to retain redundant employees due to overlapping skills and functions, which facilitates more efficient workforce integration and cost synergies (e.g., O'Shaughnessy and Flanagan, 1998; Lee et al., 2018; Tate and Yang, 2024). Building on these findings, we perform subsample analyses and report results in Table 6.

Columns (1) and (2) present results for same-industry acquisitions and columns (3) and (4) analyze deals in which the acquirer and target belong to different industries. If our firms' layoff decisions primarily drive our baseline results, we should expect stronger results for same-industry deals. The results in Table 6 show supporting evidence for the former hypothesis. We find significantly higher turnover rates for same-industry acquisitions. Specifically, the coefficients on *Post* range from 11.3% to 11.7% for deals in which the acquirer and target belong to the same industry. In contrast, these coefficients range from 4.8% to 4.9% for different-industry acquirer-target pairs. These findings confirm that, within subsamples of same-industry acquisitions, post-merger turnover is more likely to reflect the acquirer's labor restructuring decisions. More importantly, the diversity effects observed in our baseline results remain highly significant and exhibit larger economic magnitudes in same-industry subsamples, where turnover is most likely a result of post-acquisition layoff decisions.

### 3.6 Salary, diversity and post-acquisition turnover

In this section, we examine the impact of wages on post-acquisition turnover and the interaction effects between wages and employee diversity on turnover rates. Prior studies show that wage levels are associated with layoff decisions, as higher-wage workers often face a greater risk of being laid off (e.g., Grossman, 1983; Schmieder and Wachter, 2010). Moreover, the literature suggests that labor cost savings through wage reductions being a key driver for acquirers' merger gains (e.g., Shleifer et al., 1987; Bhagat et al., 1990). If the acquirer seeks to cut labor costs and enhance operational efficiency, we would expect that, ceteris paribus, employees earning higher wages to be more likely to leave the target firm.

However, recent studies, such as Ouimet and Zarutskie (2020), show that some firms pursue mergers to acquire and retain skilled personnel from target companies, offering higher wages to retain them. In such cases, where the acquisition aims to retain skilled labor who are more likely to receive higher salaries, the relationship between salary and post-merger turnover might be negative. Therefore, it remains an empirical question whether high salaries are associated with higher or lower post-merger turnover. To investigate these questions, we estimate a triple-interaction regression by interacting *Post*, *Race* (*Female*), and *Salary*. *Salary* is either the standardized natural logarithm of the dollar amount of salary or an indicator that equals one if the salary of the employee is above the median salary. All other empirical specifications are the same as Eq. (1).

Table 7 presents the regression results. In column (1), we find that the coefficient on *Salary* is negative and highly significant, indicating that, before the merger, higher-wage employees tend to have lower turnover rates. However, the coefficient on the interaction term between *Post* and *Salary* is positive and significant, suggesting that higher-wage employees experience a larger increase in turnover rate following the acquisition than low-wage employees. These results indicate that on average, labor cost savings through wage reductions are a significant factor in the acquirers' merger gains.

Column (2) explores whether the impact of salary on turnover varies by race and gender. We focus on the coefficients of the triple interaction terms among *Salary*, *Diversity*, and *Post*. We find that the diversity effect on post-acquisition employee turnover does not vary with employee salary. In columns (3) and (4), we conduct a similar analysis using a dummy variable, *High Salary*, indicator variables equal to one if the employee's salary exceeds the median salary within the firm for that year. The results are consistent with those from the continuous salary variable, except for API employees. API employees with higher wages experience a decreased turnover rate compared to their White counterparts.

## 3.7 Diversity and Post-turnover Labor Outcomes

To further distinguish whether the differences in turnover rates between race and gender groups are driven by voluntary departure versus external pressure from acquirers, we analyze post-turnover labor outcomes. Our focus is on employees who leave the target firm within one year after the acquisition (e.g., $Turnover_{t=0} = 1$). If turnover is primarily the result of voluntary employee decisions, we expect those who experience a higher turnover rate (e.g., Black and Hispanic employees) to be better off than those who experience a lower turnover rate (e.g., White and API employees). In contrast, if turnover is largely driven by external pressures from the acquirer, we would anticipate high turnover groups to experience negative subsequent labor market outcomes, such as prolonged unemployment or greater difficulty finding comparable or better employment.

In Panel A of Table 8, we report the results on the likelihood of remaining unemployed for one, two, and three years following turnover. Specifically, we regress $Unemployment_{t+\tau}$, indicator variables equal to one if the employee is unemployed for $\tau$ years after leaving the target firm, on our race and gender indicators. We find an insignificant coefficient on *API*, and significantly positive coefficients on *Black*, *Hispanic*. These results suggest that Black, Hispanic, and female employees have a significantly higher probability of remaining unemployed for up to three years after their departure from the target firm, compared to White employees. Moreover, the coefficient on *Female* is also positive and significant, suggesting that female employees are more likely to experience unemployment than male employees, after departing from the target firm.

Panel B of 8 reports the characteristics of subsequent jobs for employees who find new employment within three years of departure. We analyze the likelihood of switching to a different job category, *Career Shift*, and the likelihood of obtaining a job with either higher or lower seniority (*Promotion* and *Demotion*). Our results indicate that Black and Hispanic employees are less likely to secure a job with higher seniority and more likely to accept a job with lower seniority compared to their White counterparts. Female employees are more likely to switch job categories and take positions with lower seniority. These findings suggest that, on average, post-acquisition turnover is more likely driven by acquirers' labor restructuring decisions rather than by voluntary employee departures.

### 3.8 Additional analysis and robustness tests

In this section, we conduct additional analyses to assess the robustness of our results. First, we investigate whether the effects of race and gender on post-acquisition turnover have intensified in recent years. As companies have become more focused on improving diversity and equality, acquirers may be more conscious of the impact of layoffs on their diversity metrics. This heightened awareness could lead to more pronounced diversity effects in recent years, as firms make strategic decisions aligned with their DEI commitments.

In Table 9, columns (1) and (2), we perform a sub-period analysis by dividing our sample into two halves. Consistent with our expectations, the results reveal stronger effects of race and gender on turnover in the latter half of the sample period. For instance, the coefficient on the interaction term between *Black* and the *Post* is -0.018 in the first half and -0.029 in the second half. Similarly, the coefficient on the interaction term between *Hispanic* and *Post* is insignificant in the first half but becomes highly significant in the second half.

In column (3), we conduct a robustness test by excluding the COVID-19 pandemic years. In columns (4) and (5), we use alternative event windows to include more years after deal announcements or more years before deal announcements. The race and gender effects on turnover rate remain robust in these specifications.

