Women in STEM and Job Quality

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Abstract

Women remain underrepresented in STEM careers that offer high average pay, and recruiting and retaining women in STEM careers is major public- and private-sector goal. The efficacy of such policies and their implications for the distribution of earnings and job satisfaction depend on the treatment effects of working in STEM for STEM-marginal women. This study uses administrative employment and survey data to shed light on the drivers of mid-career entry into and exit from STEM. We use difference-in-difference approaches to document three main findings. Our first finding is that women entering STEM professions see their earnings rise by 17 and also experience gains in non-pecuniary career satisfaction. Our second finding is that while earnings effects are approximately symmetric for STEM exiters, career satisfaction effects are not: earnings fall by 14 for women who leave STEM, but non-pecuniary job satisfaction weakly increases. Third, we find suggestive evidence that job satisfaction in STEM declines over time, indicating that exit behavior could be driven by compensating differentials. Our results highlight the possibility that improving STEM workplace amenities may reduce STEM career exits for women.

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1 Introduction

The demand for skilled labor in Science, Technology, Engineering, and Math (STEM) occupations has grown rapidly in the last decade. From 2011 to 2023, wage growth in STEM (12.9%) outpaced wage growth in other occupations (9.1%), even as the fraction of workers with STEM jobs increased from 11.4% in 2011 to 13.7% in 2021, according to American Community Survey (ACS) data. The Bureau of Labor Statistics expects wage growth in the sector to continue to outpace other occupations as demand for STEM talent continues to grow faster than supply (Bureau of Labor Statistics, 2024).

Compared to other highly-paid occupations with large shares of highly-educated workers, STEM occupations stand out for how little their gender composition has changed over time. In the ACS, among workers between the ages of 25 and 60, women have recently achieved near-parity in terms of representation among doctors, lawyers, and managers, as seen in Figure 1. The female share of workers in these occupations all grew dramatically from 2001 to 2021, rising from 29% to 44% for doctors, 33% to 44% for lawyers, and 33% to 42% for managers. In contrast, the share of women in STEM occupations grew only two percentage points, from 27% to 29%.[1] Given the current and projected future growth in STEM occupations and their importance to innovation, policy and education leaders continue to focus on increasing diversity in STEM so that individuals from all backgrounds can benefit from skill-biased technological change towards STEM.

Why do women remain underrepresented in STEM? Previous work has highlighted both pay and non-pay dimensions of job quality that may make women less likely to join or stay in STEM (Fry et al., 2021; Moss-Racusin et al., 2012; Spoon et al., 2023; Hunt, 2016). For example, in a descriptive analyses using ACS data, Fry et al. (2021) find that the median earnings of women in STEM occupations was $66,200, which is just 74% of the median STEM

[1] We categorize occupations using the Census STEM, STEM-Related and Non-STEM-Related Code List, which is based on the recommendations issued by the Standard Occupational Classification Policy Committee (SOCPC). STEM includes computer and mathematical occupations; engineering occupations; life, physical, and social science occupations; and managers of those previous groups. STEM does not include health occupations.

earnings for men of $90,000. A major challenge in this literature is understanding the causal effects of shifts into or out of STEM on the policy-relevant population of STEM-marginal women, which may differ from gaps measured in the cross section. This distinction has important policy implications. If earnings losses for women who leave STEM are small, then policies that aim to retain women in STEM careers may do little to address gender earnings gaps. Conversely, if women leave STEM despite experiencing large earnings losses when they do, then retention policies based on promises of increased pay may not be effective.

We study STEM career dynamics for women using novel administrative employment data from the state of New Jersey's Unemployment Insurance (UI) system linked to private vendor resume data (hereafter, the "UI-resume" data). The resumes were compiled by Draup, a leading talent intelligence company that leverages global labor market datasets, covering 850M+ resumes and 450M+ job postings in 120 countries. Draup's resume records indicate gender and provide detailed measures of occupation history that are not otherwise reflected in the underlying administrative records.[2] The unusual combination of features – administrative earnings records paired with information on occupations – make the linked sample particularly well-suited to studying STEM occupation choices after women have already entered the workforce. Moreover, the post-schooling career decisions of women in STEM are arguably understudied relative to a large literature that focuses on female educational choices and the decisions to specialize and complete training in science and technical fields (e.g., Bettinger and Long, 2005; Griffith, 2010; Carrell et al., 2010; Bostwick and Weinberg, 2022).

Our analysis is based on analyzing careers for samples of women who make mid-career entries and exits into and from the STEM workforce. We create these samples using the linked UI-resume data to study earnings before and after entry and exit. To ensure comparability, we create weights for the exit sample based on the distribution of occupation changes in the entrant sample. As a key supplement to this analysis, we also use data from the

[2]The UI data include quarterly earnings, an employer identifier, and the industry of employment (6-digit NAICS) for each individual working in NJ. In the resume data, Draup infers gender from first names.

National Survey of College Graduates (NSCG) which provides information on overall and detailed measures of job satisfaction. We create analogous entrant and exit samples using the NSCG data to study non-monetary outcomes associated with STEM careers.

For both monetary and non-monetary outcomes, our analysis focuses on estimating the returns to STEM career entry and exit using difference-in-difference approaches. For example, to estimate the impact of switches into STEM from non-STEM occupations, we compare STEM entrants to other workers who switch between two distinct non-STEM occupations. Importantly, this approach estimates impacts as the change in earnings from entering STEM relative to entering a different non-STEM occupation. We use an analogous approach to study career exit where the comparison group is defined as women who make career transitions but remain in a STEM job.

We estimate that women who enter STEM during mid-career experience substantial earnings gains relative to their peers in the comparison group who enter non-STEM jobs. We estimate a return of 17% ($12,497) in the UI-resume sample. We find a similarly large, positive impact based on our analysis of the entrant sample created using the NSCG surveys. In line with the results in our STEM entrant sample, we find comparable magnitude earnings relative losses from leaving the STEM workforce. For example, in the UI-resume sample, we find that leaving STEM careers is associated with 14% lower earnings relative to the comparison group of women who change occupations but remain in STEM.[3]

Next, our analysis turns to non-monetary returns to STEM careers using the NSCG samples of women who exit and enter STEM. We focus on standardized measures of overall job satisfaction as well as indices of satisfaction based on non-pay aspects of job satisfaction. Relative to their comparison group counterparts, women entering STEM see a significant increase in total non-pay satisfaction of 0.27 standard deviations. These impacts appear to be driven primarily by increases in reported satisfaction with their job's opportunities for advancement, intellectual challenge, independence, and level of responsibility. When we

[3] In the NSCG sample, we find a similar 21% reduction in earnings for women who exit STEM, relative to within-STEM switchers.

turn to study women leaving STEM, we see no evidence of declines in either satisfaction measure—instead, we find a significant increase in non-pay satisfaction.

Overall, the entrant and exit results provide consistent evidence that suggests there are strong wage incentives to join or stay in the STEM workforce. Moreover, we create analogous entrant and exit samples for men and estimate returns to STEM careers that are comparable in magnitude to our estimates for women. The comparable gains for women and men suggest that pay discrimination may not necessarily prevent participation in STEM for the types of mid-career women we are able to study using our administrative and survey data.

At the same time, the job satisfaction results do not paint a clear picture on the non-pay incentives for women in STEM. Mid-career women who join STEM appear to experience substantive gains on several important measures of satisfaction. At the same time, women who leave the STEM workforce also report experiencing non-pay gains. Moreover, those leaving STEM do not experience detectable reductions in overall satisfaction even though the estimated impact on their earnings is negative.

As a final exercise, we provide evidence to clarify the interpretation of the pattern of results that we find for job satisfaction. One hypothesis is that women may experience decreases in the non-pay returns to STEM careers over time. The ideal data to test this idea would contain high-frequency measures of job satisfaction that cover a long-period during a given worker's career. Whereas the NCSG survey does not provide such longitudinal coverage, we instead rely on a cross-sectional analysis that compares STEM and non-STEM worker job satisfaction by age. At relatively young ages, we find that women in STEM typically report having high non-pay job satisfaction relative to their peers of the same age working in non-STEM fields. This non-pay premium declines sharply with age and becomes negative when workers are in their mid-40s. These results are consistent with the possibility that non-monetary returns to STEM careers weaken over time, although an important caveat is that our approach does not control for compositional changes in the STEM workforce over the career life-cycle.

This paper's findings contribute to understanding STEM careers and female labor participation. As noted above, much of the prior literature within economics focuses on the years leading up to labor force entry by studying human capital and barriers to women in STEM courses and educational tracks (Kahn and Ginther, 2017). Our work is most closely related to previous quantitative investigations that study exit from STEM careers (Hunt, 2016; Delaney and Devereux, 2022; Speer, 2023). We innovate relative to this work primarily by focusing on mid-career decisions and providing novel quantitative evidence on how monetary and non-monetary factors drive both entry and exit decisions. More broadly, our work complements recent studies that have focused on how workplace flexibility and hours shape career decisions in STEM and other professional occupations (Gicheva, 2013; Cortes and Pan, 2017; Wasserman, 2023).

2 Background

2.1 Gender Gaps in Employment

In the twentieth century, women in the US entered the labor force in unprecedented numbers, transitioning from intermittent employment to supplement their households' income to primary earners with developed career paths (Goldin, 2006). Prior research has documented that women have historically been segregated in the labor market in terms of their occupations (Blau et al., 2013). While there has been recent progress in many high-education occupations, STEM has been an important exception. As noted above, Figure 1 demonstrates that the share of STEM workers who are female has remained less than 30% of STEM workers over the last twenty years, while among doctors, lawyers, and managers, the female share increased to nearly 50%. Top executive positions are not yet near 50% female representation, but unlike STEM, the female share increased substantially between 2001 and 2021, from 22% to 33%.

A basic descriptive analysis suggests that all of these high-education occupations offer women a strong earnings premium relative to other non-STEM occupations. Female doctors, lawyers, and managers (other than top executives) are paid 201%, 143%, and 72% more than women in other non-STEM occupations, respectively, while women in STEM are paid 46% more than those female non-STEM workers (see Appendix Table A.1). If we adjust for age, education level, and children, female doctors earn 163% more than other female non-STEM workers, lawyers earn 110% more, managers earn 67% more, and STEM workers earn 45% more.

