Employee Turnover in the Spotlight: Evidence from Mergers and Acquisitions *

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Using machine learning on over one million LinkedIn profiles, we construct a comprehensive dataset to examine how demographics influence employee turnover post-acquisitions. We find that Black, Hispanic, and female employees experience lower increases in turnover rate than White and male employees. Evidence suggests that the turnover gaps are driven by acquirers' decisions during the merger process and are larger for acquirers facing greater legal risk and media scrutiny. Conditional on leaving, Black, Hispanic, and female employees experience worse subsequent labor market outcomes. Moreover, labor cost savings are significantly associated with bidder announcement returns and merger synergies.

Keywords: Mergers and acquisitions, Workforce composition, Labor restructuring, Merger synergies

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1 Introduction

Recent developments in diversity, equity, and inclusion (DEI) initiatives have highlighted a growing divergence in corporate responses. While some firms have scaled back their DEI efforts amid political and market pushback (Times, 2025), others have reaffirmed or even intensified their commitment to fostering inclusive workplaces (Reuters, 2025). This divergence raises important questions about the extent to which DEI principles are integrated into broader corporate decision-making processes, particularly during periods of strategic change. Prior research in finance has largely focused on board diversity, highlighting the role of diversity leadership at the highest level.[1] However, much less is known about how firm-level demographic dynamics unfold below the boardroom in response to corporate events.

This gap is especially salient in the context of mergers and acquisitions (M&As), which represent major firm-level shocks often accompanied by significant workforce restructuring (e.g., Maksimovic et al., 2011). Because labor costs account for a substantial share of corporate expenditures and is a key source of synergy creation (e.g., Bhagat et al., 1990; Dessaint et al., 2017), acquirers often make rapid and strategic decisions regarding employee retention and layoffs to eliminate redundant or inefficient labor. Evidence from labor economics and sociology literature shows that racial minorities and women face significantly higher layoff rates, particularly during periods of economic contraction or crisis (e.g., Zwerling and Silver, 1992; Wilson and McBrier, 2005; Couch and Fairlie, 2010; Dias, 2021). These patterns raise concerns that post-acquisition workforce reductions may disproportionately affect underrepresented groups. However, such labor restructuring decisions unfold under growing public scrutiny and legal risk, particularly when outcomes appear discriminatory. As a result, firms must navigate a tension between achieving cost efficiencies and avoiding reputational or legal consequences, making workforce decisions during M&A integration both

[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.

high-stakes and consequential for equity in the workplace. In this paper, we investigate whether DEI-related considerations influence workforce restructuring in the wake of M&A transactions and whether workforce restructuring aligns with value-maximizing objectives from the perspective of shareholders.

Studying these dynamics requires data that are both extensive in scale and detailed in content, particularly with respect to individual demographics and employment histories. Such data have historically been difficult to obtain. We address this challenge by constructing a novel dataset on workers' race and gender using over one million LinkedIn profiles and machine learning techniques. Specifically, we leverage data from Revelio Labs to track employees at U.S. public target firms involved in M&A transactions between 1990 and 2022. First, we infer the race and gender of target employees by analyzing LinkedIn profile pictures with DeepFace, a deep learning-based facial attribute tool. Then, we train a Random Forest classifier that integrates image-based features from DeepFace and name-based features from Revelio Labs. This approach outperforms standard classification methods, achieving accuracies of 96% for race and 99% for gender.

Leveraging this dataset, we provide the first large-sample evidence on the relationship between employee demographics and post-acquisition employment outcomes. We begin by documenting a significant increase in turnover among target firm employees following acquisitions. The turnover rates increase from 19.7% in the three years prior to the merger to 28.6% in the year following the deal, representing a 45% increase in the probability of turnover. Interestingly, this post-acquisition increase in turnover varies substantially by race. White and Asian Pacific Islander (API) employees experience similar increases of approximately 9.1 and 9.6 percentage points, while Hispanic employees show an 8.3 percentage point increase. Black employees exhibit the smallest increase in turnover at 6.4 percentage points. We also observe differences by gender, with female employees experiencing a smaller increase in turnover relative to male employees. These findings provide initial evidence that race and gender are associated with differential turnover outcomes after acquisitions.

Next, we implement a within-deal difference-in-differences (DID) approach that compares turnover outcomes across demographic groups within the same M&A transaction, effectively controlling for deal-level unobservables. The analysis controls for year, job category, seniority, and education through fixed effects, as well as employee characteristics such as salary, target firm tenure, and work experience. This empirical design allows us to compare the increases in turnover between different racial and gender groups, while benchmarking these changes against pre-existing turnover patterns within the same deal. 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 difference in the increase in turnover rates between API and White employees.

We further examine the interaction between race and gender. Post acquisition, Black female employees show the lowest increase in turnover rate, whereas White male and API employees, regardless of gender, experience the highest increases. These findings contrast with much of the existing literature in labor economics and sociology, and offer new evidence on demographic differences in employee turnover following mergers.

While target firms often experience substantial labor restructuring following acquisitions (e.g., Maksimovic et al., 2011; Gehrke et al., 2025), it is important to recognize that not all turnovers are acquirer-initiated layoffs. To strengthen the interpretation of our findings, we conduct additional tests that leverage variation in deal characteristics. First, we examine withdrawn deals, acquisitions that do not complete. In these cases, turnovers cannot be attributed to acquirer decisions and any race and gender effects would likely reflect voluntary departures. We find no abnormal turnover following withdrawal deals. Moreover, the race 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. These results

help us distinguish between the effects of acquirers' layoff decisions and voluntary departures.

To further explore the role of acquirer-driven restructuring, we next examine variation based on industry-relatedness. Prior studies suggest that the acquirer has a greater ability to lay off target employees and reduce labor costs in same-industry acquisitions because the potential for employee redundancy is high in such horizontal mergers with overlapping operations (e.g., O'Shaughnessy and Flanagan, 1998; Lee et al., 2018; Tate and Yang, 2024). Therefore, turnover following same-industry acquisitions is more likely to reflect acquirer-initiated labor restructuring rather than voluntary departures by employees. Accordingly, if the race and gender effects we document reflect layoff decisions, we would expect these patterns to persist or strengthen in the same industry deals. Our results first confirm that turnover rates are 2.8 times greater following the same industry acquisitions. More importantly, the racial effects observed in our baseline results remain statistically significant and show a larger economic magnitude in this subsample.

We also investigate if differences in external job opportunities influence our findings. White male employees, who might have better job prospects after acquisition could voluntarily leave more often. Inconsistently, we find that that the lower post acquisition turnover of Black and female employees is not driven by differences in outside employment opportunities. Black and female employees are less likely to leave than their White male counterparts regardless of whether local employment growth is high or low. This evidence further supports the interpretation that our results reflect acquirers' retention decisions rather than voluntary exits by White male employees with better external opportunities.

Next, we examine potential factors that influence acquirers' decisions to retain minority employees. We begin by considering the role of external pressures. Specifically, whether exposure to litigation or media scrutiny affects post-acquisition turnover patterns. If acquirers anticipate greater legal or reputational risks, they may be more cautious about making layoff decisions that disproportionately impact minority or female employees. Using proxies for litigation risk and media attention, we find that the turnover gap between Black, Hispanic,

and female employees, relative to White and male employees, is larger in industries where acquirers face greater legal exposure and among firms subject to more intense media scrutiny. These findings suggest that demographic differences in turnover partly reflect concerns over legal consequences and public perception.

Beyond external pressures, we also explore whether internal factors, namely, corporate culture, play a role in shaping labor restructuring decisions. Specifically, we assess whether the strength of a firm's DEI orientation affects the observed turnover patterns. Using proxies for DEI emphasis, we find that the racial turnover effects identified in our baseline results are primarily driven by acquirers with stronger internal DEI initiatives.[2]

In the final part of the paper, we examine the consequences of employee turnover following mergers, focusing on both the subsequent labor market outcomes for target employees and the shareholder wealth effects for acquirers. We find that minority employees who separate from target firms exhibit a significantly higher propensity to experience sustained unemployment in the subsequent years. Among those who find new jobs, they are more likely to experience demotions and less likely to receive promotions compared to White male employees. Taken together, these results suggest that post-acquisition turnover is driven, at least in part, by acquirers' labor restructuring decisions, has lasting negative effects on the career trajectories of affected minority groups.

We next examine whether labor cost savings are associated with acquisition performance. If a significant portion of employee turnover is driven by acquirers' strategic labor restructuring efforts, and if the market anticipates the resulting cost savings, we would expect a positive market reaction. In contrast, if turnover primarily reflects employees' voluntary departures – particularly the loss of key talent – we would not expect a positive market response, as such attrition could undermine post-acquisition integration and performance. Consistent with the restructuring view, we find that estimated labor cost savings are positively and significantly associated with acquirer announcement returns and overall merger synergies. The results are

[2]We also examine three alternative explanations in Section 5.4.3 and find no supporting evidence.

both statistically and economically meaningful: a 1% increase in annual labor cost saving corresponds to a 1.60 percentage point increase in three-day acquirer abnormal returns and a 3.1 percentage point increase in the three-day combined return. These findings suggest that labor restructuring is a key driver of merger value creation and support the interpretation that post-acquisition turnover largely reflects deliberate, value-enhancing cost reduction strategies by acquirers. However, we find no significant difference between cost savings arising from reductions in minority or female employment and those from reductions in white employees, suggesting that investors respond primarily to the magnitude of expected cost reductions rather than their demographic composition.

2 Related Literature

This paper contributes to several strands of literature. First, we contribute to the corporate finance literature by providing new evidence on how workforce diversity shapes and is shaped by corporate restructuring. Despite increasing attention to corporate DEI practices, little is known about how demographic characteristics influence employee retention outcomes in the context of mergers and acquisitions. The finance literature on diversity has predominantly focused on the effects of board diversity on firm governance and performance.[3] This gap is largely due to data limitations. We construct a novel, large-scale dataset that tracks over one million target workers, enabling us to provide the first comprehensive evidence on how post-acquisition turnover varies across demographic groups.

Second, we contribute to the literature on labor markets in corporate takeovers. While decades of research have focused on the value creation in M&As, such as deal structure, market timing, and managerial motives (e.g., Andrade et al., 2001; Harford, 2005; Rhodes-Kropf and Viswanathan, 2004), less attention has been paid to the post-acquisition reallocation of

[3]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.

human capital under DEI constraints. We document that turnover increases significantly following acquisitions, and that these increases are not evenly distributed across demographic groups. Our findings extend the literature on M&A labor outcomes by introducing an explicit diversity lens, a dimension largely absent in existing M&A research. Furthermore, while cost reductions aimed at achieving economies of scale are widely understood to be a major source of merger synergies (e.g., Houston et al., 2001), empirical research linking labor cost savings to acquisition performance remains limited (e.g., Kaplan, 1989; Bhagat et al., 1990). Our analysis bridges this gap by connecting employee-level restructuring outcomes to firm-level market reactions. These patterns are consistent with acquirers making strategic labor decisions that account for both operational and reputational costs.

