External Labor Market Punishment in Finance[*]

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We examine the extent of external labor market punishment for misconduct in finance and contrast the consequences for those in non-finance sectors. Using detailed proprietary data on individual job separations and income, we document that finance employees involuntarily separated for misconduct earn 2.8% to 8.6% higher income than similar employees laid-off for no fault of their own. These results are less likely to be explained by differences across workers involuntarily separated for misconduct versus no fault. They are driven by misconduct employees separated from firms with fewer fraud related consumer complaints (or more timely responses to complaints) but who get rehired by employers with higher levels of such complaints (or lower levels of timely responses). Our results are most consistent with assortative matching in the finance labor market where misconduct separation acts as an informative signal of certain characteristics for employers who value and pay a premium for such employees. Finance is unique in that these patterns are reversed for non-finance sectors, do not show up for any other sector in the economy even when these are evaluated individually, and are absent for workers employed in non-finance-related jobs within the finance sector.

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1 Introduction

Fraud, bad faith dealings, and misconduct remain prevalent in the finance sector. For example, Egan et al. (2019) document that up to 15% of financial advisors in large firms have a misconduct record. Such activities likely contribute towards the low public trust in finance professionals and financial institutions (Guiso et al., 2008).[1] Given these potential costs for firm and industry reputation, it is not clear why these misbehaviors remain commonplace. One plausibility may be that the benefits of such misbehaviors outweigh the costs for both firms and individuals perpetrating them. For example, employees involved in misconduct may not bear high personal costs for these activities in terms of their career outcomes. In this paper, we evaluate this potential and study the extent of *external* labor market punishment for misconduct in the finance and insurance sector and contrast this to consequences in non-finance sectors.

The external labor market can compound or undo, either partially or completely, the internal punishment. To evaluate this hypothesis, we focus on employees involuntarily separated for misconduct and examine how their income evolves post separation from the firm. Ours is the first paper to examine the consequences for labor income for employees directly involved in misconduct. We are also the first to study a large sample of employees representing the entire finance and insurance sector (NAICS 52) and compare the outcomes for employees in other sectors.[2]

Ex-ante, it is not obvious how income would evolve for those separated for misconduct. If the external labor markets punish employees with misconduct background or there are

1. Sapienza and Zingales maintain a financial trust index which has fluctuated between 20-35% between 2008 to present. See here for more details: http://www.financialtrustindex.org/about.htm

2. In contrast the literature focuses on employees with specific roles. For example, among others, Dimmock and Gerken (2012); Parsons et al. (2018); Egan et al. (2019) evaluate misconduct among financial advisers; Ellul et al. (2020) document under-performance for asset managers; Griffin et al. (2019) focus on employees involved in residential mortgage-backed security securitization; Gao et al. (2020) examine loan officers who structured poorly performing corporate loans.

reputational costs to hiring them, these employees may experience income declines. Alternatively, if there are information frictions in the labor market and potential employers find it difficult to identify employees with misconduct background, one may expect to find no income effects. Yet another possibility is that if there is tolerance for misconduct or even preference for such employees (e.g., because they have demonstrated a willingness to cut corners), they may not experience income declines or may even be rewarded, as the external market may (partially) undo internal punishment.

The analysis in the paper leverages anonymized proprietary data from Equifax Inc., a company that offers unemployment management and verification services (e.g., employment) among other products. Employers that subscribe to these services report information on all separations in their workforce and reasons for the separation, along with employment information including wages, job tenure, and employment location among others. The data covers over 5,000 employers with 20-25% of all separations in the US during our sample period from 2011 to 2018. Our definition of misconduct comes from the reason of separation reported by the employer wherein involuntary separations are reported in three categories, namely, no fault layoffs, misconduct, and under-performance.

Evaluating income progression for those involuntarily separated for misconduct is empirically challenging because these employees experience separation from their employers, which by itself has been shown to affect income irrespective of employees' involvement in misconduct. A large literature documents that employees laid-off for no fault of their own (e.g., due to lack of work) experience significant declines in income (e.g., Jacobson et al., 1993; Couch, 2001; Jacobson et al., 2005; Von Wachter et al., 2009; Schmieder et al., 2010; Couch and Placzek, 2010). This can happen for a number of non-exclusive reasons including loss of firm-specific human capital (Topel, 1991; Neal, 1995; Kletzer, 1998), loss of favorable employer-employee matches and firm rents (Krueger and Summers, 1988; Abowd et al., 1999; Bronars and Famulari, 1997; Card et al., 2013; Lachowska et al., 2020; Song et al., 2019;

Moore and Scott-Clayton, 2019), demotion in the job ladder (Jarosch, 2021; Krolikowski, 2017), and changes in occupation (Huckfeldt, 2022) among others. Hence, without controlling for this "separations effect", we may wrongly attribute entire changes in income to misconduct. We overcome this issue by using income response for those laid-off for no fault (i.e., no fault layoffs) as a benchmark in our setting.

Since our analysis introduces new data, we begin by replicating the results in the literature that estimate the changes in income around no-fault layoffs (i.e., the separations effect) to help establish the validity of the sample. We follow Jacobson et al. (1993) (JLS, henceforth) — the standard in the literature — and estimate a difference-in-differences specification that compares employees laid-off for no fault to those who continue to be employed before and after separation. This specification includes individual fixed effects that account for time-invariant individual level differences, industry (6-digit NAICS) time effects, and wage-bin ($1,000 bins) time effects that control for all time varying differences across industry and income levels respectively. We find that employees laid-off for no fault across all industries experience an income decline of 28% relative to those who continue to be employed. While income trends similarly between laid-off employees and those who continue to remain employed prior to separation, the decline occurs sharply at the time of separation and remains persistent with income for separated employees being 23% lower four years following separation. Both the patterns and the magnitudes of the results are similar to those documented in the literature (e.g., Couch, 2001; Jacobson et al., 2005; Couch et al., 2011; Moore and Scott-Clayton, 2019).

To evaluate the income evolution following misconduct related involuntary separations in finance, we focus on employees separated from firms in the finance and insurance sector defined by the NAICS code of 52. We estimate a difference-in-differences specification similar to JLS and compare income for employees involuntarily separated for misconduct to those who continue to remain employed. To account for the separations effect on income, we compare this estimate to a similar coefficient for no fault layoffs. This yields estimates akin to a triple differences model. In addition to a specification that replicates the fixed effects in JLS, we estimate another specification that appends to the JLS specification firm x 3-digit zipcode x time effects that allow us to compare employees separated from the same firm residing in the same geographic region thereby controlling for all time-varying differences at the separated firm x 3 digit zipcode combination (e.g., economic conditions, regulation faced by firms etc.), and tenure x time effects that accounts for time varying differences across employees with different tenure (measured in years). Across both specifications, we find that employees involuntarily separated for misconduct earn 2.5% to 8.6% higher income relative to those laid-off for no fault in the finance sector. Even though both types of employees experience income declines in absolute terms post separation, the differences arise from relatively lower income declines for those separated for misconduct.

A concern in our setting is that differences across employees separated for misconduct versus no fault or non-separated employees may bias our results. We take a number of steps to help address this concern. First, our baseline specification saturates the difference-in-differences model with multiple fixed effects to non-parametrically account for a number of factors including time varying differences in industry, employees with different levels of income and job tenure, and firm-location combinations, and time invariant differences across employees. These fixed effects allow us to control for different levels of time-varying skills (captured by income and job tenure), inherent capabilities (through individual fixed effects), firm regulation, and differences in regional and industry job market conditions. Second, the absence of differential pre-trends in income across employees involuntarily separated for misconduct and those who continue to remain employed for two years prior to separation further provides some reassurance that our specification appropriately captures differences across different types of employees. Third, we re-estimate our baseline results with a collapsed triple interaction specification that allows for the estimation of fixed effects for the entire sample simultaneously instead of across different sub-samples. That we find our estimates to be unchanged further helps reassure that differences between employees separated for different reasons are less likely to explain our results. This specification also allows us to include separation cohort time effects thereby comparing misconduct and no-fault employees separated during the same year-month.

Fourth, we examine similar effects for non-finance sectors and, in sharp contrast to finance, find that those involuntarily separated for misconduct earn 4.4% to 8.1% *lower* income post separation than those experiencing no fault layoffs. Hence, differences across employees separated for misconduct and no fault cannot explain our findings unless they systematically vary across industries. Fifth, we re-estimate the triple interaction using no fault layoffs that were part of a mass layoff. Firms may choose to layoff less productive employees when letting go of only a few employees and this may lead to differences between those separated for layoff and misconduct. However, this choice is less likely to be a factor in a mass layoff. We find results similar to our baseline with this sample less subject to firm discretion. Finally, we estimate heterogeneity in our results confining to employees only separated from the finance sector based on the industry of subsequent employment. We find that our results are driven by those rehired within the finance and insurance sector. Specifically, conditional on finding employment within finance, those separated for misconduct earn 3.7% higher income relative to no-fault layoffs. This pattern does not hold for those rehired in non-finance sectors, suggesting that systematic differences across employees separated for misconduct and layoffs from firms within the finance sector are less likely to be driving our results.

Our results so far show that the labor market consequences in finance are less severe for employees involuntarily separated for misconduct than no fault. One mechanism that can help explain these potentially surprising findings is assortative matching in the labor markets where firms with a propensity to take more risks, or operate in the 'twilight zone' may value employees with a misconduct background as these individuals have shown a disposition towards such behavior themselves. We evaluate this plausibility by examining heterogeneity in our findings based on different types of firms that employees get separated from and rehired in. Specifically, we use the number of fraud related complaints filed by consumers against the financial firm to the consumer financial protection bureau (i.e., CFPB) and firms' timely response rates to these complaints as measures of firm's propensity to engage in risky behavior. We find our results to be concentrated for employees separated from firms with below median number of complaints (non-timely responses) who get rehired in firms with above median complaints (non-timely responses). Our results are absent for employees who move in the opposite direction. Employees involuntarily separated for misconduct are also more likely to be rehired within firms receiving higher number of complaints or less likely to timely respond to complaints. Misconduct employees stay 10-15% longer when rehired within firms with high complaints (low timely responses) relative to the other type of firms. Overall, these results are consistent with assortative matching in the labor market where employers with higher propensity to engage in potentially risky or grey area behavior pay a wage premium for employees with a misconduct background.

Another plausible mechanism maybe that those separated for misconduct in finance search for jobs longer and hence are able to be find higher paying jobs. However, contrary to this hypothesis we find that employees separated for misconduct find jobs quicker and are more likely to find one within the finance sector. Since we cannot directly measure the job finding rates as employees may drop out of our sample either because they did not find a job post separation or found one at a firm not covered in our data, we measure the drop out rates and again find that those separated for misconduct are less likely to drop out of our sample than no fault separations.

Differences in regulation may also contribute towards our findings. Firms in heavily regulated sectors may be more risk averse and consider minor offenses to be grounds for misconduct separation. The labor market may recognize this difference and be more willing to undo such punishment. We evaluate this conjecture by estimating heterogeneity in our results based on strictness of regulation across different sectors within finance. We find similar estimates for employees separated from firms that face different levels of regulation.

A natural question at this point is whether finance is unique in the extent of external market punishment for the misconduct employees or are there other sectors where we may find similar patterns. We examine this by re-estimating our main triple interaction specification for all major sectors in the economy (i.e., all industries with different 2-digit NAICS codes) and find that though there is heterogeneity across different sectors, those involuntarily separated for misconduct earn higher income than no fault layoffs only within the finance sector. One feature that makes finance unique may be that most services and products sold are based on future cash flows. This likely makes it more difficult for consumers or other stakeholders to disentangle bad luck from a deliberate risky or unethical transaction in case of losses, thereby reducing the costs of engaging in such behavior for employees. To evaluate this hypothesis, we re-estimate our findings across employees with different types of jobs within the finance sector and consistent with it find our results to be concentrated for finance-related jobs and absent for non-finance jobs within the sector.