# 4 Labor restructuring and acquisition performance

In this section, we analyze the relation between labor cost savings and merger outcomes including acquisition premiums, acquirer announcement returns, and merger synergies. This analysis is useful for several reasons. First, a positive relation between labor cost saving and merger outcomes would support the notion that labor restructuring and cost reduction are significant motivations for acquisitions, addressing the mixed empirical evidence existing literature. For example, Bhagat et al. (1990) and Kaplan (1989) find limited evidence that layoffs can explain takeover premiums. However, Dessaint et al. (2017) show that employment protection is significantly related to premiums, bidder gains and merger synergies.

Moreover, a positive relation strengthens the argument that post-acquisition turnover is a reflection of acquirers' strategic decisions rather than the voluntary departure of target employees. Finally, this analysis provides insights into how the market responds to labor cost savings resulting from layoffs of minority employees. To this end, we investigate the relationship between labor cost savings and acquisition performance by estimate the following regression:

$$Performance_i = Total\ Salary\ Saved_i + \Gamma Z_i + \text{Fixed Effects}, \tag{2}$$

where $i$ index for deal. *Performance* is either $CAR$, the deal announcement abnormal returns of the acquirer, *Synergy*, the deal announcement value-weighted average bidder-target cumulative abnormal returns, following Bradley et al. (1988), or *Premium*, the offer price to target stock price premium - 4 weeks prior to the announcement, provided by SDC. We measure

*CAR* and *Synergy* over one-day and three-day, starting from the deal announcement date. The key independent variables are *Total Salary Saved*, which is the sum of the estimated salary of employees who leave the target firm within two years of the deal announcement. $Z_{i,j}$ includes a set of control variables. We include acquirer industry and year fixed effects and double cluster our standard by acquirer industry and year.

Table 10 reports the regression results. In Panel A, the key independent variable, *Total Salary Saved*, is calculated using the salaries of all departing employees. In Panels B and C, we differentiate between minority employees (i.e., API, Black, Hispanic, or female employees) and non-minority employees (i.e., White male employees). We scale *Total Salary Saved* by the acquirer's pre-merger market capitalization when analyzing the impact on acquirer cumulative abnormal returns (*CAR*) in columns (1) and (2), by the combined market capitalization when examining the effect on merger synergies (*Synergy*) in columns (3) and (4), and by the target's pre-merger market capitalization when evaluating acquisition premiums (*Premium*) in column (5).

Results in Panel A show that the estimated labor cost savings are positively and significantly related to acquirer announcement returns, merger synergies, and takeover premiums. Specifically, a 1% increase in annual labor cost saving is associated with 0.86% to 1.01% higher acquirer abnormal returns and a 1.63% to 2.05% increase in combined returns at the merger announcement. These results suggest that the market anticipates synergies from post-acquisition labor restructuring at the time of the announcement. Column (5) further shows that a 1% increase in annual labor cost saving is associated with a 1.9% higher takeover premium, indicating that target shareholders capture a portion of the synergy gains from labor restructuring.

In Panels B and C, when estimating labor cost savings from layoffs of minority versus non-minority employees, the coefficients are both positive and significant. However, the coefficients in Panel B, which focuses on minority employees, are larger, indicating that minority labor cost savings have a more substantial effect per unit of firm market capitalization. This evidence suggests that the market responds more favorably to labor cost savings associated with terminating minority employees, revealing a market preference for less constrained labor cost optimization. Overall, these results support the idea that labor cost reduction is a significant factor in acquisitions, with both acquirers and target shareholders benefiting from post-acquisition labor restructuring.

# 5 Conclusion

In this paper, we present novel evidence on how race and gender diversity are related to employee turnover following acquisitions. Despite the growing importance of corporate DEI issues and increasing attention to this topic, empirical evidence remains limited.

Using machine learning techniques and LinkedIn profile pictures as a primary input, we identify the race and gender of over 400,000 employees from more than 1,100 publicly traded target firms. Our unique dataset reveals several key findings. Post-merger, the turnover rate increases by nearly 50% compared to pre-merger levels. However, this increase in turnover varies significantly by employee race and gender. White and Asian employees are much more likely to leave the firm following the merger compared to Black and Hispanic employees, while female employees experience a smaller increase in turnover relative to their male counterparts.

Next, we investigate whether the diversity effect we document is more likely attributable to voluntary employee departures or to the acquirers' layoff decisions. We find no significant gender or race effects in a sample of withdrawn deals, where layoff decisions by the acquirer are absent. Furthermore, the results are stronger in same-industry acquisitions, where acquirers have stronger incentives to reduce redundant workforce. Higher-wage employees experience increased turnover following the acquisition, and labor cost reductions are positively and significantly associated with acquirer announcement returns, merger synergies, and takeover premiums.

Collectively, our evidence supports the idea that labor cost reduction is a crucial factor in acquisitions and plays a significant role in driving acquirers' merger gains. All else being equal, acquirers appear to avoid terminating minority employees, particularly Black and female employees, especially in the current era of increased focus on DEI. These findings make a valuable contribution to both the M&A literature and the literature on corporate diversity, providing important insights into how diversity considerations intersect with labor restructuring strategies in the context of mergers and acquisitions.

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Table 1: Descriptive Statistics

This table presents descriptive statistics of our sample. Panel A reports employee characteristics at the deal-employee-year level. We report *Salary* in thousands of dollars, adjusted to 2022 dollars. *Experience* and *Tenure* are in months. Panel B reports deal and firm characteristics at the deal level. Panel C reports the number of deals and the average number of employees per deal by year.

| Panel A: Employee Characteristics | | | | | | |
|---|---|---|---|---|---|---|
| | N | Mean | Std. Dev. | $25^{th}$ Pctl. | $50^{th}$ Pctl. | $75^{th}$ Pctl. |
| API | 1,121,897 | 0.07 | 0.26 | 0.00 | 0.00 | 0.00 |
| Black | 1,121,897 | 0.08 | 0.27 | 0.00 | 0.00 | 0.00 |
| Hispanic | 1,121,897 | 0.07 | 0.25 | 0.00 | 0.00 | 0.00 |
| White | 1,121,897 | 0.78 | 0.41 | 1.00 | 1.00 | 1.00 |
| Female | 1,121,897 | 0.44 | 0.50 | 0.00 | 0.00 | 1.00 |
| Admin | 1,121,897 | 0.08 | 0.26 | 0.00 | 0.00 | 0.00 |
| Finance | 1,121,897 | 0.20 | 0.40 | 0.00 | 0.00 | 0.00 |
| Marketing | 1,121,897 | 0.06 | 0.24 | 0.00 | 0.00 | 0.00 |
| Operations | 1,121,897 | 0.06 | 0.23 | 0.00 | 0.00 | 0.00 |
| Scientist | 1,121,897 | 0.05 | 0.22 | 0.00 | 0.00 | 0.00 |
| Sales | 1,121,897 | 0.27 | 0.45 | 0.00 | 0.00 | 1.00 |
| Engineer | 1,121,897 | 0.28 | 0.45 | 0.00 | 0.00 | 1.00 |
| Associate | 795,358 | 0.08 | 0.26 | 0.00 | 0.00 | 0.00 |
| Doctor | 795,358 | 0.05 | 0.21 | 0.00 | 0.00 | 0.00 |
| High School | 795,358 | 0.03 | 0.17 | 0.00 | 0.00 | 0.00 |
| MBA | 795,358 | 0.14 | 0.34 | 0.00 | 0.00 | 0.00 |
| Master | 795,358 | 0.15 | 0.36 | 0.00 | 0.00 | 0.00 |
| Bachelor | 795,358 | 0.56 | 0.50 | 0.00 | 1.00 | 1.00 |
| Experience | 1,121,897 | 118.06 | 95.08 | 44.00 | 96.00 | 169.00 |
| Tenure | 1,121,897 | 57.90 | 63.56 | 14.00 | 36.00 | 78.00 |
| Salary | 1,004,938 | 113.87 | 72.20 | 67.45 | 102.00 | 139.15 |
| Seniority | 1,121,897 | 2.77 | 1.54 | 2.00 | 2.00 | 4.00 |