Third, our paper contributes to the literature in labor economics and sociology, which has traditionally focused on firm layoff decisions during periods of economic crisis and typically rely on small-scale survey data (e.g., Zwerling and Silver, 1992; Wilson and McBrier, 2005; Couch and Fairlie, 2010). By examining employee-level turnover following mergers and acquisitions, typically growth-oriented rather than survival-driven events, we offer new insights into how workforce composition influences corporate restructuring in a markedly different context. On the one hand, our finding that acquirers are more likely to retain, rather than disproportionately lay off, minority employees contrasts with evidence from downturn-related layoffs, suggesting that firm decisions about workforce composition differ systematically between periods of expansion and contraction. On the other hand, we find that among employees who do exit post-acquisition, minority workers tend to experience worse subsequent labor market outcomes, consistent with prior findings in the labor economics literature. Together, these findings highlight both the distinctiveness of M&A-driven turnover and the persistence of structural inequalities in labor market trajectories.

3 Data and Methodology

3.1 Data sources

We obtain M&A transactions from the Securities Data Company (SDC) database between 1990 and 2022. We require that both the acquirer and the target be public firms. We also require that the deal value reported by SDC be at least $1 million 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. We merge SDC data with the Center for Research in Securities Prices (CRSP) and Compustat data to obtain stock market and fundamentals information. We obtain 3,172 M&A deals after applying these standard filters.

We obtain target employee information from 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 race. Revelio Labs has been widely used in recent studies (e.g., Baker et al., 2024; Charoenwong et al., 2024) and provides a broadly reliable view of workforce demographics in U.S. public firms, particularly for white-collar and managerial roles (Zhang, 2023). Although it underrepresents blue-collar and late-career workers, validation against EEO-1 filings and ACS benchmarks shows that its aggregate gender and racial patterns closely align with official labor statistics, supporting its use in diversity research (Berry et al., 2024).

A key advantage of the Revelio Labs dataset is its ability to track post-merger career paths of target-firm employees, showing how their employment status changes after an acquisition. This individual-level perspective enables us to compare demographic differences in turnover outcomes within the same deal, rather than relying on aggregated statistics at the acquirer,

target, or establishment level. We merge the M&A sample with Revelio Labs and retain deals where there are at least five U.S. employees with profile pictures on LinkedIn. This reduces the M&A sample to 1,089 deals.

3.2 Measuring race and gender

3.2.1 Assessing Revelio accuracy

Our main variables of interest are the race and gender of employees. 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 female and 0.3 for male. Similarly, the database identifies an individual's race using first name, last name, and location based on US census data. While this method reasonably captures the aggregate distribution of gender and race in the labor force, it may not provide accurate information for individual-level identification, making it less suitable for detailed employee-level analysis. Indeed, previous literature has documented significant biases created by name-based algorithms among race and gender groups in the analysis of public firm employees (e.g, Cook et al., 2022; Berry et al., 2024).

To assess the accuracy of Revelio's race and gender predictions, we manually reviewed a random sample of 24,000 LinkedIn profile pictures. This exercise served two purposes: to evaluate the performance of name-based demographic estimations and to construct an annotated dataset for training our own classification model (see Section 3.2.2 for more details). Despite efforts to minimize error, we find that human annotators are not immune to judgment errors when inferring demographic characteristics from profile pictures. For example, Latin-American annotators may misclassify South Asian individuals as Hispanic, while East Asian annotators may confuse African-American individuals with those of South Asian descent. To mitigate these biases, we use ChatGPT 4.0 Vision and retain 22,345 profile

pictures where human annotators and ChatGPT agree on race and gender.[4]

Panel A of Table A2 of the Appendix reports Revelio's race predictions across four prevalent categories within our randomly selected sample. Our findings indicate that Revelio estimates have a weighted precision below 80%. Prediction accuracy is particularly low among White and Black employees. 37.4% of Black and 14.9% white employees are erroneously classified as White and Black, respectively. Similarly, Panel F of Table A2 of the Appendix reveals that 11.4% of females and 4.8% of males are misclassified as the opposite gender.

3.2.2 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, 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.[5] We randomly divide the 22,345-observation annotated sample into three subsets: a training sample (80% of the sample) and two validation samples (each 10% of the sample). The trained random forest algorithm allows us to effectively handle non-linear relationships among picture- and name-based features when classifying race and gender, while producing more accurate outcomes compared to other conventional classification models,

[4]We upload LinkedIn profile images, along with individuals' names and countries of work, to the vision-based large language model to cross-validate human and algorithmic demographic classifications. For race, we use the four dominant categories adopted by Revelio: Black, White, Hispanic, and Asian Pacific Islander.

[5]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).

such as logistic regression and support vector machines.[6]

Panel C and F of Table A2 of the Appendix shows that our model achieves at least 96.0% accuracy for race groups and 99.6% accuracy for gender groups in our annotated sample. Moreover, Panels D and E of Table A2 of the Appendix demonstrate an expected and minor reduction in prediction accuracy when we apply our random forest model to two validation samples that were not used in model training. To assess the feature importance, we plot the feature contributions to our predictive models in Panels A and B of Figure A1 of the Appendix. Neither the picture-based nor the 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% to the race prediction, respectively. 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 professionals for whom we can obtain pictures from LinkedIn, ensuring the accuracy of our diversity analysis.

3.3 Summary statistics

Panel A of Table 1 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%.[7] In terms of education, 56% of our sample 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 (i.e., engineering, sales, and finance) account for 75% of the workforce. On average, the annual salary (inflation-adjusted to 2022 dollars) is approximately $113,850, with a median of $101,990.

[6]The weighted average F1-score for the random forest model is 94% for race 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 race prediction and 97% and 97% for gender prediction, respectively.

[7]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.

Panel B of Table 1 presents summary statistics for the sample deals. The mean deal size is 2.65 billion, with a median of 0.57 billion. Approximately 54% of the deals are same-industry acquisitions and 21% 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 -0.72% (-0.94%), whereas the average one-day (three-day) combined return is 1.48% (1.82%).

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 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.[8]

4 Race, Gender, and post-M&A employee turnover

4.1 Empirical strategy

To investigate how race and gender are related to target employee turnover after an acquisition, we track the employment of target employees in our sample 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, including cases where the employee transitions to the acquirer post-

[8]To gauge the coverage of our sample, we compare the number of employees in our dataset to the number reported in Compustat. In the later part of the sample period, our data accounts for approximately 30% of the Compustat figures, while in the earlier years (e.g., 2000), this coverage drops to around 10%. This discrepancy is likely due to (1) Compustat including part-time, seasonal, and foreign employees and (2) the absence of LinkedIn profiles or profile pictures for some employees, particularly earlier in the sample period.

announcement, 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 $t = 0$ is the deal announcement year. To estimate the effect on turnover 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*, 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.

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

after the acquisition.

4.2 Univariate analyses

As a prelude to our main analysis, we conduct univariate analyses on the effect of race and gender 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 28.6% after the acquisition. The difference is statistically and economically significant. This finding aligns with studies suggesting that acquirers reduce labor costs post-acquisition through workforce reductions (e.g., Healy et al., 1992), with magnitudes comparable to Brazil and Germany evidence (Lagaras, 2025; Gehrke et al., 2025).[9]

Panel B of Table 2 presents statistics by employee race. The results show significant variations in turnover rates based on race. Asian employees experience a higher increase in turnover rate (9.6%) than their White counterparts (9.1%). Hispanic employees see a lower increase in turnover rate at 8.3%. Notably, Black employees show the smallest increase in turnover rate at 6.4%. These differences are both economically and statistically significant, as White and Asian employees are 67% more likely to experience turnover 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

[9]We also examine whether employees at the acquirer experience similar increases in turnover. The average acquirer employee sees only a 1.6 percentage point increase in the annual turnover rate, representing 12.5% of the pre-deal announcement average turnover rate (12.8%). In contrast, the increase in annual turnover among target employees is substantially larger – an 8.9 percentage point rise – which corresponds to 45% of their pre-deal average turnover rate (19.7%).

female employees respond to mergers in terms of their likelihood of leaving the firm.

4.3 Regression analysis

Table 3 reports the regression results from Equation (1). 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 columns. 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, and female employees exhibit slightly higher turnover relative to male employees. After the deal announcement, all racial and gender groups experience increases in turnover rate. However, there exists a 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. While White employees experience an increase in turnover rate of 7.4%, Black employees experience an increase in turnover rate of 4.7% ($7.4\% - 2.7\%$). This amounts to a 36% ($2.7\% \div 7.4\%$) reduction in the turnover rate increase. In contrast, API employees experience an increase in turnover rate that is not statistically different from that of White employees.[10]

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 significant effects, the impacts on API male and API female

[10]Table IA1 of the Internet Appendix shows that our results are robust when various interacted fixed effects.

employees are statistically insignificant.

Overall, the results in Tables 2, 3, and 4 offer new evidence from a large sample of target firms, showing that the likelihood of employee turnover varies significantly by gender and race. These findings stand in contrast to much of the existing literature in labor economics and sociology, as well as to a few prior studies based on smaller samples, which have suggested a higher likelihood of employer-initiated layoffs for Black or female employees (e.g., Elvira and Zatzick, 2002; Berry et al., 2024).

5 Acquirer Decisions vs. Employee Choices

Although our M&A setting facilitates the identification of acquirer-driven layoffs, being a target firm may signal organizational instability and career uncertainty (e.g., Agrawal and Walkling, 1994; Maksimovic and Phillips, 2001). These conditions can prompt employees, particularly those with stronger outside opportunities, to exit voluntarily. As such, the observed race and gender effects on turnover may reflect a mixture of acquirers' layoff decisions and employees' voluntary departures in response to the uncertainty and disruption associated with M&A activity. To strengthen the interpretation of our findings, we conduct additional analyses in contexts where turnover likely reflects either acquirers' labor restructuring or employees' voluntary exits for better opportunities, and test whether our baseline results persist.

5.1 Analyses of withdrawn deals

We first turn to withdrawn deals, a setting where takeovers do not complete, and thus, acquirer-led restructurings are absent. In such cases, employee turnover should not be attributed to downsizing or layoff decisions by the acquirer. If our earlier results are primarily driven by voluntary exits, we expect to observe similar patterns in withdrawn deals, particularly if takeover announcements are perceived as signals of heightened employment

uncertainty. Conversely, if acquirer-initiated layoffs are the main driver, we should not observe the same turnover patterns in these withdrawn transactions. To avoid confounding effects from future acquisitions, we restrict the sample to target firms that are not acquired within two years following the withdrawn deal's announcement. This yields 263 withdrawn deals involving 160,576 unique employees. We apply the same methodology for identifying employee race and gender and conduct a similar analysis to that in Table 3.[11]

Table 5, columns (1) to (4), presents the regression results for all withdrawn deals. The coefficient estimates on *Post* are insignificant for all columns. In contrast, the coefficients on *Post* in Table 3 range from 7.0% to 7.4%, 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: *Race* × *Post* and *Female* × *Post* are all statistically insignificant and economically minimal. In column (5), we exclude withdrawn deals where the target board publicly rejected the bidder. These firms likely had no intention of selling, possibly due to stronger internal growth prospects, and may differ systematically from target firms in completed deals. The results in column (5) show that removing target firms that were never serious candidates for acquisition does not affect the results. Overall, these results support our main finding that the post-acquisition turnover gaps experienced by Black, Hispanic, and female employees reflect acquirers' post-acquisition layoff decisions.

