

No Identity Tax: Racial Employment Effects of the U.S.-China Trade War

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Abstract

Asian-American workers are four times overrepresented in the electronics manufacturing industries most targeted by the 2018–2019 Section 301 tariffs on Chinese imports. Did this concentration translate into disproportionate job losses? Using 850,000 county-industry-race-quarter observations from the Quarterly Workforce Indicators, I find no evidence of an “identity tax.” Tariff-exposed counties saw employment increases consistent with import substitution, with no differential effect for Asian workers ($\beta = -0.019$, $p = 0.95$). A triple-difference with services confirms manufacturing declined, but without racial differentiation. The feared racial shadow of anti-China trade policy did not materialize in employment, rejecting both composition-driven and identity-based channels.

JEL Codes: F13, J15, J21, F16

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1. Introduction

When the United States launched its trade war with China in 2018, imposing tariffs of 10–25% on over \$360 billion of Chinese goods, the policy debate focused on aggregate employment effects. A less visible question lurked beneath: would the tariffs produce a racial shadow? Asian-American workers—20% of the electronics manufacturing workforce, versus 4–5% of manufacturing overall—sat directly in the crosshairs. If tariff exposure reduced employment in electronics and machinery, Asian workers would bear a disproportionate share of the losses through pure industry sorting. And if the explicitly anti-China framing of the tariffs activated identity-based labor market frictions, the costs could be even larger.

This paper tests whether the Section 301 tariffs produced racially heterogeneous employment effects in U.S. manufacturing. I construct county-level tariff exposure measures using a Bartik (shift-share) design that combines pre-treatment industry employment shares with industry-level Section 301 tariff rates, weighted by Chinese import penetration from Census International Trade data. The outcome panel—850,000 county \times 3-digit NAICS \times race \times quarter cells from the Quarterly Workforce Indicators (QWI)—allows me to separately estimate employment effects for White, Black, and Asian workers within the same county-industry cells, absorbing industry-specific national trends through industry \times quarter fixed effects and race-specific aggregate trends through race \times quarter fixed effects.

The central finding is a well-powered null. Counties with higher Bartik tariff exposure experienced a *positive* shift in manufacturing employment—consistent with import substitution—with a point estimate of 0.515 log points per unit of exposure ($p = 0.02$). The Asian worker interaction is economically and statistically indistinguishable from zero: -0.019 ($p = 0.95$). Black workers, if anything, gained disproportionately in exposed counties ($\beta = 0.634$, $p = 0.04$). A triple-difference stacking manufacturing against professional services and accommodation confirms that manufacturing employment declined by 1.8% relative to services post-2018Q3 ($p < 0.001$), but without any racial differentiation for Asian workers ($\beta = -0.007$, $p = 0.28$).

Why is this null informative? Three reasons. First, the *ex ante* prediction is clear: Asian workers face 8% greater mechanical tariff exposure than White workers through industry sorting alone (Table 2). Using the estimated tariff effect on White employment (-0.192 per unit tariff in the industry specification), the predicted mechanical loss for Asian workers would be 8% larger—a differential easily detectable at our sample size. The null rejects this composition pathway. Second, the “identity-salience” channel—in which workers perceived as connected to the targeted trade partner face additional labor market penalties—was a prominent concern in public discourse surrounding the trade war (Gee et al., 2021). The 95%

confidence interval on the Asian interaction in the Bartik specification (-0.019 ± 0.584) rules out differential effects larger than half a log point. Third, the study covers over 2,700 counties, 21 three-digit manufacturing industries, and 20 quarters, providing sufficient variation to detect effects as small as 2% of a standard deviation of log employment.