Table 1: Continued

| Panel B: Deal and Firm Characteristics | | | | | | |
|---|---|---|---|---|---|---|
| | N | Mean | Std. Dev. | $25^{th}$ Pctl. | $50^{th}$ Pctl. | $75^{th}$ Pctl. |
| Deal Size | 1,195 | 2.44 | 6.22 | 0.13 | 0.47 | 1.86 |
| Pct Cash | 1,195 | 49.89 | 45.17 | 0.00 | 50.85 | 100.00 |
| Tender Offer | 1,195 | 0.19 | 0.39 | 0.00 | 0.00 | 0.00 |
| Same SIC3 | 1,195 | 0.53 | 0.50 | 0.00 | 1.00 | 1.00 |
| Relative Size | 1,085 | 0.28 | 0.35 | 0.04 | 0.14 | 0.38 |
| CAR1 | 1,192 | -0.77 | 5.63 | -3.07 | -0.41 | 1.33 |
| CAR3 | 1,192 | -0.98 | 7.93 | -4.67 | -0.63 | 2.45 |
| Synergy1 | 1,084 | 1.44 | 5.62 | -1.30 | 0.53 | 3.57 |
| Synergy3 | 1,084 | 1.82 | 7.53 | -2.02 | 1.14 | 5.31 |
| Premium | 1,118 | 41.39 | 40.47 | 18.20 | 33.33 | 56.36 |
| Acquirer Market Cap | 1,192 | 19.57 | 40.88 | 0.76 | 3.01 | 14.03 |
| Acquirer BM | 1,163 | 0.48 | 0.34 | 0.24 | 0.40 | 0.64 |
| Acquirer Prior Year Return | 1,191 | 0.24 | 0.59 | -0.08 | 0.14 | 0.42 |
| Target Market Cap | 1,086 | 1.73 | 3.87 | 0.10 | 0.37 | 1.37 |
| Target BM | 1,031 | 0.64 | 0.52 | 0.30 | 0.49 | 0.81 |
| Target Prior Year Return | 1,085 | 0.10 | 0.57 | -0.24 | 0.03 | 0.31 |

Table 1: Continued

| Panel C: Sample Distribution | | | |
|---|---|---|---|
| Year | Number of Deals | Percent of Deals | Average Number of Employee |
| 1990 | 8 | 0.67% | 351 |
| 1991 | 6 | 0.50% | 55 |
| 1992 | 9 | 0.75% | 48 |
| 1993 | 6 | 0.50% | 43 |
| 1994 | 16 | 1.34% | 725 |
| 1995 | 24 | 2.01% | 55 |
| 1996 | 33 | 2.76% | 80 |
| 1997 | 48 | 4.02% | 271 |
| 1998 | 53 | 4.44% | 581 |
| 1999 | 70 | 5.86% | 123 |
| 2000 | 57 | 4.77% | 785 |
| 2001 | 52 | 4.35% | 60 |
| 2002 | 39 | 3.26% | 76 |
| 2003 | 41 | 3.43% | 61 |
| 2004 | 43 | 3.60% | 183 |
| 2005 | 44 | 3.68% | 116 |
| 2006 | 63 | 5.27% | 119 |
| 2007 | 58 | 4.85% | 157 |
| 2008 | 37 | 3.10% | 114 |
| 2009 | 37 | 3.10% | 344 |
| 2010 | 31 | 2.59% | 167 |
| 2011 | 24 | 2.01% | 238 |
| 2012 | 32 | 2.68% | 469 |
| 2013 | 28 | 2.34% | 251 |
| 2014 | 46 | 3.85% | 702 |
| 2015 | 46 | 3.85% | 406 |
| 2016 | 43 | 3.60% | 478 |
| 2017 | 37 | 3.10% | 1,605 |
| 2018 | 36 | 3.01% | 670 |
| 2019 | 35 | 2.93% | 1,090 |
| 2020 | 23 | 1.92% | 413 |
| 2021 | 41 | 3.43% | 780 |
| 2022 | 29 | 2.43% | 347 |
| Total | 1,195 | 100% | 11,963 |

Table 2: Average Turnover

This table presents the target firm employee turnover rates before and after the acquisition. Panel A presents the turnover rates of all employees. Panel B (C) presents the turnover rates of all employees by race groups (gender). We report *t*-statistics based on standard errors clustered by acquirer industry and deal announcement year. Significance levels: *** p< .01; ** p<.05; * p<.1.

| Panel A: Average Turnover | | |
|---|---|---|
| Pre | Post | Post−Pre |
| 0.197 | 0.289 | 0.092*** |
| | | (12.269) |

| Panel B: Average Turnover by Race | | | | |
|---|---|---|---|---|
| | Pre | Post | Post−Pre | Diff.-in-Diff. Baseline=White |
| API | 0.225 | 0.324 | 0.099*** | 0.005 |
| | | | (12.884) | (1.106) |
| Black | 0.225 | 0.291 | 0.066*** | -0.028*** |
| | | | (16.016) | (-4.348) |
| Hispanic | 0.212 | 0.298 | 0.086*** | -0.008 |
| | | | (12.362) | (-1.509) |
| White | 0.190 | 0.284 | 0.094*** | |
| | | | (13.731) | |

| Panel C: Average Turnover by Gender | | | | |
|---|---|---|---|---|
| | Pre | Post | Post−Pre | Diff.-in-Diff. Baseline=Female |
| Male | 0.190 | 0.287 | 0.098*** | 0.013** |
| | | | (10.722) | (2.360) |
| Female | 0.207 | 0.291 | 0.084*** | |
| | | | (20.755) | |

