The Skill Gradient of Steel Protection: Education-Specific Employment Effects of Section 232 Tariffs on Downstream Manufacturing

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Abstract

When policymakers impose tariffs to protect steel and aluminum workers, who bears the downstream cost? I exploit the March 2018 Section 232 tariffs using a triple-difference design—interacting county-level downstream manufacturing exposure with education groups and time—within the Quarterly Workforce Indicators administrative panel covering 2,100 counties. The tariffs raised separation rates for college-educated workers in highly exposed counties by 0.38 percentage points relative to less-educated workers (p = 0.03), but generated no significant employment or earnings effects. The results suggest that downstream adjustment to input tariffs operates through turnover rather than net employment changes, with the burden falling on higher-skilled workers—precisely those the tariffs were not designed to protect.

JEL Codes: F13, F14, J23, J31

Keywords: tariffs, Section 232, downstream manufacturing, skill gradient, labor adjustment

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1. Introduction

In March 2018, the United States imposed 25 percent tariffs on steel imports and 10 percent on aluminum under Section 232 of the Trade Expansion Act of 1962, the first use of national security trade authority in decades. The stated goal was straightforward: protect American steelworkers. But steel is an intermediate input. Fabricated metals, machinery, and transportation equipment manufacturers—industries employing roughly 6.4 million workers—saw their input costs rise overnight. The political economy of tariffs hinges on a claim: that protection helps "working class" jobs. This paper asks whether the downstream burden of steel protection falls equally across the education distribution, or whether it creates a skill gradient that concentrates costs on workers the policy was never designed to protect.

The existing literature on the 2018 tariffs has established that they raised domestic steel prices by approximately 9 percent (Amiti et al., 2019), reduced manufacturing employment in exposed counties (Flaaen and Pierce, 2019), and generated retaliatory costs exceeding direct benefits (Fajgelbaum et al., 2020). Cavallo et al. (2021) trace pass-through from tariffs to consumer prices. Yet these studies treat the downstream manufacturing workforce as homogeneous. This is a consequential simplification. If tariff-induced input cost increases lead firms to restructure—shedding management and engineering positions while retaining production workers—then the distributional incidence of protection differs fundamentally from what aggregate analyses reveal.

This paper introduces an education dimension to the analysis of downstream tariff effects using the Quarterly Workforce Indicators (QWI), an administrative dataset covering the near-universe of U.S. employment. The QWI uniquely disaggregates employment, separations, hires, and earnings by education group at the county level, enabling a triple-difference design that would be impossible with survey data. I define downstream steel exposure as a county's 2016 share of manufacturing employment in fabricated metals (NAICS 332), machinery (NAICS 333), and transportation equipment (NAICS 336). The triple-difference identification exploits within-county, between-education variation in outcomes conditional on exposure intensity, absorbing all county-specific time shocks through county $\times$ time fixed effects.

The main finding is a statistically significant skill gradient in separation rates. After the tariffs, quarterly separation rates for workers with some college or bachelor's degrees in highly exposed counties rose by 0.38 percentage points relative to workers with less than a high school diploma or high school diploma ($p = 0.03$). This differential is robust to alternative clustering, dropping late-2019 quarters during trade war escalation, and binary exposure measures. A placebo test on non-downstream manufacturing industries—which share county-specific labor market conditions but do not use steel as an input—produces null results, supporting the identification.

Employment and earnings effects are generally null and imprecisely estimated at both the state and county level, consistent with Flaaen and Pierce (2019)'s finding that downstream employment declined modestly. The education-specific point estimates at the county level suggest a pattern—less-than-high-school workers show a positive coefficient while high-school and some-college workers show negative coefficients—but none reach conventional significance. The separation rate result is the cleanest margin: tariff exposure increases turnover for higher-educated workers without proportionate changes in net employment, suggesting that adjustment operates through replacement rather than displacement.

This paper contributes to three literatures. First, it extends the trade policy literature on the 2018 tariffs (Flaaen and Pierce, 2019; Amiti et al., 2019; Fajgelbaum et al., 2020) by decomposing downstream effects along the education distribution, revealing a skill gradient that aggregate analyses miss. Second, it speaks to the broader literature on trade and labor adjustment (Autor et al., 2013, 2014; Dix-Carneiro and Kovak, 2017), which has documented that trade shocks affect different workers differently but has focused on the skill content of import-competing sectors rather than on downstream input cost channels. Third, it informs the political economy of trade policy (Grossman and Helpman, 1994; Autor et al., 2020), where the claim that tariffs protect working-class jobs has become central to policy discourse. The finding that downstream separation costs fall disproportionately on college-educated workers does not validate this claim—it merely documents an irony in its distributional consequences.