5.2 Analyses of industry relatedness

In this section, we examine employee turnover based on industry relatedness within the acquirer-target pair. The literature indicates that acquirers are better positioned to reduce labor costs and lay off target employees in same-industry acquisitions. This is due to overlapping skills and functions that facilitate more efficient workforce integration and cost synergies (e.g., O'Shaughnessy and Flanagan, 1998; Lee et al., 2018; Tate and Yang, 2024). Building

[11] For the analysis of withdrawn deals, we cluster the standard errors by target industry and year.

on these findings, we perform subsample analyses and report results in Table 6.

We first use the two-digit SIC industry classification. Column (1) presents results for same-industry acquisitions and column (2) analyzes deals in which the acquirer and target belong to different industries. If acquirers' layoff decisions primarily drive our baseline results, we should expect stronger results for same-industry deals. Table 6 show supporting evidence for this hypothesis. Specifically, we find significantly higher increases in turnover rates for same-industry acquisitions (11.2%) than different-industry acquisitions (3.9%). This is consistent with post-acquisition turnover being more likely to reflect the acquirer's labor restructuring decisions. More importantly, the race and gender effects observed in our baseline results remain significant and exhibit larger economic magnitudes in the same-industry subsamples, where turnover is more likely a result of post-acquisition layoff decisions.

In columns (3) and (4), we repeat the same analyses, using the Text-based Network Industry Classifications (TNIC) from Hoberg and Phillips (2010). TNIC measures product-market similarity and allows for finer distinctions in product overlap. However, it may also capture broader strategic similarities that are less directly tied to employment integration than those reflected in SIC classifications.[12] We find that same-TNIC acquisitions are associated with higher post-acquisition turnover and more pronounced race and gender effects. The TNIC-based results support our conjecture that demographic effects intensify with greater product-market similarity between acquirer and target, although the contrast is weaker compared to results based on SIC classifications.

5.3 Analyses of outside employment opportunities

In this section, we examine whether our findings are driven by differences in outside employment opportunities. A potential concern with our main results is that White male employees may have better external job prospects and thus be more likely to leave voluntarily.

[12] As noted in Hoberg and Phillips (2010, 2016), TNIC similarity captures a broad spectrum of competitive and strategic relatedness based on product descriptions, which may extend beyond operational integration, including aspects such as employment structures.

To test this alternative explanation, we conduct subsample analyses by splitting employees into markets with below or above the median annual employment growth, measured as the year-over-year percentage change in local employment. If our results were primarily driven by voluntary exits of White males, we would expect the lower turnover among Black and female employees to be concentrated in markets with high local employment growth.

Table 7 reports the regression results. Columns (1) and (2) examine employee turnover in areas with below- and above-median overall local employment growth, measured as the year-over-year percentage change in the number of individuals employed in the same metro area, based on data from Revelio Lab. Columns (3) and (4) refine this analysis by measuring local employment growth within the same job category, while Columns (5) and (6) explicitly focus on employment growth among White males in the local labor market.

Across all specifications, and consistent with our baseline findings, the interaction terms *Black*×*Post* and *Female*×*Post* remain negative and significant in both low- and high-growth markets, indicating that Black and female employees continue to experience lower turnover relative to White males. Importantly, these effects persist even after conditioning on White male-specific employment growth, suggesting that the results are not driven by differential outside job opportunities available to White males. Overall, the evidence supports the interpretation that the lower turnover among minority employees reflects acquirers' retention decisions rather than voluntary exits by White male employees with better external opportunities.

5.4 Why do acquirers retain minority employees?

To better understand the underlying drivers of acquirers' decisions to retain minority employees following an acquisition, we examine several potential channels that may shape these outcomes. Specifically, we assess whether external pressures, such as heightened legal risk or media scrutiny, constrain post-acquisition employment decisions. We also consider the role of internal firm commitments to DEI. Finally, we explore three alternative explanations

that may account for the observed retention patterns.

5.4.1 External pressures and acquirers' labor restructuring decisions

We first examine whether exposure to litigation or media scrutiny affects post-acquisition turnover patterns. High-profile discrimination lawsuits and their associated reputational costs may lead firms to be more attentive to diversity retention during workforce consolidations, especially during disruptive events such as mergers and acquisitions.[13] Firms that operate in industries that see more such lawsuits may learn from legal precedents and be more cautious against these lawsuits.[14] Such expectations could translate into more conservative minority or female layoff decisions. Therefore, we posit that our baseline findings should be more concentrated in acquirers that belong to more litigious industries.

Empirically, we use corporate litigation data from Audit Analytics, which tracks civil cases involving public companies filed in U.S. federal district courts (excluding New Mexico). We perform subsample analyses for deals in which the acquirer is in an SIC-2 industry with and without any employee-related lawsuits. We include lawsuits in the employment law, labor law, fair labor standards act, civil rights, and other civil rights categories.[15] We report results in columns (1) and (2) of Table 8. We find that the effects of race and gender on turnover rates are attenuated for acquirers in no-lawsuit industries. The coefficient estimates on *Hispanic* × *Post* and *Female* × *Post* are statistically insignificant. The coefficient on

[13]Several high-profile class-action lawsuits illustrate the legal and reputational risks firms face in cases of perceived discrimination. For example, Coca-Cola's 1999 racial discrimination lawsuit resulted in a $192.5 million settlement. In 2003, Merrill Lynch faced a suit from African American brokers over discriminatory practices in compensation and career advancement. That same year, Abercrombie & Fitch was sued for allegedly discriminating against African Americans, Hispanics, Asians, and women in hiring and promotions. In 2004, Novartis was the subject of a class-action lawsuit filed by female sales representatives alleging gender-based disparities in pay, promotions, and pregnancy-related treatment. In this context, acquiring firms may act preemptively to avoid disproportionate dismissals of underrepresented employees, reduce the risk of discrimination claims, and safeguard reputational capital. Litigation risk thus emerges as a plausible mechanism behind the relatively higher retention of underrepresented group employees observed in our data.

[14]See Robinson et al. (2025), who show that peer lawsuits influence firms' environmental disclosure behavior; and Ashraf (2022), who finds firms respond to peer risk events by strengthening governance.

[15]Our results are robust when expanding our definition of employee-related litigation to include civil rights - accommodations, civil rights - employment, and labor/management relations.

Black × *Post* remains significant, though its magnitude is smaller than that of the full-sample analysis (-0.019 vs. -0.027). In contrast, in the subsample with at least one lawsuit, all coefficient estimates on the interaction terms involving *Black*, *Hispanic*, *Female*, and *Post* are significant and exhibit larger magnitudes.

Similar to employee-related lawsuits, media scrutiny could also affect post-acquisition turnover patterns. Acquiring firms may act preemptively to avoid headlines about layoffs disproportionately affecting underrepresented employees, especially when they receive more media coverage. We conjecture that the turnover gaps for Black, Hispanic, and female employees should be more concentrated in acquirers that are subject to greater media attention. To measure media attention, we use RavenPack data to count the number of news articles mentioning the acquirer during the 12 months ending one month prior to the deal announcement, thereby excluding articles are merger-driven.[16] We perform subsample analyses for deals involving acquirers with below and above-median media coverage and report the results in columns (3) and (4) of Table 8. Indeed, we find that Black, Hispanic, and female employees experience turnover gaps predominantly when the acquirers are well-covered by the media.[17] Overall, the results in 8 are consistent with the notion that exposure to litigation and media scrutiny may shape acquirers' post-acquisition layoff decisions.

5.4.2 The role of internal DEI focuses

In addition to external pressures, internal firm priorities and corporate culture may also shape post-acquisition layoff decisions. Firms that actively promote DEI, through inclusive organizational structures, dedicated initiatives, or leadership accountability, may be more cautious about implementing layoffs that disproportionately affect minority employees. In

[16]To comprehensively capture media exposure, we utilize the full RavenPack database and restrict attention to news items with a relevance score above 75, which indicates that the article is significantly related to the acquirer.

[17]As a robustness exercise, we also classify acquirers using the number of distinct news sources, rather than article counts. While this alternative classification yields minor differences in the composition of the groups, the results remain qualitatively similar.

this section, we investigate whether acquirers with a stronger internal emphasis on DEI exhibit different post-acquisition retention patterns across demographic groups.

To assess the acquirer DEI-related firm culture, we rely on two measures from Li et al. (2021) that are positively and significantly related to the diversity aspect of firm culture: *Respect* and *Innovation*.[18] We perform subsample analyses for deals with below and above-median *Respect* and *Innovation* scores. The results are reported in columns (1) – (4) of Table 9. We find that Hispanic and female employees experience a lower increase in turnover rate for acquirers with above-median *Respect* and *Innovation* scores. For example, the turnover rate for Hispanic employees increases by 9.4% (0.095 − 0.001) in the low-*Respect* group, compared to 6.3% (0.081 − 0.018) in the high-*Respect* group. For female employees, the corresponding increases are 8.2 and 6.4 percentage points, respectively. We observe similar patterns across the high- and low-*Innovation* subsamples. The coefficient on *Black* × *Post* is significant in all subsamples.

Next, we use the self-disclosed LinkedIn profile descriptions of acquirers' senior human resources managers and C-suite executives to capture their organizational commitment to diversity. Specifically, we examine whether the acquirer employs at least one human resources manager or executive whose LinkedIn profile includes diversity-related responsibilities.[19] We then repeat our prior analyses, splitting our sample accordingly. We report the results in columns (5) and (6) of Table 9. Consistent with earlier findings, the coefficients on

[18] Li et al. (2021) show that an innovative culture extends beyond traditional metrics of innovation, such as R&D spending or patent counts, as firms may also innovate through unique marketing strategies or governance practices. They also find that the cultural value of respect is positively and significantly associated with the best employer ranking by Fortune. Their dataset also offers a valuable, long-run, and broad-coverage view of corporate culture compared to traditional sources such as the KLD database, which, while including some diversity indicators, has limited coverage (e.g., only about 650 firms prior to 2000) and becomes increasingly stale towards 2016, when it was effectively absorbed into MSCI's broader ESG framework following MSCI's acquisition.

[19] We identify such individuals by searching for keywords such as "diversity," "inclusion," "affirmative action," and "equal employment opportunity" in the job descriptions of personnel categorized by Revelio Labs under titles such as "recruiting," "HR consultant," "talent acquisition consultant," "labor relations," at senior-level roles. To minimize misclassification, we manually reviewed job descriptions to ensure that diversity-related responsibilities were accurately captured.

Hispanic × *Post* and *Female* × *Post* are statistically significant only for acquirers with diversity-oriented senior human resources managers and C-suite executives. The turnover rate for Hispanic (female) employees increases by 4.6% (4.3%) and 8.9% (8.4%) among deals with and without such personnel, respectively.

5.4.3 Alternative explanations

Lastly, we consider three alternative explanations that may account for the observed retention patterns of minority employees following acquisitions. First, the higher retention rates may reflect the fact that minority employees occupy roles that are essential to the firm's ongoing operations. Prior research in labor economics has shown that employees in non-essential or peripheral positions are more likely to be laid off during organizational restructuring or downturns (e.g., Gibbons and Katz, 1991; Lazear and Gibbs, 2014). If minority employees disproportionately hold operationally critical roles, their retention may be a function of operation necessity rather than diversity-related considerations. Empirically, we examine whether employees who experience turnover gaps, on average, earn higher salaries, hold more senior positions, or occupy roles with a greater quantitative emphasis (i.e., jobs that belong to the Engineer, Finance, or Scientist category). As shown in Table IA2 of the Internet Appendix, we do not find evidence supporting this hypothesis.