2.2 Mid-Career STEM Entry and Exit

This paper focuses on mid-career occupation transitions into and out of STEM occupations, which stands in contrast to much of the prior literature studying female enrollment in STEM college major choices (Kahn and Ginther, 2017). Our analysis is motivated by the fact that workers continue to make choices about career paths in STEM after completing their education. In addition to contributing directly to the gender ratio in the STEM workforce, later-career shifts may reveal facts about occupations that explain patterns in initial career choices. Appendix Table A.2 reports summary statistics on workers entering and exiting STEM based on data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey. The ASEC survey asks workers about their job in the previous as well as the current year. Among female STEM workers, 2.9% are new entrants who entered STEM from a non-STEM occupation and 2.5% exited STEM for a non-STEM occupation in the previous year. The average age among female STEM entrants and exiters was 37.4 and 37.9, respectively. Many switchers had graduate degrees, with 30% of female STEM entrants having a master's degree or higher and 33% of STEM exiters having a master's degree or higher. These patterns for women distinctly differ substantively from what we observe for men in the ASEC. For instance, the flow of STEM entry and exit is significantly higher for women while the average education levels are detectably elevated.[4]

[4] The fraction of female STEM workers who are new entrants is significantly greater than the fraction of male STEM workers who are new entrants, with a p-value of less than 0.001. The fraction of female STEM

3 Data

Our analysis relies on three main sources of data. First, we access records from New Jersey's Unemployment Insurance (UI) system that track workers' earnings in each quarter. The UI data contain over 700 million worker-by-firm-by-quarter records from 1998 Q1 to 2021 Q2, covering 616,390 unique firms and 13,823,731 unique workers. The records include worker and firm identification numbers as well as the total earnings paid by the firm to the worker. In each quarter, a worker-by-firm pair only appears if the firm paid that worker a positive amount in that quarter. We deflate all earnings records to 2020 dollars. A key limitation in the UI records is that they do not contain any indication of workers' occupations. While the data do provide information on firm industries, this is only weakly correlated with occupations.[5]

We address the need for indicators of workers' occupations by linking the UI records to private vendor resume data. The resume data consist of snapshots of work histories from 2021 which include job titles, start dates, end dates, and firm names. We determine occupations from these work histories using Sockit, a natural-language processing tool developed specifically to map unstructured text from job titles, job postings, and resumes to Standard Occupational Classification (SOC) codes (Dixon et al., 2023). The resume data also provide information on educational attainment.[6]

Third, we analyze data from the National Survey of College Graduates (NSCG) to learn

workers who exited STEM is significantly greater than the same for men ($p < 0.001$). The average age for women entering STEM is not significantly different from the same for men ($p = 0.107$). The average age for women exiting STEM is significantly less than the same for men ($p = 0.009$). The fraction non-white is not statistically different between male and female STEM entrants and exiters ($p = 0.477$ and $p = 0.243$, respectively). The fractions of both STEM entrants and exiters who had a masters degree or higher are significantly greater for women ($p < 0.001$ for both).

[5] Using BLS 2020 employment estimates by 2-digit NAICS code and 2-digit SOC code, we find that the Cramer's V (a measure of correlation between categorical variables) of the industry-occupation matrix is 0.46.

[6] For 358,248 linked records, there is an indication of the worker's education, but many entries are missing institutions, start dates, end dates, majors, or all four. For each worker, we determine the observed education level attained by any given date. We specify the education levels to include high school, certificate, associate, bachelor, master, and doctoral/professional. We also note the start date of the first post-secondary education enrollment, which we utilize as a proxy for age. Draup infers gender from first names, and so for all linked records we have have this gender indication from the resume data.

about workers' preferences and job satisfaction. The NSCG is a survey taken by a subset of American Community Survey (ACS) respondents. The survey includes information about respondents' employment, income, and occupation, as well as a detailed questionnaire about their job satisfaction. Key to our approach, we utilize the fact that the NSCG has a panel structure, with a subset of respondents completing multiple surveys. For a limited cross-sectional analysis, we utilize the 2003-2021 NSCG surveys, while for our main panel analysis, we link records from the 2003-2015 NSCG surveys.

3.1 UI-Resume Linked Samples

We link the state of New Jersey UI and resume records to assemble a person-by-quarter panel that includes information on occupation and quarterly earnings. All UI earnings records are deflated to January 2020 using the Consumer Price Index (OECD, n.d.). We restrict the panel to focus on employees who make direct employer-to-employer transitions (i.e., there are no employment gaps) and who switch occupations between 12 and 40 years after their first post-secondary enrollment as measured in their resume history. Appendix Table A.3 provides demographic, education, and employment summary statistics from the American Community Survey (ACS) and the linked UI-resume data.[7] The first two columns show statistics for recently employed working-age US and NJ adults from the ACS, while the third and fourth columns show statistics for samples of workers with linked UI-resume records. Overall, these descriptive results demonstrate that those in the linked UI-resume data who switch occupations in mid-career are generally older, attain greater levels of education, and have higher annual earnings relative to typical working-age adults in New Jersey.[8]

With the restricted sample of workers who make mid-career transitions, we create two analytic samples of employed women.[9] First, we create an entrant sample which is comprised of "entry treatment" workers in non-STEM occupations who make direct transitions

[7]We focus on 2021 because these are the most recent records in our linked UI-resume data.

[8]The linked UI-resume data generally contains records for younger workers relative to the ACS (see Column 3).

[9]We create analogous samples for men and discuss relevant results throughout our analysis.

into a STEM occupation and a comparison group of non-STEM workers who make transitions into a new, non-STEM occupation. Similarly, we form an exit sample that includes "exit treatment" workers in STEM careers who make direct transitions into a non-STEM occupation and a comparison group of STEM workers who make transitions into new STEM occupations. As we discuss in Section 4, the comparison group in both samples implies that our empirical strategy will isolate the effect of entering or leaving a STEM occupation that nets out the general impact of changing occupations. We provide further discussion of the treatment and comparison groups in our samples below.

3.2 NSCG Samples

We create additional analytic samples from the NSCG that focus on female respondents for whom we observe at least two survey instances. Our sample is created by initially linking individuals across survey years to construct a panel of 81,177 individuals with two surveys each where the first survey year is between 2003 and 2013.[10] In the resulting two-survey panel of NSCG respondents, we restrict the data to employed persons who switched occupations between the first and second surveys and were between 25 and 60 years old during the first survey.[11] This latter restriction maintains our focus on mid-career workers who make occupation transitions. As a point of comparison, the final column of Appendix Table A.3 shows that occupation switchers in the NSCG sample have similar age at the time of their transition, although they are less likely to be White, more likely to have a master's degree and have lower prior year earnings. Using this sample of occupation transition workers, we create entrant and exit samples where the treatment and comparison group definitions mirror the definitions that we use with the UI-resume samples.

A key feature of the NSCG is the set of survey questions that address job satisfaction. In addition to asking about respondents' overall satisfaction with their principal job, the

[10] Appendix Table A.4 shows the number of workers in each pair of surveys; workers generally appear in consecutive surveys.

[11] We only include those workers who both moved to a new employer and also changed their occupations between the first and second survey.

survey asks them to rate their satisfaction with several specific aspects of their job on a scale of 1 (Very satisfied) to 4 (Very dissatisfied). The aspects that respondents are asked about include salary, benefits, opportunities for advancement, intellectual challenge, independence, job security, location, level of responsibility, and contribution to society. Respondents also indicate the level of importance of each of those aspects on a scale of 1 (Very important) to 4 (Not important at all). In our analysis, we reverse the sign of all of these responses so that higher numbers correspond to more satisfaction and more importance, and we standardize the responses so that they have a mean of 0 and a variance of 1 in the full NSCG pooled cross-section that includes surveys from 2003 through 2021.

4 Empirical Strategy

4.1 Models

We estimate the impact of a career change from a non-STEM occupation to a STEM occupation using two types of differences-in-differences approaches. First, in the quarterly earnings panels constructed from UI-resume records, we estimate a generalized difference-in-difference (event study) specification. Formally, our event-study specification is:

$$y_{it} = \phi_i + \sum_{k \neq -4} \mathbb{1}(t - t_i^* = k) \left(\theta_k + f_k(\boldsymbol{y}_{i,pre}, \boldsymbol{x}_i)\right) + \sum_{k \neq -4} \beta_k \, \mathbb{1}(t - t_i^* = k) \times d_i + \epsilon_{it} \tag{1}$$

where y_{it} is worker i's earnings in calendar quarter t. The model includes an individual-level fixed effect ϕ_i to control for time-invariant differences between workers. The indicator d_i is equal to 1 if worker i transitioned to a STEM occupation, and each of the $k-$many indicators $\mathbb{1}(t - t_i^* = k)$ take a value of 1 at the "event-time" k which is measured relative to t_i^*, the calendar quarter of worker i's occupation change. The set of θ_k coefficients on these event time indicators account for earnings changes around occupation transitions that are exhibited by both treatment group and comparison group workers. We also control for interactions between the event-time indicators and measures of a limited set of pre-transition earnings and other baseline characteristics (i.e., $f_k(\boldsymbol{y}_{i,pre}, \boldsymbol{x}_i)$ in Equation 1) to account for the fact that workers switching from non-STEM-to-STEM and non-STEM-to-non-STEM occupations have different career histories.[12,13]

In Equation 1, our main interest are the estimates of the set of β_k coefficients which represent the mean difference in a worker's outcome relative to an omitted event time period, which we specify as event time $k = -4$, the period four quarters prior to the worker's occupation transition. Given the definition of our comparison groups (i.e., non-STEM workers who transition occupations in the entrant sample and STEM workers who transition in the exit sample), these estimates of β_k represents the *differential* return to entering STEM.