Systematic differences in inherent culture across the finance sector and others may also contribute towards our findings. It is well known that finance is unique in a different aspect: it is a high-skill and high-wage sector where returns to talent have increased more relative to other sectors (e.g., Philippon and Reshef, 2012; Celerier and Vallee, 2019). Similarly, finance may be unique in some aspect positively correlated with the propensity to engage in risky or potentially unethical/fraudulent behavior (e.g., Gill et al., 2022).[3] On the contrary, differences in regulation across sectors are less likely to explain our results because estimates for other heavily regulated sectors like health care, real estate etc. are statistically indis-

3. It is worth noting that systematic differences in culture and marginal returns to fraud-related behaviors may not necessarily be mutually exclusive.

tinguishable from coefficients for less regulated sectors like retail trade, waste management etc. We also perform a number of analyses to evaluate whether differences in the type of misconduct across different sectors explain our results but do not find evidence supporting this hypothesis.

Our study contributes to a growing literature that examines the extent of misconduct and fraud within the finance sector (e.g., Dimmock and Gerken, 2012; Griffin and Maturana, 2016; Gurun et al., 2016; Mian and Sufi, 2017; Gurun et al., 2018; Parsons et al., 2018; Dimmock et al., 2021)., and how financial institutions and labor markets discipline finance employees for both poor performance and misconduct/fraud (e.g., Chevalier and Ellison, 1999; Egan et al., 2019; Griffin et al., 2019; Ellul et al., 2020; Gao et al., 2020; Tookes and Yimfor, 2021). Ellul et al. (2020) document that asset managers working for funds liquidated following persistently poor performance experience demotions and declines in imputed compensation. The authors attribute this decline to a drop in managers' reputation. Similarly, Gao et al. (2020) show that banks discipline loan officers involved in originating corporate loans that end up performing poorly.

The results in our study are most closely related to two papers that examine the presence of misconduct in finance and the subsequent associated labor market consequences. Griffin et al. (2019) investigate labor market ramifications for employees involved in residential mortgage-backed security (RMBS) securitization and find that these employees did not experience differential job retention, promotion, and external job opportunities relative to similar non-RMBS employees, even if they were signatories of RMBS deals with high loss and misreporting rates or deals implicated in lawsuits. Egan et al. (2019) document the widespread nature of misconduct among financial advisers and that the labor market partially undoes internal punishment by rehiring advisers with misconduct background. The authors argue that co-existence of firms persistently engaging in misconduct with clean firms explains this pattern. We complement the findings in these papers in two distinct ways. First, we document the income evolution for employees spanning the entire finance and insurance sector following involuntary separations owing to misconduct. The level of earnings can act as an important disciplining mechanism in addition to the employment in the labor markets and can either diminish or amplify the employment effects. Our findings show that not only are finance employees separated for misconduct rehired by firms within the same sector but conditional on being rehired they earn higher income as firms more likely to engage in fraud related activities pay a wage premium for them. Second, our results highlight that the finance sector is unique in exhibiting such patterns likely because the difficulty in guaging performance of services and products based on future cash flows reduces the expected costs for employees to engage in such behavior.

2 Data and Empirical Strategy

This section describes the data used in the analyses, discusses our sample, and details our empirical strategy.

2.1 Data

The data from Equifax Inc. contains anonymized employment information across two dimensions: job separation events and employment characteristics.

Job separation data are disseminated to Equifax Inc. by self-reporting employers who subscribe to Unemployment Insurance (UI) management services provided by the company. When a UI claim is filed, government agencies reach out to the ex-employer to acquire information on the terms of separation in order to verify UI eligibility.[4] Many states require employers to respond to all such government requests to facilitate the efficient administration of UI claims. In order to adhere to such requirements, participating employers subscribe to

4. Most states require that claimants must have separated from the employer involuntarily due to no fault of their own.

the UI management services from Equifax Inc. which manages all such inquiries on their behalf. As a result, participating employers report data related to all incidences of job separation to the company. The job separations data includes close to 20% of all separations reported in the Bureau of Labor Statistics (BLS)'s Job Openings and Labor Turnover Survey (JOLTS) data over our sample period.[5] Using this anonymized data, for each job separation, we are able to observe the date of the job separation and the reason for the separation.

The employment data contains anonymized information reported by employers who subscribe to the verification services. They report information on monthly earnings, job locations, job tenures, type of jobs, and industry of employees among other firm level details. The data contains over 5000 employers who report information on all their employees on a payroll-to-payroll basis. The data covers over 100 million employees and is representative of the U.S. labor force along several dimensions, including median personal incomes and median employee tenures. In addition, the data closely tracks aggregate U.S. private sector payroll growth, hiring, and separations. While most industries are represented in the correct proportions, the share of employment in the retail trade industry is significantly higher in the data than in the population. The average firm in the data is also significantly larger than the average firm in the U.S. population. Kalda (2020) shows that the credit profiles of employees in the data are similar to those of the U.S. population. Both datasets cover periods from 2010 through 2021.

2.2 Sample and Summary Statistics

Since we need to observe both income and the separation reason, we begin with a sample of employees separated from firms that subscribe to both UI management and verification services. We confine the separations event to be between 2011 and 2018. This allows us to use one year of data both prior to the first and following last separations and to avoid

5. The JOLTS program from BLS provides data on job openings, hires, and separations.

the pandemic period. We then further require the employees to be re-employed within the firms that subscribe to the verification services within 12 months following the separation so that we can observe income in the post-separation period. This results in a sample of 455k separations comprising 54k and 401k from finance and non-finance sectors respectively.

The sample includes two main categories of involuntary separations — no fault layoffs and misconduct. The no fault layoffs comprise separations reported under the sub-categories like lack of work, position eliminated, location shut down etc. Misconduct separations include over 25 sub-categories/specific reasons including violation of company policy, removal of company property or funds, gross misconduct among others. Table A1 reports top 10 reasons that account for over 90% of all separations along with their contributions for both the finance and non-finance sectors separately.

Figure 1 shows the composition of the separations in our sample (including all sectors) that comprises of 48.1% no fault separations and 51.9% misconduct related separations. No fault separations comprise 60.9% of all separations in the finance sector with misconduct separations comprising 39.1%. The composition is skewed less towards no fault separations in non-finance sectors as they account for 46.4% of all separations while misconduct contributes the remaining. Figure 2 plots how this composition evolves through time in the sample. The plot shows that there are several thousand separations every month throughout our sample period. The total number of separations increases over time because the number of employers subscribing to the UI management services increases over time. However, the distribution of the separations across no fault and misconduct related remains stable.

For each separated employee we include up to five employees working in the same firm and region but who do not get separated involuntarily for at least 12 months. This gives us our final sample. Table 1 reports summary statistics for pre-separation annual income across six different groups: separated and non-separated employees across all sectors, finance and non-finace sectors.[6] The separated employees are then further categorized into the two reasons of separation — no fault and misconduct. Sections A and B report these stats for the entire sample. The average annual income among separated employees in our sample is just over \$70k. Those separated for no fault have higher income than those separated for misconduct. The next sections report similar stats for finance (sections C and D) and non-finance (sections E and F) sectors separately. While earnings in finance are higher across all groups, the differences between misconduct and the no fault layoffs are similar across sectors. Income for those separated for misconduct is on average \$49.3k and \$46.6k lower than their no fault counterparts in finance and non-finance sectors respectively. Overall, there are differences in the type of employees separated for misconduct versus no-fault but these differences don't seem to vary systematically across sectors.

2.3 Sample Validation and Empirical Methodology

Employees included in our sample may not be representative of the US workforce. They are employed in firms that subscribe to both UI management and verification services in the pre-separation period and get rehired within firms that subscribe to verification services within 12 months of separation. Since employers who subscribe to these services tend to be larger, the employees are those who were employed in one of the larger firms and got re-employed in a large firm. To the extend, employees working for larger firms are different our sample may not be representative of the population.

To help address this issue, we first replicate results in the literature for no-fault layoffs. We follow JLS — the standard in the literature — and estimate a difference-in-differences specification that compares employees laidoff for no fault to those who continue to be employed before and after separation. Specifically, we estimate the following model:

6. For non-separated employees, we use the separation date for their separated counterparts that dictated their inclusion in the sample to calculate pre-separation earnings.

$$y_{i,j,w,t} = \beta \times Separation_{i,j,w} \times Post_t + \alpha_i + \gamma_{j,t}(\gamma_t) + \delta_{w,t} + \epsilon_{i,j,w,t} \tag{1}$$

where y measures log monthly earnings for employee i in industry j with income in wage bin w at year-month t. The industry j is defined at the 6-digit NAICS code level and wage bins w are at $1,000 width. *Separation* is a dummy variable that takes a value of one for employees who get separated at some point in our sample, and *Post* is a dummy variable that takes a value of one during the months following separation. α_i denotes individual fixed effects that control for time-invariant individual level differences, $\gamma_{j,t}$ indicates industry x year-month fixed effects and accounts for all time varying changes at 6-digit NAICS level, and $\delta_{w,t}$ represents wage-bin ($1,000 bins) time effects that control for all time varying differences across employees with different income levels. Robust standard errors are clustered at the employee level.

Table 2 reports estimates for this analyses. Instead of only showing the results with the same fixed effects as in the JLS model, we report three different specifications to establish the robustness of the results. While column (1) includes only individual and year-month fixed effects, column (2) includes individual and industry x year-month fixed effects and column (3) in addition adds wage bin x year-month fixed effects. Across all specifications, we find that employees laid-off for no fault experience significant income declines relative to those who continue to be employed. The estimates of the results are very close to each other varying between 28.5% and 29.4%. These magnitudes are similar to the literature as most papers find a decline between 25% and 30% (e.g., Couch, 2001; Jacobson et al., 2005; Couch et al., 2011; Moore and Scott-Clayton, 2019).

To assess how long lasting are the effects on income and explicitly test whether trends in the separated and non-separated groups are parallel before the separation, we estimate the dynamic version of Equation 1 given as follows:

$$y_{i,j,w,t} = \sum_{\substack{k=-8 \\ k\neq -4}}^{16} \beta_k \times Separation_{i,j,w} \times D_k + \alpha_i + \gamma_{j,t}(\gamma_t) + \delta_{w,t} + \epsilon_{i,j,w,t} \quad (2)$$

where D_k is an indicator that equals one for observations corresponding to employee i when the observation month belongs to k quarters to or from separation. All other variables are same as defined earlier. The omitted baseline category is fourth quarter prior to separation. The coefficient of interests are β_k where each of these coefficients captures the differential response of income for separated employee relative to the non-separated ones. Figure 3 plots estimates for this analysis along with 99% confidence intervals. We find that while income trends similarly between laid-off employees and those who continue to remain employed prior to separation, the decline occurs sharply at the quarter of separation and remains persistent with income for separated employees being 23% lower four years following separation. Both the absence of pre-trends and long-lasting effects with the magnitude four year post separation are similar to that documented in the literature (e.g., Moore and Scott-Clayton, 2019).

3 Main Results

In this section, we evaluate changes in income following involuntary separations owing to misconduct relative to no fault layoffs in finance sector, and contrast these changes to those in non-finance sectors.

3.1 Income following Misconduct Separations

To evaluate the income evolution following misconduct separations, we split the sample into the finance and insurance sector defined by the NAICS code of 52 and non-finance sectors that include all other industries. We estimate income following misconduct separations and no fault layoffs separately using difference-in-differences equations and compare the estimates. Specifically, we estimate Equation 1 that compares income for employees fired for misconduct (no fault) to those who continue to remain employed in both finance and non-finance sectors. In addition, we employ a more stringent specification and include additional fixed effects namely firm x 3-digit zipcode x year-month fixed effects that allow us to compare employees from the same separated firm residing in the same geographic region thereby controlling for all time-varying differences at the separated firm-3 digit zipcode combination (e.g., economic conditions, firm level time varying policies, local job market characteristics that affect employees working in certain industries of firms etc.), and tenure x year-month fixed effects that account for time varying differences across employees with different tenure in years.