Second, in situations where severance or "salvage" packages are offered during post-acquisition workforce consolidations, minority employees may be less likely to accept them. If non-minority employees are more willing or able to take such offers and exit voluntarily, this could mechanically result in higher observed retention among minority employees. However, we argue that this is unlikely to be the case. While severance packages are common in crisis-driven restructuring or mass layoffs, they are less prevalent in strategic, growth-oriented M&A settings. To evaluate the plausibility of this explanation, we conduct a comprehensive text-based search of SEC filings for all target firms from the deal announcement through one year after deal completion, focusing on references to voluntary separation or severance

programs.[20] We identify only 41 deals in which the target firm mentions such programs in any form and, upon closer review, only 19 of these explicitly link these offers to an acquisition. Mentions in conference calls are even rarer. Overall, these instances account for less than 2% of the sample, providing little support for the idea that differential take-up of exit incentives drives the observed retention patterns.

Third, sociology research has shown that White individuals and men have historically held disproportionate access to senior positions, with entrenched hierarchies often limiting advancement opportunities for minorities and women (Elliott and Smith, 2004). Disruptive events like M&As can destabilize these structures, leading firms to lay off older or high-ranking managers who no longer align with organizational needs or political dynamics (Ibarra, 1992). Zhang (2021) finds that M&As are associated with a significant decline in the proportion of White male managers. If so, our results may reflect the exit of entrenched White male leaders rather than the retention of underrepresented groups. To test this alternative explanation, we exclude employees with high seniority or over 30 years of work experience. As shown in Table IA3 of the Internet Appendix, our findings remain robust.

Taken together, while these alternative explanations may account for some variation in post-acquisition turnover, the evidence suggests they are unlikely to fully explain the systematic demographic patterns we document.

5.5 Additional analysis and robustness tests

5.5.1 Linkedin data quality

Prior to the 2000s, Linkedin has limited coverage of employee career histories. This could introduce survivorship bias and skew the interpretation of our results. To mitigate

[20] Specifically, we review all relevant filings (8-K, 10-K, 10-Q, DEF 14A, etc.) for keywords such as "voluntary separation," "voluntary severance," "enhanced severance package," "early retirement," "voluntary redundancy," "voluntary layoff," "golden handshake," and related terms. We also conduct a parallel search of target firms' post-M&A announcement conference call transcripts, including M&A and earning calls, from S&P.

this concern, we exclude deals announced before the year 2000. As shown in column (1) of Table 10, our results remain robust to this restriction.

5.5.2 Potential influence of pandemic

The COVID-19 pandemic introduced unprecedented economic and labor market disruptions, which may have influenced firm decision-making. To ensure that our results are not driven by these pandemic-related factors, we restrict the sample to deals announced before 2019 and report the results in column (2). Our findings remain robust.

5.5.3 Alternative turnover windows

In some M&A deals, acquirers could take more than one year to make and enforce layoff decisions. To better capture these cases, we use alternative event windows to include one year after deal announcements. Our results are not sensitive to this alternative specification, as shown in column (3).

5.5.4 State fixed effect

State-level political and regulatory environments may influence acquirers' layoff decisions, particularly with regard to underrepresented employees. For example, acquirers may act more cautiously when operating in states with stronger protections for workers or more progressive social norms. To account for these potential influences, we include state fixed effects using LinkedIn employee locations. The results, shown in column (4), remain robust.

5.5.5 Excluding turnovers with subsequent promotions

To further ensure that our results are not driven by voluntary exits, we exclude the exit year for employees who received a subsequent promotion (i.e., increase in seniority) after leaving the target firms. These results are presented in column (5), and our findings continue to hold.

5.5.6 Entropy balancing

A potential concern is that underrepresented employees may hold job positions with characteristics that are systemically different from those held by their White male counterparts. To ensure that these differences do not drive the observed turnover gap, we implement entropy balancing to account for such differences (Hainmueller, 2012; Imbens and Rubin, 2015). Specifically, we balance the means and variances of *Ln(Salary)*, *Experience*, *Tenure*, *Job Category*, *Seniority*, and *Highest Education Degree* between underrepresented groups and White male employees. Using the entropy-balanced sample, we reestimate our baseline regression. The race and gender effects, shown in column (6), on turnover rate remain robust.

6 Implications for labor markets and shareholders

In the final part of the paper, we explore the consequences of post-acquisition employee turnover, focusing on the labor market outcomes for displaced workers and the shareholder wealth effects for acquiring firms.

6.1 Post-turnover Labor Outcomes

First, we focus on employees who leave the target firm within one year after the acquisition announcement ($Turnover_{t+1} = 1, t = 0$) and examine whether post-acquisition turnover is associated with sustained unemployment, downward career mobility, or occupational disruption. In doing so, we aim to assess whether the burden of labor restructuring falls disproportionately on minority and female employees, raising concerns about the distributional equity and welfare costs of M&A-driven employment changes.

In Panel A of Table 11, we examine 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 τ 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* and *Hispanic*. These results suggest that Black and Hispanic 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 Table 11 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 higher and 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.

Taken together, our findings indicate that minority and female employees displaced into the external labor market face worse outcomes, suggesting greater frictions or barriers to reemployment. While firms may tend to retain underrepresented employees after the acquisition, those minority employees who do exit experience disadvantages in career progression.[21] These patterns align with recent evidence that female executives displaced by acquisitions face more limited reemployment prospects and slower advancement than their male peers (Guo et al., 2024).

6.2 Labor restructuring and acquisition performance

In this final section, we examine the relation between workforce restructuring and value creation, as well as the value implications of acquirers' decisions to retain minority and female

[21] Extending the same empirical approach, we examine labor outcomes for employees who remain at the merged firm and find qualitatively similar patterns. In particular, underrepresented groups are less likely to experience upward mobility post-acquisition. Female employees who remain are especially likely to switch job categories and face demotions within one year of the acquisition announcement.

employees after mergers. To assess how workforce restructuring affects value creation, we first examine the relation between *overall* labor cost savings and acquisition performance. This analysis serves two purposes. 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 (e.g., Bhagat et al., 1990; Kaplan, 1989; Dessaint et al., 2017). Second, 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. We test this relation by estimating 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 or *Synergy*, the deal announcement value-weighted average bidder-target cumulative abnormal returns, following Bradley et al. (1988). We measure *CAR* and *Synergy* over one-day and three-day periods, starting from the deal announcement date. These are market-based proxies for expected synergy and deal value, capturing investors' immediate reactions rather than the ex-post outcomes of the M&A integration process. The key independent variables are *Total Salary Saved*, which is the sum of the estimated salaries of employees who leave the target firm within one year after the deal announcement. $Z_{i,j}$ includes a set of control variables. We include acquirer industry and year fixed effects, and cluster our standard errors by acquirer industry.[22]

Panel A of Table 12 reports the regression results. We scale *Total Salary Saved* by the acquirer's pre-merger market capitalization when analyzing the impact on acquirer cumulative abnormal returns in columns (1) and (2) and by the combined market capitalization when examining the effect on merger synergies in columns (3) and (4). We also multiply the

[22]We find similar results when double clustering our standard errors by industry and year.

scaled *Total Salary Saved* by 100. The results show that the estimated labor cost savings are positively and significantly related to acquirer announcement returns and merger synergies. Specifically, a 1% increase in annual labor cost saving is associated with 1.19% to 1.64% higher acquirer abnormal returns and a 2.33% to 3.15% 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.

After documenting that investors reward acquirers for labor cost savings, we next examine whether the composition of retained employees, specifically minority and female workers, also affects merger value. Retaining a diverse workforce may enhance firm value by strengthening the acquirer's reputation and preserving firm-specific human capital, such as knowledge, client relationships, and innovative capacity that might otherwise be lost through turnover. However, if the retention decision is driven primarily by social or political pressures rather than economic motives, keeping employees for symbolic or compliance reasons could limit the acquirer's ability to realize cost synergies and reduce efficiency gains.

Empirically, we interact *Total Salary Saved* with *Minority Turnover Ratio*, defined as the ratio of non-White-male employees who left the target post-merger to the total number of departing employees. The interaction coefficient captures the incremental effect of market reaction to labor cost savings driven by the departure of minority employees. Results in Panel B of Table 12 show that the coefficient estimates on the interaction terms are generally insignificant, except when using one-day CAR as the dependent variable, where the coefficient is positive and significant at the 5%. The absence of a significant difference between cost savings arising from reductions in minority or female employment and those from reductions in white employees suggests that investors do not differentiate the demographic composition of these savings when assessing merger value. In Table IA4 of the Internet Appendix, we further separately calculate *Total Salary Saved* using minority (i.e., non-White male) and non-minority (i.e., White male) employees. We find that both estimated labor cost savings from minority and non-minority positively contribute to deal performance.

Overall, the evidence implies that markets reward expected cost efficiency, and any potential incremental benefits (such as enhanced reputation or innovation) or costs (such as reduced flexibility or integration frictions) associated with the demographic composition of retained or displaced employees are second-order relative to overall efficiency expectations. In other words, while diversity retention may carry longer-term strategic or reputational implications, the market's immediate response at the announcement stage is dominated by expectations of cost efficiency and synergy realization.

7 Conclusion

In this paper, we present novel evidence on how race and gender diversity are related to employee turnover following acquisitions. Using machine learning techniques and LinkedIn profile pictures as primary input, we identify the race and gender of employees from over 1,000 publicly traded target firms. Our unique dataset reveals several key findings. After acquisitions, 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 API employees are much more likely to leave the target firm following the merger compared to Black and Hispanic employees, while female employees experience a smaller increase in turnover relative to their male counterparts.

Additional analyses suggest that these patterns are more consistent with acquirers' restructuring decisions than voluntary departures. The effects are absent in withdrawn deals and more pronounced when cost-cutting incentives are stronger – such as in same-industry mergers. Furthermore, the turnover gap between White and minority employees is larger when acquirers face higher labor litigation risk and media scrutiny. The turnover gap is stronger for acquirers with a strong commitment to DEI. We also show that underrepresented employees who exit face worse labor market outcomes, and that labor cost reductions are positively associated with acquirer returns, reinforcing the link between turnover and

synergy realization.

These findings reveal a potential trade-off between M&A-driven efficiency and labor market equity. Importantly, while acquirers may avoid disproportionately terminating minority employees, those who are displaced face greater reemployment challenges. 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.

While our setting, focusing on large, publicly traded firms, captures transactions of significant economic importance, the findings may not fully generalize to smaller or privately held companies. Future research could explore how labor restructuring unfolds in these alternative contexts, where resource constraints, governance structures, and public visibility differ markedly.

References

Adams, Renée B, and Daniel Ferreira, 2009, Women in the boardroom and their impact on governance and performance, *Journal of Financial Economics* 94, 291–309.

Agrawal, Anup, and Ralph A Walkling, 1994, Executive careers and compensation surrounding takeover bids, *The Journal of Finance* 49, 985–1014.