Table 3: Diversity and Post-acquisition Employee Turnover

This table reports the effect of diversity on post-acquisition employee turnover. The dependent variable is $Turnover_{t+1}$, an indicator variable equal to one if the employee leaves the target firm in year $t+1$. *Post*, an indicator variable equal to one if the given year is the deal announcement year ($t = 0$). $API$, *Black*, *Hispanic*, and *Female* are indicator variables equal to one if the employee belongs to the Asian Pacific Islander, Black, Hispanic, and female, respectively. Variable definitions are in Table A1 of the Appendix. We also include deal, year, job category, seniority, and highest degree fixed effects. The $t$-statistics are reported in parentheses and standard errors are clustered by acquirer industry and deal announcement year. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table 3: Continued

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post | 0.072*** | 0.075*** | 0.076*** | 0.076*** |
| | (6.756) | (7.158) | (7.142) | (7.159) |
| API×Post | 0.000 | -0.000 | 0.000 | 0.000 |
| | (0.068) | (-0.068) | (0.051) | (0.062) |
| Black×Post | -0.026*** | -0.028*** | -0.028*** | -0.028*** |
| | (-6.619) | (-9.754) | (-8.495) | (-8.562) |
| Hispanic×Post | -0.010*** | -0.011*** | -0.012*** | -0.012*** |
| | (-5.837) | (-6.760) | (-6.251) | (-5.481) |
| Female×Post | -0.014** | -0.016*** | -0.016*** | -0.016*** |
| | (-2.518) | (-3.112) | (-3.029) | (-3.034) |
| API | 0.017*** | 0.020*** | 0.018*** | 0.020*** |
| | (5.138) | (5.397) | (4.648) | (5.534) |
| Black | 0.016** | 0.012*** | 0.013*** | 0.014*** |
| | (2.466) | (2.800) | (2.912) | (3.350) |
| Hispanic | -0.001 | -0.004 | -0.003 | -0.002 |
| | (-0.520) | (-1.414) | (-1.307) | (-0.691) |
| Female | -0.006** | -0.012*** | -0.011*** | -0.010*** |
| | (-2.319) | (-5.619) | (-5.110) | (-4.867) |
| Ln(Salary) | | -0.115*** | -0.108*** | -0.112*** |
| | | (-3.724) | (-3.867) | (-3.953) |
| Tenure | | | -0.007*** | -0.012*** |
| | | | (-2.954) | (-6.780) |
| Experience | | | | 0.013*** |
| | | | | (4.981) |
| Deal FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Job Category FE | YES | YES | YES | YES |
| Seniority FE | YES | YES | YES | YES |
| Highest Degree FE | YES | YES | YES | YES |
| Observations | 795,349 | 719,782 | 704,818 | 704,818 |
| Adjusted $R^2$ | 0.068 | 0.070 | 0.069 | 0.070 |

Table 4: Race, Gender, and Post-acquisition Employee Turnover

This table reports the effects of race and gender on post-acquisition employee turnover. The dependent variable is $Turnover_{t+1}$, an indicator variable equal to one if the employee leaves the target firm in year $t+1$. *Post*, an indicator variable equal to one if the given year is the deal announcement year ($t=0$). *API*, *Black*, *Hispanic*, and *Female* are indicator variables equal to one if the employee is Asian Pacific Islander, Black, Hispanic, and female, respectively. Variable definitions are in Table A1 of the Appendix. We also include deal, year, job category, seniority, and highest degree fixed effects. The $t$-statistics are reported in parentheses and standard errors are clustered by acquirer industry and deal announcement year. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post | 0.073*** | 0.077*** | 0.077*** | 0.077*** |
| | (6.932) | (7.372) | (7.364) | (7.375) |
| API×Female×Post | -0.003 | -0.006 | -0.004 | -0.005 |
| | (-0.559) | (-1.117) | (-0.764) | (-0.794) |
| Black×Female×Post | -0.040*** | -0.043*** | -0.043*** | -0.043*** |
| | (-3.504) | (-4.268) | (-4.032) | (-4.045) |
| Hispanic×Female×Post | -0.018*** | -0.021*** | -0.023*** | -0.024*** |
| | (-3.028) | (-4.066) | (-3.899) | (-3.946) |
| White×Female×Post | -0.017*** | -0.019*** | -0.019*** | -0.019*** |
| | (-2.829) | (-3.464) | (-3.315) | (-3.318) |
| API×Male×Post | -0.008 | -0.009 | -0.009 | -0.009 |
| | (-1.033) | (-1.128) | (-1.033) | (-1.013) |
| Black×Male×Post | -0.030*** | -0.033*** | -0.032*** | -0.032*** |
| | (-5.155) | (-5.689) | (-4.854) | (-4.964) |
| Hispanic×Male×Post | -0.019*** | -0.020*** | -0.020*** | -0.020*** |
| | (-3.878) | (-3.964) | (-3.897) | (-3.844) |
| API×Female | 0.011*** | 0.008** | 0.006 | 0.009** |
| | (2.753) | (2.103) | (1.483) | (2.432) |
| Black×Female | 0.007 | -0.002 | -0.001 | 0.001 |
| | (0.678) | (-0.229) | (-0.160) | (0.149) |
| Hispanic×Female | -0.010* | -0.017*** | -0.016*** | -0.013*** |
| | (-2.014) | (-4.589) | (-3.896) | (-3.385) |
| White×Female | -0.004* | -0.011*** | -0.010*** | -0.009*** |
| | (-1.813) | (-4.900) | (-4.356) | (-4.113) |

Table 4: Continued

| | | | | |
|---|---|---|---|---|
| API×Male | 0.019*** | 0.021*** | 0.019*** | 0.021*** |
| | (3.954) | (4.059) | (3.671) | (4.306) |
| Black×Male | 0.021*** | 0.016*** | 0.017*** | 0.018*** |
| | (4.809) | (4.380) | (4.636) | (4.949) |
| Hispanic×Male | 0.003 | -0.001 | -0.000 | 0.001 |
| | (0.752) | (-0.152) | (-0.122) | (0.245) |
| Ln(Salary) | | -0.115*** | -0.108*** | -0.112*** |
| | | (-3.724) | (-3.867) | (-3.952) |
| Tenure | | | -0.007*** | -0.012*** |
| | | | (-2.916) | (-6.533) |
| Experience | | | | 0.013*** |
| | | | | (5.021) |
| Deal FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Job Category FE | YES | YES | YES | YES |
| Seniority FE | YES | YES | YES | YES |
| Highest Degree FE | YES | YES | YES | YES |
| Observations | 795,349 | 719,782 | 704,818 | 704,818 |
| Adjusted $R^2$ | 0.068 | 0.070 | 0.069 | 0.070 |