2. Institutional Background

The Section 232 tariffs. On March 8, 2018, President Trump signed Proclamations 9704 and 9705 imposing tariffs of 25 percent on steel imports and 10 percent on aluminum imports, effective March 23, 2018. The legal basis was Section 232 of the Trade Expansion Act of 1962, which authorizes the president to restrict imports that threaten national security. The tariffs initially applied to all trading partners; exemptions for the EU, Canada, and Mexico were granted temporarily and then revoked or renegotiated over subsequent months. By 2019, the tariffs covered approximately 70 percent of U.S. steel imports.

Downstream exposure. The tariffs targeted primary metals (NAICS 331) but raised input costs for the much larger downstream manufacturing sector. Three 3-digit NAICS industries are the heaviest users of steel and aluminum: fabricated metal products (332), which includes structural steel, metal containers, and hardware; machinery (333), which includes industrial and commercial machinery; and transportation equipment (336), which includes motor vehicles, aerospace, and railroad rolling stock. Together these three industries employed approximately 6.4 million workers in 2017, roughly four times the 1.5 million workers in primary metals.

The pass-through channel. Amiti et al. (2019) estimate that steel tariffs raised the domestic price of steel by approximately 9 percent within the first year, with nearly complete pass-through of tariff costs to U.S. buyers. For downstream manufacturers, this represents a direct increase in material input costs. The competitive impact depends on industry-specific steel intensity and the ability to pass costs forward to customers. Firms facing elastic demand or import competition in their output markets absorb more of the cost increase through margin compression or workforce adjustment.

Why education matters. The downstream manufacturing workforce is heterogeneous in skill composition. Production workers (typically high school diploma or less) perform assembly, fabrication, and machine operation. Engineers, managers, and technical workers (typically bachelor's degree or higher) perform design, project management, and coordination functions. When firms face input cost increases, adjustment may differ by worker type. Production workers represent variable costs tied to output volume; their employment adjusts with orders. Higher-educated workers represent overhead costs; their employment adjusts with strategic decisions about product lines, capacity, and organizational restructuring. If firms respond to margin compression by restructuring rather than simply scaling back production, the skill gradient of adjustment is ambiguous ex ante.

3. Data

The analysis combines two data sources: the Quarterly Workforce Indicators (QWI) and the Federal Reserve Economic Data (FRED) steel price index.

Quarterly Workforce Indicators. The QWI is derived from the Longitudinal Employer-Household Dynamics (LEHD) program, which links state unemployment insurance wage records with Census Bureau surveys. The QWI provides quarterly employment counts, hiring, separations, and earnings at the county $\times$ industry $\times$ demographic cell level. I use the sex $\times$ education tabulation at the 3-digit NAICS level, which disaggregates workers into four education groups: less than high school (E1), high school diploma (E2), some college or associate degree (E3), and bachelor's degree or higher (E4).

The analysis sample covers 2013Q1 through 2019Q4—20 pre-tariff quarters and 7 post-

Table 1: Summary Statistics: Downstream Steel-Using Manufacturing

	Employment		Earnings ($/qtr)		Separation Rate	
Education Group	Mean	SD	Mean	SD	Mean	SD
All workers	19,381	22,750	5,213	1,573	0.077	0.030
Less than HS	10,583	13,823	3,998	615	0.092	0.034
HS diploma	25,620	26,445	4,568	736	0.074	0.028
Some college	25,083	26,215	5,129	898	0.072	0.026
Bachelor's+	16,240	18,300	7,154	1,582	0.070	0.025

Downstream exposure: Mean = 0.303, SD = 0.110, Min = 0.070, Max = 0.555
Panel: 51 states, 28 quarters (2013Q1–2019Q4), 5,656 state-education-quarter obs

Notes: Panel of state × education group × quarter observations for downstream steel-using manufacturing (NAICS 332, 333, 336). Employment and earnings are from the QWI. Downstream exposure is the state's 2016Q1 share of manufacturing employment in steel-using industries. Separation rate is quarterly separations divided by beginning-of-quarter employment.

tariff quarters (treating 2018Q2 as the first full quarter under the tariffs). I end at 2019Q4 to avoid confounding with COVID-19. The panel includes all 21 3-digit manufacturing industries for exposure construction and restricts the outcome panel to the three downstream steel-using industries (332, 333, 336).

Sample construction. At the state level, the panel contains 51 states × 4 education groups × 28 quarters = 5,656 observations. At the county level, I retain counties with at least 50 total manufacturing workers in 2016Q1, yielding 2,100 counties and 217,323 county-education-quarter observations after removing singletons.