Identifying causal estimates of the parameter β_k for event time periods $k > 0$ relies on assuming a common trend assumption between workers in our treatment and comparison groups. For example, our entrant analysis assumes that workers moving into STEM occupations would have had the same earnings as the comparison group of workers who make within-non-STEM transitions in the counterfactual world where the treatment group never entered STEM, after conditioning on our set of controls. As is standard, this event study approach is specified to provide an important falsification test that addresses the potential concern of differential trends. Specifically, if earnings were evolving similarly for treatment and comparison group workers, we would expect that estimates of β_k to be small and not statistically significant in the k periods that precede an occupation transition. By design, our main falsification test is based on examining coefficients for event time periods that occur more than a year prior to treatment (i.e., $k \in -8, -7, -6, -5$). The choice to focus on $k \in -8, -7, -6, -5$ is driven by our inclusion of controls for pre-transition earnings in event time periods $k \in -3, -2, -1$.

Our second approach is a restricted difference-in-difference approach that compares out-

[12] In the UI sample, we have eight quarters of pre-transition outcomes available, but we include only quarters $t = -3$ to -1 in $\boldsymbol{y}_{i,pre}$.

[13] Our use of controls bears similarity to previous studies that use event study models and propensity score weighting strategies to estimate effects of worker displacement and job loss (e.g., Stepner 2019).

comes for treated and comparison group workers before and after their career transitions. This model allows us to analyze the NSCG respondents where only two time periods are available for each worker included in our samples. Our estimating equation is:[14]

$$y_{is} = \psi_i + g_s(\boldsymbol{y}_{i,pre}, \boldsymbol{x}_i) + \lambda Post_s \times d_i + \varepsilon_{is}, \tag{2}$$

where y_{is} is a worker i's earnings or job satisfaction in survey wave s (where $s = 1$ for their first survey and $s = 2$ for their second survey). As in our event study, we include an individual-level fixed effect ψ_i to control for baseline (pre-transition) differences between workers. As above, the indicator d_i is equal to 1 if worker i transitioned into or from a STEM occupation, and the indicator $Post_s$ takes a value of 1 when $s = 2$, which by construction is the survey wave after an individual makes an occupation transition.

In Equation 2, our main object of interest is the coefficient λ which represents the differential change in earnings for treated workers relative to their comparison group counterparts after conditioning on a basic set of controls specified in $g_k(\boldsymbol{y}_{i,pre}, \boldsymbol{x}_i)$. The specific controls we use include: education level, year of first survey, occupation in first survey, sector (public or private) in first survey, a quadratic in age, tenure at the new job, indicators for the presence of children over and under 6 years old in the household, and pre-transition job aspect importance scores.

Distinct from our event study approach, a key limitation in this two-period difference-in-difference framework is that we are unable to perform the same test to assess the parallel trends assumption necessary for causal inference. That said, we can estimate Equation 2

[14] To summarize the event study results, we also estimate a version of Equation 2 using the UI-resume linked samples. The key distinction in this case is that we replace the set of controls $g_s(\boldsymbol{y}_{i,pre}, \boldsymbol{x}_i)$ with a distinct set of controls, denoted $f(\boldsymbol{y}_{i,pre}, \boldsymbol{x}_i)$. The differences in the set of controls used are determined by data availability in underlying data sources. In the NSCG samples, the covariates include level of education, first survey year, a quadratic in age, tenure in new position, indicators for children in the household, sending occupation, sending sector, and job aspect importance scores from the first survey. In the UI-resume sample, the covariates include level of education, a quadratic in year, a quadratic in the age proxy (years since first postsecondary record), sending occupation, sending industry, indicators for race/ethnicity, log earnings 1-4 quarters before the occupation transition, and the number of quarters employed in the year before the occupation transition.

using the earnings measures in the UI-resume sample where it is possible to conduct pre-trend analysis. In this way, we can provide limited evidence on potential identification concerns by comparing results for earnings in the NSCG and the linked UI-resume samples.

4.2 Weights

We create weights to hold constant the composition of STEM occupations across the STEM entrant and exit results. Specifically, we anchor all samples to the distribution of occupations for STEM entrants in the UI-resume linked sample. The weights are used in our UI-resume linked exit analysis as well as both of the STEM entrant and exit analysis using the NSCG samples. In Appendix Table A.5, we report a parallel set of results without weights. The unweighted results are qualitatively unchanged relative to our main results.

5 Results

5.1 Summary Statistics

In Table 1, we present summary statistics for our STEM entrant and exit samples. The table provides means for the treatment and comparison groups in our UI-resume (Columns 1-4) and NSCG (Columns 5-8) samples, respectively. An important finding from these results is that our treatment and comparison groups tend to differ on important demographic characteristics such as race and education levels. In addition, the treated and comparison group of workers also appear to differ non-trivially in terms of pre-period earnings. For instance, in both the UI-resume and NSCG samples, we see that STEM entrants tend to have higher earnings than the comparison group prior to any occupation changes. These findings collectively highlight the importance of our using a difference-in-difference type of approach that addresses concerns over time-invariant differences across workers. Moreover, the patterns motivate our initial event study analysis using the UI-resume sample where we can shed light on the validity of the common trends assumption necessary for a causal interpretation of our results.

5.2 Event Study

Next, we estimate the effects of STEM transitions on earnings for women using the event study approach and the UI-resume linked samples.[15] Figures 2a and 2b plot estimates of the set of β_k coefficients from Equation (1) for women who enter and exit STEM occupations, respectively. We specify the earnings outcome y_{it} as $log(Earnings_{it} + 1)$ due to the presence of outliers in terms of their earnings in some quarters.[16]

We begin with two observations from Figure 2a which compares STEM entrants to the comparison group of non-STEM workers transitioning into other non-STEM careers. First, the coefficients for event time periods $-4 \leq k \leq -1$ are by construction equal to zero. This is due to the fact that the $k = -4$ period is the omitted category while the results for periods $k \in -3, -2, -1$ are due to the fact that we include controls for earnings in these periods fully interacted with event time and the event time by treatment indicators. Second, the coefficients for periods $-8 \leq k \leq -5$ are close to zero, indicating that the treatment and comparison groups were on similar trends prior to their occupation transition after conditioning on our set of baseline controls. This supports our identification assumption.

The main conclusion based on Figure 2a is that entry into STEM increased earnings relative to the transitions from non-STEM-to-non-STEM occupations for the comparison group. The pattern of effects throughout the post treatment period (i.e., event time periods $k > 0$) does not appear to be particularly dynamic over the two years that we analyze as the coefficients for periods $0 \leq k \leq 8$ are close together around 17% (0.16 log points).

Similarly, Figure 2b compares STEM exiters to workers who stay in STEM but transition

[15] We later benchmark these results for women in STEM by providing analogous results for men in Section 6.1.

[16] These results do not condition on employment (i.e., workers with zero earnings in a quarter will have $y_{it} = log(1) = 0$. A concern for the interpretation is that these results are driven by differences in employment rather than differences in earnings among employed individuals. In Appendix Figures A.4a and A.4b, we also show estimates where the outcome y_{it} is an indicator of nonzero earnings, $\mathbb{1}(Earnings_{it} > 0)$. Employment appears to be unrelated to these occupation transitions.

between STEM occupations. Here, the coefficients for the pre-transition periods $-8 \leq k \leq -5$ are close to zero, supporting the validity of our design for causal interpretation. Exiting STEM, earnings decreased for women. The estimates do not look dynamic, with similar coefficients for all periods in periods $0 \leq k \leq 8$ at just under -16%. The magnitude is similar (but opposite signed) to what we find for the STEM entrant sample.

These results provide consistent evidence that STEM careers provide an earnings premium. However, it is worth noting that the magnitude of the premium is much less than an observational estimated return to STEM employment based on comparing STEM and non-STEM workers. As seen in Appendix Table A.1, STEM workers earn 45% more than their non-STEM counterparts with a basic adjustment for differences in age, children, and education level. A natural interpretation of the difference in results is the fact that our event-study results better capture the relative returns to STEM by focusing on a more comparable comparison group of workers.

5.3 Differences-in-Differences

5.3.1 Earnings

Table 2 reports results from estimating Equation 2 using the UI-resume and NSCG samples in Columns 1 and 2, respectively. The first row contains results for STEM entrants, while the second row contains results for STEM exiters. As expected given the consistent pattern of coefficients, the estimates in Column 1 show that women entering STEM see their earnings increase relative to women switching between non-STEM occupations by 17% (0.157 log points). Similarly, women exiting STEM see their earnings decrease relative to women switching between STEM occupations by 14% (0.152 log points).

The main new earnings result in Table 2 is that we obtain generally similar estimated impacts of STEM entry and exit in the weighted NSCG samples. Women entering STEM see their earnings increase relative to women switching between non-STEM occupations by 21% (0.192 log points). Their peers exiting STEM see their earnings decrease relative to women switching between STEM occupations by 18% (0.201 log points). As with our event study results using the UI-resume linked samples, these results for the NSCG samples suggest that the earnings premium is economically significant although smaller in magnitude relative to basic comparisons in the ACS of earnings for workers who do and do not work in STEM occupations.

The comparability of the estimated impacts in the UI-resume and NSCG samples is striking given some important distinctions in how we implement the two difference-in-difference approaches. First, the research design differs due to distinctions in the sets of controls available to use in our specifications. As we discussed in Section 4.1, the main distinction is that we include richer demographic and job preference controls in our NSCG analysis but relatively more detailed measures for earnings histories in our specifications using the UI-resume sample. Second, there are important differences in data quality and measurement. In the UI-resume linked sample, we have administrative records of total labor earnings in each quarter for nine quarters immediately following an occupation transition. In contrast, the NSCG samples contain survey responses to questions about annual salary measured in two survey waves separated by between two and seven years (depending on the survey cohort).

5.3.2 Job Satisfaction

One recurring explanation for the persistent gender gaps in STEM employment is that overall job satisfaction in science and technology careers is particularly low for women. Prior qualitative work suggest that discrimination and uncomfortable work environments may make STEM careers unappealing for women (Spoon et al., 2023). In addition, STEM careers may be less satisfying due to inflexible work hours or the fact that some women may place a higher priority on other job attributes such as a sense of contribution to society that are more attainable in non-STEM careers (Cortes and Pan, 2017). For any of these reasons, the earnings gains to working in STEM documented above may not be sufficient to attract women and increase female representation.