Table 5: Race, Gender, and Employee Turnover for Withdrawn Deals

This table reports the effects of race and gender on employee turnover for withdrawn deals. The dependent variable is $Turnover_{t+1}$, an indicator variable equal to one if the employee leaves the target firm in year $t+1$. *Post*, an indicator variable equal to one if the given year is the deal announcement year ($t = 0$). *API*, *Black*, *Hispanic*, and *Female* are indicator variables equal to one if the employee is Asian Pacific Islander, Black, Hispanic, and female, respectively. Variable definitions are in Table A1 of the Appendix. We also include deal, year, job category, seniority, and highest degree fixed effects. The $t$-statistics are reported in parentheses and standard errors are clustered by target industry and deal announcement year. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table 5: Continued

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Post | -0.018 | -0.015 | -0.016 | -0.016 |
| | (-1.602) | (-1.490) | (-1.585) | (-1.585) |
| API×Post | -0.014* | -0.015* | -0.014* | -0.014* |
| | (-1.822) | (-1.912) | (-1.914) | (-1.931) |
| Black×Post | 0.002 | 0.002 | 0.001 | 0.002 |
| | (0.430) | (0.311) | (0.301) | (0.335) |
| Hispanic×Post | 0.000 | -0.001 | -0.002 | -0.002 |
| | (0.078) | (-0.160) | (-0.559) | (-0.609) |
| Female×Post | -0.003 | -0.003 | -0.002 | -0.002 |
| | (-0.551) | (-0.573) | (-0.442) | (-0.454) |
| API | 0.036*** | 0.040*** | 0.034*** | 0.034*** |
| | (3.192) | (3.358) | (3.614) | (3.897) |
| Black | 0.011 | 0.008 | 0.007 | 0.007 |
| | (1.525) | (1.272) | (1.003) | (1.098) |
| Hispanic | -0.001 | -0.002 | -0.003 | -0.002 |
| | (-0.162) | (-0.532) | (-0.649) | (-0.432) |
| Female | -0.005 | -0.012** | -0.011** | -0.010** |
| | (-1.090) | (-2.246) | (-2.205) | (-2.042) |
| Ln(Salary) | | -0.152*** | -0.138*** | -0.140*** |
| | | (-6.823) | (-7.160) | (-7.372) |
| Tenure | | | -0.014*** | -0.016*** |
| | | | (-3.104) | (-5.309) |
| Experience | | | | 0.006 |
| | | | | (1.272) |
| Deal FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Job Category FE | YES | YES | YES | YES |
| Seniority FE | YES | YES | YES | YES |
| Highest Degree FE | YES | YES | YES | YES |
| Observations | 320,144 | 289,099 | 282,806 | 282,806 |
| Adjusted $R^2$ | 0.063 | 0.073 | 0.071 | 0.071 |

Table 6: Race, Gender, and Post-acquisition Employee Turnover: Acquirer-Target Similarity

This table reports how the effects of race and gender on post-acquisition employee turnover vary with acquirer-target similarity. We measure similarity using the SIC-3 industry classification. The dependent variable is $Turnover_{t+1}$, an indicator variable equal to one if the employee leaves the target firm in year $t+1$. $Post$, an indicator variable equal to one if the given year is the deal announcement year ($t = 0$). $API$, $Black$, $Hispanic$, and $Female$ are indicator variables equal to one if the employee is Asian Pacific Islander, Black, Hispanic, and female, respectively. Variable definitions are in Table A1 of the Appendix. We also include deal, year, job category, seniority, and highest degree fixed effects. The $t$-statistics are reported in parentheses and standard errors are clustered by acquirer industry and deal announcement year. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table 6: Continued

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Same Industry | | Different Industry | |
| Post | 0.113*** | 0.117*** | 0.048*** | 0.049*** |
| | (7.460) | (7.594) | (3.715) | (3.723) |
| API×Post | -0.012 | -0.012 | 0.008 | 0.008 |
| | (-0.979) | (-0.947) | (0.773) | (0.817) |
| Black×Post | -0.030*** | -0.032*** | -0.018*** | -0.019*** |
| | (-4.898) | (-5.004) | (-2.886) | (-3.040) |
| Hispanic×Post | -0.019** | -0.021*** | -0.002 | -0.004 |
| | (-2.668) | (-2.870) | (-0.295) | (-0.579) |
| Female×Post | -0.010* | -0.012** | -0.012 | -0.014* |
| | (-1.981) | (-2.378) | (-1.446) | (-1.785) |
| API | 0.019** | 0.019** | 0.017*** | 0.022*** |
| | (2.674) | (2.682) | (2.860) | (3.709) |
| Black | 0.021*** | 0.019*** | 0.010 | 0.008 |
| | (3.713) | (4.325) | (1.428) | (1.500) |
| Hispanic | 0.000 | -0.001 | -0.003 | -0.003 |
| | (0.111) | (-0.199) | (-0.806) | (-0.732) |
| Female | -0.009*** | -0.014*** | -0.004 | -0.009** |
| | (-3.806) | (-5.740) | (-1.075) | (-2.430) |
| Controls | NO | YES | NO | YES |
| Deal FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Job Category FE | YES | YES | YES | YES |
| Seniority FE | YES | YES | YES | YES |
| Highest Degree FE | YES | YES | YES | YES |
| Observations | 362,074 | 335,654 | 328,717 | 328,717 |
| Adjusted $R^2$ | 0.077 | 0.079 | 0.079 | 0.079 |

Table 7: Race, Gender, and Post-acquisition Employee Turnover: Salary Effect

This table reports how the effects of race and gender on post-acquisition employee turnover vary with employee salary. We measure employee salary using the within-target-year standardized dollar amount of salary and an indicator variable equal to one if the employee salary is above the target-year median. The dependent variable is $Turnover_{t+1}$, an indicator variable equal to one if the employee leaves the target firm in year $t+1$. $Post$, an indicator variable equal to one if the given year is the deal announcement year ($t=0$). $API$, $Black$, $Hispanic$, and $Female$ are indicator variables equal to one if the employee is Asian Pacific Islander, Black, Hispanic, and female, respectively. Variable definitions are in Table A1 of the Appendix. We also include deal, year, job category, seniority, and highest degree fixed effects. The $t$-statistics are reported in parentheses and standard errors are clustered by acquirer industry and deal announcement year. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table 7: Continued