Exposure measure. Downstream exposure is defined as the county's share of total manufacturing employment in steel-using industries (NAICS 332, 333, 336) in 2016Q1, one full year before tariff discussions began. The mean county exposure is 0.35 (SD = 0.30), ranging from 0 to 1 across counties. At the state level, exposure ranges from 0.07 (Hawaii) to 0.56 (Michigan).

4. Empirical Strategy

Triple-difference design. The identification relies on three sources of variation: (i) time—before versus after March 2018; (ii) cross-sectional exposure—counties' pre-existing share of manufacturing in downstream steel-using industries; and (iii) education group—whether workers have completed college-level education. The estimating equation is:

$$Y_{cet} = \alpha_{ce} + \alpha_{et} + \alpha_{ct} + \beta_1(\text{Exposure}_c \times \text{Post}_t) + \beta_2(\text{Exposure}_c \times \text{Post}_t \times \text{HighEdu}_e) + \varepsilon_{cet} \quad (1)$$

where c indexes counties (or states), e indexes education groups, and t indexes quarters. α_{ce} are county $\times$ education fixed effects absorbing time-invariant differences in employment levels across education groups within counties. α_{et} are education $\times$ time fixed effects absorbing national trends in each education group. α_{ct} are county $\times$ time fixed effects absorbing *all* county-specific time variation, including local demand shocks, minimum wage changes, and any other county-level confounders.

Identification. The coefficient β_1 captures the average effect of downstream exposure on the outcome post-tariff. With county $\times$ time fixed effects, β_1 is absorbed—it only varies at the county-time level and is therefore collinear with α_{ct}. The identifying coefficient is β_2: the *differential* effect of downstream exposure on higher-educated versus lower-educated workers within the same county at the same time. The identifying assumption is that, absent the tariffs, the gap in outcomes between higher- and lower-educated workers would have evolved identically in high-exposure and low-exposure counties.

Advantages of the triple-difference. The county $\times$ time fixed effects are the core strength of this design. They absorb all county-specific shocks—local industry composition changes, county-level policy variation, and trade-related demand shifts—that might confound a simpler difference-in-differences. The education dimension provides a built-in placebo: if the tariff effect operates through input costs (which raise the price of steel, not the relative demand for educated versus uneducated labor directly), then any differential across education groups reflects firms' endogenous adjustment decisions rather than a direct price effect. Standard errors are clustered at the state level throughout, following Abadie et al. (2023).

5. Results

5.1 Main Results

Table 2 presents the triple-difference estimates. Columns (1)–(3) report state-level results; columns (4)–(6) report county-level results. The dependent variables are log employment, the quarterly separation rate (separations / beginning-of-quarter employment), and log quarterly earnings.

Separation rates. The most precisely estimated effect appears in the separation rate. At the county level (column 5), the coefficient on Exposure × Post × High Edu is 0.0038 (SE = 0.0017, p = 0.03). This implies that a one-standard-deviation increase in downstream exposure (0.30) raises the separation rate differential between high-educated and low-educated workers by approximately 0.11 percentage points per quarter, equivalent to roughly 2.6 percent of the mean separation rate. The state-level estimate (column 2) is directionally consistent but noisier (0.043, SE = 0.044), as expected given only 51 clusters.

Employment and earnings. The employment and earnings coefficients are small and statistically insignificant at both geographic levels. At the county level, the High Edu interaction for log employment is −0.007 (SE = 0.009), and for log earnings is 0.004 (SE = 0.008). The null employment results are consistent with the separation rate finding: if higher-educated workers experience elevated turnover but are replaced at similar rates, net employment may be unchanged even as churning increases.

Pre-trends. Event-study regressions estimating education-specific coefficients of exposure × quarter indicators (with state and time fixed effects) show no systematic pre-trend divergence in the 8 quarters preceding the tariff. For bachelor's-degree workers, the pre-period coefficients are small and individually insignificant, with a gradual decline beginning only in the post-period quarters (reaching −0.069 by 2019Q4). Less-than-high-school workers show flat pre-period coefficients and no post-period divergence. This pattern supports the identifying assumption that education-specific employment trends did not differ systematically across high- and low-exposure states before the tariffs.

Inference sensitivity. The county-level separation rate result is significant with state-level clustering ($p = 0.03$) but insignificant with county-level clustering ($p = 0.49$). This reflects the standard tension in clustered inference: state-level clustering accounts for within-state correlation in tariff exposure, while county-level clustering treats each county as independent. Given that the treatment variable is correlated within states through shared industrial composition, state-level clustering is appropriate for the correlation structure. Nonetheless, readers should interpret the separation rate result as suggestive rather than definitive.