Ahern, Kenneth R, and Amy K Dittmar, 2012, The changing of the boards: The impact on firm valuation of mandated female board representation, *Quarterly Journal of Economics* 127, 137–197.

Andrade, Gregor, Mark Mitchell, and Erik Stafford, 2001, New evidence and perspectives on mergers, *Journal of Economic Perspectives* 15, 103–120.

Ashraf, Musaib, 2022, The role of peer events in corporate governance: Evidence from data breaches, *The Accounting Review* 97, 1–24.

Baker, Andrew C, David F Larcker, CHARLES G McCLURE, Durgesh Saraph, and Edward M Watts, 2024, Diversity washing, *Journal of Accounting Research* 62, 1661–1709.

Berry, Alexander, Elizabeth M Maloney, and David Neumark, 2024, The missing link? using linkedin data to measure race, ethnic, and gender differences in employment outcomes at individual companies, Technical report, National Bureau of Economic Research.

Bhagat, Sanjai, Andrei Shleifer, Robert W Vishny, Gregg Jarrel, and Lawrence Summers, 1990, Hostile takeovers in the 1980s: The return to corporate specialization, *Brookings Papers on Economic Activity. Microeconomics* 1990, 1–84.

Bradley, Michael, Anand Desai, and E Han Kim, 1988, Synergistic gains from corporate acquisitions and their division between the stockholders of target and acquiring firms, *Journal of Financial Economics* 21, 3–40.

Carter, David A, Betty J Simkins, and W Gary Simpson, 2003, Corporate governance, board diversity, and firm value, *Financial Review* 38, 33–53.

Cassel, Johan, James Weston, and Emmanuel Yimfor, 2023, Board diversity in private vs. public firms, *Public Firms (November 3, 2023)* .

Charoenwong, Ben, Zachary T Kowaleski, Alan Kwan, and Andrew G Sutherland, 2024, Regtech: Technology-driven compliance and its effects on profitability, operations, and market structure, *Journal of Financial Economics* 154, 103792.

Cook, Lisa D, Matt Marx, and Emmanuel Yimfor, 2022, Funding black high-growth startups, Technical report, National Bureau of Economic Research.

Couch, Kenneth A, and Robert Fairlie, 2010, Last hired, first fired? black-white unemployment and the business cycle, *Demography* 47, 227–247.

Dessaint, Olivier, Andrey Golubov, and Paolo Volpin, 2017, Employment protection and takeovers, *Journal of Financial Economics* 125, 369–388.

Dias, Felipe A, 2021, The racial gap in employment and layoffs during covid-19 in the united states: a visualization, *Socius* 7, 2378023120988397.

Eaton, Gregory W, Feng Guo, Tingting Liu, and Micah S Officer, 2022, Peer selection and valuation in mergers and acquisitions, *Journal of Financial Economics* 146, 230–255.

Eckbo, B Espen, 2009, Bidding strategies and takeover premiums: A review, *Journal of Corporate Finance* 15, 149–178.

Eckbo, B Espen, Knut Nygaard, and Karin S Thorburn, 2022, Valuation effects of norway's board gender-quota law revisited, *Management Science* 68, 4112–4134.

Elliott, James R, and Ryan A Smith, 2004, Race, gender, and workplace power, *American sociological review* 69, 365–386.

Elvira, Marta M, and Christopher D Zatzick, 2002, Who's displaced first? the role of race in layoff decisions, *Industrial Relations: A Journal of Economy and Society* 41, 329–361.

Ewens, Michael, and Richard R Townsend, 2020, Are early stage investors biased against women?, *Journal of Financial Economics* 135, 653–677.

Ferrari, Giulia, Valeria Ferraro, Paola Profeta, and Chiara Pronzato, 2022, Do board gender quotas matter? selection, performance, and stock market effects, *Management Science* 68, 5618–5643.

Frankel, Richard, Jared Jennings, and Joshua Lee, 2022, Disclosure sentiment: Machine learning vs. dictionary methods, *Management Science* 68, 5514–5532.

Gehrke, Britta, Ernst G Maug, Stefan Obernberger, and Christoph Schneider, 2025, Post-merger restructuring of the labor force, *European Corporate Governance Institute–Finance Working Paper* .

Giannetti, Mariassunta, and Tracy Yue Wang, 2023, Public attention to gender equality and board gender diversity, *Journal of Financial and Quantitative Analysis* 58, 485–511.

Giannetti, Mariassunta, and Mengxin Zhao, 2019, Board ancestral diversity and firm-performance volatility, *Journal of Financial and Quantitative Analysis* 54, 1117–1155.

Gibbons, Robert, and Lawrence F Katz, 1991, Layoffs and lemons, *Journal of labor Economics* 9, 351–380.

Gormley, Todd A, Vishal K Gupta, David A Matsa, Sandra C Mortal, and Lukai Yang, 2023, The big three and board gender diversity: The effectiveness of shareholder voice, *Journal of Financial Economics* 149, 323–348.

Griffin, Dale, Kai Li, and Ting Xu, 2021, Board gender diversity and corporate innovation: International evidence, *Journal of Financial and Quantitative Analysis* 56, 123–154.

Guernsey, Scott, Feng Guo, Tingting Liu, and Matthew Serfling, 2022, Classified boards: Endangered species or hiding in plain sight, *Available at SSRN* .

Guo, Xiaohu, Vishal K Gupta, Sandra Mortal, and Vikram Nanda, 2024, Gender and managerial job mobility: Career prospects for executives displaced by acquisitions, *Journal of Financial and Quantitative Analysis* 59, 3299–3339.

Hainmueller, Jens, 2012, Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies, *Political analysis* 20, 25–46.

Harford, Jarrad, 2005, What drives merger waves?, *Journal of Financial Economics* 77, 529–560.

Healy, Paul M, Krishna G Palepu, and Richard S Ruback, 1992, Does corporate performance improve after mergers?, *Journal of financial economics* 31, 135–175.

Hoberg, Gerard, and Gordon Phillips, 2010, Product market synergies and competition in mergers and acquisitions: A text-based analysis, *The Review of Financial Studies* 23, 3773–3811.

Hoberg, Gerard, and Gordon Phillips, 2016, Text-based network industries and endogenous product differentiation, *Journal of political economy* 124, 1423–1465.

Houston, Joel F, Christopher M James, and Michael D Ryngaert, 2001, Where do merger gains come from? bank mergers from the perspective of insiders and outsiders, *Journal of Financial Economics* 60, 285–331.

Ibarra, Herminia, 1992, Homophily and differential returns: Sex differences in network structure and access in an advertising firm, *Administrative science quarterly* 422–447.

Imbens, Guido W, and Donald B Rubin, 2015, *Causal inference in statistics, social, and biomedical sciences* (Cambridge university press).

Kaplan, Steven, 1989, The effects of management buyouts on operating performance and value, *Journal of Financial Economics* 24, 217–254.

Kim, Daehyun, and Laura T Starks, 2016, Gender diversity on corporate boards: Do women contribute unique skills?, *American Economic Review* 106, 267–271.

Lagaras, Spyridon, 2025, M&as, employee costs and labor reallocation, *Journal of Finance forthcoming* .

Lazear, Edward P, and Michael Gibbs, 2014, *Personnel economics in practice* (John Wiley & Sons).

Lee, Kyeong Hun, David C Mauer, and Emma Qianying Xu, 2018, Human capital relatedness and mergers and acquisitions, *Journal of Financial Economics* 129, 111–135.

Li, Kai, Feng Mai, Rui Shen, and Xinyan Yan, 2021, Measuring corporate culture using machine learning, *The Review of Financial Studies* 34, 3265–3315.

Maksimovic, Vojislav, and Gordon Phillips, 2001, The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains?, *The journal of finance* 56, 2019–2065.

Maksimovic, Vojislav, Gordon Phillips, and Nagpurnanand R Prabhala, 2011, Post-merger restructuring and the boundaries of the firm, *Journal of Financial Economics* 102, 317–343.

Miric, Milan, Nan Jia, and Kenneth G Huang, 2023, Using supervised machine learning for large-scale classification in management research: The case for identifying artificial intelligence patents, *Strategic Management Journal* 44, 491–519.

O'Shaughnessy, KC, and David J Flanagan, 1998, Determinants of layoff announcements following m&as: An empirical investigation, *Strategic Management Journal* 19, 989–999.

Reuters, 2025, Factbox: Us companies drop diversity policies after trump's order, https://www.reuters.com/world/us/factbox-us-companies-drop-diversity-policies-after-trumps-order-2025-02-27/, Accessed: 2025-07-26.

Rhodes-Kropf, Matthew, and Steven Viswanathan, 2004, Market valuation and merger waves, *The Journal of Finance* 59, 2685–2718.

Robinson, Scott A, A Nicole Skinner, and Jasmine Wang, 2025, Does litigation risk shape environmental disclosure decisions? evidence from peers' environmental disclosure lawsuits, *The Accounting Review* 100, 445–475.

Tate, Geoffrey, and Liu Yang, 2024, The human factor in acquisitions: Cross-industry labor mobility and corporate diversification, *Review of Financial Studies* 37, 45–88.

Times, 2025, These u.s. companies are not ditching DEI amid trump's crackdown, https://time.com/7261857/us-companies-keep-dei-initiatives-list-trump-diversity-order-crackdown, Accessed: 2025-07-26.

Wilson, George, and Debra Branch McBrier, 2005, Race and loss of privilege: African american/white differences in the determinants of job layoffs from upper-tier occupations, in *Sociological Forum*, volume 20, 301–321, Springer.

Zhang, Letian, 2021, Shaking things up: Disruptive events and inequality, *American Journal of Sociology* 127, 376–440.

Zhang, Shiyi, 2023, Does the market mis-value non-executive employee diversity?, *University of Miami Business School Research Paper* .

Zwerling, Craig, and Hilary Silver, 1992, Race and job dismissals in a federal bureaucracy, *American Sociological Review* 651–660.

