

**Post-COVID-19 Shifts in Returns to STEM and Non-STEM Degrees  
in the U.S Labor Market**

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**Abstract:**

This paper examines whether the onset of the COVID-19 pandemic and the post 2020 shifts in the labor market altered the earnings differential between STEM and non-STEM workers, and whether any such effects varied systematically by gender. Using a difference-in-differences model framework applied to repeated cross-sectional data from the American Community Survey (IPUMS), this analysis restricts the sample to workers aged 24–64 holding a bachelor's degree or higher. Two specifications are estimated: a baseline model capturing the overall post-2020 STEM earnings differential, and an extended model incorporating a triple interaction between STEM status, the post-2020 indicator, and gender, with all specifications controlling for individual characteristics, state fixed effects, and year fixed effects. The baseline results indicate that the STEM  $\times$  Post2020 interaction is statistically insignificant and economically trivial, with the implied earnings differential amounting to no more than \$446 annually at the 75th percentile of the earnings distribution. The extended model reveals a statistically significant but economically negligible gender-differentiated post-2020 STEM earnings effect, with female STEM workers experiencing an additional earnings penalty of approximately 1.05% relative to their male counterparts. These findings suggest that the post-2020 period did not produce the anticipated widening of the STEM earnings premium, with implications for STEM education policy and gender equity initiatives within technical occupations.

## **Introduction**

The objective of this paper is to explore how the post COVID-19 economic shift (2021-23) altered the earnings premium of STEM majors relative to non-STEM majors in the United States, and to what extent these changes vary across geographic regions and differentially impacted graduates based on the intersection of gender, race, and the local cost of living.

This differential impact is expected because the pandemic triggered asymmetric labor demand shocks: STEM fields, particularly technology and health-related majors experienced increased remote work opportunities and sectoral growth, while non-STEM fields, such as art, hospitality, and in-person service sectors, faced contraction or slower recovery. Geographic variation arises because high-cost urban hubs and tech-intensive states benefitted more from these shifts, whereas regions dependent on in-person industries experienced slower wage growth.

Understanding these dynamics is important for policymakers and educators. Insights into how STEM and non-STEM graduates fared post-pandemic can inform workforce development strategies, targeted upskilling programs, and regional economic policies. For instance, regions lagging in STEM employment growth may require incentives to attract technology industries or support retraining initiatives, while addressing wage disparities across gender and racial groups can promote equity in the recovering labor market.

This topic is also of academic and practical interest because it sheds light on how major shocks, such as a global pandemic, reshaping the returns to education and influence long-term career, migration, and labor market outcomes. This paper contributes to the literature by quantifying these effects for STEM versus non-STEM graduates across states and demographic groups.

## **Literature Review**

Moellman et al. (2026) examine labor market outcomes for undergraduate economics majors in the United States using 2014–2023 American Community Survey data on over four million individuals aged 25–65. They estimate log-linear earnings regressions comparing general, agricultural, and business economics degrees, controlling for extensive individual and state-level characteristics. To analyze labor force participation, they employ both ordered probit and linear probability models to study weeks worked per year.

The authors find a positive and statistically significant earnings premium for economics majors, particularly for general economics degrees, while finding limited evidence that occupational sorting or differences in weeks worked explain this premium. Their results suggest that the return to an economics degree operates primarily through higher wages rather than labor supply or occupation choice.

Altonji and Zhong (2021) estimate the labor market returns to a broad set of graduate degrees including engineering, nursing, education, psychology, and social work, among others, using National Science Foundation data. To control for heterogeneity in preferences and ability, the authors employ fixed effects for combinations of field-specific undergraduate and graduate degrees, essentially comparing individual earnings before and after degree completion. The study

finds large differences in earnings effects across graduate fields, with returns often depending on the undergraduate major, and documents that simple regression-based estimates of returns to graduate fields can be highly misleading.

However, their analysis does not explicitly examine how structural shocks, such as the COVID-19 pandemic, altered the returns to economics degrees over time or whether these effects varied across geographic regions. My paper builds on this literature by investigating whether the post-COVID economic shift changed the relative returns to STEM versus non-STEM majors and whether these effects differed across cost-of-living environments and demographic groups.