Using the NSCG samples, we study two main measures of job satisfaction. The first measure is a response to a question on overall job satisfaction. The second is the sum of the responses to each of the survey questions on satisfaction with job attributes that do not directly relate to pay: opportunities for advancement, intellectual challenge, independence, job security, location, level of responsibility, and contribution to society. We standardized each of these two measures to have mean zero and variance one in the full NSCG pooled sample of cross-sections.

Table 2 provides our main satisfaction results based on Equation 2 and shows that we observe distinct impacts in the entrant and exit samples. Relative to women switching between non-STEM occupations, the point estimate in the first row shows that women entering STEM see their index measure of overall satisfaction increase by 0.148 standard deviations (Column 3), although this increase is not statistically different from zero. We obtain more precise results for the index of non-pay satisfaction (Column 4) which increases by 0.267 standard deviations and is significant at the one percent level.

However, we also find that job satisfaction appears to increase as women leave STEM. The non-pay satisfaction index increases by 0.150 standard deviations and is significantly different from zero at the five percent level. Examining this result alongside what we obtain in the entrant sample suggests that job satisfaction—particularly on the non-pay dimension—may not be a constant occupational feature.

Appendix Table A.10 breaks down results into each of the individual job satisfaction components. Increases in non-pay satisfaction among STEM entrants seem to be driven by increases in satisfaction with intellectual challenge, independence, level of responsibility, and contribution to society. For STEM exiters, the increase in non-pay satisfaction is driven by increases in satisfaction with job security, level of responsibility, and contribution to society.

6 Discussion

6.1 Effects of Mid-Career STEM Entry and Exit for Men

A natural comparison for the results for women are the corresponding estimated impacts of STEM entry and exit for men. Using similar sample definitions based on the UI-resume and NSCG records, we create entry and exit samples for men.[17] We also create a parallel weighting scheme for men that anchors the distribution of STEM occupations to the STEM entrants in the men's UI-resume sample but is not linked to any occupation distribution in the women's UI-resume sample. For men, Appendix Figures A.5a and A.5b report event study results, and Appendix Table A.7 reports the difference-in-difference estimates.

The entry and exit results for men show that STEM has a large and statistically significant earnings premium relative to non-STEM occupations. Relative to our results for women, there is less clarity on the exact magnitude as there are important differences in the point estimates for men who enter and leave STEM. For instance, based on Equation 2, we estimate that male entrant earnings increase by 12% (0.113 log points) and male exiter earnings decrease by only 5% (0.05 log points), respectively. In addition, we also find important differences in results based on whether we analyze the UI-resume and NCSG samples. Here, we find the estimates tend to be larger in magnitude (e.g., a 30 percent or 0.265 log point effect on salary) in the NSCG samples.[18]

Another key observation is that the difference-in-difference results from Appendix Table A.7 shows that men transitioning into STEM have no detectable changes in either the overall job satisfaction measure or the non-pay job satisfaction index. While the estimates for men and women are not statistically distinct for overall satisfaction, we can reject the null hypothesis of equal impacts for the non-pay index in the entrant sample (e.g., the increase of 0.287 standard deviations for female STEM entrants is significantly different from the

[17] Appendix Table A.6 reports summary statistics for the entry and exit samples of men.

[18] Similar to our results for women, Figures A.5a and A.5b show there is no obvious temporal pattern; earnings immediately jump and fall after entering and leaving STEM occupations, respectively.

decrease of 0.023 standard deviations for male STEM entrants at the five percent level).

We draw two main conclusions from these results. First, the comparable STEM earnings returns for both women and men suggests that pay discrimination may not necessarily drive gender differences in rates of mid-career entry and exit from STEM. There is some evidence that the earnings premium for STEM vs. non-STEM occupations is greater for women as observed from the larger point estimates in the UI-resume entry and exit samples.[19] Second, the pattern of job satisfaction results on non-pay dimensions suggest that non-pay aspects of job quality may be distinct concerns for women. In particular, the results for the entrant and exit samples suggest that women have relatively larger gains in non-pay satisfaction when entering or leaving their STEM occupations.

6.2 Age and Job Satisfaction

In our investigation of the incentives for women to pursue careers in STEM, our results show that women gain an earnings premium of between 14% and 21% by working in a STEM occupation. Our results are less clear on whether STEM occupations offer women better non-pay amenities. While female non-STEM-to-STEM switchers experience a relative increase in non-pay job satisfaction when working in STEM, female STEM-to-non-STEM switchers also experience a relative increase in non-pay job satisfaction.

We attempt to resolve the potential tension in our results by exploring a pertinent difference between STEM entrants and STEM exiters: STEM entrants are at the beginning of a STEM employment spell, while STEM exiters are at the end of a STEM employment spell. Ideally, we would observe non-pay job satisfaction evolve over the course of individuals' careers in STEM and non-STEM occupations. However, the short panel structure of the NSCG does not lend itself to a high-frequency analysis. In place of this, we examine the non-pay job satisfaction premium of STEM occupations by age using the cross-section

[19] When we specify the dependent variable as quarterly earnings in levels, we also find larger point estimates for the impact of joining the STEM workforce for women compared to men. See Appendix Tables A.8 and A.9.

of NSCG respondents.

For each two-year age bin, we estimate the difference in non-pay job satisfaction between STEM and non-STEM occupations in a pooled NSCG cross-section covering 2003-2021. We use the following model:

$$y_{ia} = \beta_a STEM_{ia} + w_i \gamma_a + \epsilon_{ia} \tag{3}$$

where $STEM_{ia}$ is equal to 1 if individual i in two-year age bin a has a STEM occupation and 0 otherwise; and w_i is a vector of covariates that include log salary, race, survey year, and indicators for the presence of children over and under six years old in the household. We estimate Equation (3) separately for age-bins that range from 24 to 64. The objects of interest are the parameters β_a, which is the relative gain or loss in non-pay job satisfaction.

Figure 3 plots our estimates of β_a and shows a pattern of non-pay job satisfaction z-scores decreasing rapidly from 0.282 to 0.025 between ages 24 and 32. Then there is a more shallow decrease to -0.129 at age 44, where it plateaus and then increases back to 0.001 at age 64. While these results come from pooled cross-sections, they suggest that the satisfaction of individual women in STEM may degrade over time, especially for women in their 20s and 30s. While the decline in the STEM satisfaction premium overlaps with common childbearing years, it does not appear to be related to having children. Our specification includes as covariates indicators for the presence of children. When we drop those indicators, $\hat{\beta}_a$ is nearly identical.

These results appear to reconcile our findings in the entrant and exit sample by suggesting that job satisfaction is not constant within STEM occupations. In addition, the results appear consistent with the idea that women may exit STEM jobs due to concerns over non-pay job satisfaction or a lack of support in the workplace. Toward the latter, Appendix B explores this idea in the NSCG sample by examining whether women in STEM have peers that are very different from their peers in non-STEM occupations, particularly on the dimension of what they value about their jobs.

7 Conclusion

Women are underrepresented in the STEM workforce. STEM jobs are strategically and politically important, and workers in STEM stand to benefit from skill-biased technological change. In light of this, the lopsided gender ratio in STEM has received much attention from policymakers and researchers. That attention tends to focus on college major choice. In this paper, we investigate the incentives for women to seek employment in STEM by analyzing the experience of women making mid-career occupation transitions.

First, we consider monetary incentives. STEM occupations have a large earnings premium in the cross-section, and we test whether individuals experience a similar premium when they switch into a STEM occupation mid-career. Using administrative earnings records from New Jersey linked to resumes, we find that women entering STEM from a non-STEM occupation see their earnings increase by 17% relative to women switching between non-STEM occupations. Mirroring this, earnings of STEM exiters decreases by 14% relative to within-STEM switchers.

Next, we consider job satisfaction across a range of non-pay aspects of employment. Using the National Survey of College Graduates, we find that female STEM entrants (relative to within-non-STEM switchers) see their non-pay satisfaction increase by 0.267 standard deviations. However, when women exit STEM, their non-pay satisfaction also increases (by 0.150 standard deviations). That is, STEM entrants and exiters appear to feel differently about STEM.

To shed light on this dynamic, we examine the STEM satisfaction premium across age in the cross-section. We see that non-pay satisfaction decreases dramatically between the ages of 24 and 44, for STEM relative to non-STEM workers. Although these cross-sectional estimates for different ages come from different subsets of workers, the result suggests that the experience of women in STEM may degrade over time.

What are the potential implications of our findings? To increase female employment, managers at STEM firms may need to improve the non-pay aspects of the careers that they offer. One finding highlighted in our NSCG analysis is the importance of perceptions of a job's contribution to society in female career exit outcomes. Similar to legal and medical settings, STEM firms can allow their workers to contribute to society through pro bono work. High-profile STEM firms such as the technology companies Adobe and IBM currently provide paid time off for employees to use their expertise to pursue charitable projects with non-profit partners (Chong and Fleming, 2014; Taproot Foundation, 2021). This dovetails with research that shows that corporate social responsibility (CSR) policies can increase gender diversity in firm employment (Kato and Kodama, 2018).

References

Bettinger, Eric P and Long, Bridget Terry. (2005). 'Do faculty serve as role models? The impact of instructor gender on female students', *American Economic Review* 95(2), 152–157.

Blau, Francine D., Brummund, Peter and Liu, Albert Yung-Hsu. (2013). 'Trends in Occupational Segregation by Gender 1970–2009: Adjusting for the Impact of Changes in the Occupational Coding System', *Demography* 50(2), 471–492.
URL: *https://read.dukeupress.edu/demography/article/50/2/471/169671/Trends-in-Occupational-Segregation-by-Gender-1970*

Bostwick, Valerie K and Weinberg, Bruce A. (2022). 'Nevertheless she persisted? Gender peer effects in doctoral STEM programs', *Journal of Labor Economics* 40(2), 397–436.

Bureau of Labor Statistics, U.S. Department of Labor. (2024), 'Employment in STEM occupations'.
URL: *https://www.bls.gov/emp/tables/stem-employment.htm*

Carrell, Scott E, Page, Marianne E and West, James E. (2010). 'Sex and science: How professor gender perpetuates the gender gap', *The Quarterly journal of economics* 125(3), 1101–1144.