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Standardized Salary | | High Salary Dummy | |
| Post | 0.070*** | 0.069*** | 0.058*** | 0.055*** |
| | (6.715) | (6.632) | (5.752) | (5.201) |
| Post×Salary | 0.028*** | 0.032*** | 0.030*** | 0.036*** |
| | (5.992) | (7.008) | (4.099) | (4.901) |
| API×Post | 0.000 | 0.001 | -0.001 | 0.011* |
| | (0.039) | (0.215) | (-0.074) | (1.824) |
| Black×Post | -0.020*** | -0.021*** | -0.024*** | -0.019*** |
| | (-4.910) | (-4.676) | (-5.583) | (-3.261) |
| Hispanic×Post | -0.006** | -0.005 | -0.010*** | -0.006 |
| | (-2.542) | (-1.633) | (-3.257) | (-0.987) |
| Female×Post | -0.008 | -0.008 | -0.012* | -0.008 |
| | (-1.188) | (-1.185) | (-1.964) | (-1.389) |
| API×Post×Salary | | -0.007 | | -0.021*** |
| | | (-0.916) | | (-2.785) |
| Black×Post×Salary | | -0.007 | | -0.012 |
| | | (-1.163) | | (-1.043) |
| Hispanic×Post×Salary | | 0.001 | | -0.007 |
| | | (0.119) | | (-0.682) |
| Female×Post×Salary | | -0.007* | | -0.007 |
| | | (-1.698) | | (-1.159) |
| API×Salary | | -0.019*** | | -0.019*** |
| | | (-5.745) | | (-3.883) |
| Black×Salary | | -0.018*** | | -0.019* |
| | | (-3.508) | | (-1.823) |
| Hispanic×Salary | | -0.016*** | | -0.014** |
| | | (-5.189) | | (-2.071) |
| Female×Salary | | -0.007** | | -0.002 |
| | | (-2.707) | | (-0.538) |
| API | 0.019*** | 0.020*** | 0.020*** | 0.030*** |
| | (4.995) | (4.962) | (5.376) | (6.315) |
| Black | 0.013*** | 0.010** | 0.015*** | 0.023*** |
| | (3.106) | (2.409) | (3.252) | (3.080) |

Table 7: Continued

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Hispanic | -0.002 | -0.004 | -0.001 | 0.005 |
| | (-1.077) | (-1.680) | (-0.466) | (1.481) |
| Female | -0.010*** | -0.010*** | -0.009*** | -0.008* |
| | (-4.679) | (-4.711) | (-3.438) | (-1.779) |
| Controls | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Deal FE | YES | YES | YES | YES |
| Job Category FE | YES | YES | YES | YES |
| Seniority FE | YES | YES | YES | YES |
| Highest Degree FE | YES | YES | YES | YES |
| Observations | 704,656 | 704,656 | 704,818 | 704,818 |
| Adjusted $R^2$ | 0.067 | 0.068 | 0.067 | 0.068 |

Table 8: Race, Gender, and Post-turnover Labor Outcomes

This table reports the effect of diversity on post-turnover labor outcomes. Panel A analyzes employees who leave the target firms within one year after the deal announcement. The dependent variable is $Unemployment_{t+\tau}$, indicator variables equal to one if the employee is unemployed for $\tau$ years after leaving the target firm. Panel B analyzes employees who leave the target firms within one year after the deal announcement and find a subsequent job in the ensuing three years. The dependent variables are $Career\ Shift$, $Promotion$, and $Demotion$, indicator variables equal to one if the subsequent job is in a different job category, has a higher seniority, and has a lower seniority, respectively. $API$, $Black$, $Hispanic$, and $Female$ are indicator variables equal to one if the employee is Asian Pacific Islander, Black, Hispanic, and female, respectively. Variable definitions are in Table A1 of the Appendix. We also include deal, year, job category, seniority, and highest degree fixed effects. The $t$-statistics are reported in parentheses and standard errors are clustered by acquirer industry and deal announcement year. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

| Panel A: Unemployment | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | $\text{Unemployment}_{t+1}$ | $\text{Unemployment}_{t+2}$ | $\text{Unemployment}_{t+3}$ |
| API | -0.005 | 0.002 | 0.006 |
| | (-0.428) | (0.163) | (0.520) |
| Black | 0.043*** | 0.029*** | 0.029*** |
| | (8.126) | (4.783) | (4.117) |
| Hispanic | 0.030*** | 0.037*** | 0.030*** |
| | (3.627) | (5.295) | (4.909) |
| Female | 0.031*** | 0.032** | 0.034*** |
| | (3.175) | (2.670) | (2.824) |
| Controls | YES | YES | YES |
| Deal FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Job Category FE | YES | YES | YES |
| Seniority FE | YES | YES | YES |
| Highest Degree FE | YES | YES | YES |
| Observations | 53,152 | 48,711 | 47,539 |
| Adjusted $R^2$ | 0.101 | 0.127 | 0.144 |

Table 8: Continued

| Panel B: Subsequent Employment | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Career Shift | Promotion | Demotion |
| API | -0.051*** | 0.001 | -0.011 |
| | (-3.487) | (0.128) | (-1.370) |
| Black | 0.011 | -0.049*** | 0.030*** |
| | (1.311) | (-4.914) | (4.050) |
| Hispanic | 0.015 | -0.022*** | 0.019** |
| | (1.613) | (-3.063) | (2.098) |
| Female | 0.032*** | -0.037*** | 0.035*** |
| | (4.328) | (-4.666) | (5.164) |
| Controls | YES | YES | YES |
| Deal FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| Job Category FE | YES | YES | YES |
| Seniority FE | YES | YES | YES |
| Highest Degree FE | YES | YES | YES |
| Observations | 39,521 | 39,521 | 39,521 |
| Adjusted $R^2$ | 0.090 | 0.122 | 0.239 |

Table 9: Race, Gender, and Post-acquisition Employee Turnover: Robustness

This table reports the robustness results on the effects of race and gender on post-acquisition employee turnover. Columns (1) and (2) present subsample analysis. Column (3) excludes COVID-19 pandemic years. Column (4) lengthens the post-years to two years ($t \in [-3, 1]$). Column (4) lengthens the pre-years to five years ($t \in [-5, 0]$). The dependent variable is $Turnover_{t+1}$, an indicator variable equal to one if the employee leaves the target firm in year $t+1$. $Post$, an indicator variable equal to one if the given year is the acquisition year ($t = 0$). $API$, $Black$, $Hispanic$, and $Female$ are indicator variables equal to one if the employee is Asian Pacific Islander, Black, Hispanic, and female, respectively. Variable definitions are in Table A1 of the Appendix. We also include deal, year, job category, seniority, and highest degree fixed effects. The $t$-statistics are reported in parentheses and standard errors are clustered by acquirer industry and deal announcement year. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table 9: Continued