### **Data and Methodology:**

Individual-level data from the 1-year American Community Survey (ACS) samples from 2017-24, as obtained from IPUMS USA, will be utilized for this research. The analysis is limited to working-age degree holders (25-64) with at least a bachelor's degree and annual earnings greater than zero, which are put in real terms using the Consumer Price Index Urban Series 2010.

Majors are classified as STEM or non-STEM based on the United States Department of Homeland Security (DHS) Designated Degree Program List, which defines STEM fields for the 24-month Optional Practical Training (OPT) extension. Given that there is no variable in the data series that captures disability status, a variable for disability status is created based on the presence of either cognitive, ambulatory, independent living, self-care, or vision or hearing difficulties. Observations with annual earnings below \$1,000 are excluded to remove individuals with minimal or irregular labor market attachment as well as potential reporting errors. This threshold ensures that the analysis focuses on economically meaningful earnings while preserving the majority of the sample. After including these restrictions, the final data sample consists of 4,131,654 observations.

The distribution of log earnings exhibits slight left skewness, with a skewness of -0.75, consistent with the income divided by 1000 transformation applied to the data. The median log earnings of 4.00 and mean of 3.91 are close in value, indicating a relatively symmetric distribution around the center. The standard deviation of 0.94 suggests moderate dispersion around the mean. The 1st and 99th percentiles are 0.93 and 6.08 respectively, indicating the presence of extreme values at both tails of the distribution. Notably, the minimum observed value of 0.011 corresponds to approximately \$1.01 in earnings, which is implausibly low for a bachelor's degree holder, suggesting the presence of outliers in the lower tail that warrant attention. The kurtosis of 4.80, exceeding the normal distribution benchmark of 3, further confirms the presence of heavier tails than would be expected under normality. It should be noted that the log transformation applied to earnings reduces right skewness and produces a more symmetric distribution suitable for the regression framework, though the remaining left skewness and excess kurtosis suggest that trimming at the 1st and 99th percentiles may be warranted to mitigate the influence of extreme observations on the regression estimates.

Figure 1 presents the mean log earnings over time for STEM and non-STEM major workers, separated by the 2020 threshold. Several observations emerge from this figure that are relevant to the empirical analysis.

Prior to 2020, the earning trajectories of both worker groups appear broadly parallel, exhibiting relatively stable mean log earnings between 2017 and 2019. The persistence of a stable earnings gap between the two groups during this period provides visual support for the parallel trends assumption underlying the differences-in-differences identification strategy. This is a necessary condition for the estimator to yield a causal interpretation of the post-2020 earnings differential.

Following 2020, both STEM and non-STEM majors experienced a pronounced decline in earnings with the broader labor market disruptions associated with the COVID-19 pandemic. The decline appears more pronounced for STEM workers relative to their pre-2020 earnings level, which is consistent with the negative and economically as well as statistically insignificant coefficient on the  $STEM_i \times Post2020_t$  interaction term as reported in Table 3. While both groups partially recover during the 2022-24 period, STEM earnings do not fully return to their pre-2020 level relative to non-STEM earnings. The linear fit lines further illustrate this dynamic, with STEM earnings exhibiting a modest downward trend over the full sample period while non-STEM earnings trend slightly upward providing a visual representation of the regression findings that follow.

### Regression Model:

The regression model that will be used in this research is as follows:

$$\ln(Earnings)_{ist} = \beta_0 + \beta_1 (STEM_i \times Post2020_t) + \beta_2 STEM_i + \gamma' X_{ist} + \delta_s + \alpha_t + \varepsilon_{ist}$$

where,  $\ln(Earnings)_{ist}$  represents the log annual earnings of individual  $i$  in state  $s$  in year  $t$ ,  $STEM_i = 1$  if major is STEM, 0 if non-STEM,  $Post2020_t = 1$  for 2020-23, 0 for 2017-2019.  $STEM_i \times Post2020_t$  captures the change in STEM wage premium after COVID-19.  $X_{ist}$  is a vector which includes individual controls for gender, race, age, age square, educational attainment, marital status, household size, disability status, and citizenship.  $\delta_s$  represents the state fixed effects,  $\alpha_t$  represents the year fixed effects, and  $\varepsilon_{ist}$  is the error term.