Chong, Rachael and Fleming, Melissa. (2014). 'Why IBM gives top employees a month to do service abroad', *HBR. org, November* 5.
URL: *https://hbr.org/2014/11/why-ibm-gives-top-employees-a-month-to-do-service-abroad*

Cortes, Patricia and Pan, Jessica. (2017). 'Cross-country evidence on the relationship between overwork and skilled women's job choices', *American Economic Review* 107(5), 105–109.

Delaney, Judith M and Devereux, Paul J. (2022). 'Gender differences in STEM persistence after graduation', *Economica* 89(356), 862–883.

Dixon, Nile, Goggins, Marcelle, Ho, Ethan, Howison, Mark, Long, Joe, Northcott, Emma, Shen, Karen and Yeats, Carrie. (2023). 'Occupational models from 42 million unstructured job postings', *Patterns* 4(7), 100757.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S2666389923001022*

Fry, Rick, Kennedy, Brian and Funk, Cary. (2021), STEM Jobs See Uneven Progress in Increasing Gender, Racial and Ethnic Diversity: Higher education pipeline suggests long path ahead for increasing diversity, especially in fields like computing and engineering, Technical report, Pew Research Center.
URL: *http://www.jstor.org/stable/resrep57656*

Gicheva, Dora. (2013). 'Working long hours and early career outcomes in the high-end labor market', *Journal of Labor Economics* 31(4), 785–824.

Goldin, Claudia. (2006). 'The Quiet Revolution That Transformed Women's Employment, Education, and Family', *American Economic Review* 96(2), 1–21.
URL: *https://pubs.aeaweb.org/doi/10.1257/000282806777212350*

Griffith, Amanda L. (2010). 'Persistence of women and minorities in STEM field majors: Is it the school that matters?', *Economics of Education Review* 29(6), 911–922.

Hunt, Jennifer. (2016). 'Why do women leave science and engineering?', *ILR Review* 69(1), 199–226.

Kahn, Shulamit and Ginther, Donna. (2017), Women and STEM, Technical report, National Bureau of Economic Research.

Kato, Takao and Kodama, Naomi. (2018). 'The Effect of Corporate Social Responsibility on Gender Diversity in the Workplace: Econometric Evidence from Japan', *British Journal of Industrial Relations* 56(1), 99–127.
URL: *https://onlinelibrary.wiley.com/doi/10.1111/bjir.12238*

Moss-Racusin, Corinne A, Dovidio, John F, Brescoll, Victoria L, Graham, Mark J and Handelsman, Jo. (2012). 'Science faculty's subtle gender biases favor male students', *Proceedings of the national academy of sciences* 109(41), 16474–16479.

OECD, Organization for Economic Co-operation and Development. (n.d.), 'Consumer Price Indices (CPIs, HICPs), COICOP 1999: Consumer Price Index: Total for United States [USACPIALLMINMEI]'.
URL: *https://fred.stlouisfed.org/series/USACPIALLMINMEI*

Speer, Jamin D. (2023). 'Bye bye Ms. American Sci: Women and the leaky STEM pipeline', *Economics of Education Review* 93, 102371.

Spoon, Katie, LaBerge, Nicholas, Wapman, K. Hunter, Zhang, Sam, Morgan, Allison C., Galesic, Mirta, Fosdick, Bailey K., Larremore, Daniel B. and Clauset, Aaron. (2023). 'Gender and retention patterns among U.S. faculty', *Science Advances* 9(42), eadi2205.
URL: *https://www.science.org/doi/10.1126/sciadv.adi2205*

Taproot Foundation. (2021), 'The Equity and Advancement Initiative: Advancing Social Equity Through Corporate Pro Bono at Adobe'.
URL: *https://taprootfoundation.org/case-study/the-equity-and-advancement-initiative-advancing-social-equity-through-corporate-pro-bono-at-adobe/*

Wasserman, Melanie. (2023). 'Hours Constraints, Occupational Choice, and Gender: Evidence from Medical Residents', *The Review of Economic Studies* 90(3), 1535–1568.
URL: *https://academic.oup.com/restud/article/90/3/1535/6648111*

Tables and Figures

Table 1: UI-Resume and NSCG Samples - Women

	NJUI				NSCG			
	Entry Sample		Exit Sample		Entry Sample		Exit Sample	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Number of Observations	20,076	1,889	862	1,934	2,146	334	831	569
Mean Age*	39.45	39.53	38.55	39.25	39.18	36.90	36.76	37.19
Fraction Non-White	0.28	0.34	0.49	0.38	0.40	0.45	0.47	0.43
Fraction With Graduate Degree	0.27	0.37	0.40	0.36	0.46	0.51	0.50	0.50
Mean Pre-Period Outcomes								
Log(Earnings or Salary)	11.27	11.61	11.76	11.63	10.69	10.85	11.24	11.05
Overall Satisfaction (Z-Score)					-0.35	-0.37	-0.16	-0.22
Non-Pay Satisfaction Index (Z-Score)					-0.34	-0.44	-0.26	-0.28
Mean Post-Period Outcomes								
Log(Earnings or Salary)	11.41	11.79	11.98	11.75	10.70	11.05	11.38	10.90
Overall Satisfaction (Z-Score)					-0.14	0.01	-0.08	-0.10
Non-Pay Satisfaction Index (Z-Score)					-0.17	-0.02	-0.13	-0.09

Source: Columns 1-4 use New Jersey UI administrative earnings records linked to private vendor resume data. Columns 5-8 use the National Survey of College Graduates 2003-2015.

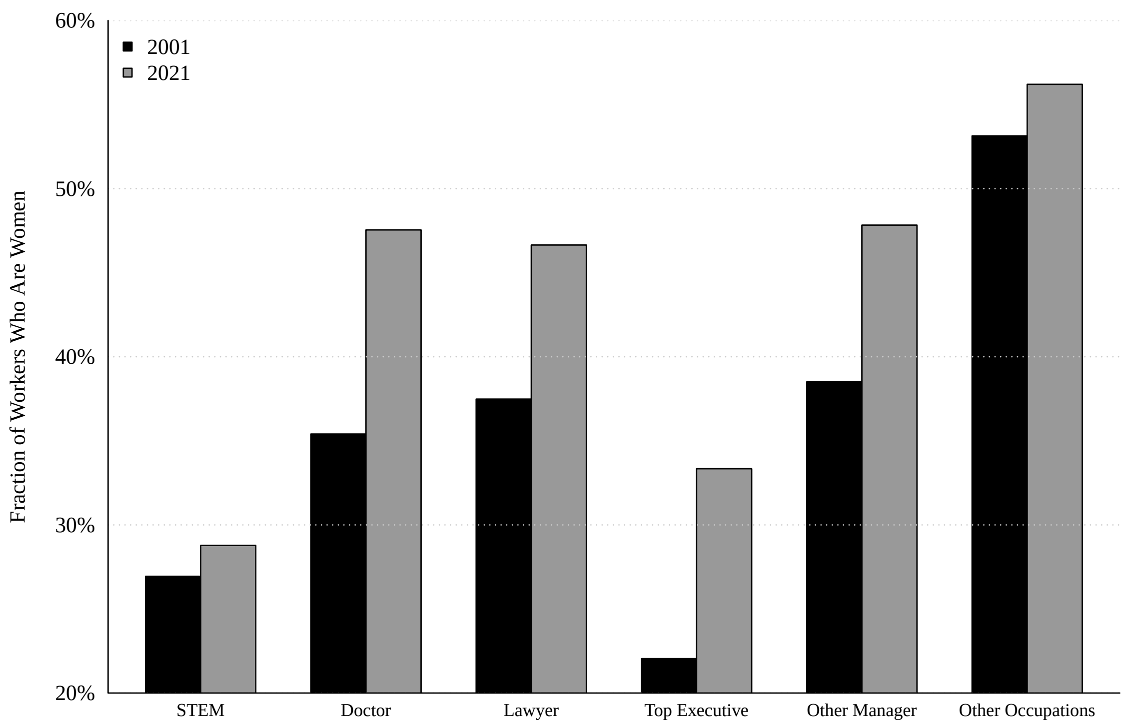
Notes: This table reports results summary statistics for women in the UI-resume and NSCG samples. Columns 1 and 5 report averages for the entrant sample comparison groups of employed persons who switched between different non-STEM occupations; columns 2 and 6 report averages for the entry treatment group of employed persons who switched from non-STEM occupations to STEM occupations; columns 3 and 7 report average for the exit sample comparison group of employed persons who switched between different STEM occupations; and columns 4 and 8 report averages for the exit sample treatment group of employed persons who switched from STEM occupations to non-STEM occupations. In columns 1-4, age is imputed by the year of the individual's first post-secondary record; we calculate age as the current year minus that first college year plus eighteen. In columns 5-8, we use the reported age of the survey participant.

Table 2: Differences-in-Differences Estimates, Women

	UI-Resume Sample	NSCG Sample		
	Log Earnings	Log Salary	Overall Satisfaction	Non-Pay Satisfaction Index
	[1]	[2]	[3]	[4]
Entry Sample	0.157***	0.192***	0.148	0.287***
	(0.024)	(0.060)	(0.104)	(0.096)
Exit Sample	-0.152***	-0.201***	0.052	0.130*
	(0.033)	(0.052)	(0.085)	(0.075)

Source: Columns 1 uses New Jersey UI administrative earnings records linked to private vendor resume data. Columns 2-4 use the National Survey of College Graduates 2003-2015.
Notes: Each coefficient comes from a separate OLS regression estimating Equation 2. The first row reports estimates of the coefficient on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. The second row reports estimates of the coefficient on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. In column 1, covariates include level of education, a quadratic in year, a quadratic in the age proxy (years since first postsecondary record), sending occupation, sending industry, indicators for race/ethnicity, log earnings 1-4 quarters before the occupation transition, and the number of quarters employed in the year before the occupation transition. In columns 2-4, covariates include level of education, first survey year, a quadratic in age, tenure in new position, indicators for children in the household, sending occupation, sending sector, and job aspect importance scores from the first survey. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-resume STEM entrant sample, as described in Section 4.2. Standard errors are clustered at the level of the individual. *, **, and *** correspond to 90%, 95%, and 99% significance levels.