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	1,121,333	0.07	0.26	0.00	0.00	0.00
Black	1,121,333	0.08	0.27	0.00	0.00	0.00
Hispanic	1,121,333	0.07	0.25	0.00	0.00	0.00
White	1,121,333	0.78	0.41	1.00	1.00	1.00
Female	1,121,333	0.44	0.50	0.00	0.00	1.00
Admin	1,121,333	0.08	0.26	0.00	0.00	0.00
Finance	1,121,333	0.20	0.40	0.00	0.00	0.00
Marketing	1,121,333	0.06	0.24	0.00	0.00	0.00
Operations	1,121,333	0.06	0.23	0.00	0.00	0.00
Scientist	1,121,333	0.05	0.22	0.00	0.00	0.00
Sales	1,121,333	0.27	0.45	0.00	0.00	1.00
Engineer	1,121,333	0.28	0.45	0.00	0.00	1.00
Associate	794,983	0.08	0.26	0.00	0.00	0.00
Doctor	794,983	0.05	0.21	0.00	0.00	0.00
High School	794,983	0.03	0.17	0.00	0.00	0.00
MBA	794,983	0.14	0.34	0.00	0.00	0.00
Master	794,983	0.15	0.36	0.00	0.00	0.00
Bachelor	794,983	0.56	0.50	0.00	1.00	1.00
Experience	1,121,333	118.06	95.08	44.00	96.00	169.00
Tenure	1,121,333	57.91	63.57	14.00	36.00	78.00
Salary	1,004,464	113.85	72.14	67.44	101.99	139.14
Seniority	1,121,333	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	969	2.65	6.39	0.17	0.57	2.05
Pct Cash	969	52.16	45.14	0.00	55.68	100.00
Tender Offer	969	0.21	0.40	0.00	0.00	0.00
Same SIC3	969	0.54	0.50	0.00	1.00	1.00
Relative Size	969	0.27	0.33	0.04	0.14	0.37
CAR1	969	-0.72	5.59	-3.03	-0.37	1.44
CAR3	969	-0.94	7.91	-4.64	-0.63	2.52
Synergy1	969	1.48	5.52	-1.26	0.53	3.64
Synergy3	969	1.82	7.43	-2.03	1.16	5.31
Acquirer Market Cap	969	21.41	43.09	0.99	3.57	16.46
Acquirer BM	969	0.47	0.33	0.24	0.39	0.63
Acquirer Prior Year Return	969	0.24	0.57	-0.07	0.15	0.43

Table 1: Continued

Panel C: Sample Distribution			
Year	Number of Deals	Percent of Deals	Average Number of Employee
1990	7	0.64%	401
1991	6	0.55%	56
1992	8	0.73%	54
1993	4	0.37%	65
1994	11	1.01%	1,054
1995	22	2.02%	60
1996	29	2.66%	92
1997	44	4.04%	296
1998	47	4.32%	656
1999	56	5.14%	153
2000	53	4.87%	845
2001	46	4.22%	69
2002	37	3.40%	81
2003	36	3.31%	70
2004	40	3.67%	197
2005	39	3.58%	131
2006	60	5.51%	125
2007	52	4.78%	175
2008	35	3.21%	121
2009	33	3.03%	386
2010	30	2.75%	173
2011	21	1.93%	272
2012	31	2.85%	485
2013	26	2.39%	271
2014	44	4.04%	735
2015	46	4.22%	406
2016	42	3.86%	490
2017	37	3.40%	1,606
2018	33	3.03%	731
2019	31	2.85%	1,231
2020	21	1.93%	452
2021	38	3.49%	842
2022	24	2.20%	419
Total	1,089	100.00%	

Table 2: Average Turnover

This table presents the target firm employee turnover rates before and after acquisitions. Panel A presents the turnover rates of all employees. Panel B (C) presents the turnover rates of all employees by racial (gender) groups. 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	0.286	0.089***
		(14.754)

Panel B: Average Turnover by Race				
	Pre	Post	Post−Pre	Diff.-in-Diff. Baseline=White
API	0.225	0.321	0.096***	0.004
			(13.035)	(1.078)
Black	0.226	0.289	0.064***	-0.028***
			(14.873)	(-4.444)
Hispanic	0.212	0.295	0.083***	-0.008
			(11.579)	(-1.409)
White	0.190	0.281	0.091***	
			(13.862)	

Panel C: Average Turnover by Gender				
	Pre	Post	Post−Pre	Diff.-in-Diff. Baseline=Male
Female	0.207	0.289	0.082***	-0.013**
			(21.474)	(-2.282)
Male	0.190	0.284	0.095***	
			(11.016)	

Table 3: Race, Gender, and Post-acquisition Employee Turnover

This table reports the effect 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* is 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 3: Continued

	(1)	(2)	(3)	(4)
Post	0.070***	0.073***	0.074***	0.074***
	(6.502)	(6.862)	(6.851)	(6.869)
API×Post	0.000	-0.001	0.000	0.000
	(0.041)	(-0.102)	(0.009)	(0.020)
Black×Post	-0.025***	-0.027***	-0.026***	-0.027***
	(-6.820)	(-9.406)	(-8.203)	(-8.276)
Hispanic×Post	-0.009***	-0.010***	-0.011***	-0.011***
	(-5.134)	(-5.988)	(-5.741)	(-5.146)
Female×Post	-0.013**	-0.014***	-0.014***	-0.014***
	(-2.373)	(-2.956)	(-2.891)	(-2.898)
API	0.017***	0.020***	0.018***	0.020***
	(5.050)	(5.325)	(4.577)	(5.457)
Black	0.015**	0.012***	0.012***	0.013***
	(2.436)	(2.756)	(2.877)	(3.318)
Hispanic	-0.001	-0.004	-0.003	-0.002
	(-0.525)	(-1.445)	(-1.333)	(-0.710)
Female	-0.006**	-0.012***	-0.012***	-0.011***
	(-2.414)	(-5.755)	(-5.301)	(-5.060)
Ln(Salary)		-0.117***	-0.110***	-0.113***
		(-3.746)	(-3.891)	(-3.976)
Tenure			-0.007***	-0.012***
			(-2.975)	(-6.921)
Experience				0.013***
				(5.017)
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	794,979	719,469	704,510	704,510
Adjusted R^2	0.067	0.069	0.068	0.069

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

This table reports the joint 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* is 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	0.072***	0.075***	0.075***	0.075***
	(6.655)	(7.038)	(7.037)	(7.049)
API×Female×Post	-0.003	-0.006	-0.004	-0.004
	(-0.483)	(-1.066)	(-0.713)	(-0.748)
Black×Female×Post	-0.038***	-0.041***	-0.040***	-0.040***
	(-3.572)	(-4.395)	(-4.111)	(-4.128)
Hispanic×Female×Post	-0.016***	-0.020***	-0.022***	-0.022***
	(-2.735)	(-3.712)	(-3.595)	(-3.643)
White×Female×Post	-0.016**	-0.018***	-0.018***	-0.018***
	(-2.647)	(-3.243)	(-3.101)	(-3.106)
API×Male×Post	-0.008	-0.009	-0.009	-0.009
	(-1.068)	(-1.152)	(-1.062)	(-1.041)
Black×Male×Post	-0.029***	-0.032***	-0.031***	-0.032***
	(-4.896)	(-5.211)	(-4.520)	(-4.623)
Hispanic×Male×Post	-0.019***	-0.020***	-0.019***	-0.019***
	(-3.673)	(-3.772)	(-3.734)	(-3.679)
API×Female	0.010**	0.007**	0.005	0.008**
	(2.718)	(2.059)	(1.434)	(2.401)
Black×Female	0.006	-0.003	-0.002	0.000
	(0.609)	(-0.362)	(-0.294)	(0.015)
Hispanic×Female	-0.010**	-0.018***	-0.016***	-0.014***
	(-2.101)	(-4.820)	(-4.109)	(-3.587)
White×Female	-0.005*	-0.011***	-0.011***	-0.010***
	(-1.881)	(-4.945)	(-4.437)	(-4.205)

Table 4: Continued

API×Male	0.019***	0.021***	0.019***	0.021***
	(3.874)	(3.997)	(3.608)	(4.232)
Black×Male	0.021***	0.016***	0.017***	0.018***
	(4.829)	(4.369)	(4.638)	(4.951)
Hispanic×Male	0.003	-0.001	-0.001	0.001
	(0.769)	(-0.161)	(-0.129)	(0.242)
Ln(Salary)		-0.117***	-0.110***	-0.113***
		(-3.744)	(-3.890)	(-3.975)
Tenure			-0.007***	-0.012***
			(-2.906)	(-6.567)
Experience				0.013***
				(5.003)
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	794,979	719,469	704,510	704,510
Adjusted R^2	0.067	0.069	0.068	0.069

Table 5: Withdrawn Deals

This table reports the effects of race and gender on employee turnover for withdrawn deals. The sample includes withdrawn deals, in which the target firms are not acquired within two years following the withdrawn deal's announcement. Columns (1)–(4) include all withdrawn deals, while column (5) excludes those in which the target board publicly rejected the bidders (i.e., hostile 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* is 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)	(5)
					Excl. Target Rejected Deals
Post	-0.021	-0.017	-0.018	-0.018	-0.017
	(-1.641)	(-1.565)	(-1.644)	(-1.643)	(-1.398)
API×Post	-0.012	-0.013	-0.012	-0.012	-0.012
	(-1.302)	(-1.446)	(-1.376)	(-1.382)	(-1.385)
Black×Post	0.004	0.004	0.004	0.004	0.007
	(0.985)	(0.823)	(0.907)	(0.947)	(1.411)
Hispanic×Post	0.002	0.001	-0.000	-0.000	0.003
	(0.608)	(0.271)	(-0.045)	(-0.087)	(0.514)
Female×Post	-0.004	-0.004	-0.003	-0.004	-0.001
	(-0.715)	(-0.811)	(-0.655)	(-0.668)	(-0.170)
API	0.036***	0.039***	0.033***	0.033***	0.035***
	(3.012)	(3.108)	(3.296)	(3.526)	(3.402)
Black	0.011	0.008	0.007	0.007	0.007
	(1.465)	(1.234)	(0.974)	(1.045)	(1.032)
Hispanic	-0.002	-0.004	-0.004	-0.004	-0.001
	(-0.553)	(-0.891)	(-0.969)	(-0.844)	(-0.358)
Female	-0.005	-0.011**	-0.011*	-0.010*	-0.015***
	(-1.066)	(-2.081)	(-2.029)	(-1.910)	(-3.532)
Ln(Salary)		-0.143***	-0.128***	-0.130***	-0.148***
		(-6.037)	(-6.307)	(-6.493)	(-5.306)
Tenure			-0.015***	-0.017***	-0.015***
			(-3.339)	(-5.912)	(-5.084)
Experience				0.005	0.007
				(1.000)	(1.077)
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	300,684	270,890	264,915	264,915	210,044
Adjusted R^2	0.067	0.076	0.073	0.073	0.079

Table 6: The Role of Industry Relatedness

This table reports how the effects of race and gender on post-acquisition employee turnover vary with acquirer-target industry relatedness. In columns (1) and (2), we use the SIC-2 industry classification. In columns (3) and (4), we use the TNIC-2 classification, following Hoberg and Phillips (2010). 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* is 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)
	Same SIC	Different SIC	Same TNIC	Different TNIC
Post	0.112***	0.039***	0.083***	0.055**
	(8.248)	(2.826)	(7.070)	(2.730)
API×Post	-0.008	0.007	-0.010	0.019
	(-0.886)	(0.776)	(-1.377)	(1.350)
Black×Post	-0.035***	-0.011	-0.031***	-0.014
	(-4.182)	(-1.691)	(-6.151)	(-1.441)
Hispanic×Post	-0.017**	-0.002	-0.009	-0.011*
	(-2.734)	(-0.338)	(-1.441)	(-2.007)
Female×Post	-0.011*	-0.011	-0.015**	-0.010
	(-2.037)	(-1.331)	(-2.314)	(-0.820)
Controls	YES	YES	YES	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	373,744	330,766	464,265	203,832
Adjusted R^2	0.083	0.057	0.067	0.071