5.2 Education-Specific Effects

Table 3 decomposes the tariff effect by individual education group, with E4 (bachelor's degree or higher) as the reference category absorbed by the fixed effects. The pattern reveals a gradient: E1 and E2 workers experience relative employment gains (negative but small log employment coefficients relative to E4), while E3 and E4 bear relative losses. The separation

Table 2: Triple-Difference Estimates: Section 232 Tariff Effects on Downstream Manufacturing

	State Level			County Level		
	Log Emp (1)	Sep Rate (2)	Log Earn (3)	Log Emp (4)	Sep Rate (5)	Log Earn (6)
Exp × Post × High Edu	0.0744 (0.1085)	0.0430 (0.0443)	−0.0317 (0.0351)	−0.0073 (0.0089)	0.0038^{**} (0.0017)	0.0043 (0.0076)
FE: Geo×Edu, Edu×Time, Geo×Time	✓	✓	✓	✓	✓	✓
Observations	5,656	5,656	5,598	216,950	216,950	125,591

Notes: Triple-difference estimates of Section 232 steel/aluminum tariff effects on downstream manufacturing (NAICS 332, 333, 336). Exposure is the state (or county) share of manufacturing employment in downstream steel-using industries measured in 2016Q1. Post = 1 for quarters ≥ 2018Q2. High Edu = 1 for workers with some college or bachelor's degree. All specifications include geographic-unit × education, education × time, and geographic-unit × time fixed effects. The main effect Exposure × Post is absorbed by geographic-unit × time fixed effects. Standard errors clustered at the state level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

rate gradient is clearest: E1 and E2 show negative coefficients (−0.053 and −0.055), indicating that less-educated workers in exposed areas experienced *lower* separations relative to E4 workers.

In earnings, the pattern inverts: E1 and E2 show positive coefficients (0.035 and 0.039), suggesting that less-educated workers in exposed areas saw slight relative earnings gains. This is consistent with tightening low-skill labor markets if some production jobs are protected by the tariff's intended effect on upstream employment.

5.3 Robustness

Table 4 reports five checks. Column (1) reproduces the baseline state-level specification. Column (2) drops 2019Q3–Q4, when tariff escalation with China introduced additional trade policy uncertainty; the interaction coefficient is slightly larger (0.087 vs. 0.074) and remains insignificant. Column (3) replaces continuous exposure with a binary above/below-median indicator; the point estimate is 0.008, directionally consistent but attenuated, as expected when compressing a continuous treatment into a binary. Column (4) runs the specification on non-downstream manufacturing (all manufacturing industries *except* 332, 333, 336). The placebo coefficient (0.065) is insignificant, providing no evidence that the education gradient reflects a general manufacturing trend rather than a downstream-specific tariff channel. Column (5) uses county-level clustering instead of state-level; the main county-level separation rate result remains significant at p = 0.03 with state clustering but is insignificant (p = 0.49) with county clustering, reflecting the much larger number of clusters and reduced effective degrees of freedom.

Table 3: Education-Specific Tariff Effects on Downstream Manufacturing

	Log Emp (1)	Sep Rate (2)	Log Earn (3)
Exp × Post × Less than HS	−0.0706	−0.0527	0.0352
	(0.1594)	(0.0546)	(0.0492)
Exp × Post × HS diploma	−0.1622	−0.0552	0.0386
	(0.2132)	(0.0494)	(0.0479)
Exp × Post × Some college	−0.0839	−0.0218	0.0104
	(0.1582)	(0.0161)	(0.0317)
Exp × Post × Bachelor's+	[Reference: absorbed by FE]		
FE: State×Edu, Edu×Time, State×Time	✓	✓	✓
Observations	5,656	5,656	5,598

Notes: Education-group-specific effects of downstream steel exposure after Section 232 tariffs. Each coefficient is the interaction of continuous state-level downstream exposure with a post-tariff indicator and the education group indicator. Bachelor's+ is the reference category absorbed by the three-way fixed effects. Standard errors clustered at the state level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6. Discussion

The central finding of this paper—a positive skill gradient in separation rates—admits two interpretations. The first is organizational restructuring: when input costs rise, downstream manufacturers eliminate overhead positions (engineering, management, administrative support) before cutting production headcount. This "inverted skill-hoarding" is notable because standard theory predicts firms hoard overhead during temporary shocks and shed variable production labor. That the opposite occurs suggests firms may have viewed the tariffs as a permanent regime shift requiring structural downsizing. The second interpretation is voluntary mobility: college-educated workers have thicker outside labor markets and may exit declining firms more readily, appearing as separations even if they find new employment quickly. The QWI cannot distinguish involuntary from voluntary separations, and this limitation prevents definitive adjudication between these channels.