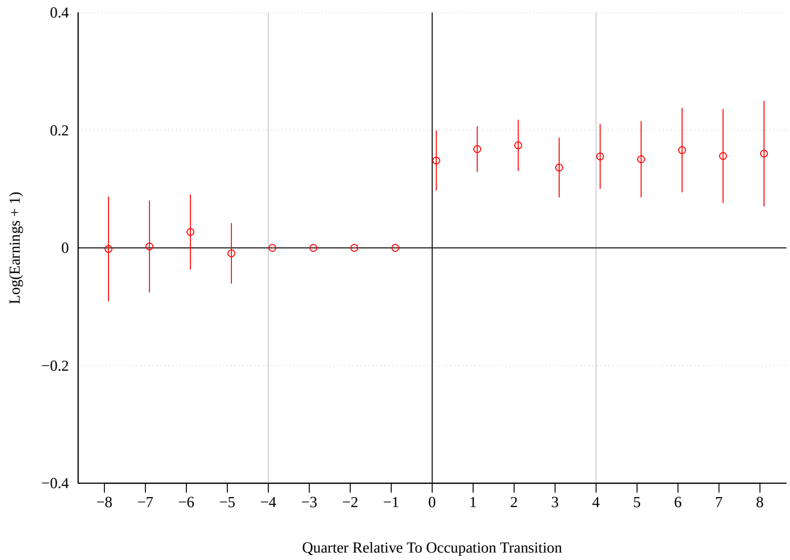
Figure 1: Female Share by Occupation in 2001 and 2021



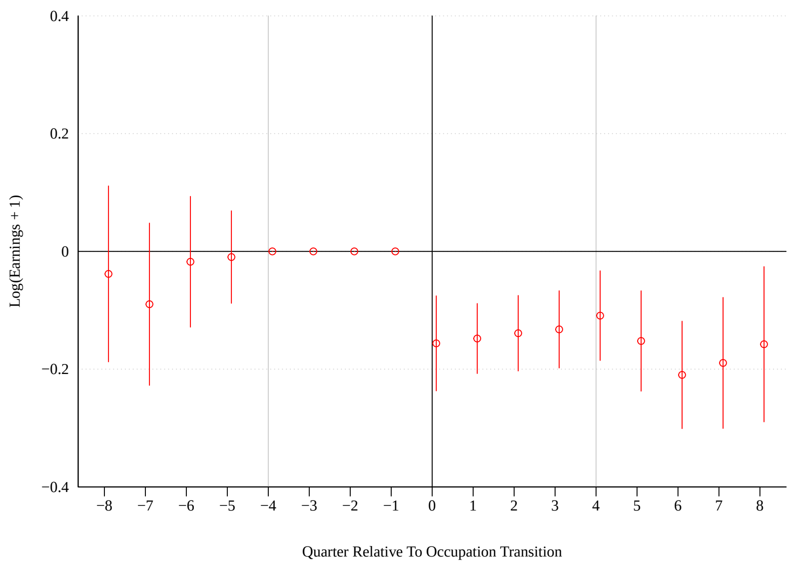
Source: American Community Survey 2001 and 2021.
Notes: This figure reports the fraction of workers in a given occupation who are female. The underlying sample includes workers with at least a bachelor's degree between the ages of 22 and 60 who are employed but not self-employed.

Figure 2: Log Earnings Event Study, Women Only

(a) STEM Entrants, Relative to Within-Non-STEM Switchers

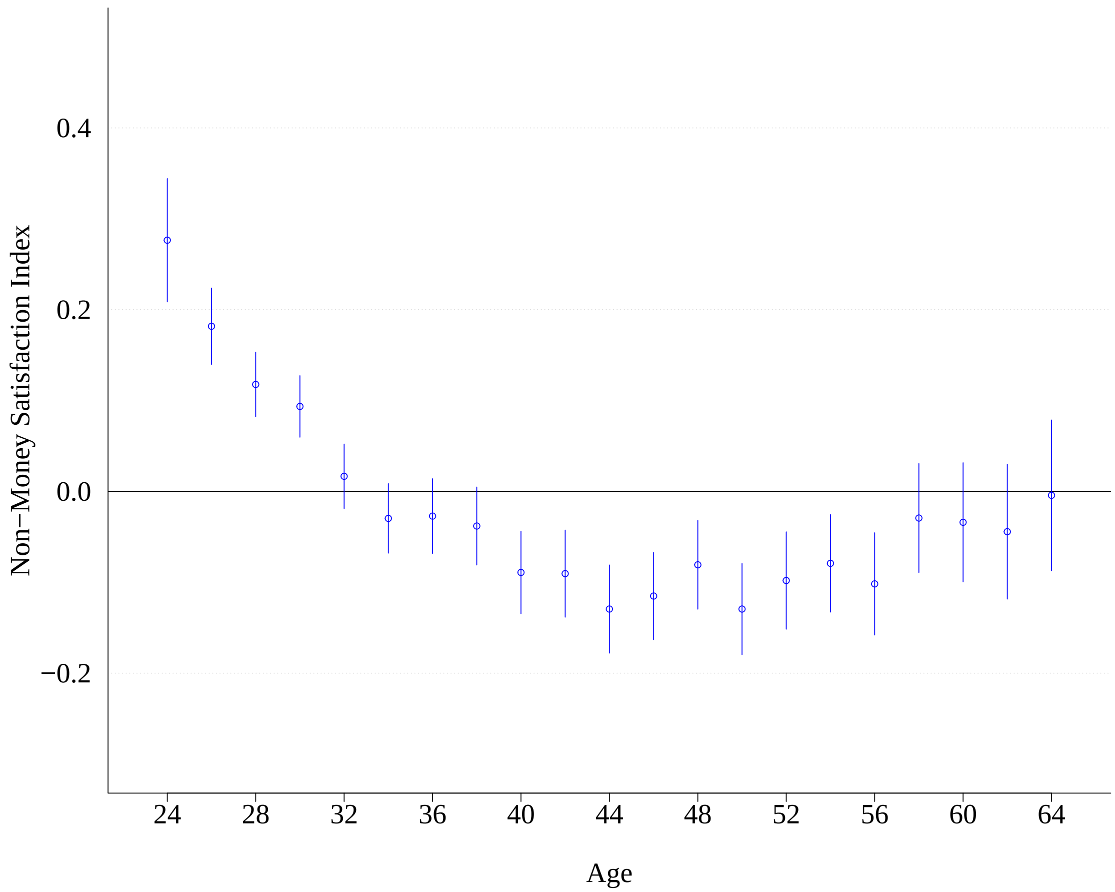


(b) STEM Exiters, Relative to Within-STEM Switchers



Source: NJ UI Quarterly Earnings records linked to private vendor resume data.
Notes: Panel 2a reports estimates of time-varying coefficients on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. Panel 2b reports estimates of time-varying coefficients on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-Resume STEM entrant sample, as described in Section 4.2. Standard errors are clustered at the level of the individual. The bars show 95% confidence intervals.

Figure 3: Non-Pay Satisfaction Among Women,
STEM Minus Non-STEM, Covariate Adjusted



Source: National Survey of College Graduates 2003-2021
Notes: This figure shows results from estimating Equation 3. Each point is a coefficient estimate on an indicator for a STEM occupation in a separate regression binned by age. Covariates include log salary, race, survey year, and indicators for the presence of children over and under 6 years old in the household. The bars show 95% confidence intervals.

A Appendix: Additional Tables and Figures

Table A.1: Women's Cross-Sectional Returns to STEM and Other Selected Occupations

	Average Earnings	Regression-Adjusted Average Earnings	% of "Other Occupations"
STEM Occupations	89,396	91,329	145%
Doctor	184,953	166,116	264%
Lawyer	149,683	132,445	210%
Top Executive	145,542	141,920	225%
Other Manager	105,545	105,575	168%
Other Occupations	61,392	62,956	

Source: ACS 2021
Notes: Column 1 is a simple mean. Column 2 is the predicted earnings for a 40-year-old woman with a bachelor's degree and no children, from a regression of earnings on occupation, age, education, and children.

Table A.2: STEM Entry and Exit in ASEC 2003-2021

	Women	Men
Fraction of STEM Workers Who:		
Entered STEM (Non-STEM Last Year, STEM This Year)	0.029	0.022
Exited STEM (STEM Last Year, Non-STEM This Year)	0.025	0.019
Average Age		
STEM Entrants	37.43	38.22
STEM Exiters	37.90	39.27
Fraction Non-White		
STEM Entrants	0.29	0.30
STEM Exiters	0.29	0.26
Fraction With Masters Degree or Higher		
STEM Entrants	0.30	0.20
STEM Exiters	0.33	0.24

Source: Current Population Survey 2003-2021 Annual Social and Economic Supplements
Notes: Among people ages 25 to 60 who had a job both in the current year and in the previous year, workers are categorized as having "entered STEM" if their occupation in the previous year was non-STEM and their occupation the current year was STEM. Workers are categorized as having "exited STEM" if their occupation in the previous year was STEM and their occupation the current year was STEM. In the first two rows, we give the number of workers in these two categories as a fraction of the number of workers with STEM occupations in the current year.

Table A.3: Comparison of Datasets - ACS, UI-Resume Sample, NSCG Sample

	ACS		UI-Resume			NSCG
	USA, Age 20-70 Employed Recently Fall 2021	NJ, Age 20-70 Employed Recently Fall 2021	Linked UI-Resume Workers Fall 2021	Occupation Switchers Fall 2021	Occupation Switchers At Time of Switch	Occupation Switchers First Survey
	[1]	[2]	[3]	[4]	[5]	[6]
Number of Observations	1,503,620	45,591	290,263	37,655	54,141	10,174
Unique Workers	1,503,620	45,591	290,263	37,655	37,655	10,003
Age*	43.691	44.579	37.464	47.017	39.592	39.461
Fraction Non-White	0.36	0.41	0.36	0.29	0.29	0.39
Highest Degree Received						
Less than Bachelor	0.60	0.48	0.05	0.05	0.07	0.00
Bachelor's Degree	0.24	0.31	0.63	0.60	0.63	0.56
Master's Degree or Higher	0.16	0.21	0.32	0.35	0.30	0.44
Quarters Employed in Previous Year	3.50	3.51	3.23	3.42	3.99	
Earnings* in Previous Year (Mean)	65,153	82,377	119,006	153,951	156,670	89,965

Source: Columns 1-2 use ACS records from 2021. Columns 3-5 use New Jersey UI administrative earnings records linked to private vendor resume data. Column 6 uses NSCG 2003-2015.

