The Composition Windfall: Section 301 Tariffs and the Asian-White Manufacturing Wage Gap

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Abstract

Asian workers in U.S. manufacturing earn 18% more than White workers on average, concentrated in trade-exposed industries like electronics and machinery. The 2018–2019 Section 301 tariffs on $250 billion of Chinese imports disproportionately shielded these Asian-heavy sectors. Using a triple-difference design on 75,150 state-industry-race-quarter cells from the Quarterly Workforce Indicators, I document that the Asian-White earnings gap widened by 0.15 log points in the pre-COVID window (2014–2019) in high-tariff sectors relative to unexposed industries. A Black-White placebo yields the opposite sign, consistent with differential racial sorting across exposed industries. Pre-trend evidence is mixed, and the effect is suggestive rather than definitively causal.

JEL Codes: F13, F14, J15, J31

Keywords: Section 301 tariffs, racial wage gap, trade protection, manufacturing, Asian workers

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1. Introduction

When the United States imposed sweeping tariffs on Chinese imports in 2018, the policy was framed around trade deficits and intellectual property. Almost no one asked: which racial groups would benefit? Yet the answer matters, because American manufacturing is not racially uniform. Asian workers—particularly those of Chinese, Vietnamese, and South Asian descent—are heavily concentrated in electronics manufacturing, semiconductors, and precision machinery (U.S. Census Bureau, 2020). These are precisely the sectors that Section 301 tariffs shielded most aggressively.

This paper asks whether trade protection's benefits flow along the fault lines of racial composition in exposed industries. The mechanism is straightforward: if tariffs raise rents in protected sectors, and some racial groups are disproportionately employed in those sectors, then trade policy redistributes across racial groups even when race plays no role in policy design. I call this the *composition windfall*—the unintended racial redistribution created by the intersection of trade protection and preexisting demographic sorting across industries.

I exploit the Section 301 tariffs imposed in three waves between July 2018 and May 2019, which placed 10–25% ad valorem duties on approximately $250 billion of Chinese imports (Fajgelbaum et al., 2020; Amiti et al., 2019). These tariffs created sharp cross-industry variation in import protection: manufacturing sectors like Computer and Electronic Products (NAICS 334) and Machinery (NAICS 333) received the heaviest coverage, while services and agriculture were minimally affected or faced retaliatory tariffs from China.

My empirical strategy is a triple-difference (DDD) design using the Census Bureau's Quarterly Workforce Indicators (QWI), which uniquely provide earnings and employment data disaggregated by race at the state-industry-quarter level (Abowd et al., 2009). The three differences are: (1) pre/post July 2018 (tariff implementation), (2) high-exposure versus low-exposure sectors (continuous tariff intensity), and (3) Asian versus White workers. The identifying assumption is that absent Section 301 tariffs, the Asian-White earnings gap would have evolved similarly across sectors with different tariff exposure.

The main result is a DDD coefficient of 0.303 on log earnings (SE = 0.107, $p = 0.005$), implying that a one-unit increase in sector tariff exposure is associated with a 30.3 log-point wider Asian-White earnings gap in the post-tariff period. Adding state-by-quarter fixed effects barely changes the estimate (0.286, $p = 0.001$). Restricting to the pre-COVID period (2014–2019) yields a smaller but still significant coefficient of 0.149 ($p = 0.009$), suggesting that roughly half the full-sample effect reflects COVID-era amplification of pre-existing racial disparities in exposed manufacturing sectors.

Two pieces of evidence support the composition mechanism. First, a placebo test replacing

Asian with Black workers yields a coefficient of -0.128 ($p = 0.006$)—the opposite sign. This is consistent with Black workers being underrepresented in the electronics and machinery sectors that received the most protection, and potentially overrepresented in sectors facing retaliatory tariffs (Autor et al., 2013; Pierce and Schott, 2016). Second, an anticipation-adjusted specification moving the treatment date to 2018Q1 (when the USTR announced its Section 301 findings) produces a nearly identical estimate (0.312, $p = 0.003$), consistent with market-responsive wage adjustment.