Table 7: The Role of Outside Employment Opportunities

This table reports how the effects of race and gender on post-acquisition employee turnover vary with employment opportunities. We split our sample based on whether employees work in markets with below- or above-median annual employment growth. In columns (1) and (2), we measures local annual employment growth using the year-over-year percentage change in the number of individuals employed in the same metro area, provided by Revelio Lab. In columns (3) and (4), we use individuals employed in the same metro area and in the same job category. In columns (5) and (6), we use White male employees in the same metro area. 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* is 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)	(5)	(6)
	All Employees		Same Job Category		White Male Only	
	Low	High	Low	High	Low	High
Post	0.080***	0.068***	0.078***	0.069***	0.077***	0.069***
	(5.954)	(6.398)	(5.909)	(7.299)	(5.882)	(6.971)
API×Post	-0.003	0.004	-0.005	0.006	-0.007	0.007
	(-0.386)	(0.496)	(-0.538)	(0.882)	(-0.719)	(0.887)
Black×Post	-0.031***	-0.022***	-0.032***	-0.022***	-0.035***	-0.019***
	(-6.503)	(-7.633)	(-7.828)	(-7.120)	(-6.736)	(-5.368)
Hispanic×Post	-0.017***	-0.006*	-0.022***	-0.003	-0.020***	-0.004
	(-2.957)	(-1.789)	(-5.946)	(-1.409)	(-3.353)	(-1.524)
Female×Post	-0.016***	-0.013**	-0.011*	-0.016***	-0.017***	-0.012*
	(-2.979)	(-2.080)	(-1.978)	(-2.901)	(-3.096)	(-1.963)
Controls	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Job Category FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
Highest Degree FE	YES	YES	YES	YES	YES	YES
Observations	315,802	388,662	324,999	379,477	339,215	365,253
Adjusted R^2	0.069	0.071	0.067	0.072	0.068	0.072

Table 8: The Role of External Pressures

This table reports how the effects of race and gender on post-acquisition employee turnover vary with external pressures to be more cautious about making layoff decisions. In columns (1) and (2), we use employee-related lawsuits to proxy external pressures. In columns (3) and (4), we use the number of news articles about the acquirer to proxy for external pressures. We use news articles mentioning the acquirer during the 12 months ending one month prior to the deal announcement, obtained from RavenPack. 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* is 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)
	Lawsuits=0	Lawsuits≥1	Low Coverage	High Coverage
Post	0.086***	0.078***	0.119***	0.074***
	(8.509)	(4.517)	(7.052)	(4.884)
API×Post	-0.001	0.001	0.021	-0.003
	(-0.271)	(0.079)	(1.402)	(-0.287)
Black×Post	-0.019**	-0.030***	-0.006	-0.030***
	(-2.584)	(-5.412)	(-0.360)	(-14.702)
Hispanic×Post	-0.005	-0.017***	-0.024	-0.009**
	(-0.780)	(-5.668)	(-1.505)	(-2.382)
Female×Post	-0.009	-0.016***	-0.004	-0.019***
	(-0.995)	(-6.197)	(-0.280)	(-3.883)
Controls	YES	YES	YES	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	352,340	352,170	82,013	477,385
Adjusted R^2	0.067	0.074	0.085	0.063

Table 9: The Role of Acquirer Firm Culture

This table reports how the effects of race and gender on post-acquisition employee turnover vary with acquirer firm culture. In columns (1) – (4), we use *Respect* and *Innovation* corporate culture values from Li et al. (2021). We separate deals by the median levels of acquirer culture measures. In columns (5) and (6), we use whether the acquirer has a human resources representative or executive whose LinkedIn profile includes diversity-related responsibilities. 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* is 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)	(5)	(6)
	Respect		Innovation		Diversity HR & Exec.	
	Low	High	Low	High	No	Yes
Post	0.095***	0.081***	0.106***	0.072***	0.097***	0.056***
	(4.866)	(4.663)	(4.673)	(4.126)	(7.689)	(3.995)
API×Post	-0.015	0.005	-0.004	0.001	0.011	-0.006
	(-0.966)	(0.498)	(-0.266)	(0.061)	(0.824)	(-0.575)
Black×Post	-0.031**	-0.025***	-0.033***	-0.026***	-0.014*	-0.024***
	(-2.597)	(-7.327)	(-2.892)	(-8.577)	(-1.803)	(-4.880)
Hispanic×Post	-0.001	-0.018***	0.001	-0.020***	-0.008	-0.010***
	(-0.040)	(-5.968)	(0.129)	(-3.661)	(-0.814)	(-3.294)
Female×Post	-0.013	-0.017**	-0.003	-0.024***	-0.013	-0.013**
	(-1.394)	(-2.405)	(-0.322)	(-4.111)	(-1.586)	(-2.124)
Controls	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Job Category FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
Highest Degree FE	YES	YES	YES	YES	YES	YES
Observations	195,454	307,083	182,553	319,984	284,819	419,691
Adjusted R^2	0.076	0.058	0.074	0.062	0.081	0.059

Table 10: Additional Results

This table reports the robustness results on the effects of race and gender on post-acquisition employee turnover. Column (1) uses post-2000 sample. Column (2) excludes COVID-19 pandemic years. Column (3) lengthens the post-years to two years ($t \in [-3, 1]$). Column (4) includes employee state fixed effects. Column (5) excludes employees who receive promotions (increase in seniority) after leaving the target firm. Column (6) uses the entropy-balanced sample. 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* is 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Post-2000	Pre-2019	[-3,1]	State FE	No Promotion	Entropy-Balanced
Post	0.081***	0.075***	0.067***	0.075***	0.068***	0.071***
	(6.084)	(6.538)	(7.366)	(6.890)	(7.127)	(6.073)
API×Post	-0.001	0.003	-0.002	-0.001	-0.002	0.002
	(-0.118)	(0.436)	(-0.452)	(-0.078)	(-0.292)	(0.274)
Black×Post	-0.029***	-0.023***	-0.024***	-0.024***	-0.020***	-0.025***
	(-14.015)	(-6.355)	(-7.236)	(-8.507)	(-6.882)	(-7.203)
Hispanic×Post	-0.011***	-0.012***	-0.008**	-0.012***	-0.012***	-0.010***
	(-3.464)	(-4.870)	(-2.209)	(-4.423)	(-3.984)	(-4.348)
Female×Post	-0.018***	-0.016***	-0.007**	-0.015***	-0.014**	-0.013**
	(-3.564)	(-3.244)	(-2.152)	(-3.012)	(-2.687)	(-2.390)
Deal FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Job Category FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
Highest Degree FE	YES	YES	YES	YES	YES	YES
State FE				YES		
Observations	559,454	608,260	836,274	689,702	655,641	704,510
Adjusted R^2	0.066	0.073	0.064	0.070	0.063	0.068

Table 11: Race, Gender, and Post-turnover Labor Outcomes

This table reports the effect of race and gender 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 τ 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	0.007
	(-0.406)	(0.179)	(0.536)
Black	0.043***	0.028***	0.029***
	(8.113)	(4.613)	(4.027)
Hispanic	0.030***	0.037***	0.030***
	(3.670)	(5.399)	(4.975)
Female	0.030***	0.031**	0.034***
	(3.062)	(2.621)	(2.769)
Controls	YES	YES	YES
Deal FE	YES	YES	YES
Job Category FE	YES	YES	YES
Seniority FE	YES	YES	YES
Highest Degree FE	YES	YES	YES
Observations	52,853	48,526	47,354
Adjusted R^2	0.098	0.126	0.141

Table 11: Continued

Panel B: Subsequent Employment			
	(1)	(2)	(3)
	Career Shift	Promotion	Demotion
API	-0.051***	0.001	-0.011
	(-3.514)	(0.127)	(-1.394)
Black	0.011	-0.049***	0.030***
	(1.306)	(-4.911)	(4.047)
Hispanic	0.015	-0.022***	0.019**
	(1.609)	(-3.059)	(2.094)
Female	0.032***	-0.037***	0.035***
	(4.362)	(-4.663)	(5.183)
Controls	YES	YES	YES
Deal FE	YES	YES	YES
Job Category FE	YES	YES	YES
Seniority FE	YES	YES	YES
Highest Degree FE	YES	YES	YES
Observations	39,510	39,510	39,510
Adjusted R^2	0.091	0.122	0.239

Table 12: 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 and $Synergy_{[0]}$ ($Synergy_{[0,2]}$), the one-day (three-day) value-weighted average announcement return of the acquirer and the target. In Panel A, the key independent variable is *Total Salary Saved*, the sum of the estimated salaries 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 also multiply the scaled *Total Salary Saved* by 100. In Panel B, we interact *Total Salary Saved* with *Minority Turnover Ratio*, the ratio of the number of non-White-male employees who left the target post-merger to the total number of employees who left. 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 acquirer industry. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table 12: Continued

Panel A: Total Salary Saved				
	(1)	(2)	(3)	(4)
	$CAR_{[0]}$	$CAR_{[0,2]}$	$Synergy_{[0]}$	$Synergy_{[0,2]}$
Total Salary Saved	1.189**	1.638**	2.335***	3.149***
	(2.431)	(2.440)	(2.906)	(3.493)
Acquirer Market Cap	0.000	0.000	-0.000	-0.000**
	(1.358)	(1.624)	(-1.663)	(-2.013)
Acquirer BM	1.061	1.066	1.643***	1.893
	(1.259)	(0.628)	(3.045)	(1.481)
Acquirer Prior Year Return	-0.188	-1.079*	-0.009	-0.663
	(-0.391)	(-1.969)	(-0.026)	(-1.439)
Relative Size	0.006	-0.181	3.588***	3.008***
	(0.007)	(-0.181)	(5.078)	(3.238)
Pct Cash	0.018***	0.035***	0.026***	0.038***
	(4.258)	(6.617)	(6.060)	(9.762)
Tender Offer	0.607	0.872	0.724	1.211
	(1.431)	(1.160)	(1.070)	(1.314)
Same SIC3	0.168	0.030	-0.083	-0.100
	(0.637)	(0.096)	(-0.254)	(-0.296)
Acquirer SIC2 FE	YES	YES	YES	YES
Deal Year FE	YES	YES	YES	YES
Observations	969	969	969	969
Adjusted R^2	0.058	0.082	0.177	0.142
Salary Scaler	Acquirer Market Cap		Acquirer+Target Market Cap	

Table 12: Continued

Panel B: Interaction Regression				
	(1)	(2)	(3)	(4)
	$CAR_{[0]}$	$CAR_{[0,2]}$	$Synergy_{[0]}$	$Synergy_{[0,2]}$
Total Salary Saved	1.186**	1.631**	2.339***	3.152***
	(2.236)	(2.529)	(2.724)	(3.632)
Minority Turnover Ratio	-0.230	-0.417	-0.213	-0.329
	(-1.226)	(-1.415)	(-1.091)	(-1.084)
Total Salary Saved	1.020**	1.045	0.908	0.986
× Minority Turnover Ratio	(2.188)	(1.232)	(1.148)	(0.932)
Acquirer Market Cap	0.000	0.000	-0.000*	-0.000**
	(1.329)	(1.638)	(-1.695)	(-2.101)
Acquirer BM	1.001	0.990	1.609***	1.848
	(1.156)	(0.582)	(2.976)	(1.448)
Acquirer Prior Year Return	-0.198	-1.098**	-0.019	-0.678
	(-0.424)	(-2.053)	(-0.058)	(-1.514)
Relative Size	0.095	-0.042	3.666***	3.118***
	(0.115)	(-0.044)	(5.279)	(3.490)
Pct Cash	0.019***	0.036***	0.027***	0.039***
	(4.313)	(6.351)	(6.014)	(9.220)
Tender Offer	0.620	0.881	0.729	1.214
	(1.432)	(1.147)	(1.066)	(1.306)
Same SIC3	0.206	0.082	-0.051	-0.059
	(0.787)	(0.262)	(-0.159)	(-0.181)
Acquirer SIC2 FE	YES	YES	YES	YES
Deal Year FE	YES	YES	YES	YES
Observations	969	969	969	969
Adjusted R^2	0.061	0.083	0.177	0.142
Salary Scaler	Acquirer Market Cap		Acquirer+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 that equals one if the year is after the deal announcement date.
API (Black, Hispanic, White)	An indicator variable equal to one if the employee belongs to the Asian Pacific Islander (Black, Hispanic, White) racial 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) category.
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.
$\text{Unemployment}_{t+\tau}$	An indicator variable equal to one if the employee is unemployed for τ 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 (Demotion)	An indicator variable equal to one if the employee has a subsequent job that has a higher (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.