Saturating the model with these fixed effects allows us to control for differences in employees separated for misconduct versus no-fault or non-separated employees across a number of important dimensions including different levels of time-varying skills (captured by income and job tenure), inherent capabilities (through individual fixed effects), regulations faced by their pre-separation employers, and differences in regional and industry job market conditions they experience. We allow these fixed effects to account for differences instead of using a matched sample because it gives us the flexibility to control for a number of dimensions non-parametrically. Using these many dimensions in a matching technique (e.g., propensity score) will lead to inefficient matches.

Table 3 reports estimates for these analyses where the difference in two difference-in-differences coefficients (i.e., those associated with misconduct separations and no fault layoffs) reported in the bottom row is the coefficient of interest as it captures the incremental effect on income for those fired for misconduct relative to those laid off for no fault. While columns (1) and (2) focus on the finance and insurance sector, the final two columns report estimates for the non-finance sectors. Column (1) reports results for the specification with the same fixed effects as JLS while column (2) reports estimates for the more stringent specification. Across both specifications, we find that employees fired for misconduct earn higher income relative to those laid off for no fault in the finance sector. The magnitudes correspond to 7.7% and 3.9% higher incomes respectively. This occurs because employees fired for misconduct experience 12.4% (=0.039/0.314) to 25.5% (=0.077/0.301) lower income declines when compared to their no fault layoff counterparts. In sharp contrast, estimates for non-finance sectors reported in columns (3) and (4) show that those fired for misconduct earn 4.8% to 8.1% lower income post separation than those experiencing no fault layoffs.

Since our main coefficient of interest is akin to a triple difference estimate, the identifying assumption is that differences in income between employees laid off for no fault and those who continue to be employed evolve similarly to the differences between employees fired for misconduct and those who remain employed. While this assumption is inherently untestable, we evaluate a more stringent assumption of absence of parallel trends in income at least in the pre-separation period between employees fired for misconduct and those who remain employed. We estimate Equation 2 for misconduct in finance. Panel (a) of Figure 4 plots these estimates. While income trends similarly between employees fired for misconduct and those who continue to remain employed for two years prior to separation, the decline occurs sharply at the quarter of separation and remains persistent with income for separated employees being significantly lower four years following separation. In non-finance sectors, we find a slight trend upward trend for the misconduct employees in the pre-separation period. Panel (b) plots these estimates where this trend seems economically small and is followed by a sharp large decline in income at the quarter of separation. Similar to the finance sector, the results remain persistent for at least four years following separation.

3.2 Do differences across Misconduct Employees and others drive our results?

A concern in our setting is that differences across employees involuntarily separated for misconduct versus no fault or non-separated employees may drive our results. As discussed in Section 2.2, the mean pre-separation income for misconduct employees is lower than those experiencing no fault layoffs and non-separated employees. To account for this concern and differences across employees, our baseline specification saturates the difference-in-differences model with multiple fixed effects to non-parametrically account for a number of factors including time varying differences in industry, income, job tenure, and firm-location combinations, and time invariant differences across individuals. The absence of pre-trends in income across employees separated for misconduct and those who continue to remain employed for two years prior to separation further provides some reassurance that our specification is able to properly account for pre-separation differences.

In addition, we re-estimate our baseline results with a collapsed triple interaction specification that allows for the estimation of fixed effects for the entire sample simultaneously instead of separately across different sub-samples. Specifically, we estimate the following model:

$$y_{i,f,j,z,w,\tau,t,c} = \beta \times Misconduct_{i,f,j,z,w,\tau,c} \times Separation_{i,f,j,z,w,\tau,c} \times Post_t + \Gamma \times Separation \times Post_t + \alpha_i + \delta_{w,t} + \gamma_{f,z,\tau,r} + \theta_{c,r} + \epsilon_{i,j,w,t} \quad (3)$$

where y measures log monthly earnings for employee i working for firm f in industry j with income in wage bin w and tenure as τ years and residing at the 3-digit zipcode z at year-month t who got separated with separation cohort c. The industry j is defined at the 6-digit NAICS code level and wage bins w are at \$1,000 width. *Misconduct* is an indicator variable that equals one for employees who involuntarily separated for misconduct. *Separation* is a dummy variable that takes a value of one for employees who get separated at some point in our sample, and *Post* is a dummy variable that takes a value of one during the months following separation. α_i denotes individual fixed effects that control for time-invariant individual level differences, $\delta_{w,t}$ represents wage-bin (\$1,000 bins) time effects that control for all time varying differences across employees with different income levels, $\gamma_{f,z,\tau,r}$ represents firm x 3-digit zipcode x tenure x year fixed effects that account for any time varying differences at firm-location-employee tenure levels, and $\theta_{c,r}$ denote separation cohort x year fixed effects that control for time varying differences across employees separated at different year-months. Robust standard errors are clustered at the employee level.

Table 4 reports the estimates for these results separately for the finance and non finance sectors. While the first column reports results for the specification that uses same fixed effects as the JLS model, the second column reports estimates using Equation 3. The estimates in column (1) show that employees separated for misconduct earn 7.5% higher income than those laid off for no fault. The estimate reduces with the more stringent specification to 2.8%. In contrast, in non-finance sectors those separated for misconduct earn 4.4% to 6.9% lower income relative to those experiencing no fault layoffs. Though we use even more stringent fixed effects that are estimated for the entire sample simultaneously instead of separately across different sub-samples, we find our estimates to be very similar as before both qualitatively and quantitatively. This further helps reassure that differences between employees experiencing misconduct separation and others are less likely to explain our findings otherwise the interaction of the fixed effects with the reason of separation that occurred with estimating difference-in-differences separately for misconduct and no fault separations would likely yield different estimates than collapsed triple interactions.

Further we find contrasting results in finance and non-finance sectors across both difference-in-differences and collapsed triple interaction specifications suggesting that differences across employees separated for misconduct and no fault cannot explain our findings unless they systematically vary across industries. To further help assuage this concern, we confine our sample to finance employees (i.e., those separated from the finance and insurance sector) and examine heterogeneity in our findings based on whether or not they were rehired within the finance sector. Table 5 reports estimates for these analyses where we report results for those rehired within the finance sector in Column (1) and those rehired in non-finance sectors in Column (2). It is worth noting that the counterfactual (i.e., employees separated for no fault) also gets rehired in finance versus non-finance sectors and hence accounts for any systematic differences between employees who stay within the sector versus those who leave. That we find our results to be concentrated among employees rehired within finance and absent for those who depart the sector suggests that differences across employees separated for misconduct and no fault can only explain our findings if they vary both across sectors and within sectors based on rehiring industries.

One plausible reason through which differences between those separated for misconduct versus no fault arise is that firms may choose to layoff less productive employees when only a few employees need to be separated. However, this choice is less likely to be a factor in mass layoffs when firms let go of significant portions of their workforce. Following the literature, we define a mass layoff to have occurred when a firm involuntarily separates at least 20% of its employees for no fault between two consecutive quarters (e.g., Jacobson et al., 1993; Moore and Scott-Clayton, 2019; Braxton et al., 2022a,b). We then re-estimate our triple interactions specification using two types of involuntary separations: misconduct and mass layoffs. Table 6 reports estimates for this analysis where we find similar results to our baseline even with this sample less subject to firm discretion.[7]

7. We also redo our validation exercise using the JLS specification to estimate the effect of separation owing to mass layoffs across all industries on income. Similar to before, we find results consistent with JLS as reported in Table A2.

Taken together, the results discussed in this section suggest that differences in employees separated for misconduct and no-fault or non-separated employees are less likely to explain our findings.

4 Mechanisms

In this section we investigate what drives the differential income for finance employees separated for misconduct versus no fault. First, we test if having a misconduct background provides informative signals to potential employers and affects assortative matching in the labor markets. Then, we study if regulation induces firms to be more strict and fire employees for misconduct for even small errors that the market recognizes and partially undoes. Third, we evaluate the role of job search wherein perhaps employees separated for misconduct in finance search longer for jobs and hence are able to secure higher paying jobs.

4.1 Assortative matching in labor markets

Our results show that the labor market consequences are less severe for finance employees involuntarily separated for misconduct than those laidoff for no fault in terms of their income declines. One plausibility that can explain these findings is assortative matching in the labor markets where firms with a propensity to take more risks, operate in the 'twilight zone', or engage in potential fraudulent activities may be more likely to hire employees with misconduct background as these individuals have shown a disposition towards such activities themselves. If firms vary in their culture and involvement in such activies, they may match with employees with different tendencies towards such behaviors. For example, if firms are more likely to adopt high pressure sales tactics they would be more inclined to hire sales employees willing to sell products even if they are not in the best interest of the consumer. Having a misconduct background may act as an informative signal that facilitates this match following employee separations. To the extent firms value this match, they may be willing to pay a wage premium for it.

We evaluate this hypothesis using the complaints data maintained by the consumer financial protection bureau (i.e., CFPB). The CFPB was established as a watchdog of financial services industry in 2010 as part of the Dodd-Frank Act. Among other things the bureau provides an avenue for consumers not satisfied with the services they receive to lodge complaints against financial institutions. They can do this in a number of different ways including the bureau's online system, email, postal mail, fax, phone, or through a referral from other agencies. These complaints are typically major serious allegations or issues that could not be resolved between the consumer and the firm (Begley and Purnanandam, 2021). This is further elaborated by the fact that the CFPB uses these complaints and their resolutions as an input in its enforcement decisions, and has fined almost $10 billion to firms since its inception. In their complaints, individuals provide information on the products and detailed accounts of events that led them to file a complaint along with the firm's name. We focus on fraud-related complaints. In particular, we manually examine the description of issues reported in the data and focus on keywords such as misleading, crime, privacy, fraud, wrong amongst others to classify complaints as being fraudulent. Some examples of the categories of complaints classified as fraud in our analysis include account opened as a result of fraud, fraudulent loan, attempt to collect wrong amount, high pressure sales tactics, overcharged, didn't receive services advertised, confusing or misleading advertising, etc. We then aggregate this data to capture the total number of complaints received against a particular firm over our sample period.

Using this aggregated data we create two different proxy measures for the culture in the firm vis-a-vis their tendency to be involved in potentially fraudulent related activities. First, we use the fraction of fraud related complaints of the total number of complaints against the firm. We use the proportion to account for the size and the type of clientelle that firms cater towards. For example, consumers for a different types of products may have different tendencies to complaint. Second, we use the timely response rates for the firms. When CFPB receives the complaints, it sends it over to the firms giving them an opportunity to reach out to the consumer and resolve the issue within a given time frame. Timely response rate captures the tendency of the firms to resolve consumer complaints or issues. We split the firms into above and below median levels based on both measures and find the culture to be persistent over time. Figure 5 shows this graphically where we plot the averages across the two groups based on both measures and find the differences to exist from 2012 through 2022.

To further account for the plausibility that complaints can be driven by both the size of the firm and the type of products or services firms provide (e.g., some may be more consumer facing than others; different products may affect consumers differently etc.), we control for both firm size and 6-digit NAICS code for the hiring firm in analyses that use these measures. We first examine whether our results vary for employees rehired within finance by firms with different levels of complaints or non-timely response rates[8]. Table 7 reports results for this analysis. Columns (1) & (2) report results for employees rehired by firms with above & below median levels of fraud related complaints respectively. We find stronger results for employees rehired by firms with higher levels of complaints. Among employees rehired by such firms, those separated for misconduct earn 6 percentage points (pp) higher income relative to their no fault counterparts. In contrast, among employees rehired by firms with below median levels of complaints those separated for misconduct experience 5.4% higher relative income. Columns (3) and (4) report results for employees rehired by firms with above & below median levels of non-timely response rates and find similar results. While misconduct employees rehired by firms with higher levels of non-timely responses earn 7.8%

8. We use the complement of timely response rate (i.e., 1-timely response rate) to make it consistent across the two measures that higher values represent undesirable characteristics of firms.

higher income relative to their no fault counterparts this difference amounts to 5.5% for those rehired by firms with lower levels of non-timely responses.