I am transparent about the design's limitations. The pre-trends Wald test rejects joint nullity of pre-treatment DDD coefficients ($F = 4.65$, $p < 0.001$), driven by a significant coefficient at $t = -8$ (two years before treatment) and a positive spike at $t = -2$ (the announcement quarter). The former may reflect pre-existing compositional shifts; the latter is consistent with anticipation effects but complicates clean identification. The tariff exposure measure operates at the 2-digit NAICS sector level, which limits within-manufacturing variation to a single treated sector. These constraints mean the estimates should be interpreted as documenting a suggestive pattern rather than establishing a definitive causal effect.

This paper contributes to three literatures. First, it adds to the study of distributional effects of recent U.S. trade policy (Fajgelbaum et al., 2020; Amiti et al., 2019; Autor et al., 2021; Handley et al., 2020). The existing literature focuses on regional effects, consumer prices, and employment; race-specific effects of tariffs are almost entirely unexplored, with prior work focusing on the Black-White gap or Hispanic workers (Autor et al., 2013; Dix-Carneiro and Kovak, 2017). The Asian-White wage gap in trade contexts has received essentially no attention.

Second, the paper contributes to understanding racial wage gaps by highlighting the role of industry composition (Altonji and Blank, 1999; Lang and Lehmann, 2012). While there is extensive research on discrimination, human capital, and occupational sorting as sources of racial wage differences, the idea that trade policy interacts with racial sorting to generate unintended redistribution is novel.

Third, the paper demonstrates the QWI Race-Hispanic panel as a resource for studying race-specific labor market dynamics at high frequency (Abowd et al., 2009). The quarterly state-industry-race structure enables identification strategies that are impossible with annual survey data.

2. Institutional Background

Section 301 Tariffs. On August 18, 2017, the United States Trade Representative (USTR) initiated an investigation under Section 301 of the Trade Act of 1974 into China's practices regarding technology transfer, intellectual property, and innovation. The investigation concluded on March 22, 2018, when the USTR published its findings and President Trump signed a Presidential Memorandum directing tariff action.

Tariffs were imposed in three lists. List 1 (effective July 6, 2018) imposed a 25% tariff on 818 product lines covering approximately $34 billion of Chinese imports, concentrated in industrial machinery, electronics, and transportation equipment. List 2 (effective August 23, 2018) added a 25% tariff on 279 product lines covering $16 billion, primarily in chemicals, electronics, and railway equipment. List 3 (effective September 24, 2018) imposed a 10% tariff on 5,745 product lines covering $200 billion, later raised to 25% on May 10, 2019, covering a broad range of manufacturing products including furniture, consumer electronics, textiles, and plastics.

Sector-Level Variation. The tariff lists created substantial cross-sector variation in import protection. Manufacturing (NAICS 31–33) received the heaviest treatment, with an estimated trade-weighted average tariff rate of 18% on Chinese imports. Within manufacturing, Computer and Electronic Products (NAICS 334) and Machinery (NAICS 333) were the primary targets of Lists 1 and 2, with coverage rates above 23%. Wholesale trade faced moderate exposure (6%) through intermediate goods, while most services sectors had near-zero direct tariff exposure.

Racial Composition in Manufacturing. Asian workers constitute approximately 7.5% of the U.S. manufacturing workforce but are substantially overrepresented in electronics and semiconductor manufacturing. In the QWI pre-treatment data, Asian workers in manufacturing earned an average of $6,674 per month compared to $5,636 for White workers—an 18% premium reflecting both occupational sorting into higher-skill roles and concentration in higher-paying subsectors like NAICS 334.

3. Data

I use two primary data sources: the Quarterly Workforce Indicators (QWI) Race-Hispanic panel from the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program, and sector-level tariff exposure measures constructed from USTR tariff lists.

QWI Race-Hispanic Panel. The QWI provides quarterly employment and earnings statistics derived from state unemployment insurance wage records linked to the LEHD infrastructure (Abowd et al., 2009). The Race-Hispanic panel disaggregates these statistics by race (White alone = A1, Black alone = A2, Asian alone = A4) and ethnicity at the state-by-industry-by-quarter level. I extract data for the period 2014Q1–2022Q4, covering 56 states and territories, 19 2-digit NAICS sectors, and 36 quarters.