The main parameter of interest in this model specification is  $\beta_1$ , which captures the differential change in earnings for STEM individuals relative to non-STEM individuals in the post 2020 period. This coefficient therefore measures the change in the STEM wage premium in COVID - 19. The central framework of this model is to test the hypothesis whether the wage gap between STEM and non-STEM individuals changes after 2020, and whether this change varies across gender.

The expected sign of  $\beta_1$  is positive, reflecting an increase in the relative returns to STEM education in the post-COVID period due to the stronger demand for technical and digital skills and the relative resilience of STEM-intensive occupations. However, the sign could be negative if the relative earnings differential between STEM and non-STEM degree workers in the post-2020 period due to changes in relative wage dynamics across occupations.

To examine heterogeneous effects by gender, the extended specification includes a triple interaction term  $STEM_i \times Post2020_t \times Sex_i$ . The key parameter of interest is  $\beta_4$ , as presented in the equation below.

$$\begin{aligned} \ln(Earnings)_{ist} &= \beta_0 + \beta_1 (STEM_i \times Post2020_t) + \beta_2 STEM_i + \beta_3 Sex_i \\ &+ \beta_4 (STEM_i \times Post2020_t \times Sex_i) + \gamma' X_{ist} + \delta_s + \alpha_t + \varepsilon_{ist} \end{aligned}$$

While the sign of  $\beta_4$  is theoretically ambiguous, with respect to this model – the expected sign of  $\beta_4$  is negative given that women are more concentrated in lower-paying STEM subfields and increased male representation among high-paying tech and engineering roles. A positive value of  $\beta_4$  indicates that the increase in the STEM wage premium after 2020 is larger for females relative to males, while a negative value would suggest a relative decline for females.

This approach is motivated by the well-documented gender gap in STEM occupations. While women have made substantial progress in educational attainment, they remain significantly underrepresented in STEM fields, particularly in high-paying technical roles. Given persistent differences in occupational sorting within STEM, variation in specialization (such as software, engineering, and applied sciences), and differences in labor market outcomes across these subfields, it is likely that the impact of the post 2020 change in STEM returns is not uniform across gender.

If post 2020 shifts in labor demand disproportionately benefitted STEM subfields where men are more heavily represented, or if changes in work arrangements and industry structure affected men and women differently within STEM, then the change in the STEM wage premium may vary systematically by gender. The triple difference estimator therefore allows for identification of whether the post 2020 change in STEM earnings differ between men and women. This provides insight into whether the recent labor market and technological shifts have widened or narrowed gender differences within STEM. Failure to account for this heterogeneity would mask important distributional effects of post 2020 labor market changes.

There is likely to be heterogeneity in the impact of the key variable of interest,  $STEM_i \times Post2020_t$ , across different groups of individuals. This is because the STEM category is not homogeneous, and the extent to which individuals benefit from the post-2020 environment varies depending on their occupation, skill, intensity, and industry of employment. For instance, individuals in STEM fields that are digitally more intensive or software-oriented may experience a larger increase in earnings relative to those in STEM occupations that are more applied or infrastructure based, as the former are more easily adapted to remote or technology-enabled work. Similarly, heterogeneity may arise across demographic groups such as gender or educational attainment, if these characteristics influence occupational sorting within STEM fields or bargaining power in the labor market. Geographic differences across states may also matter, as regions with higher concentration of technology-intensive industries may exhibit stronger changes in the STEM wage premium. Therefore, the average effect captured by  $\beta_1$  may mask meaningful variation in the magnitude of the post-2020 change in returns to STEM education across individuals and contexts.