The next part of our analysis hypothesizes that assortative matching should lead to asymmetric results depending on which type of firms employees are separated from and who rehires them. Conditional on employees being separated from firms with below median levels of complaints and rehired by those with above median levels of complaints, the matching improves for those separated for misconduct but not necessarily for those separated for no fault. However, this differential does not exist for employees with reverse job switches. We test this plausibility and report the results in Table 8. Consistent with the hypothesis, we find that our results are concentrated for the pool of employees separated from employers with below median levels of complaints (or non-timely response rates) who moved to employers with above median complaints (or non-timely response rates). Columns (2) and (4) report estimates for this group where we find that those separated for misconduct earn 9.1% and 9.9% higher relative income respectively. In contrast, among those who switch jobs from employers with above median to below median levels of complaints or non-timely response rates earnings are statistically indistinguishable between those separated for misconduct and no fault. Similar patterns emerge for match rates and tenure with the new employer. Among those separated from firms with below median levels of complaints, 49% of those separated for misconduct and rehired within finance were rehired by employers with above median levels of complaints. In contrast, 33% of those separated for no fault made a transition from firms with below to above median levels of complaints.[9] Following switching from employers with less to more complaints, tenure for employees with misconduct background are 10%-15% higher than those with opposite moves.

Overall, these results are consistent with assortative matching in the finance labor market where employers with higher propensity to engage in risky behavior or potential fraudulent

9. The remaining 18% move to firms not covered in the CFPB complaints database.

activities pay a wage premium for employees with a misconduct background.

4.2 Does stricter regulation drive our effects?

Regulation may affect how firms react to employee misconduct. For example, higher regulatory costs may incentivize firms to fire employees even for minor offences and errors of judgement. The labor markets may recognize this and undo part of this 'abnormally strict' internal punishment subsequently. We evaluate this plausibility in our setting by estimating the heterogeneity in our findings based on severity of regulation faced by different sub-sectors within the finance and insurance sector. The RegData provides information that helps quantify the size and scope of regulations affecting different sub-sectors. Based on the 3-digit classification, the sub-sector that houses firms in credit intermediation and related activities receives the most amount of regulatory scrutiny with over 60,000 regulatory restrictions imposed on the sector as of 2016.[10]

We estimate the heterogeneity in our findings across firms in the credit intermediation sector and those operating in other sub-sectors. Table 9 reports the results for this analysis where column (1) reports results for employees separated from the credit intermediation sector while column (2) reports estimates for all other employees. We find similar results across the two groups suggesting that regulation is less likely to drive our results.

4.3 Job Search

Another plausible mechanism consistent with our findings may be that workers separated for misconduct in finance search longer for jobs which allows them to find higher paying jobs. This can especially be true for high income employees who potentially have more resources to help remain unemployed longer while searching. We evaluate this plausibility

10. This link provides more information on the heterogeneity of regulation across sub-sectors: https://www.mercatus.org/publications/regulation/regulatory-accumulation-financial-sector

by examining the time it takes for employees across different separation categories in our sample to find re-employment. Table A3 reports average time to re-employment measured in months by different income categories. For employees in bottom 90% of the income distribution, those separated for misconduct take 11.1% less time to find re-employment relative to those separated for no fault. Specifically, the former on average take 4.8 months relative to 5.4 months for the latter. Similar patterns hold even for high income employees belonging to the top decile of income distribution. Overall, our results are less likely to be explained by differences in job search duration across employees separated for misconduct and no fault.

5 Is Finance Unique?

A natural question at this point is whether finance is unique in the lack of external market punishment for the misconduct employees or are there other sectors where we may find similar patterns. We examine this by re-estimating our main triple interaction specification for all major sectors in the economy (i.e., all industries with different 2-digit NAICS codes). Figure 6 plots the main triple interaction coefficients for all sectors in the economy except Agriculture and Public Administration as there are either no or very few employers from these two sectors covered in our sample.[11] Though there is heterogeneity across different sectors, those involuntarily separated for misconduct earn higher income relative to those separated for no fault layoffs only within the finance and insurance sector.

One feature that makes finance unique may be that most services and products sold are based on future cash flows. This likely makes it more difficult for consumers and other stakeholders to disentangle bad luck from a deliberate risky or unethical transaction in case

11. A list of all sectors based on 2-digit NAICS code is available through census using this link: https://www.census.gov/programs-surveys/economic-census/year/2022/guidance/understanding-naics.html

of losses, thereby reducing the expected costs of engaging in such behavior for employees. To evaluate this hypothesis, we re-estimate our findings across employees in finance-related and non-finance jobs within the finance sector. Table 10 reports estimates for this analysis. Consistent with the hypothesis, we find our results to be concentrated for employees separated from finance-related jobs and absent for non-finance jobs within the sector.

Another plausibility consistent with our findings may be that the inherent culture in the finance sector may be systematically different than other sectors. For instance, the literature has shown that finance is unique in a different aspect: it is a high-skill and high-wage sector and returns to talent in finance have substantially increased over the years relative to other sectors (e.g., Philippon and Reshef, 2012; Celerier and Vallee, 2019). Similarly, it can help explain our results if the sector is also unique in a characteristic (e.g., subscribing to "success at all costs" mentality) that bolsters the net returns to risky or potentially unethical/fraudulent behavior (e.g., Gill et al., 2022).

Differences in regulation across sectors is less likely to explain our results because estimates for other heavily regulated sectors such as health care, real estate etc. are statistically indistinguishable to coefficients for less regulated sectors like retail trade, waste management etc as plotted in Figure 6.

6 Other Robustness

While presenting our results we have discussed at length one of the main concerns in our analysis: differences in employees separated for misconduct versus no fault or non-separated employees and the steps we took to help address this concern. In this section, we describe some other potential limitations and the robustness of our findings.

6.1 Misconduct measure

Our measure of misconduct comes from the employer reported reason of separation where it is explicitly stated as misconduct. In addition, the employers also report a more detailed description and classify misconduct separations into over 25 sub-categories including violation of company policy, improper conduct, and gross misconduct among others. Table A1 reports top 10 reasons that account for over 90% of all separations along with their contributions for both the finance and non-finance sectors separately. While our data and setting have several strengths and are rich along a number of dimensions, one limitation is that these sub-categories describing the reasons for misconduct might not be very informative given that the distribution of our sample is skewed towards less informative sub-categories like violation of company policy and improper conduct. This restricts our ability to observe the exact type of misconduct covered in our sample and raises the concern that the type of misconduct might be different across sectors and these differences may explain our findings.

We overcome this limitation by examining indirect evidence through different sub-sample analyses. First, our heterogeneity estimation based on whether employees work in finance-related versus non-finance jobs within the finance sector helps us evaluate the extent to which financial misconduct and offences are captured by our measure. That we find our results to be concentrated among employees working in finance-related jobs (as reported in Table 10) suggests that our measure is able to capture financial misconduct along with other types. Second, we estimate the heterogeneity in our findings across different types of reasons by splitting the sample into those separated for violation of company policy versus all others.[12] Table A6 reports our baseline results for these sub-samples where we find similar results across both types of misconduct. Third, we re-estimate our findings within the same job type but across different sectors: sales and marketing professionals. To the extent that

12. We do not have enough observations in most of these sub-categories to estimate our triple interaction coefficients separately for them.

employees involved in sales jobs are likely to be involved in similar type of misconduct (e.g., adopting aggressive sales strategies like lying to clients, overselling etc), the issue is likely to be less severe for this sub-sample. Table A9 reports results for these estimations where we find patterns similar to our baseline: while those separated for misconduct earn higher income relative to no fault separations in finance, opposite occurs for other sectors. Overall, these results suggest that the differences in the type of misconduct across sectors are less likely to drive our estimates.

While there are some reported reasons that should not be preferrable for potential employers (e.g., removal of company property, unauthorised use of company credit card etc.), we do not have enough number of separations in these sub-categories to examine heterogeneity based on whether or not the misconduct separation reason is potentially unacceptable for hiring employers. However, we split the sample based on top three reasons versus all others and compare average industry departure rates. Since these analyses do not include the fixed effects as our baseline specifications, they are less demanding in terms of the number of separations required for estimation. Table A7 reports these results where we find the industry departure rates to be significantly higher following misconduct separations which include the potentially undesirable categories, i.e., outside of the top-3 categories.

6.2 Job finding rates

Our sample consists of employees who get rehired within firms that subscribe to verification services within twelve months of separation. This creates two potential issues. First, there could be selection in who gets rehired that can bias our findings. Our replication and sample validation exercise discussed in Section 2.3 helps assuage this concern. Second, if those separated for misconduct are much less likely to find a job, our interpretation of lack of external punishment in finance based on the income results from our sample may be misleading. We overcome this second issue by examining drop out rates from our sample by reason of separation across sectors.

Since we cannot directly measure the job finding rates as employees may drop out of our sample either because they did not find a job post separation or found one at a firm not covered in our data, we measure the drop out rates and report them in Table A8. We find that across all sectors those separated for misconduct are about 14% less likely to drop out of our sample relative to no fault separations. This large difference seems to be driven by the finance sector as there is considerable heterogeneity in the difference in drop out rates between misconduct and no fault across sectors. While those separated for misconduct are 15% less likely to drop out relative to no fault counterparts in finance, they are only 4.2% less likely to drop out in non-finance sectors. These results are consistent with significantly less or no punishment for misconduct separations in finance relative to other sectors. Taken together with the earlier results that those separated for misconduct find jobs faster, these findings further support our interpretation of lack of external punishment in finance.

7 Conclusion

Though misconduct in the finance sector potentially contributes towards the low public trust in finance professionals and financial institutions, it remains prevalent. One plausible reason why it persists is that perpetrators of such behavior do not bear sufficiently high personal costs, especially in terms of their labor market outcomes. Using detailed data on job separations and income, we study the extent of *external* labor market punishment for misconduct in the finance and insurance sector (NAICS 52) and contrast this to consequences in non-finance sectors.

We focus on employees involuntarily separated for misconduct and examine how their income evolves post separation from the firm. Because these employees get separated from the firm, examining only their income pre- and post-separation can be misleading as separation itself affects income irrespective of involvement in misconduct. Our data allows us to overcome this empirical challenge by using income response for those laid-off for no fault (i.e., no fault layoffs) as a benchmark in our setting.

We find that finance employees involuntarily separated for misconduct earn 2.8% to 8.6% higher income than those laid-off for no fault post separation. These patterns are less likely to be driven by differences across workers involuntarily separated for misconduct vs no fault. In sharp contrast to finance, non-finance employees separated for misconduct experience 4.4% to 8.1% lower income than their no fault counterparts. Even amongst employees separated from the finance sector, results are concentrated amongst those who get rehired within finance and are absent for those rehired in other sectors. The patterns are most consistent with assortative matching in the finance labor market. Our results are concentrated among employees separated from firms with fewer fraud related consumer complaints (or more timely responses to complaints) but who get rehired by employers with higher levels of such complaints (or lower levels of timely responses). Those separated for misconduct are more likely to be rehired within firms with more complaints or less timely responses and once matched with such firms employees stay 10-15% longer relative to when matched with the other type of firms.

Longer job search by employees separated for misconduct does not explain our findings as these employees find jobs quicker and are less likely to depart from the industry relative to no fault layoffs. Differences in regulation is also less likely to explain our findings.