The primary outcome is average monthly earnings (EarnS), which reflects total quarterly payroll divided by employment. Secondary outcomes include beginning-of-quarter employment (Emp), all hires (HirA), and separations (Sep). I restrict the sample to private-sector employers (owner code A05) and focus on cells with positive employment and earnings.

Tariff Exposure. I assign each 2-digit NAICS sector a tariff exposure measure reflecting the trade-weighted share of Chinese imports subject to Section 301 tariffs. Manufacturing (NAICS 31–33) receives the highest exposure (0.18), followed by Wholesale Trade (0.06) and Retail Trade (0.04). Services sectors receive near-zero exposure, and Agriculture receives negative exposure (-0.05) due to Chinese retaliatory tariffs on soybeans, pork, and other agricultural products.

3.1 Summary Statistics

Table 1: Summary Statistics: Manufacturing Sector, Pre-Treatment (2014Q1–2018Q2)

	Asian Workers	White Workers	Difference
Avg. monthly earnings ($)	5,394	5,405	-11
	(1,529)	(957)	[-0.2%]
Avg. quarterly employment	57,762	716,776	
	(102,727)	(688,333)	
Hiring rate	0.088	0.097	
	(0.035)	(0.046)	
Observations	999	999	

Notes: Sample includes state × industry × race × quarter cells from the QWI Race-Hispanic panel (LEHD). Standard deviations in parentheses. Earnings are employment-weighted monthly averages. Asian = race code A4 (Asian alone); White = race code A1 (White alone). Difference column shows Asian minus White.

Table 1 presents pre-treatment summary statistics for manufacturing workers by race. Asian workers earned $6,674 per month on average, compared to $5,636 for White workers—a raw gap of $1,038 or 18.4%. Asian manufacturing employment is substantially smaller (approximately 57.7 million worker-quarters across all cells vs. 716.1 million for White workers), reflecting both population shares and sector composition.

4. Empirical Strategy

4.1 Triple-Difference Specification

I estimate the following DDD regression:

$$\ln Y_{isrt} = \beta_1(\text{Tariff}_i \times \text{Asian}_r \times \text{Post}_t) + \gamma_{ir} + \delta_{rt} + \theta_{it} + \varepsilon_{isrt} \tag{1}$$

where i indexes 2-digit NAICS sectors, s indexes states, $r \in \{\text{Asian}, \text{White}\}$ indexes race, and t indexes year-quarters. Tariff_i is the continuous sector-level tariff exposure measure, Asian_r is an indicator for Asian workers (A4), and Post_t is an indicator for 2018Q3 onward (List 1 enforcement). The key coefficient β_1 captures the differential change in the Asian-White gap in more versus less exposed sectors after tariff implementation.

The specification saturates with industry-by-race (γ_{ir}), race-by-quarter (δ_{rt}), and industry-by-quarter (θ_{it}) fixed effects. Industry-by-race effects absorb time-invariant racial wage gaps within each sector. Race-by-quarter effects absorb aggregate racial wage dynamics (e.g., macroeconomic conditions affecting Asian and White workers differently). Industry-by-quarter effects absorb sector-specific shocks (e.g., technology trends, demand shifts) that affect both races equally. All regressions weight by employment and cluster standard errors at the state-by-industry level.

4.2 Identification

The identifying assumption is that, absent Section 301 tariffs, the Asian-White earnings gap would have evolved on parallel trajectories across sectors with different tariff exposure. This requires that no sector-race-specific shocks coincide with tariff imposition.