Notes: In columns 3-5, age is imputed by the year of the individual's first post-secondary record; we calculate age as the current year minus that first college year plus eighteen. In column 6, we use a survey question about annual salary in place of earnings.

Table A.4: NSCG Linked Respondent Survey Waves

First Survey Year	Second Survey Year	Number of Observations
2003	2010	16,358
2010	2013	28,210
2010	2015	719
2013	2015	35,890

Notes: This table reports the number of survey respondents that can be linked between each set of NCSG survey waves.

Table A.5: Unweighted Differences-in-Differences Estimates, Women

	UI-Resume Sample	NSCG Sample		
	Log Earnings	Log Salary	Overall Satisfaction	Non-Pay Satisfaction Index
	[1]	[2]	[3]	[4]
Entry Sample	0.157***	0.170***	0.196**	0.264***
	(0.024)	(0.056)	(0.086)	(0.079)
Exit Sample	-0.154***	-0.295***	0.075	0.125*
	(0.033)	(0.051)	(0.078)	(0.072)

Source: Columns 1 uses New Jersey UI administrative earnings records linked to private vendor resume data. Columns 2-4 use the National Survey of College Graduates 2003-2015.

Notes: Each coefficient comes from a separate OLS regression estimating Equation 2. The first row reports estimates of the coefficient on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. The second row reports estimates of the coefficient on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. In column 1, covariates include level of education, a quadratic in year, a quadratic in the age proxy (years since first postsecondary record), sending occupation, sending industry, indicators for race/ethnicity, log earnings 1-4 quarters before the occupation transition, and the number of quarters employed in the year before the occupation transition. In columns 2-4, covariates include level of education, first survey year, a quadratic in age, tenure in new position, indicators for children in the household, sending occupation, sending sector, and job aspect importance scores from the first survey. All observations are weighted equally. Standard errors are clustered at the level of the individual. *, **, and *** correspond to 90%, 95%, and 99% significance levels.

Table A.6: UI-Resume and NSCG Samples - Men

	NJUI				NSCG			
	Entry Sample		Exit Sample		Entry Sample		Exit Sample	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Number of Observations	17,033	2,948	2,240	2,912	2,082	658	2,505	1,049
Mean Age*	39.90	40.25	39.34	40.18	41.11	40.66	39.39	40.36
Fraction Non-White	0.25	0.32	0.38	0.34	0.33	0.35	0.40	0.36
Fraction With Graduate Degree	0.28	0.31	0.30	0.34	0.41	0.45	0.40	0.44
Mean Pre-Period Outcomes								
Log(Earnings or Salary)	11.27	11.61	11.76	11.63	11.16	11.20	11.48	11.41
Overall Satisfaction (Z-Score)					-0.31	-0.38	-0.20	-0.19
Non-Pay Satisfaction Index (Z-Score)					-0.36	-0.39	-0.33	-0.27
Mean Post-Period Outcomes								
Log(Earnings or Salary)	11.41	11.79	11.98	11.75	11.09	11.37	11.57	11.31
Overall Satisfaction (Z-Score)					-0.10	-0.02	0.01	-0.05
Non-Pay Satisfaction Index (Z-Score)					-0.17	-0.14	-0.14	-0.07

Source: Columns 1-4 use New Jersey UI administrative earnings records linked to private vendor resume data. Columns 5-8 use the National Survey of College Graduates 2003-2015.

Notes: In columns 1-4, age is imputed by the year of the individual's first post-secondary record; we calculate age as the current year minus that first college year plus eighteen. In columns 5-8, we use the reported age of the survey participant.

Table A.7: Differences-in-Differences Estimates, Men

	UI-Resume Sample	NSCG Sample		
	Log Earnings	Log Salary	Overall Satisfaction	Non-Pay Satisfaction Index
	[1]	[2]	[3]	[4]
Entry Sample	0.113***	0.265***	0.093	-0.023
	(0.021)	(0.046)	(0.068)	(0.065)
Exit Sample	-0.050**	-0.202***	-0.040	0.053
	(0.024)	(0.036)	(0.053)	(0.054)

Source: Columns 1 uses New Jersey UI administrative earnings records linked to private vendor resume data. Columns 2-4 use the National Survey of College Graduates 2003-2015.
Notes: Each coefficient comes from a separate OLS regression estimating Equation 2. The first row reports estimates of the coefficient on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. The second row reports estimates of the coefficient on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. In column 1, covariates include level of education, a quadratic in year, a quadratic in the age proxy (years since first postsecondary record), sending occupation, sending industry, indicators for race/ethnicity, log earnings 1-4 quarters before the occupation transition, and the number of quarters employed in the year before the occupation transition. In columns 2-4, covariates include level of education, first survey year, a quadratic in age, tenure in new position, indicators for children in the household, sending occupation, sending sector, and job aspect importance scores from the first survey. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-resume STEM entrant sample, as described in Section 4.2. Standard errors are clustered at the level of the individual. *, **, and *** correspond to 90%, 95%, and 99% significance levels.

Table A.8: Differences-in-Differences Estimates, Women, Additional Outcomes

	Earnings [1]	Employment [2]	Log Earnings [3]
Entry Sample	3124.153***	0.001	0.157***
	(519.001)	(0.002)	(0.024)
Exit Sample	-2125.556**	-0.002	-0.155***
	(861.529)	(0.002)	(0.032)

Source: New Jersey UI administrative earnings records linked to private vendor resume data.
Notes: Each coefficient comes from a separate OLS regression estimating Equation 2. The first row reports estimates of the coefficient on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. The second row reports estimates of the coefficient on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. Covariates include level of education, a quadratic in year, a quadratic in the age proxy (years since first postsecondary record), sending occupation, sending industry, indicators for race/ethnicity, log earnings 1-4 quarters before the occupation transition, and the number of quarters employed in the year before the occupation transition. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-resume STEM entrant sample, as described in Section 4.2. In column 1, earnings are topcoded at $200,000 per quarter. Standard errors are clustered at the level of the individual. *, **, and *** correspond to 90%, 95%, and 99% significance levels.

Table A.9: Differences-in-Differences Estimates, Men, Additional Outcomes

	Earnings [1]	Employment [2]	Log Earnings [3]
Entry Sample	2575.124***	0.001	0.113***
	(490.657)	(0.002)	(0.021)
Exit Sample	-1080.911	-0.001	-0.050**
	(666.691)	(0.002)	(0.024)

Source: New Jersey UI administrative earnings records linked to private vendor resume data.
Notes: Each coefficient comes from a separate OLS regression estimating Equation 2. The first row reports estimates of the coefficient on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. The second row reports estimates of the coefficient on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. Covariates include level of education, a quadratic in year, a quadratic in the age proxy (years since first postsecondary record), sending occupation, sending industry, indicators for race/ethnicity, log earnings 1-4 quarters before the occupation transition, and the number of quarters employed in the year before the occupation transition. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-resume STEM entrant sample, as described in Section 4.2. In column 1, earnings are topcoded at $200,000 per quarter. Standard errors are clustered at the level of the individual. *, **, and *** correspond to 90%, 95%, and 99% significance levels.

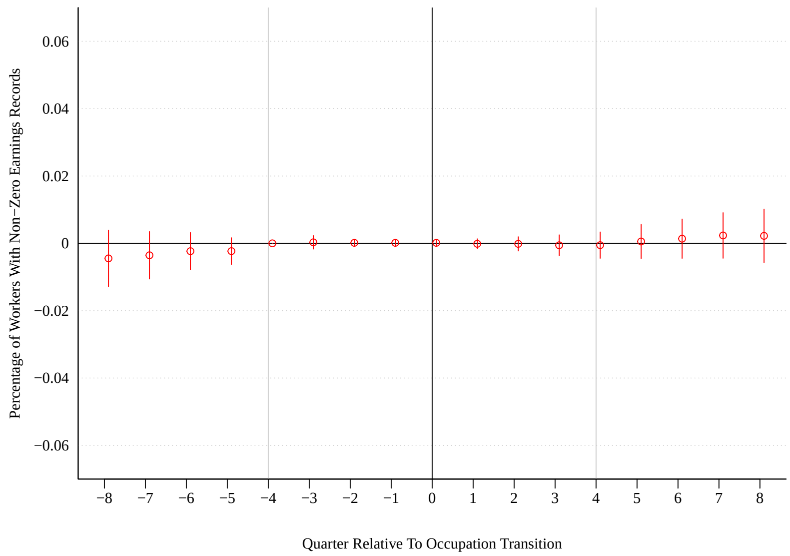
Table A.10: Differences-in-Differences Estimates - Satisfaction with Job Aspects

Treatment Group	Advancement	Benefits	Int. Challenge	Independence	Job Security	Location	Responsibility	Salary	Contribution to Society
Entry Sample	0.203**	0.147	0.387***	0.229**	0.119	-0.040	0.321***	-0.038	0.157
	(0.094)	(0.092)	(0.100)	(0.103)	(0.091)	(0.094)	(0.098)	(0.085)	(0.105)
Exit Sample	0.070	-0.066	0.045	0.009	0.154*	0.057	0.151*	-0.051	0.153*
	(0.079)	(0.080)	(0.082)	(0.087)	(0.088)	(0.095)	(0.085)	(0.089)	(0.085)

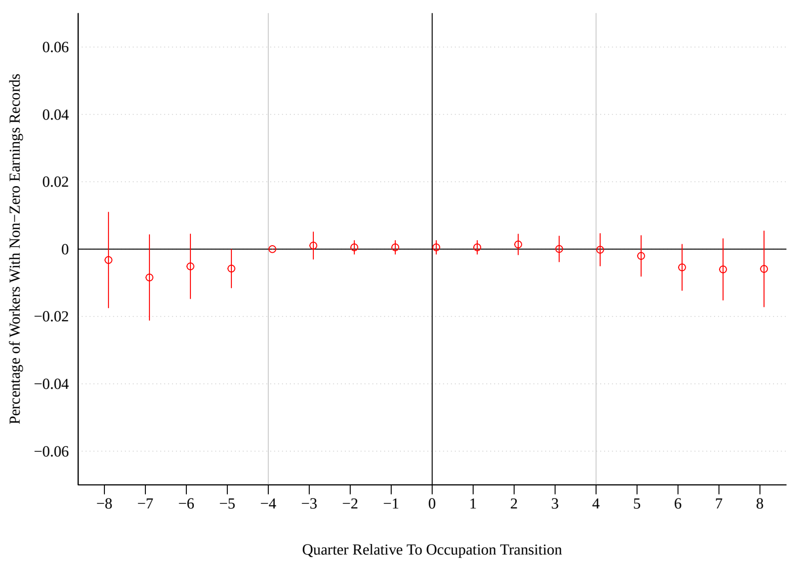
Notes: Each coefficient comes from a separate OLS regression. The outcomes are the z-score of satisfaction with each job aspect. The first row reports estimates of the coefficient on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. The second row reports estimates of the coefficient on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-Resume STEM entrant sample, as described in Section 4.2. Standard errors are clustered at the level of the individual. *, **, and *** correspond to 90%, 95%, and 99% significance levels.