We find the finance sector to be unique in exhibiting such patterns. One feature that may make finance unique is that most products transacted upon in the sector are based on future cash flows which makes it more difficult for consumers or other stakeholders to disentangle bad luck from deliberate risky or unethical transaction in case of losses, thereby reducing the costs of engaging in such behavior for employees. Consistent with this argument, we find our results to be concentrated among employees with finance-related jobs and absent for non-finance jobs within the finance sector.

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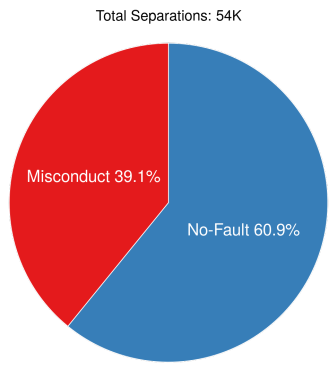
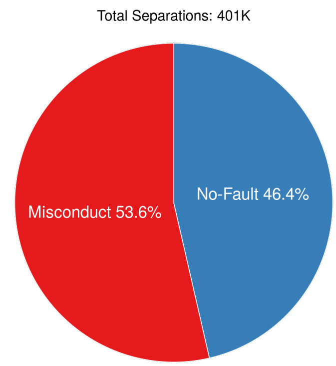
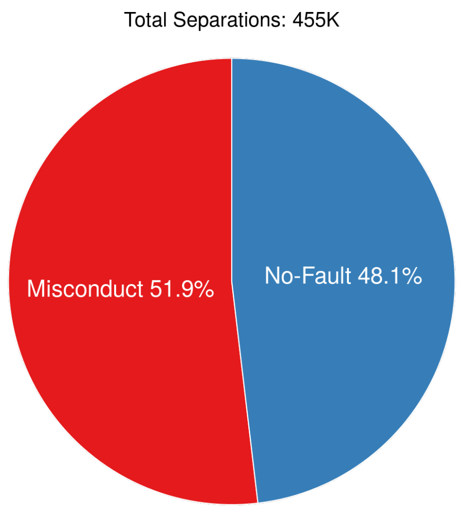


(a) Finance



(b) Non-Finance



(c) All Professions

Figure 1: Separations Composition
This figure shows the distribution of separations by separation type. Panel (a) and (b) plots the distribution for finance and non-finance sectors respectively and panel (c) plots the distribution for all professions.

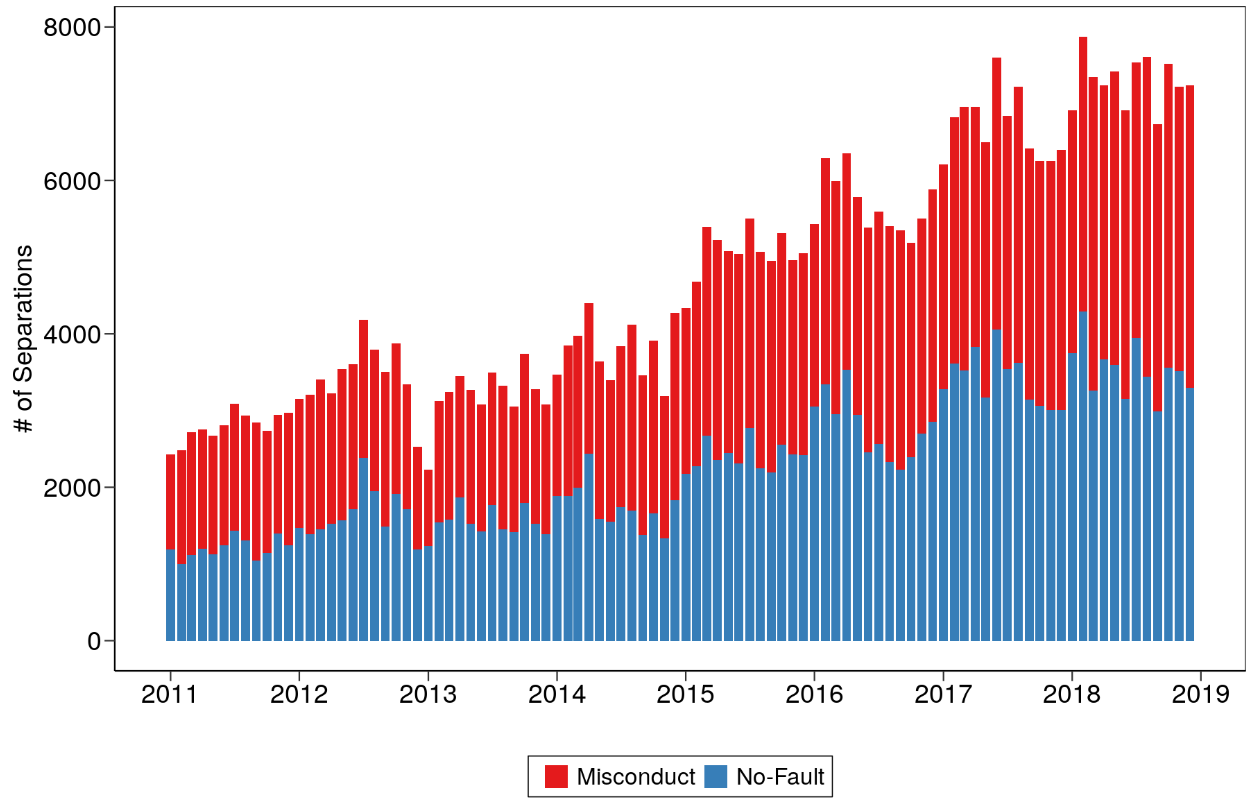


Figure 2: Separations Composition over Time
This figure plots the time-series of the distribution of separations from Jan 2011 through Dec 2018 by different separation types.

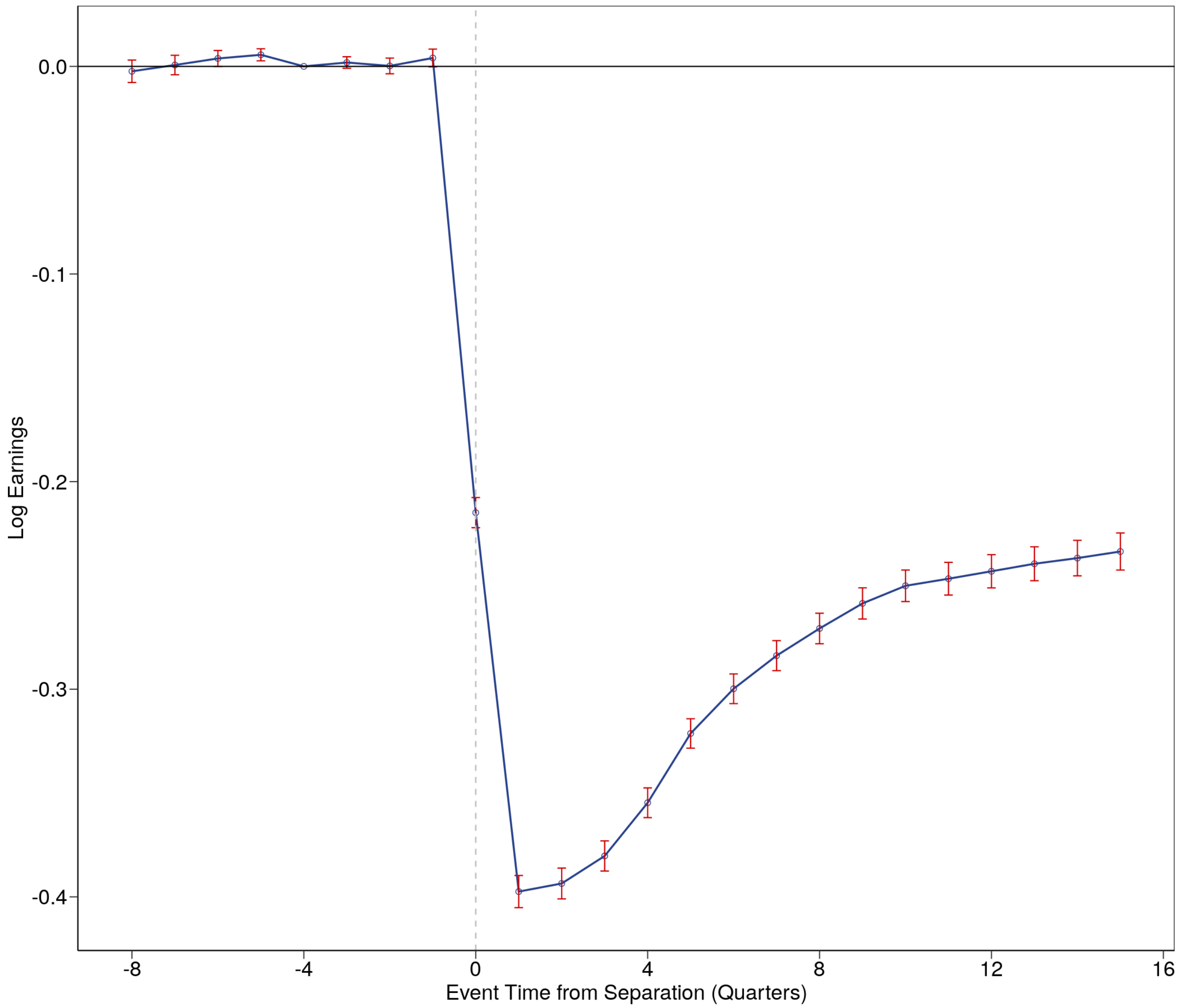


Figure 3: Income dynamics around No fault Layoffs: All Industries
This figure plots the coefficients for the association between earnings and no fault layoffs in event-time around separation estimated for employees across all sectors. We modify equation (1) to include a vector of 24 indicator variables that correspond to the event time around separation date (in quarters) instead of the collapsed post dummy. The vertical bars correspond to 99% confidence levels.