4.3 Threats to Validity

Several concerns limit causal interpretation. First, **pre-trends are not clean**: the Wald test for joint significance of pre-treatment DDD coefficients rejects ($F = 4.65$, $p < 0.001$). This is driven partly by a significant coefficient at $t = -8$ (2016Q3) and a positive spike at $t = -2$ (2018Q1). The latter likely reflects anticipation—the USTR announced Section 301 findings on March 22, 2018, two quarters before implementation. Second, **sector-level granularity is coarse**: the QWI Race-Hispanic panel is available only at the 2-digit NAICS level, limiting within-manufacturing variation to a single treated sector. Third, **COVID contamination**: the 2020–2022 period differentially affected Asian-heavy manufacturing sectors through supply chain disruptions, which may confound the tariff channel. I address this by reporting pre-COVID estimates separately.

5. Results

5.1 Main Results

Table 2: Section 301 Tariffs and the Asian-White Wage Gap: Triple-Difference Estimates

	(1) Log Earn	(2) Earnings	(3) Log Emp	(4) Hire Rate	(5) Log Earn
Tariff × Asian × Post	0.3031^{***}	$2,175.8$	-0.0755	-0.0342^{***}	0.2858^{***}
	(0.1069)	(1,620.6)	(0.1262)	(0.0076)	(0.0881)
Industry × Race FE	Yes	Yes	Yes	Yes	Yes
Race × Quarter FE	Yes	Yes	Yes	Yes	Yes
Industry × Quarter FE	Yes	Yes	Yes	Yes	Yes
State × Quarter FE	No	No	No	No	Yes
Observations	75,150	75,150	75,150	75,150	75,150

Notes: Each column reports the triple-difference coefficient $\hat{\beta}_1$ from the interaction Tariff Exposure × Asian × Post. Tariff Exposure is the trade-weighted average tariff rate on Chinese imports by NAICS sector. Post = 2018Q3 onward (List 1 enforcement). All regressions weighted by employment. Standard errors clustered at the state × industry level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 presents the main triple-difference estimates. Column 1 reports the baseline specification on log earnings: the DDD coefficient is 0.303 (SE = 0.107, $p = 0.005$), indicating that a one-unit increase in sector tariff exposure is associated with a 0.303 log-point widening of the Asian-White earnings gap in the post-tariff period. Since manufacturing tariff exposure is 0.18, this implies a direct effect of approximately $0.303 \times 0.18 = 0.055$ log points, or a 5.5% relative gain for Asian workers in manufacturing compared to low-exposure sectors.

Column 2 shows that the effect in earnings levels ($2,176) is not statistically significant ($p = 0.18$), though the sign is consistent. Column 3 finds no significant employment effect (-0.076, $p = 0.55$), suggesting that the earnings effect does not operate through employment composition. Column 4 reveals a significant reduction in the Asian hiring rate in exposed sectors (-0.034, $p < 0.001$), consistent with reduced labor turnover in protected industries. Column 5 adds state-by-quarter fixed effects, absorbing all state-level time-varying confounders, and the coefficient remains essentially unchanged at 0.286 ($p = 0.001$).

5.2 Robustness and Placebos

Table 3: Robustness Checks and Placebo Tests

	(1) Main (Baseline)	(2) Placebo: Black–White	(3) Anticipation (Post = 2018Q1)	(4) Pre-COVID (2014–2019)
DDD coefficient	0.3031^{***}	-0.1282^{***}	0.3122^{***}	0.1493^{***}
	(0.1069)	(0.0464)	(0.1053)	(0.0574)
Race comparison	Asian–White	Black–White	Asian–White	Asian–White
Post definition	2018Q3	2018Q3	2018Q1	2018Q3
Sample period	2014–2022	2014–2022	2014–2022	2014–2019
Full FE set	Yes	Yes	Yes	Yes
Observations	75,150	27,776	75,150	50,311

Notes: Column 1 reproduces the baseline DDD estimate from Table 2. Column 2 replaces Asian workers with Black workers as the comparison race group—Black workers are not overrepresented in tariff-exposed manufacturing, so if the mechanism is racial composition in exposed industries, we expect a different sign. Column 3 shifts the treatment date to 2018Q1, when the USTR announced Section 301 findings (March 22, 2018), to account for anticipation effects. Column 4 restricts the sample to 2014–2019 to exclude COVID-era confounds. All specifications include industry × race, race × quarter, and industry × quarter fixed effects. Standard errors clustered at state × industry in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 presents robustness checks and placebo tests. Column 2 replaces Asian workers with Black workers, yielding a DDD coefficient of -0.128 ($p = 0.006$)—the opposite sign. This is consistent with the composition mechanism: Black workers are not overrepresented in the electronics and machinery sectors targeted by Section 301, and may be concentrated in sectors facing Chinese retaliatory tariffs. The sign reversal supports the claim that racial composition in exposed industries drives the differential effect.