A key empirical concern in this specification is the potential presence of endogeneity arising from omitted variable bias, reverse causality, and selection into STEM major fields. This could arise from unobservable individual characteristics, such as ability, motivation, or cognitive skills, are correlated with both the choice of a STEM major and earnings outcomes. Although the inclusion of individual controls and state and year fixed effects mitigate some of this concern,

time-varying unobservables that may differentially affect STEM and non-STEM workers could still bias the estimate of  $\beta_1$ . It is important to note that selection into STEM majors is non-random, and individuals who choose STEM fields may have systematically different earning trajectories even prior to 2020, which could confound the interpretation of the interaction term if pre-trends are not parallel.

This motivates the need to interpret  $\beta_1$  as a difference-in-difference estimate under the parallel trends assumption. Reverse causality is less of a concern in this setting since earnings do not determine prior field of study; however, anticipated labor market conditions could influence major choice, which would again reinforce selection concerns rather than true reverse causality. While fixed effects help address some source of bias, the identification of  $\beta_1$  relies on the assumption that in the absence of the post-2020 shift, earnings trends for STEM and non-STEM individuals would have evolved similarly.

### **Empirical Analysis:**

Table 3 presents the regression results of the baseline regression model without the gender interaction term. From the results, it is observed that the key variable of interest  $STEM_i \times Post2020_t$ , carries a coefficient of -0.0052 but is economically insignificant. However, even though statistically and economically insignificant, the results suggest that STEM workers earned approximately 0.5% less relative to non-STEM workers post 2020, a negligible differential, given mean log earnings of 10.78 in the sample.

To further assess economic significance, the differential impact of  $STEM_i \times Post2020_t$  is evaluated at the tails of the earnings distribution. At the 25<sup>th</sup> percentile of log earnings, the implied annual earnings loss associated with being a STEM worker post 2020 amounts to approximately \$0.168 thousand (\$168), while at the 75<sup>th</sup> percentile (11.364), this figure rises to approximately \$0.446 thousand (\$446) annually. These magnitudes represent a mere 0.52% change in earnings at both percentiles, confirming that the effect is economically trivial across the entire earnings distribution.

The baseline STEM wage premium is statistically significant but does not exhibit economic significance. The results suggest a \$100.02 higher wage when compared to their non-STEM counterparts. The results for the control variables are broadly consistent with established findings in the labor economics literature. Female workers earn approximately 39.9% less than their male counterparts (standardized coefficient of 0.211 which is economically significant as well as statistically significant), reflecting the well-documented gender wage gap.

Workers of white race earn approximately 12% more than non-white workers. The positive coefficient on age (0.115) and negative coefficient on age squared (-0.0012) confirm the standard concave earnings-age profile consistent with human capital theory, whereby earnings rise with experience at a diminishing rate. Each additional education unit is associated with approximately 24.9% higher earnings. Married workers earn approximately 20.2% more than unmarried workers, consistent with the marriage wage premium documented extensively in the literature. Household size is negatively associated with earnings. Disabled workers face a substantial

earnings penalty of approximately 28.4% relative to non-disabled workers, while American citizens earn approximately 3.4% more than non-citizens.

The year fixed effects reveal interesting dynamics over the sample period. Relative to the omitted base year 2017, earnings were broadly stable in 2018 before rising significantly in 2019 and 2020. Notably, the 2021 coefficient is small and statistically insignificant, suggesting that once state fixed effects and individual controls are accounted for, the COVID-19 earnings disruption visible in the raw data is largely absorbed by other controls. Earnings subsequently recover and trend upward through 2022, 2023, and 2024, with the 2024 coefficient indicating earnings approximately 3.9% above the 2017 baseline ( $p < 0.01$ ). State fixed effects are included in all specifications but not reported in the table.

The coefficient of primary interest in Model 2 is the triple interaction term  $STEM_i \times Post2020_t \times Sex_i$ , which carries a coefficient of -0.0105, which is statistically significant but economically insignificant— suggesting that the gender differentiated post 2020 STEM earnings effect is trivially small in economic terms. To further assess economic significance at the tails of the earnings distribution, at the 25<sup>th</sup> percentile -\$338 annually and -\$899. While larger in magnitude compared to the estimator in Model 1, these dollar amounts remain economically modest, representing approximately 1.05% of earnings at any point in the distribution, confirming that the triple interaction effect, though statistically detectable, carries no meaningful economic significance.