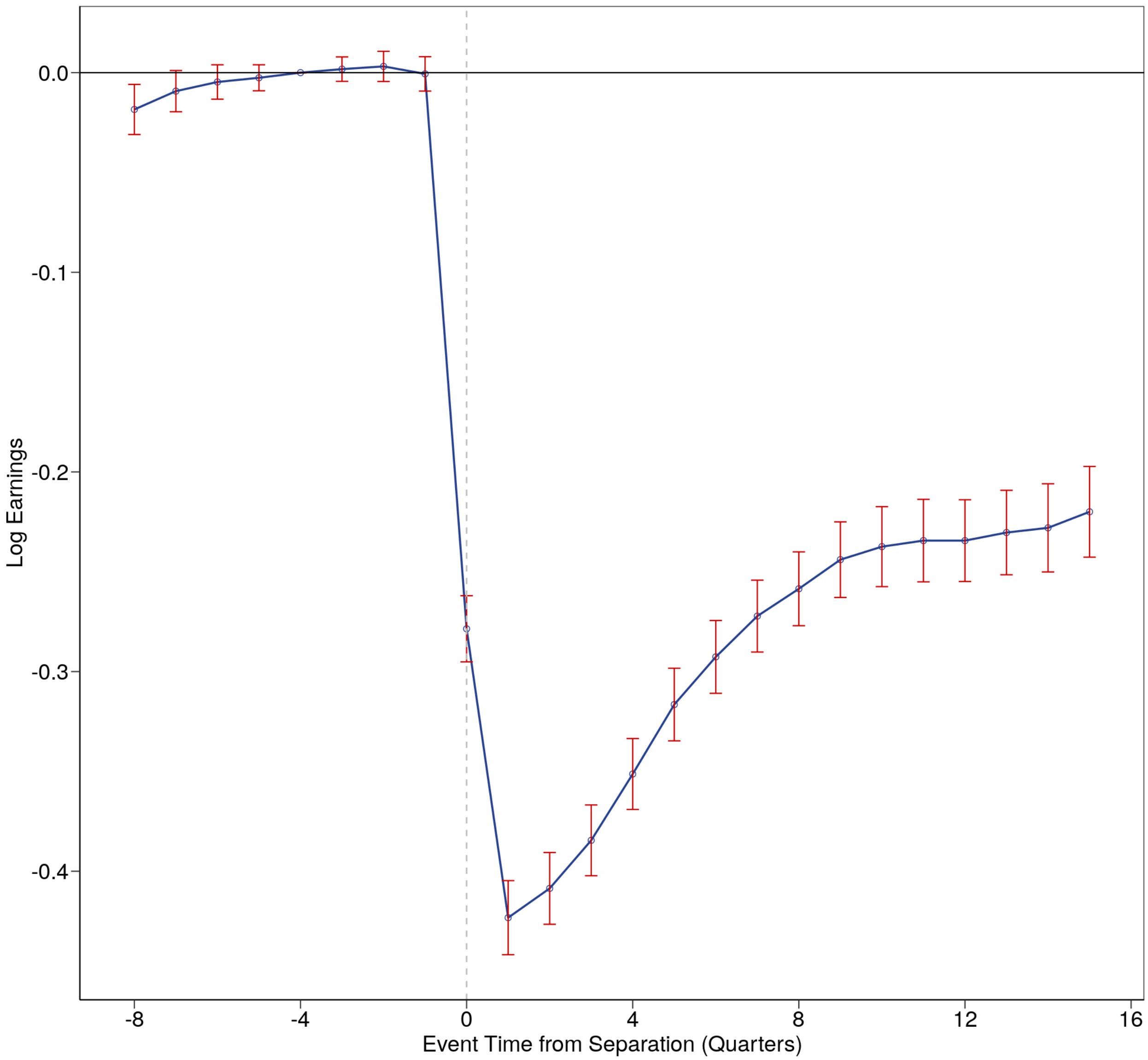


Figure 4: Income dynamics around Misconduct Separations: Finance
This figure plots the coefficients for the association between earnings and involuntary separations owing to misconduct in event-time around separation estimated for employees separated from the finance sector. We modify equation (1) to include a vector of 24 indicator variables that correspond to the event time around separation date (in quarters) instead of the collapsed post dummy. The vertical bars correspond to 99% confidence levels.

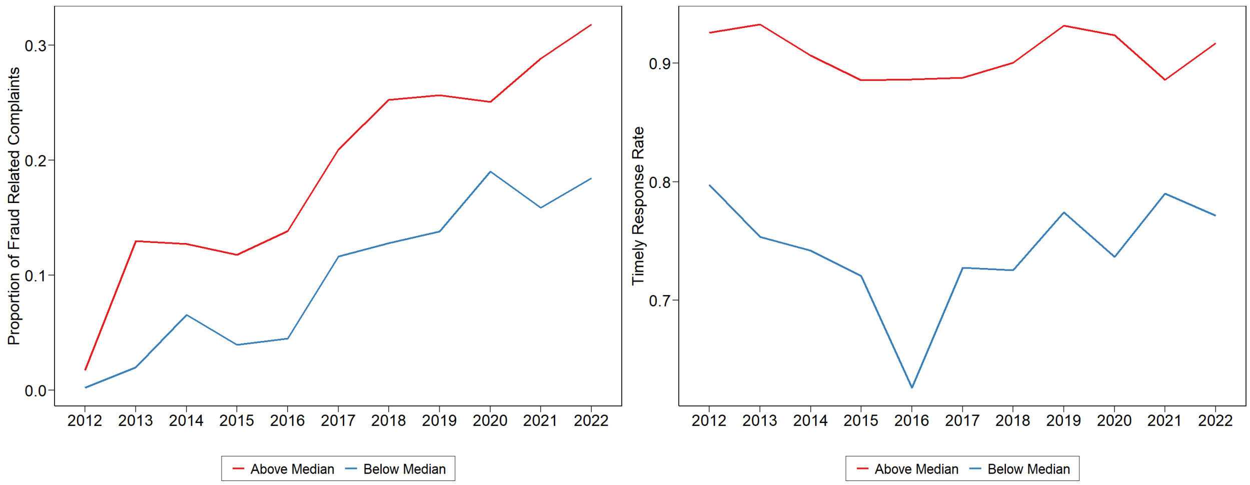


Figure 5: Persistent difference across types of firms in Finance
This figure plots the average proportion of fraud related complaints (left panel) and timely response rate to these complaints (right panel) over 2012 through 2022. Red (blue) color represents firms with above (below) median levels of fraud related proportion of complaints or timely response rates.

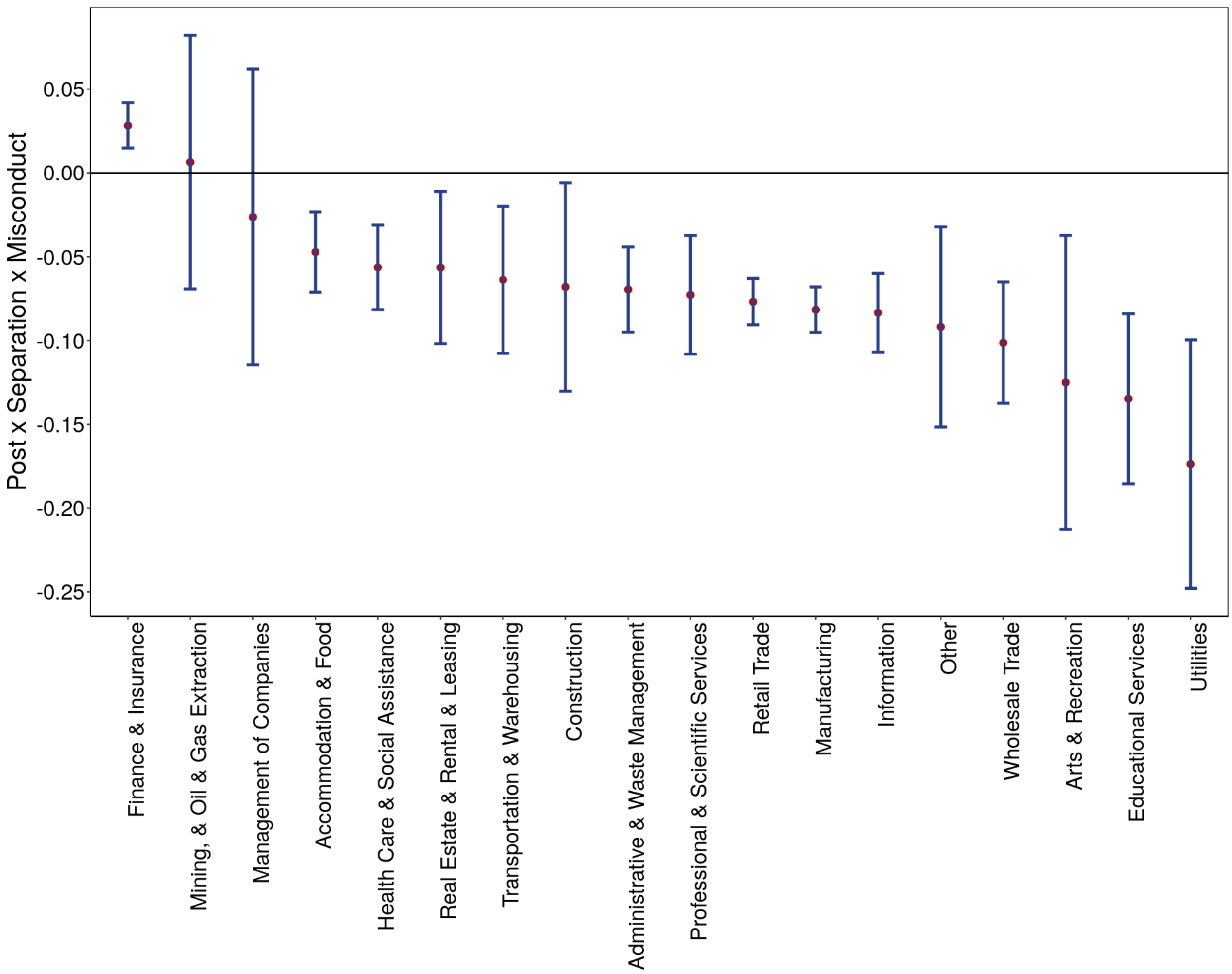


Figure 6: Distribution of Separations by Industry
This figure plots the association between earnings and involuntary separations owing to misconduct estimated using the triple interactions from Equation 3. The vertical bars correspond to 99% confidence levels.

Table 1: Summary of Pre-Separation Annual Income (in '000 Dollars)
This table summarizes annual earnings for employees in our sample. *Separated* comprises of employees who were involuntarily separated eiter for misconduct or no fault. *Remain employed* refers to employees who continue working in the corresponding separation firms until atleast one year from the respective sample separation dates. Annual earnings are reported in thousands of dollars and are measured as of the month prior to separation. Finance sector corresponds to the NAICS code of 52.

	Mean	Std. Dev.	p25	Median	p75
A. All Industries: Separated					
All Workers	70.1	64.7	32.1	49.7	82.3
No fault	99.9	82.0	46.2	74.7	123.6
Misconduct	52.2	41.2	28.5	42.0	61.6
B. All Industries: Remain employed					
All Workers	87.3	78.5	41.1	64.4	104.7
C. Finance: Separated					
All Workers	86.1	81.9	40.7	58.4	96.6
No fault	111.0	98.01	50.9	77.5	130.4
Misconduct	61.7	52.0	36.3	47.5	67.5
D. Finance: Remain employed					
All Workers	105.3	94.5	50.3	76.2	121.3
E. Non-Finance: Separated					
All Workers	67.9	61.8	30.9	48.5	80.4
No fault	97.8	78.5	45.3	74.2	122.4
Misconduct	51.2	39.8	27.7	41.3	60.9
F. Non-Finance: Remain employed					
All Workers	77.4	66.0	36.2	58.2	95.0

Table 2: Income following No fault Layoffs: All Industries

This table reports the results of the OLS regressions specified in Equation 1. The sample comprises employees from all sectors laid off for no fault and their corresponding non-separated counterparts. *Layoff* is an indicator equal to 1 if a worker was laid off between 2011 to 2018 and 0 otherwise. *Post* is a dummy equal to 1 for months following separation and 0 otherwise. *Month* refers to the calender year-month, *Industry* refers to the 6 digit NAICS code for the separated firm, and *Wage Bins* are constructed at $1,000 width for pre-separation income. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings		
Variables	(1)	(2)	(3)
Layoff × *Post*	-0.294***	-0.287***	-0.285***
	(0.002)	(0.002)	(0.002)
Individual FE	Y	Y	Y
Month FE	Y	N	N
Industry × *Month FE*	N	Y	Y
Wage Bin × *Month FE*	N	N	Y
N	62,618,513	62,618,513	62,618,513
$Adj.R^2$	0.842	0.844	0.845

Table 3: Income following Misconduct Separation

This table reports the results of the OLS regressions specified in Equation 1. The sample comprises employees involuntarily separated for misconduct and their corresponding non-separated counterparts. Columns (1)-(2) report the estimates for employees separated from the finance sector defined as all firms in the NAICS code of 52. Columns (3)-(4) report the estimates for employees separated from all other sectors. *Misconduct* is an indicator equal to 1 if an employee was separated for misconduct between 2011 to 2018 and 0 otherwise. *Post* is a dummy equal to 1 for months following separation and 0 otherwise. *Month* refers to the calender year-month, *Industry* refers to the 6 digit NAICS code for the separated firm, *Wage Bins* are constructed at $1,000 width for pre-separation income, *Firm* represents the separated firm, *Location* corresponds to the 3-Digit Zipcode, and *Tenure* is constructed as deciles from the distribution of tenure as of the month prior to separation. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings			
	Finance		Non-Finance	
	(1)	(2)	(3)	(4)
Misconduct × *Post*	-0.224***	-0.275***	-0.330***	-0.379***
	(0.005)	(0.005)	(0.002)	(0.002)
Individual FE	Y	Y	Y	Y
Wage Bin × *Month FE*	Y	Y	Y	Y
Industry × *Month FE*	Y	N	Y	N
Firm × *Location* × *Year FE*	N	Y	N	Y
Tenure × *Year FE*	N	Y	N	Y
N	19,279,776	19,279,776	43,521,289	43,521,289
$Adj.R^2$	0.884	0.897	0.817	0.838
Layoff × *Post*	-0.301	-0.314	-0.282	-0.298
Difference	**0.077*** **	**0.039*** **	**-0.048*** **	**-0.081*** **