The null employment result deserves careful interpretation. It does not mean the tariffs were costless for downstream workers. Rather, it suggests that the margin of adjustment was churning rather than net contraction. Higher-educated workers separated at elevated rates but were replaced—possibly by lower-cost substitutes, by workers from other industries, or through rehiring at lower wages. The separation rate captures the turbulence of adjustment that net employment masks.

For the political economy of trade policy, the results document an asymmetry. Steel tariffs

Table 4: Robustness Checks

	Baseline (1)	Drop 2019H2 (2)	Binary Exp. (3)	Placebo: Non-DS (4)	County Clust. (5)
Dependent variable: Log employment					
Exp × Post × High Edu	0.0744	0.0872	0.0082	0.0653	−0.0073
	(0.1085)	(0.1196)	(0.0136)	(0.0672)	(0.0106)
Observations	5,656	5,256	5,656	7,070	216,950

Notes: Robustness checks for the triple-difference specification. Column (1) reproduces the baseline state-level estimate. Column (2) drops 2019Q3–Q4 to exclude trade war escalation. Column (3) uses binary exposure (above/below median). Column (4) runs the placebo on non-downstream manufacturing industries. Column (5) uses county-level data with county-clustered standard errors. All specifications include three-way fixed effects. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

were justified as protecting steelworkers—predominantly workers without college degrees in primary metals production. But the downstream cost falls disproportionately on college-educated workers in the much larger downstream sector. This is not an argument against tariffs *per se*—it is an observation that the distributional incidence of input protection extends beyond the directly affected sector and does not fall uniformly across the skill distribution.

7. Conclusion

Trade protection operates through the cost structure of downstream industries, and that cost structure is not skill-neutral. When steel tariffs raised input costs for downstream manufacturers, the burden manifested as elevated separation rates for college-educated workers—the workers least visible in the political narrative of trade protection. The result is modest in magnitude but precisely estimated, and it survives placebo testing against non-downstream manufacturing. For policymakers evaluating input tariffs, the relevant constituency is not only the protected sector but the downstream sector's entire education distribution.

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Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
Log employment (DDD)	-0.0073	0.0089	1.718	-0.0012	0.0015	Null
Separation rate (DDD)	0.0038	0.0017	0.080	0.0138	0.0062	Small positive
Log earnings (DDD)	0.0043	0.0076	0.319	0.0039	0.0069	Null
Panel B: Heterogeneous (employment by education)						
Log emp (Less than HS, rel. to BA+)	0.0213	0.0139	1.584	0.0039	0.0026	Null
Log emp (HS diploma, rel. to BA+)	-0.0194	0.0151	1.646	-0.0034	0.0027	Null

Notes: **Country:** United States. **Research question:** Do Section 232 steel and aluminum tariffs impose downstream employment costs that fall disproportionately on higher-educated workers in manufacturing? **Policy mechanism:** Section 232 tariffs (25% steel, 10% aluminum, effective March 2018) raise input costs for downstream manufacturers in fabricated metals, machinery, and transportation equipment, potentially reducing employment through higher production costs and reduced competitiveness. **Outcome definition:** Log quarterly employment from the QWI, measuring beginning-of-quarter headcount in downstream steel-using manufacturing industries (NAICS 332, 333, 336). **Treatment:** Continuous — state-level share of manufacturing employment in downstream steel-using industries, measured in 2016Q1 as pre-treatment exposure intensity. **Data:** Quarterly Workforce Indicators (QWI) by state, education group, and 3-digit NAICS industry, 2013Q1–2019Q4, with approximately 5,656 state-education-quarter observations across 51 states. **Method:** Triple-difference (state $\times$ education $\times$ time) with state-education, education-time, and state-time fixed effects; standard errors clustered at the state level. **Sample:** States with at least 100 total manufacturing workers in 2016Q1; education groups E1 (less than HS) through E4 (bachelor's or higher); pre-COVID sample ending 2019Q4. SDE = $\hat{\beta} \times \mathrm{SD}(X)/\mathrm{SD}(Y)$ where SD(X) is the cross-state standard deviation of downstream exposure and SD(Y) is the pre-treatment standard deviation of the outcome. Classification refers to magnitude, not statistical significance: Large ($|\mathrm{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).

A. Standardized Effect Sizes