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Pre-2007 | Post-2007 | Pre-2019 | $t \in [-3, 1]$ | $t \in [-5, 0]$ |
| Post | 0.065*** | 0.080*** | 0.076*** | 0.087*** | 0.068*** |
| | (3.566) | (5.533) | (6.649) | (8.887) | (7.604) |
| API×Post | -0.004 | 0.002 | 0.003 | -0.001 | -0.002 |
| | (-0.493) | (0.205) | (0.495) | (-0.092) | (-0.328) |
| Black×Post | -0.018 | -0.029*** | -0.024*** | -0.027*** | -0.023*** |
| | (-1.529) | (-14.833) | (-6.384) | (-6.774) | (-8.084) |
| Hispanic×Post | -0.010 | -0.011*** | -0.012*** | -0.011*** | -0.008** |
| | (-1.461) | (-4.063) | (-4.697) | (-2.877) | (-2.185) |
| Female×Post | -0.003 | -0.021*** | -0.015*** | -0.017*** | -0.007* |
| | (-0.516) | (-3.673) | (-3.248) | (-3.170) | (-1.853) |
| API | 0.016* | 0.023*** | 0.015*** | 0.020*** | 0.020*** |
| | (2.056) | (5.554) | (3.190) | (5.342) | (5.127) |
| Black | -0.004 | 0.017*** | 0.011** | 0.012** | 0.014*** |
| | (-0.564) | (7.864) | (2.522) | (2.712) | (3.402) |
| Hispanic | -0.005 | -0.002 | -0.001 | -0.003 | -0.001 |
| | (-0.925) | (-0.597) | (-0.577) | (-1.655) | (-0.542) |
| Female | -0.009 | -0.012*** | -0.010*** | -0.011*** | -0.011*** |
| | (-1.415) | (-5.511) | (-4.736) | (-5.316) | (-4.648) |
| Controls | YES | YES | YES | YES | YES |
| Deal FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |
| Job Category FE | YES | YES | YES | YES | YES |
| Seniority FE | YES | YES | YES | YES | YES |
| Highest Degree FE | YES | YES | YES | YES | YES |
| Observations | 207,357 | 497,461 | 608,522 | 983,338 | 836,023 |
| Adjusted $R^2$ | 0.078 | 0.065 | 0.074 | 0.064 | 0.065 |

Table 10: Total Salary Saved and Deal Outcomes

This table reports the effect of total salary saved on deal outcomes. The dependent variables are $CAR_{[0]}$, $CAR_{[0,2]}$, the one-day (three-day) deal announcement return of the acquirer, $Synergy_{[0]}$, $Synergy_{[0,2]}$, the one-day (three-day) value-weighted average announcement return of the acquirer and the target, and *Premium*, the offer price to target stock price premium 4 weeks prior to deal announcement, provided by SDC. *Total Salary Saved* is the sum of the estimated salary of employees who leave the target firm within one year after the deal announcement. We scale *Total Salary Saved* by different market capitalizations, depending on the specification (indicated by the last row in the table). We calculate *Total Salary Saved* using all employees for Panel A, using API, Black, Hispanic, and female employees for Panel B, and using White male employees for Panel C. Variable definitions are in Table A1 of the Appendix. We also include industry and deal year fixed effects. The $t$-statistics are reported in parentheses and standard errors are clustered by industry and year. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table 10: Continued

| Panel A: All Employees | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | $CAR_{[0]}$ | $CAR_{[0,2]}$ | $Synergy_{[0]}$ | $Synergy_{[0,2]}$ | Premium |
| Total Salary Saved | 0.861** | 1.006** | 1.633*** | 2.052*** | 1.947*** |
| | (2.386) | (2.238) | (2.712) | (3.086) | (2.947) |
| Acquirer Market Cap | 0.000 | 0.000 | -0.000* | -0.000 | |
| | (0.179) | (0.620) | (-1.920) | (-1.636) | |
| Acquirer BM | 1.070 | 1.537 | 1.575** | 2.401** | |
| | (1.330) | (1.184) | (2.357) | (2.359) | |
| Relative Size | -0.872 | -0.983 | 2.979*** | 2.444** | -18.556*** |
| | (-0.945) | (-0.784) | (3.347) | (2.121) | (-4.619) |
| Pct Cash | 0.019*** | 0.035*** | 0.030*** | 0.042*** | 0.091** |
| | (4.111) | (4.199) | (7.939) | (7.067) | (2.611) |
| Tender Offer | 0.316 | 0.653 | 0.286 | 0.928 | 4.700 |
| | (0.686) | (0.892) | (0.484) | (1.147) | (1.208) |
| Same SIC3 | 0.071 | 0.031 | -0.095 | -0.085 | -5.179 |
| | (0.180) | (0.068) | (-0.265) | (-0.194) | (-1.477) |
| Acquirer Prior Year Return | -0.055 | -0.864* | 0.185 | -0.425 | |
| | (-0.121) | (-1.927) | (0.721) | (-1.054) | |
| Target Market Cap | | | | | 0.000 |
| | | | | | (0.772) |
| Target BM | | | | | 5.469 |
| | | | | | (1.418) |
| Target Prior Year Return | | | | | 1.346 |
| | | | | | (0.659) |
| Acquirer SIC3 FE | YES | YES | YES | YES | |
| Target SIC3 FE | | | | | YES |
| Deal Year FE | YES | YES | YES | YES | YES |
| Observations | 1,029 | 1,029 | 1,029 | 1,029 | 942 |
| Adjusted $R^2$ | 0.047 | 0.083 | 0.146 | 0.148 | 0.158 |
| Salary Scaler | Acquirer Market Cap | | Acquirer+Target Market Cap | | Target Market Cap |

Table 10: Continued

| Panel B: Minority Employees | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | $CAR_{[0]}$ | $CAR_{[0,2]}$ | $Synergy_{[0]}$ | $Synergy_{[0,2]}$ | Premium |
| Total Salary Saved | 2.288** | 2.670** | 4.390** | 5.887*** | 4.228** |
| | (2.377) | (2.128) | (2.273) | (3.091) | (2.494) |
| Controls | YES | YES | YES | YES | YES |
| Acquirer SIC3 FE | YES | YES | YES | YES | |
| Target SIC3 FE | | | | | YES |
| Deal Year FE | YES | YES | YES | YES | YES |
| Observations | 1,029 | 1,029 | 1,029 | 1,029 | 942 |
| Adjusted $R^2$ | 0.050 | 0.085 | 0.149 | 0.153 | 0.155 |
| Salary Scaler | Acquirer Market Cap | | Acquirer+Target Market Cap | | Target Market Cap |

| Panel C: Non-minority Employees | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | $CAR_{[0]}$ | $CAR_{[0,2]}$ | $Synergy_{[0]}$ | $Synergy_{[0,2]}$ | Premium |
| Total Salary Saved | 1.054* | 1.292* | 2.594*** | 3.092** | 3.048*** |
| | (1.749) | (1.689) | (2.998) | (2.471) | (2.678) |
| Controls | YES | YES | YES | YES | YES |
| Acquirer SIC3 FE | YES | YES | YES | YES | |
| Target SIC3 FE | | | | | YES |
| Deal Year FE | YES | YES | YES | YES | YES |
| Observations | 1,029 | 1,029 | 1,029 | 1,029 | 942 |
| Adjusted $R^2$ | 0.044 | 0.081 | 0.144 | 0.145 | 0.157 |
| Salary Scaler | Acquirer Market Cap | | Acquirer+Target Market Cap | | Target Market Cap |