Table 4: Income following Misconduct Separation: Collapsed

This table reports results of the OLS regressions specified in Equation 3. The sample comprises of employees involuntarily separated either for no fault or misconduct and their corresponding non-separated counterparts. Columns (1)-(2) report the estimates for employees separated from the finance sector defined as all firms in the NAICS code of 52. Columns (3)-(4) report the estimates for employees separated from all other sectors. *Misconduct* is an indicator equal to 1 if an employee was separated for misconduct between 2011 to 2018 and 0 otherwise. *Separated* is a dummy equal to 1 if the employee was separated between 2011 to 2018 and 0 otherwise. *Post* is a dummy equal to 1 for months following separation and 0 otherwise. *Month* refers to the calender year-month, *Industry* refers to the 6 digit NAICS code for the separated firm, *Wage Bins* are constructed at \$1,000 width for pre-separation income, *Firm* represents the separated firm, *Location* corresponds to the 3-Digit Zipcode, *Tenure* is constructed as deciles from the distribution of tenure as of the month prior to separation, and *Separation Cohort* refers to the year of separation. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings			
	Finance		Non-Finance	
	(1)	(2)	(3)	(4)
Misconduct$\times$ *Separated* $\times$ *Post*	0.075***	0.028***	-0.044***	-0.069***
	(0.007)	(0.007)	(0.003)	(0.003)
Separated $\times$ *Post*	-0.303***	-0.320***	-0.290***	-0.310***
	(0.004)	(0.004)	(0.002)	(0.002)
Individual FE	Y	Y	Y	Y
Wage Bin $\times$ *Month FE*	Y	Y	Y	Y
Industry $\times$ *Month FE*	Y	N	Y	N
Firm $\times$ *Location* $\times$ *Tenure* $\times$ *Year FE*	N	Y	N	Y
Separation Cohort $\times$ *Year FE*	N	Y	N	Y
N	21,152,903	21,152,903	52,471,961	52,471,961
$Adj.R^2$	0.880	0.896	0.817	0.849

Table 5: Income following Separation: Stay vs Depart

This table reports heterogeneity in log earnings following separation for different sub-samples. While Column (1) reports the estimates for separated employees who find a job within the finance industries post-separation, Column (2) reports them for employees hired outside of the finance industry following separation. *Misconduct* is an indicator equal to 1 if an employee was separated for misconduct between 2011 to 2018 and 0 otherwise. *Separated* is a dummy equal to 1 if the employee was separated between 2011 to 2018 and 0 otherwise. *Post* is a dummy equal to 1 for months following separation and 0 otherwise. *Month* refers to the calender year-month, *Industry* refers to the 6 digit NAICS code for the separated firm, *Wage Bins* are constructed at $1,000 width for pre-separation income, *Firm* represents the separated firm, *Location* corresponds to the 3-Digit Zipcode, *Tenure* is constructed as deciles from the distribution of tenure as of the month prior to separation, and *Separation Cohort* refers to the year of separation. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings	
	Stay	Depart
	(1)	(2)
Misconduct × *Separated* × *Post*	0.037***	0.018
	(0.008)	(0.011)
Separated × *Post*	-0.205***	-0.427***
	(0.004)	(0.007)
Individual FE	Y	Y
Wage Bin × *Month FE*	Y	Y
Firm × *Location* × *Tenure* × *Year FE*	Y	Y
Separation Cohort × *Year FE*	Y	Y
N	19,563,489	19,578,473
$Adj.R^2$	0.901	0.899

Table 6: Income following Separation: Mass Layoffs as Counterfactual

This table reports results of the OLS regressions specified in Equation 3. The sample comprises of employees involuntarily separated either for misconduct or in no fault mass layoff. Columns (1)-(2) report the estimates for employees separated from the finance sector defined as all firms in the NAICS code of 52. Columns (3)-(4) report the estimates for employees separated from all other sectors. *Misconduct* is an indicator equal to 1 if an employee was separated for misconduct between 2011 to 2018 and 0 otherwise. *Separated* is a dummy equal to 1 if the employee was separated between 2011 to 2018 and 0 otherwise. *Post* is a dummy equal to 1 for months following separation and 0 otherwise. *Month* refers to the calender year-month, *Industry* refers to the 6 digit NAICS code for the separated firm, *Wage Bins* are constructed at $1,000 width for pre-separation income, *Firm* represents the separated firm, *Location* corresponds to the 3-Digit Zipcode, *Tenure* is constructed as deciles from the distribution of tenure as of the month prior to separation, and *Separation Cohort* refers to the year of separation. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings			
	Finance		Non-Finance	
	(1)	(2)	(3)	(4)
Misconduct$\times$ *Separated* $\times$ *Post*	0.105***	0.075**	-0.054***	-0.071***
	(0.024)	(0.025)	(0.009)	(0.008)
Separated $\times$ *Post*	-0.329***	-0.367***	-0.276***	-0.314***
	(0.023)	(0.025)	(0.009)	(0.008)
Individual FE	Y	Y	Y	Y
Wage Bin $\times$ *Month FE*	Y	Y	Y	Y
Industry $\times$ *Month FE*	Y	N	Y	N
Firm $\times$ *Location* $\times$ *Tenure* $\times$ *Year FE*	N	Y	N	Y
Separation Cohort $\times$ *Year FE*	N	Y	N	Y
N	19,328,073	19,328,073	44,210,510	44,210,510
$Adj.R^2$	0.884	0.901	0.817	0.852

Table 7: Heterogeneity by Complaints

This table reports heterogeneity in our findings based on different levels of consumer complaints received against or timely response rates to these complaints of the rehiring employers. Columns (1) and (2) report the estimates for sub-sample of employees rehired by employers with above and below median levels of fraudulent complaints respectively. Similarly Columns (3) and (4) report the estimates for those rehired by employers with above and below median levels of non-timely response rates. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings			
	Fraud Related Complaints		Non-Timely Response	
	Above Median	Below Median	Above Median	Below Median
	(1)	(2)	(3)	(4)
Misconduct $\times$ *Separated* $\times$ *Post*	0.060***	0.054**	0.078***	0.055***
	(0.013)	(0.023)	(0.017)	(0.014)
Separated $\times$ *Post*	-0.198***	-0.250***	-0.231***	-0.201***
	(0.009)	(0.014)	(0.010)	(0.011)
Individual FE	Y	Y	Y	Y
Wage Bin $\times$ *Month FE*	Y	Y	Y	Y
Firm $\times$ *Location* $\times$ *Tenure* $\times$ *Year FE*	Y	Y	Y	Y
Separation Cohort $\times$ *Year FE*	Y	Y	Y	Y
Hiring Firm Size $\times$ *Hiring Firm Industry*	Y	Y	Y	Y
N	6,656,028	4,348,275	5,124,947	5,879,356
$Adj.R^2$	0.901	0.899	0.904	0.898

Table 8: Assortative Matching between Employer and Employees

This table reports heterogeneity in our findings based on the types of separated and rehiring employers. The different types of employers are measured as levels of consumer complaints received against or non-timely response rates to these complaints made by these employers. While Column (1) reports the estimates for sub-sample of employees separated from employers with above median levels of fraudulent complaints who get rehired by firms with below median levels of complaints Column (2) reports results for opposite moves. Similarly Column (3) reports the estimates for those separated from employers with above median levels of timely response rates who get rehired in firms with below median response rates and Column (4) reports results for the opposite moves. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings			
	Fraud Related Complaints		Non-Timely Response	
	Above to Below Median	Below to Above Median	Above to Below Median	Below to Above Median
	(1)	(2)	(3)	(4)
Misconduct × *Separated* × *Post*	0.048	0.091***	0.020	0.099***
	(0.029)	(0.031)	(0.022)	(0.022)
Separated × *Post*	-0.182***	-0.215***	-0.162***	-0.210***
	(0.017)	(0.017)	(0.015)	(0.012)
Individual FE	Y	Y	Y	Y
Wage Bin × *Month FE*	Y	Y	Y	Y
Firm × *Location* × *Tenure* × *Year FE*	Y	Y	Y	Y
Separation Cohort × *Year FE*	Y	Y	Y	Y
Hiring Firm Size × *Hiring Firm Industry*	Y	Y	Y	Y
N	5,862,987	4,175,508	4,575,474	5,578,247
$Adj.R^2$	0.904	0.901	0.909	0.897

Table 9: Heterogeneity by Extent of Regulation

This table reports heterogeneity in our findings based on the strictness of regulation faced by separated employers. While Column (1) reports the estimates for sub-sample of employees separated from employers in heavily regulated sub-sectors within finance Column (2) reports it for employers in less regulated sub-sectors. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings	
	More Regulated	Less Regulated
	(1)	(2)
Misconduct $\times$ *Separated* $\times$ *Post*	0.025***	0.029*
	(0.006)	(0.012)
Separated $\times$ *Post*	-0.303***	-0.382***
	(0.004)	(0.006)
Individual FE	Y	Y
Wage Bin $\times$ $Month\ FE$	Y	Y
Firm $\times$ *Location* $\times$ *Tenure* $\times$ $Year\ FE$	Y	Y
Separation Cohort $\times$ $Year\ FE$	Y	Y
N	14,226,556	7,703,891
$Adj.R^2$	0.898	0.890

Table 10: Heterogeneity by Type of Job Profile

This table reports heterogeneity in our findings based on the pre-separation job profile within the finance sector. While Column (1) reports the estimates for sub-sample of employees with finance-related pre-separation jobs Column (2) reports them for employees with non-finance job profiles . Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings	
	Finance Job Profile	Non-Finance Job Profile
	(1)	(2)
Misconduct $\times$ *Separated* $\times$ *Post*	0.061***	0.031
	(0.013)	(0.019)
Separated $\times$ *Post*	-0.227***	-0.153***
	(0.008)	(0.013)
Individual FE	Y	Y
Wage Bin $\times$ $Month\ FE$	Y	Y
Firm $\times$ *Location* $\times$ *Tenure* $\times$ $Year\ FE$	Y	Y
Separation Cohort $\times$ $Year\ FE$	Y	Y
N	8,632,563	3,999,109
$Adj.R^2$	0.909	0.906

Table 11: Income following Misconduct Separation for Sales Professionals
This table reports heterogeneity in log earnings following separation for sales and marketing employees across finance and non-finance sectors respectively. While Column (1) reports the estimates for employees separated within the finance sector Column (2) reports them other sectors. *Misconduct* is an indicator equal to 1 if an employee was separated for misconduct between 2011 to 2018 and 0 otherwise. *Separated* is a dummy equal to 1 if the employee was separated between 2011 to 2018 and 0 otherwise. *Post* is a dummy equal to 1 for months following separation and 0 otherwise. *Month* refers to the calender year-month, *Wage Bins* are constructed at $1,000 width for pre-separation income, *Firm* represents the separated firm, *Location* corresponds to the 3-Digit Zipcode, *Tenure* is constructed as deciles from the distribution of tenure as of the month prior to separation, and *Separation Cohort* refers to the year of separation. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings	
	Finance	Non-Finance
	(1)	(2)
Misconduct $\times$ *Separated* $\times$ *Post*	0.056*	-0.071***
	(0.030)	(0.017)
Separated $\times$ *Post*	-0.350***	-0.344***
	(0.023)	(0.014)
Individual FE	Y	Y
Wage Bin $\times$ $Month\ FE$	Y	Y
Firm $\times$ *Location* $\times$ *Tenure* $\times$ $Year\ FE$	Y	Y
Separation Cohort $\times$ $Year\ FE$	Y	Y
N	1,727,408	3,918,612
$Adj.R^2$	0.957	0.956