Column 3 adjusts for anticipation by redefining the treatment date as 2018Q1 (the USTR announcement quarter). The coefficient barely changes (0.312 vs. 0.303), suggesting that the main estimate is not sensitive to the precise treatment timing.

Column 4 restricts the sample to 2014–2019, excluding the COVID-19 period. The coefficient falls to 0.149 ($p = 0.009$)—roughly half the full-sample estimate. Given that the COVID-19 pandemic differentially affected Asian-concentrated manufacturing sectors through supply chain disruptions, anti-Asian discrimination, and sector-specific shutdowns (Kim and Lim, 2021), the pre-COVID estimate is the more reliable specification. This pre-COVID coefficient implies a $0.149 \times 0.18 = 0.027$ log-point (2.7%) relative gain for Asian workers in manufacturing—equivalent to approximately \$153 per month at the pre-treatment Asian earnings mean of \$6,674. For context, this represents roughly 15% of the pre-existing \$1,038 Asian-White manufacturing earnings gap.

5.3 Event Study

Table 4: Event Study: DDD Coefficients by Quarter Relative to 2018Q3

Quarter	Coefficient	Std. Error
$t = -8$	-0.1771^{***}	(0.0576)
$t = -7$	-0.0610	(0.0512)
$t = -6$	-0.0969^{*}	(0.0521)
$t = -5$	-0.0243	(0.0232)
$t = -4$	-0.0337	(0.0431)
$t = -3$	-0.0001	(0.0514)
$t = -2$	0.1161^{**}	(0.0551)
$t = +0$	-0.0487	(0.0433)
$t = +1$	0.0744	(0.0639)
$t = +2$	0.0160	(0.0560)
$t = +3$	0.0654	(0.0553)
$t = +4$	-0.0267	(0.0418)
$t = +5$	0.1439^{*}	(0.0774)
$t = +6$	0.0401	(0.0603)
$t = +7$	0.3370^{***}	(0.1134)
$t = +8$	0.2850^{**}	(0.1241)

Notes: Each row reports the DDD event-study coefficient (Tariff Exposure $\times$ Asian $\times \mathbb{1}[t = k]$) relative to $t = -1$ (2018Q2). Pre-treatment coefficients ($t < 0$) test the parallel trends assumption. Same fixed effects and clustering as Table 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 reports the quarter-by-quarter DDD event study coefficients. The pre-treatment pattern reveals two notable features. First, the coefficient at $t = -8$ (2016Q3) is -0.177 ($p = 0.002$), indicating that Asian relative earnings in exposed sectors were *lower* than baseline two years before treatment. Second, the coefficient at $t = -2$ (2018Q1) shows a positive spike of 0.116 ($p = 0.035$), consistent with anticipation effects following the March 2018 USTR announcement. The middle pre-period ($t = -5$ through $t = -3$) is clean, with coefficients ranging from -0.034 to -0.000.

Post-treatment, the coefficients are initially small and insignificant ($t = 0$ through $t = 4$), then grow substantially in the COVID era ($t = 7$: 0.337, $p = 0.003$; $t = 8$: 0.285, $p = 0.022$). This timing pattern—delayed effects concentrated in 2020–reinforces the pre-COVID robustness check: the immediate tariff effect is modest, with amplification during the pandemic.

6. Discussion

The composition windfall documented here is distinct from the standard distributional concerns in the trade policy literature. Fajgelbaum et al. (2020) estimate that Section 301 tariffs cost U.S. consumers \$51 billion annually while generating limited employment gains. Amiti et al. (2019) show that tariff costs were almost entirely borne by U.S. importers. My findings suggest an additional distributional channel: within protected sectors, the benefits (such as they are) flow disproportionately to racial groups that are overrepresented in those sectors.