Figure A.4: Employment Event Study, Women Only

(a) STEM Entrants, Relative to Within-Non-STEM Switchers



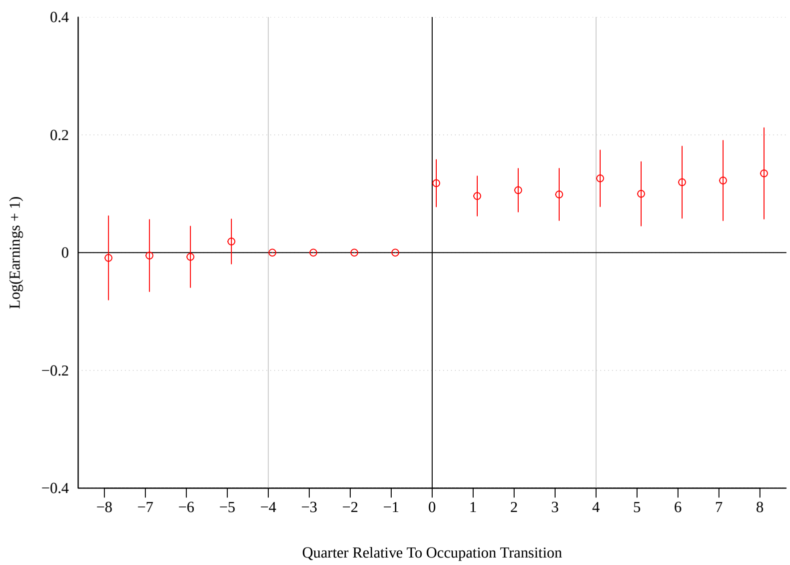
(b) STEM Exiters, Relative to Within-STEM Switchers



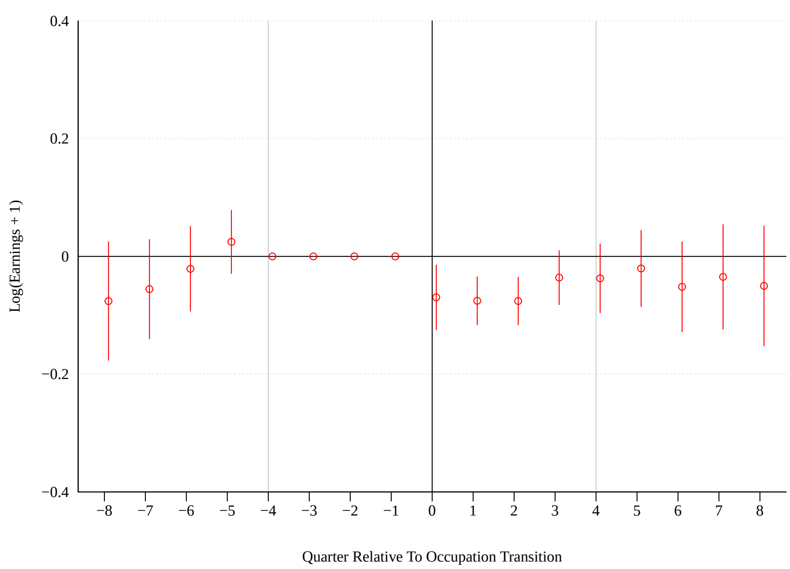
Source: NJ UI Quarterly Earnings records linked to private vendor resume data.
Notes: Panel A.4a reports estimates of time-varying coefficients on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. Panel A.4b reports estimates of time-varying coefficients on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-Resume STEM entrant sample, as described in Section 4.2. Standard errors are clustered at the level of the individual. The bars show 95% confidence intervals.

Figure A.5: Log Earnings Event Study, Men Only

(a) STEM Entrants, Relative to Within-Non-STEM Switchers



(b) STEM Exiters, Relative to Within-STEM Switchers



Source: NJ UI Quarterly Earnings records linked to private vendor resume data.
Notes: Panel A.5a reports estimates of time-varying coefficients on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. Panel A.5b reports estimates of time-varying coefficients on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-Resume STEM entrant sample, as described in Section 4.2. Standard errors are clustered at the level of the individual. The bars show 95% confidence intervals.

B Peer Values in STEM

In this section, we discuss how the composition of peers change as women enter and exit STEM occupations. Using the empirical strategy laid out in Section 4, we analyze a set of outcomes in the NSCG sample related to workers' occupational peers.

Several questions in the NSCG survey ask how workers rate the importance of salary and benefits as well as various non-compensation elements of their jobs: opportunities for advancement, intellectual challenge, independence, job security, location, level of responsibility, and contribution to society. For each element, responses can either be "Very Important,", "Somewhat Important", "Somewhat Unimportant", or "Very Unimportant". We code these responses numerically as 4, 3, 2, and 1, then standardize responses into z-scores with a mean of 0 and a standard deviation of 1 across the full NSCG pooled cross-section. We refer to these z-scores as "importance scores."

For each element, we derive two measures of peer composition from these importance scores. For a given worker i with occupation o, we define as peers P_o the set of NSCG respondents (from the full NSCG pooled cross-section) with the same occupation code. The first measure, "peer values," is the mean importance score among P_o. The second measure, "peer difference," is the difference between worker i's importance score and P_o.

In Appendix Table B.11, we report coefficient estimates for the impact on peer values of entering and exiting STEM occupations, among female entrants and exiters. When women enter a STEM occupation, they shift to a peer group that values salary and benefits more and all other elements less. The largest effect is in the average peer's importance score for their contribution to society, where female entrants shift to a peer group with an average importance score that is 0.074 standard deviations lower than women switching between non-STEM occupations. For female exiters, the results are generally mirrored, with peers in their new occupations valuing salary and benefits less and other elements more. Again, the largest effect is in contribution to society, where female exiters shift to a peer group with an average importance score that is 0.099 standard deviations higher than women switching between STEM occupations.

In Appendix Table B.12, we report coefficient estimates for the impact on peer difference of entering and exiting STEM occupations, among female entrants and exiters. Many of these coefficients are statistically significant, but there is no effect greater than 0.02 standard deviations in either direction. When women enter a STEM occupation, they shift to a peer group that is significantly more different from them in terms of their importance scores for opportunities for advancement, independence, and location. When women exit a STEM occupation, they shift to a peer group that is significantly more similar to them in terms of their importance scores for opportunities for advancement, intellectual challenge, independence, job security, and location. Female exiters' new peer groups are also more different from them in terms of their importance scores for benefits but more similar in terms of their importance scores for salary.

Table B.11: Differences-in-Differences Estimates - Peer Values (Women Only)

	Advancement	Benefits	Int. Challenge	Independence	Job Security	Location	Responsibility	Salary	Contribution to Society
Entry Sample	-0.010***	0.012***	0.022***	-0.044***	-0.016***	-0.023***	-0.046***	0.005*	-0.074***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.005)	(0.003)	(0.005)
Exit Sample	0.012***	-0.012***	0.005	0.070***	0.011***	0.024***	0.077***	-0.008**	0.099***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.001)	(0.004)	(0.003)	(0.006)

Notes: Each coefficient comes from a separate OLS regression among women in the NSCG sample. The outcome is the average importance score of each job aspect among other workers (of any gender) in one's own occupation. The first row reports estimates of the coefficient on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. The second row reports estimates of the coefficient on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-Resume STEM entrant sample, as described in Section 4.2. Standard errors are clustered at the level of the individual. *, **, and *** correspond to 90%, 95%, and 99% significance levels.

Table B.12: Differences-in-Differences Estimates - Peer Difference (Women Only)

	Advancement	Benefits	Int. Challenge	Independence	Job Security	Location	Responsibility	Salary	Contribution to Society
Entry Sample	0.009**	-0.005	-0.002	0.014***	0.003	0.005***	0.006	0.001	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.002)	(0.006)	(0.004)	(0.009)
Exit Sample	-0.008**	0.009**	-0.010**	-0.017***	-0.009***	-0.006***	0.002	-0.007*	0.011
	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.001)	(0.006)	(0.004)	(0.008)

Notes: Each coefficient comes from a separate OLS regression among women in the NSCG sample. The outcome is the difference between one's own importance score for each job aspect and the average importance score for that aspect among other workers (of any gender) in one's own occupation. The first row reports estimates of the coefficient on an indicator for STEM entry, within the sample of STEM entrants and within-non-STEM switchers. The second row reports estimates of the coefficient on an indicator for STEM exit, within the sample of STEM exiters and within-STEM switchers. Weights are set according to the gender-specific occupation transition frequency matrix from the UI-Resume STEM entrant sample, as described in Section 4.2. Standard errors are clustered at the level of the individual. *, **, and *** correspond to 90%, 95%, and 99% significance levels.