External Labor Market Punishment in Finance

Appendix for Online Publication

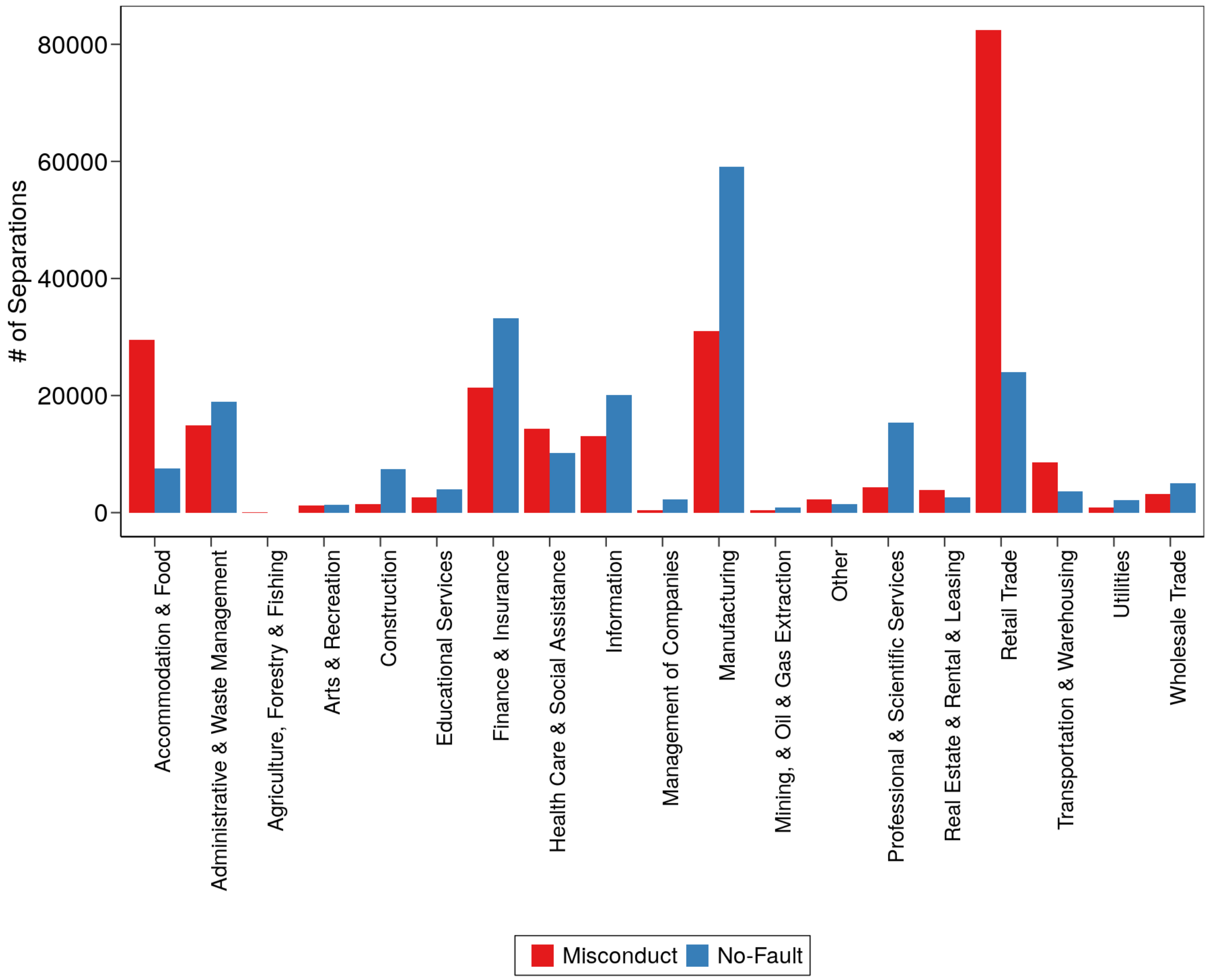


Figure A1: Distribution of Separations by Industry
This figure plots the distribution of separations across different separation types by sectors in the economy.

Table A1: Misconduct Firing: Top 10 Separation Reasons

This table summarizes the distribution of misconduct separations across the top 10 sub-categories. Each row reports the proportion of misconduct firings attributable to a certain sub-category. While Column (1) reports the distribution within the finance sector Column (3) does so for the non-finance sectors.

	Proportion of Separations	
	Finance	Non-Finance
	(1)	(2)
Violation of Company Policy	0.49	0.54
Improper Conduct	0.24	0.11
Misconduct Related Performance	0.09	0.09
Gross Misconduct	0.03	0.04
Removal of Company Property or Funds	0.01	0.03
Falsification of Records	0.02	0.02
Violation of Safety Rules	0.00	0.02
Insubordination	0.01	0.02
Falsification	0.02	0.02
Failure to Report	0.01	0.02
Total	0.92	0.92

Table A2: Income following No fault Mass-Layoffs: All Industries

This table reports the results of the OLS regressions specified in Equation 1. The sample comprises employees from all sectors laid off for no fault and their corresponding non-separated counterparts. *Layoff* is an indicator equal to 1 if a worker was laid off as part of a mass layoff between 2011 to 2018 and 0 otherwise. *Post* is a dummy equal to 1 for months following separation and 0 otherwise. *Month* refers to the calender year-month, *Industry* refers to the 6 digit NAICS code for the separated firm, and *Wage Bins* are constructed at $1,000 width for pre-separation income. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings		
Variables	(1)	(2)	(3)
Layoff × *Post*	-0.225***	-0.230***	-0.225***
	(0.010)	(0.010)	(0.010)
Individual FE	Y	Y	Y
Month FE	Y	N	N
Industry × *Month FE*	N	Y	Y
Wage Bin × *Month FE*	N	N	Y
N	7,174,790	7,174,790	7,174,790
$Adj.R^2$	0.854	0.858	0.858

Table A3: Time to Re-employment

This table reports the average time (in months) for separated employees to be rehired after separation (conditional on being rehired). This statistic is reported separately for individuals belonging to the top 10% and bottom 90% of income distribution respectively. The sample is restricted to finance professionals only.

	Time to Re-employment (in Months)	
	Top 10%	Bottom 90%
Misconduct	4.5	4.8
Layoff	5.1	5.4

Table A4: Industry Departure Rates

This table reports departure rates from the finance sector defined as the share of employees who find employment outside the finance industry following separation. Departure rate is measured over either a two year (Panel A) or a 4 year (Panel B) horizon following separation. Industry is either classified using 6-Digit NAICS or 2-Digit NAICS code.

	Misconduct	Layoff	Misconduct vs Layoff
	(1)	(2)	(1) - (2)
	A. Within 2 Years of Separation		
6-Digit	69.4%	74.9%	-5.5%***
2-Digit	59.0%	60.0%	-1.0%**
	B. Within 4 Years of Separation		
6-Digit	70.6%	75.6%	-5.0%***
2-Digit	60.0%	60.7%	-0.7%*

Table A5: Heterogeneity by Hiring Firm Size

This table reports heterogeneity in our findings based on the size of the hiring firm. While Column (1) reports the estimates for the sub-sample of employees rehired by firms with size above the median Column (2) reports the estimates for sub-sample of employees rehired by firms with size below the median level. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings	
	Above Median	Below Median
	(1)	(2)
Misconduct × *Separated* × *Post*	0.054***	0.027*
	(0.012)	(0.015)
Separated × *Post*	-0.196***	-0.232***
	(0.007)	(0.010)
Individual FE	Y	Y
Wage Bin × *Month FE*	Y	Y
Firm × *Location* × *Tenure* × *Year FE*	Y	Y
Separation Cohort × *Year FE*	Y	Y
N	8,629,441	8,345,707
$Adj.R^2$	0.895	0.906

Table A6: Heterogeneity by Type of Misconduct

This table reports heterogeneity in our findings by the type of misconduct. While Columns (1) and (3) report the estimates for the sub-sample of employees separated for violation of company policies; Columns (2) and (4) report the estimates for sub-sample of employees separated for all other Misconduct reasons. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings			
	Finance		Non-Finance	
	Violation of Company Policy	Other Reasons	Violation of Company Policy	Other Reasons
	(1)	(2)	(3)	(4)
Misconduct $\times$ *Separated* $\times$ *Post*	0.046***	0.052***	-0.075***	-0.059***
	(0.011)	(0.011)	(0.004)	(0.003)
Separated $\times$ *Post*	-0.199***	-0.199***	-0.309***	-0.309***
	(0.005)	(0.005)	(0.003)	(0.003)
Individual FE	Y	Y	Y	Y
Wage Bin $\times$ *Month FE*	Y	Y	Y	Y
Firm $\times$ *Location* $\times$ *Tenure* $\times$ *Year FE*	Y	Y	Y	Y
Separation Cohort $\times$ *Year FE*	Y	Y	Y	Y
N	19,268,640	19,280,184	48,036,954	47,008,123
$Adj.R^2$	0.901	0.901	0.853	0.852

Table A7: Industry Departure Rates by Misconduct Reasons

This table reports departure rates from the finance sector defined as the share of employees who find employment outside the finance sector following separation. Departure rate is measured over a two year horizon following separation in Panel A and over a 4 year in Panel B. Industry is either classified using 6-Digit NAICS or 2-Digit NAICS code.

	Top-3 Misconduct Reasons	Others
	(1)	(2)
A. Within 2 Years of Separation		
6-Digit	68.5%	73.2%
2-Digit	57.8%	64.2%
B. Within 4 Years of Separation		
6-Digit	69.9%	73.7%
2-Digit	59.0%	64.5%

Table A8: Sample Drop-out Rate

This table summarizes the drop-out rates in our sample by separation types and across sectors.

	Drop out rate		
	Overall	Finance	Non-Finance
Misconduct	55.1%	51.1%	65.3%
No-Fault	69.0%	66.16%	69.55%

Table A9: Income following Company Policy Violation Separation for Sales Professionals

This table reports log earnings following separation for sales and marketing employees across finance and non-finance sectors respectively. While Column (1) reports the estimates for employees separated within the finance sector Column (2) reports them other sectors. *Misconduct* is an indicator equal to 1 if an employee was separated for misconduct attributable to violation of company policy between 2011 to 2018 and 0 otherwise. *Separated* is a dummy equal to 1 if the employee was separated between 2011 to 2018 and 0 otherwise. *Post* is a dummy equal to 1 for months following separation and 0 otherwise. *Month* refers to the calender year-month, *Wage Bins* are constructed at \$1,000 width for pre-separation income, *Firm* represents the separated firm, *Location* corresponds to the 3-Digit Zipcode, *Tenure* is constructed as deciles from the distribution of tenure as of the month prior to separation, and *Separation Cohort* refers to the year of separation. Robust standard errors are reported in parentheses and clustered at the individual level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

	Log Earnings	
	Finance	Non-Finance
	(1)	(2)
Misconduct × *Separated* × *Post*	0.070*	-0.063***
	(0.041)	(0.019)
Separated × *Post*	-0.293***	-0.264***
	(0.025)	(0.013)
Individual FE	Y	Y
Wage Bin × *Month FE*	Y	Y
Firm × *Location* × *Year FE*	Y	Y
Separation Cohort × *Year FE*	Y	Y
N	1,642,767	3,473,614
$Adj.R^2$	0.949	0.945