### **Conclusion:**

The results indicate that the post-2020 period did not produce the anticipated widening of the STEM earnings premium among bachelor's degree holders, and that any differential effects by gender were economically negligible. Several factors may account for these findings. The rapid expansion of remote work following 2020 may have compressed geographic wage differentials that previously benefited STEM workers concentrated in high-wage metropolitan areas.

Additionally, the well-documented wave of technology sector layoffs beginning in 2022 may have softened demand for STEM skills, dampening any post-pandemic earnings premium. Compositional shifts in the STEM workforce, including increased entry of workers from adjacent fields drawn by pandemic-era demand signals, may have further diluted the relative earnings advantage of established STEM workers.

These findings also carry several important policy implications. First, the absence of a widening STEM earnings premium post-2020 suggests that supply-side interventions aimed at expanding STEM education and workforce participation may not translate directly into earnings gains for workers, at least in the short run. Policymakers should exercise caution in framing STEM education investments solely as a pathway to higher earnings, as labor market conditions can rapidly alter the returns to technical skills.

Second, the finding that female STEM workers experienced a relative earnings disadvantage in the post-2020 period, even if economically modest, underscores the continued importance of targeted gender equity policies within STEM occupations. Initiatives aimed at reducing

occupational segregation within STEM fields, addressing negotiation gaps, and expanding access to flexible work arrangements may help mitigate the gender earnings differential that persists even among highly educated STEM workers. Finally, the substantial disability earnings penalty of approximately 28-33% documented across both model specifications highlights the need for policies that support labor market inclusion for disabled workers, including enforcement of workplace accommodation requirements and expansion of supported employment programs.

## Reference

Altonji, Joseph G., and Zhong Ling. 2020. "The Labor Market Returns to Advanced Degrees." *National Bureau of Economic Research* 1-10.

Moellman, Nicholas, Danko Tarabar, and Alexander Tsiukes. 2026. "Job Market Outcomes for Undergraduate Economics Majors." *Eastern Economic Journal* 1-13.

Steven Ruggles, Sarah Flood, Matthew Sobek, Daniel Backman, Grace Cooper, Julia A. Rivera Drew, Stephanie Richards, Renae Rodgers, Jonathan Schroeder, and Kari C.W. Williams. 2025. *IPUMS USA: Version 16.0 [dataset]*. <https://doi.org/10.18128/D010.V16.0>, Minneapolis, MN: IPUMS.

## Appendix:

The central framework of the first model is to test the hypothesis whether the wage gap between STEM and non-STEM individuals changes after 2020, and whether this change varies across genders. This can be formally defined as follows:

### Model 1:

$$H_0: \beta_1 = 0$$

$$H_1: \beta_1 > 0$$

### Model 2:

$$H_0: \beta_4 = 0$$

$$H_1: \beta_4 < 0$$

### Calculation of Statistical and Economic Significance:

Statistical significance is identified by conducting a t-test. The t statistic is calculated using the formula listed below:

$$t = \frac{\hat{\beta}_k}{se(\hat{\beta}_k)}$$

The null hypothesis is rejected if  $|t| > z_\alpha$ .

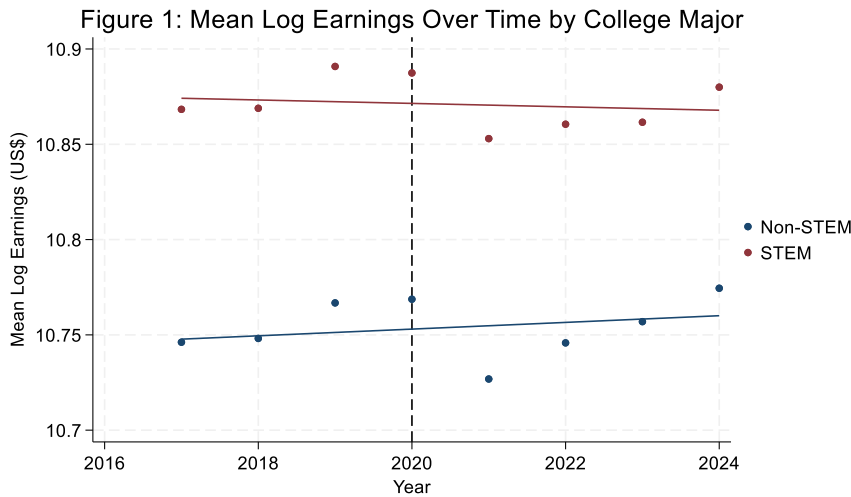
To analyze the regression results in detail, both statistical as well as economic significance is computed.