Table A1: Variable Definitions

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.
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 12). We also multiply the scaled *Total Salary Saved* by 100.

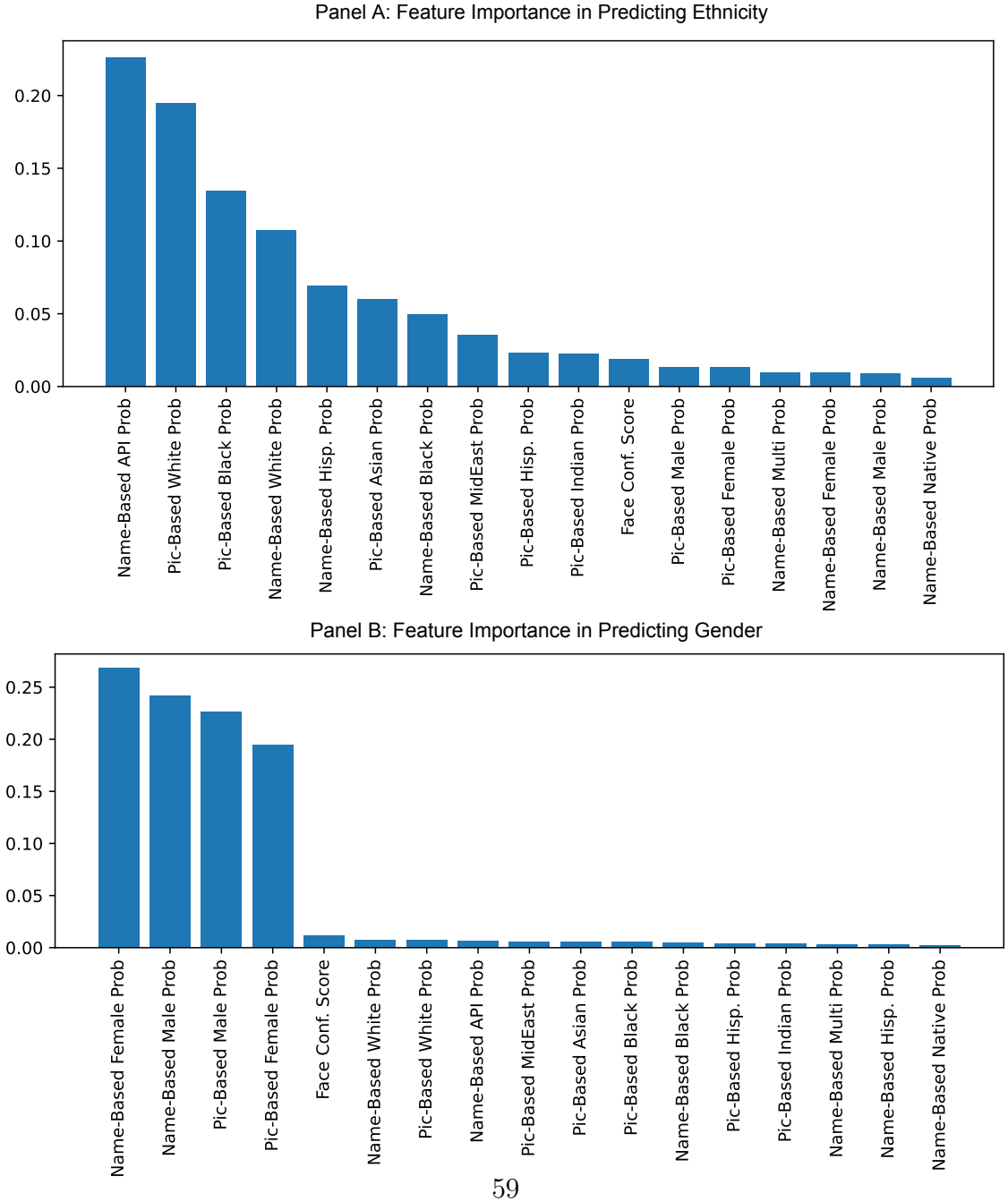
Table A2: Assessing Revelio, DeepFace, Random Forest Accuracy

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.



Internet Appendix for

Employee Turnover in the Spotlight: Evidence from Mergers and Acquisitions

In this appendix, we tabulate results of robustness and supplementary analyses referenced in the paper. The set of tables is as follows:

- Table IA1. Return Predictability of Anomalies
- Table IA2. Average Employee Characteristics
- Table IA3. The Role of Entrenched Employees
- Table IA4. Total Salary Saved and Deal Outcomes

Table IA1: Additional Fixed Effects

This table reports the effect of race and gender on post-acquisition employee turnover with additional fixed effects. 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* is 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. Fixed effects are indicated at the bottom of the table. 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	0.074***	0.074***	0.074***	0.116***
	(6.814)	(6.785)	(6.849)	(6.546)
API×Post	0.000	0.000	0.001	0.001
	(0.005)	(0.013)	(0.096)	(0.159)
Black×Post	-0.027***	-0.027***	-0.027***	-0.025***
	(-8.214)	(-8.473)	(-8.296)	(-5.726)
Hispanic×Post	-0.012***	-0.011***	-0.011***	-0.009***
	(-6.355)	(-5.421)	(-5.667)	(-3.269)
Female×Post	-0.014**	-0.015***	-0.015***	-0.016***
	(-2.643)	(-2.803)	(-2.908)	(-3.382)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Job Category FE		YES	YES	
Seniority FE	YES		YES	YES
Highest Degree FE	YES	YES		YES
Deal×Job Category FE	YES			
Deal×Seniority FE		YES		
Deal×Highest Degree FE			YES	
Post×Job Category FE				YES
Observations	704,510	704,191	704,206	704,232
Adjusted R^2	0.069	0.071	0.069	0.069

Table IA2: Average Employee Characteristics

This table presents the target firm employee characteristics before acquisitions. Panel A presents the turnover rates of all employees by race groups. Panel B presents the turnover rates of all employees by gender groups. 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 Characteristics by Race						
	Ln(Salary)		Ln(Seniority)		Quant. Job	
	Mean	Diff.	Mean	Diff.	Mean	Diff.
API	11.633	0.098**	0.939	0.017	0.723	0.184***
	(2.690)		(0.576)		(5.287)	
Black	11.289	-0.247***	0.658	-0.264***	0.488	-0.052**
	(-10.635)		(-14.523)		(-2.675)	
Hispanic	11.322	-0.214***	0.695	-0.227***	0.466	-0.074***
	(-11.712)		(-15.988)		(-4.235)	
White	11.536		0.922		0.539	

Panel B: Average Characteristics by Gender						
	Ln(Salary)		Ln(Seniority)		Quant. Job	
	Mean	Diff.	Mean	Diff.	Mean	Diff.
Female	11.362	-0.267***	0.754	-0.238***	0.440	-0.184***
		(-8.185)		(-7.864)		(-6.985)
Male	11.629		0.992		0.624	

Table IA3: The Role of Entrenched Employee

This table reports whether the effects of race and gender on post-acquisition employee turnover is driven by entrenched employees. In columns (1) and (2), we exclude employees with high seniority levels. In columns (3) and (4), we exclude employees with long working experiences. In columns (5) and (6), we exclude employees with long tenures at the target firm. 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* is 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)	(5)	(6)
	Sen. < 7	Sen. < 6	Exp. < 480	Exp. < 360	Tenure < 240	Tenure < 120
Post	0.071***	0.067***	0.074***	0.072***	0.073***	0.073***
	(6.671)	(6.342)	(6.869)	(6.836)	(6.949)	(7.135)
API×Post	0.001	0.001	0.000	0.002	0.001	0.002
	(0.175)	(0.176)	(0.063)	(0.349)	(0.101)	(0.383)
Black×Post	-0.025***	-0.023***	-0.026***	-0.025***	-0.027***	-0.028***
	(-8.262)	(-7.490)	(-8.151)	(-7.800)	(-8.471)	(-7.591)
Hispanic×Post	-0.010***	-0.009***	-0.011***	-0.011***	-0.011***	-0.014***
	(-5.124)	(-4.402)	(-5.229)	(-4.597)	(-4.881)	(-6.689)
Female×Post	-0.013**	-0.011**	-0.014***	-0.014***	-0.014***	-0.016***
	(-2.581)	(-2.335)	(-2.919)	(-2.937)	(-2.950)	(-3.093)
Controls	YES	YES	YES	YES	YES	YES
Deal FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Job Category FE	YES	YES	YES	YES	YES	YES
Seniority FE	YES	YES	YES	YES	YES	YES
Highest Degree FE	YES	YES	YES	YES	YES	YES
Observations	699,192	674,105	703,168	688,801	696,389	640,879
Adjusted R^2	0.069	0.068	0.069	0.069	0.069	0.069

Table IA4: 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 and $Synergy_{[0]}$ ($Synergy_{[0,2]}$), the one-day (three-day) value-weighted average announcement return of the acquirer and the target. *Total Salary Saved* is the sum of the estimated salaries of employees who leave the target firm within one year after the deal announcement, scaled by different market capitalizations (indicated by the last row in the table). We calculate *Total Salary Saved* using non-White male (White male) employees for Panel A (B). 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 acquirer industry. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Non-White Male Employees				
	$CAR_{[0]}$	$CAR_{[0,2]}$	$Synergy_{[0]}$	$Synergy_{[0,2]}$
Total Salary Saved	3.095**	3.746**	3.775**	4.894***
	(2.326)	(2.178)	(2.424)	(3.155)
Controls FE	YES	YES	YES	YES
Acquirer SIC3 FE	YES	YES	YES	YES
Deal Year FE	YES	YES	YES	YES
Observations	969	969	969	969
Adjusted R^2	0.061	0.083	0.181	0.144
Salary Scaler	Acquirer Market Cap		Acquirer+Target Market Cap	

Panel B: White Male Employees				
	$CAR_{[0]}$	$CAR_{[0,2]}$	$Synergy_{[0]}$	$Synergy_{[0,2]}$
Total Salary Saved	1.438*	2.436**	2.418***	3.670***
	(1.797)	(2.284)	(3.077)	(3.649)
Controls FE	YES	YES	YES	YES
Acquirer SIC3 FE	YES	YES	YES	YES
Deal Year FE	YES	YES	YES	YES
Observations	969	969	969	969
Adjusted R^2	0.055	0.080	0.174	0.141
Salary Scaler	Acquirer Market Cap		Acquirer+Target Market Cap	