Table A1: Variable Definitions

| | |
|---|---|
| Turnover | An indicator variable equal to one if the employee leaves the target firm in a given year. |
| Post | An indicator variable equal to one if the given year is the acquisition year or after the acquisition year. |
| API (Black, Hispanic, White) | An indicator variable equal to one if the employee belongs to the Asian Pacific Islander (Black, Hispanic, White) race group. |
| Female | An indicator variable equal to one if the employee belongs to the female gender group. |
| Admin (Finance, Marketing, Operations, Scientist, Sales, Engineer) | An indicator variable equal to one if the employee's job category belongs to the administrator (finance, marketing, operations, scientist, sales, engineer) group. |
| Associate (Doctor, High School, MBA, Master, Bachelor) | An indicator variable equal to one if the employee's highest education degree is an associate degree (doctorate, high school, MBA, master's degree, bachelor's degree). |
| Experience | The natural logarithm of the number of months since the start of the first job. |
| Tenure | The natural logarithm of the number of months since the start of the first job in the target firm. |
| Ln(Salary) | The natural logarithm of the dollar amount of salary. Salary is adjusted to 2022 dollars. |
| Seniority | The level of seniority. This variable ranges from 1 to 7, where 7 is the highest seniority level. |
| High Salary Dummy | An indicator variable equal to one if the employee's salary is above the median for a given firm-year. |
| $\text{Unemployment}_{t+\tau}$ | An indicator variable equal to one if the employee is unemployed for $\tau$ years after leaving the target firm within one year after the deal announcement. |
| Career Shift | An indicator variable equal to one if the employee has a subsequent job that is in a different job category than the job at the target firm. We only consider employees who leave the target firms within one year after the deal announcement and find a subsequent job in the ensuing three years. |
| Promotion | An indicator variable equal to one if the employee has a subsequent job that has a higher seniority than the job at the target firm. We only consider employees who leave the target firms within one year after the deal announcement and find a subsequent job in the ensuing three years. |

Table A1: Variable Definitions

| | |
|---|---|
| Demotion | An indicator variable equal to one if the employee has a subsequent job that has a lower seniority than the job at the target firm. We only consider employees who leave the target firms within one year after the deal announcement and find a subsequent job in the ensuing three years. |
| Deal Size | The dollar amount of deal size in billions. |
| $CAR_{[0]}$ | The one-day deal announcement abnormal returns of the acquirer, starting from the deal announcement date. |
| $CAR_{[0,2]}$ | The three-day deal announcement abnormal returns of the acquirer, starting from the deal announcement date. |
| $Synergy_{[0]}$ | The one-day deal announcement value-weighted average abnormal returns of the acquirer and the target, starting from the deal announcement date. |
| $Synergy_{[0,2]}$ | The three-day deal announcement value-weighted average abnormal returns of the acquirer and the target, starting from the deal announcement date. |
| Premium | The offer price to target stock price premium - 4 weeks prior to the announcement, provided by SDC. |
| Pct Cash | The percent of deal size paid in cash. |
| Tender Offer | An indicator variable equal to one if the deal is a tender offer. |
| Same SIC3 | An indicator variable equal to one if the acquirer and the target belong to the same 3-digit SIC industry. |
| Relative Size | The ratio of target firm market cap to the acquirer firm market cap. |
| Market Cap | The market cap of the acquirer or target in billions. |
| BM | The book-to-market ratio of the acquirer or target. |
| Prior Year Return | The cumulative return of the acquirer or target over one year prior to the deal announcement. |
| Total Salary Saved | The sum of the estimated salary of employees who leave the target firm within one year of the deal announcement. We scale Total Salary Saved by different market capitalizations, depending on the specification (indicated by the last row in the Table 10) |

Table A2: Assessing Revelio, DeepFace, Random Forest Accuracy

This table presents the prediction accuracy of several estimation models. Panel A (F) shows the accuracy of Revelio's name-based model. Panel B (G) displays the accuracy of the DeepFace face-based model. Panels C (H) detail the performance of random forest models that combine name-based and face-based features. Panels D and E report the prediction accuracy of the random forest model with two out-sample data.

| | API | Black | Hispanic | White |
|---|---|---|---|---|
| Panel A: Estimated Ethnicity Based on Revelio's Name-based model | | | | |
| Asian Pacific Islander | 84.98% | 3.26% | 1.59% | 10.16% |
| Black | 0.68% | 59.98% | 1.97% | 37.37% |
| Hispanic | 1.28% | 4.75% | 76.17% | 17.80% |
| White | 0.82% | 14.88% | 2.55% | 81.75% |
| Panel B: Estimated Ethnicity based on DeepFace model | | | | |
| API | 88.15% | 1.90% | 3.45% | 6.50% |
| Black | 9.38% | 82.16% | 3.46% | 5.00% |
| Hispanic | 25.52% | 3.18% | 42.32% | 28.98% |
| White | 10.65% | 1.81% | 6.52% | 81.02% |
| Panel C: Estimated Ethnicity based on Random Forest model | | | | |
| API | 99.27% | 0.19% | 0.09% | 0.45% |
| Black | 0.18% | 98.72% | 0.21% | 0.89% |
| Hispanic | 0.64% | 0.46% | 95.96% | 2.94% |
| White | 0.18% | 0.40% | 0.28% | 99.14% |
| Panel D: Validation Sample 1 - Based on Random Forest model | | | | |
| API | 95.51% | 0.93% | 0.62% | 2.94% |
| Black | 0.77% | 93.83% | 0.77% | 4.63% |
| Hispanic | 2.99% | 2.99% | 76.05% | 17.96% |
| White | 0.96% | 1.49% | 0.96% | 96.59% |
| Panel E: Validation Sample 2 - Based on Random Forest model | | | | |
| API | 97.30% | 0.90% | 0.30% | 1.50% |
| Black | 1.08% | 93.28% | 1.34% | 4.30% |
| Hispanic | 3.77% | 1.89% | 81.13% | 13.21% |
| White | 0.79% | 2.44% | 1.83% | 94.94% |

| | Female | Male |
|---|---|---|
| Panel F: Estimated Gender Based on Revelio's Name-based model | | |
| Female | 88.58% | 11.42% |
| Male | 4.75% | 95.25% |
| Panel G: Estimated Gender Based on DeepFace model | | |
| Female | 68.09% | 31.91% |
| Male | 0.43% | 99.57% |
| Panel H: Estimated Gender based on random forest model | | |
| Female | 99.56% | 0.44% |
| Male | 0.40% | 99.60% |

Figure A1: Feature contributions of the predictive model

This figure illustrates the feature contributions in a random forest model designed to predict the ethnicity and gender of professionals based on their names and profile pictures. The model incorporates name-based probabilities from Revelio and facial features extracted from profile pictures using the DeepFace package. The importance of each feature is depicted by its relative contribution to reducing the overall prediction error, highlighting the key factors the model relies on to make ethnicity and gender predictions. Panels A and B report the importance of features for ethnicity and gender, respectively.