Economic Significance is computed by the standardized coefficient. The formula is listed below:

$$\beta_k \times \frac{\text{standard deviation}(x)}{\text{standard deviation}(y)}$$

where k represents the coefficient for which economic significance is calculated for. The standard deviations for all variables included in the regression are listed in the summary statistics. A coefficient is defined economically significant if its standardized coefficient is greater than 0.1.

### Set of Figures



### Set of Tables

Table 1: Variable Definitions

Variable	Definition
year	Census year (2014-24)
stem	1 if STEM major, 0 if non-STEM major
post2020	1 if after 2020, 0 if before and including 2020
sex	1 if female, 0 if male
race	1 if white, 0 if not
age	Age: 24-64
educ	Educational Attainment: 10 if Bachelor's Degree, 11: if Higher
married	Marital Status: 1 if married, 0 if not
hhsz	Household Size
disabled	1 if disabled, 0 if not

Citizen_	1 if American Citizen, 0 if not
ln_incwage_2010	Earnings in Real Terms (CPI Urban 2020)
stem_post2020	1 if STEM major and post 2020
stem_post2020_sex	1 if STEM major, post 2020, and female

**Table 2: Summary Statistics**

(1)

	mean	sd	min	max
ln_incw~2010	3.912	0.940	0.011	6.484
stem_po~2020	0.302	0.459	0.000	1.000
female_~2020	0.153	0.360	0.000	1.000
stem_female	0.284	0.451	0.000	1.000
post_female	0.283	0.451	0.000	1.000
stem	0.563	0.496	0.000	1.000
post2020	0.537	0.499	0.000	1.000
sex	0.525	0.499	0.000	1.000
race_	0.737	0.440	0.000	1.000
age	42.904	11.387	24.000	64.000
educ	10.393	0.488	10.000	11.000
married	0.654	0.476	0.000	1.000
hhsiz	2.849	1.417	1.000	20.000
disabled	0.041	0.198	0.000	1.000
citiz	0.115	0.319	0.000	1.000
N	4131654			

**Table 3: Results from Models 1 and 2**

Variables	ln_incwage_cpiu_2010	
stem_post2020	-0.0052 (1.31)	
stem	0.1002 (8.97)**	
sex	-0.3990 (36.90)**	
race_	0.1201 (12.96)**	0.1205 (13.09)**
age	0.1146 (47.51)**	0.1146 (47.37)**
age2	-0.0012	-0.0012

	(43.42)**	(43.32)**
educ	0.2490	0.2488
	(44.16)**	(44.65)**
married	0.2020	0.2018
	(27.66)**	(27.74)**
hhsiz	-0.0407	-0.0406
	(12.41)**	(12.39)**
disabled	-0.2842	-0.2845
	(53.58)**	(53.58)**
citiz	0.0335	0.0331
	(4.91)**	(4.87)**
1.stem		0.1163
		(9.05)**
1.post2020		0.0153
		(2.75)**
1.stem#1.post2020		0.0022
		(0.42)
1.sex		-0.4001
		(30.02)**
1.stem#1.sex		-0.0322
		(5.34)**
1.post2020#1.sex		0.0419
		(12.37)**
1.stem#1.post2020#1.sex		-0.0105
		(2.62)*
$R^2$	0.15	0.15
$N$	4,131,654	4,131,654

\*  $p < 0.05$ ; \*\*  $p < 0.01$

Robust standard errors clustered at state level. State and year fixed effects included but not reported.