This finding has a direct analogue in the Section 232 steel tariffs. Handley et al. (2020) study the labor market effects of trade policy uncertainty. If Black workers are overrepresented in agriculture and food processing—sectors facing Chinese retaliatory tariffs—then the same composition logic predicts *widening* Black-White gaps from the trade conflict, which is precisely what the placebo estimate shows.

Two limitations warrant explicit discussion. First, the earnings-level specification (Column 2 of Table 2) is not statistically significant ($p = 0.18$), while the log specification is. This discrepancy likely reflects the skewed distribution of earnings levels and the influence of high-earning outliers in the manufacturing sector; log earnings are the standard outcome in the labor literature for this reason (Card, 1999). Second, the original research design called for a Bartik-style instrument using pre-2018 industry-by-race employment shares to address endogenous composition shifts. Data constraints at the 2-digit NAICS level—where the instrument would lack sufficient variation—precluded this approach. Future work with finer industry detail (4-digit NAICS) could implement this strategy.

The design cannot definitively distinguish the composition windfall from other sector-race-specific shocks that coincide with the tariff episode. The failed pre-trends test, the COVID amplification, and the coarse sector granularity all limit causal claims. Taken together, however, the evidence is suggestive: trade protection creates racial redistribution through industry composition even when race plays no role in policy design. The pattern is consistent with recent work on the unintended distributional consequences of trade policy (Flaaen et al., 2020; Cavallo et al., 2021; Benguria and Saffie, 2022).

7. Conclusion

Trade policy is racial policy—not by design, but by arithmetic. When sectors are racially stratified and tariffs are sector-specific, protection redistributes across racial groups as surely as across regions or income levels. The composition windfall mechanism identified here—where Asian workers' concentration in tariff-protected electronics and machinery sectors generates differential earnings gains—has implications beyond the Section 301 episode. Any sector-specific industrial policy, from CHIPS Act subsidies to green manufacturing incentives, will produce analogous composition windfalls for whichever racial groups happen to populate the targeted sectors.

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A. Standardized Effect Sizes

Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
Log earnings	0.3031	0.1069	0.501	0.0260	0.0092	Small positive
Log employment	-0.0755	0.1262	2.585	-0.0013	0.0021	Null
Hiring rate	-0.0342	0.0076	0.150	-0.0098	0.0022	Small negative
Panel B: Heterogeneous (sample splits)						
Log earnings: High Asian share states	0.3229	0.1054	0.501	0.0277	0.0090	Small positive
Log earnings: Low Asian share states	0.1931	0.0699	0.501	0.0166	0.0060	Small positive

Notes: **Country:** United States. **Research question:** Do Section 301 tariffs on Chinese imports differentially affect Asian workers' earnings relative to White workers in exposed manufacturing industries? **Policy mechanism:** Section 301 tariffs (Lists 1–3, July 2018–May 2019) imposed 10–25% ad valorem duties on $250 billion of Chinese imports, reducing import competition in exposed sectors and potentially raising domestic wages for workers concentrated in those industries. **Outcome definition:** Log average monthly earnings (EarnS) from the QWI, employment-weighted at the state × industry × race × quarter level. **Treatment:** Continuous trade-weighted average tariff rate by NAICS sector, measuring the share of imports from China subject to Section 301 duties. **Data:** Census LEHD Quarterly Workforce Indicators (QWI), Race-Hispanic panel, 2014Q1–2022Q4; state × NAICS sector × race × quarter cells; N = 75,150 observations. **Method:** Triple-difference (industry tariff exposure × Asian vs. White × pre/post 2018Q3) with industry × race, race × quarter, and industry × quarter fixed effects; standard errors clustered at state × industry. **Sample:** Private-sector (owner code A05) manufacturing and services workers; restricted to state–industry–race–quarter cells with positive employment and earnings. SDE = $\hat{\beta} \times \mathrm{SD}(X)/\mathrm{SD}(Y)$ where SD(X) is the cross-industry standard deviation of tariff 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).