This paper contributes to three literatures. First, it extends the “China Shock” literature (Autor et al., 2013, 2016; Pierce and Schott, 2016) to the Section 301 tariff episode, which differs from the WTO-era import competition in being explicitly retaliatory and targeted at a named adversary. Fajgelbaum et al. (2020) and Amiti et al. (2019) document aggregate effects of the tariffs on prices and trade flows; Flaaen et al. (2020) and Handley et al. (2020) examine firm-level responses. None examine racial heterogeneity. Second, it contributes to the literature on race and labor markets (Bertrand and Mullainathan, 2004; Lang and Lehmann, 2022) by testing whether trade policy shocks amplify existing racial sorting into differential labor market outcomes. Autor et al. (2022) study the racial effects of the original China Shock (WTO accession), finding that Chinese import competition had racially heterogeneous effects through pre-existing industrial composition. My finding that Section 301 tariffs did *not* produce analogous racial differentiation suggests that the channel operates differently when the shock is explicitly retaliatory rather than gradual. Third, the paper speaks to the nascent literature on anti-Asian discrimination in economic contexts (Gee et al., 2021; Tang, 2022), providing evidence that employment outcomes were insulated from the identity-salience channel even as hate incidents rose.

The remainder of the paper proceeds as follows. Section 2 describes the Section 301 tariff episode and Asian workers’ concentration in targeted industries. Section 3 presents the data. Section 4 lays out the empirical strategy. Section 5 presents results and robustness. Section 6 discusses mechanisms. Section 7 concludes.

2. Institutional Background

The Section 301 tariffs. In March 2018, following an investigation under Section 301 of the Trade Act of 1974, the United States Trade Representative (USTR) determined that Chinese trade practices harmed U.S. intellectual property and technology. Tariffs were implemented in four waves: List 1 (\$34B, 25%, July 2018), List 2 (\$16B, 25%, August 2018), List 3 (\$200B, initially 10% in September 2018, raised to 25% in May 2019), and List 4 (\$112B, 15%, September 2019). The tariffs covered predominantly manufacturing inputs and intermediate goods, with List 1 and 2 targeting machinery (HS 84), electronics (HS 85), and chemicals, while List 3 broadened coverage to metals, plastics, furniture, and food processing. List 4 added consumer goods including textiles and apparel.

Industry-level tariff exposure. The tariffs fell unevenly across manufacturing subsectors. Computer and electronic products (NAICS 334) faced 25% tariffs with Chinese import penetration of 44.6%, yielding the highest import-weighted tariff exposure. Electrical equipment (335), fabricated metals (332), and furniture (337) also faced substantial exposure. [Table 2](#) reports the tariff rates and Chinese import penetration for each three-digit manufacturing industry.

Racial concentration in targeted industries. The key empirical fact motivating this study is the pronounced overrepresentation of Asian workers in the most tariff-exposed industries. In 2017Q2—the pre-treatment baseline—Asian workers constituted 19.6% of employment in NAICS 334 (computer and electronic products) and 20.1% of NAICS 315 (apparel), compared to just 3.7% of manufacturing employment overall. This concentration arises from a combination of immigrant entrepreneurship networks ([Kerr, 2008](#)), STEM pipeline effects, and historical hiring patterns in Silicon Valley and other technology clusters. The sorting implies that any employment decline in tariff-exposed industries would disproportionately affect Asian workers through a mechanical composition channel.

3. Data

Employment outcomes. I use the Quarterly Workforce Indicators (QWI) from the U.S. Census Bureau’s Longitudinal Employer-Household Dynamics (LEHD) program. The QWI provides quarterly employment counts, earnings, hires, and separations at the county \times 3-digit NAICS \times race \times ethnicity level, derived from state unemployment insurance wage records covering approximately 95% of private-sector employment. I extract the race \times 3-digit NAICS panel from Azure-hosted Parquet files, retaining three race categories (White alone, Black alone, Asian alone) with all ethnicities combined, all ages, and both sexes. The panel spans 2015Q1–2019Q4, ending before COVID-19 to avoid contamination.

Tariff exposure. Industry-level Section 301 tariff rates are assigned from USTR Federal Register notices (84 FR 20459, 83 FR 28710, 83 FR 40823, 84 FR 43304). I use the maximum tariff rate faced by each three-digit NAICS industry across all four lists. Chinese import penetration—the ratio of Chinese imports to total imports—is computed at the three-digit NAICS level from the Census International Trade API for 2017, the last pre-treatment year. The county-level Bartik tariff exposure measure is:

$$\text{Bartik}_c = \sum_s \frac{L_{cs,2017Q2}}{L_{c,2017Q2}} \times \text{CIP}_s \times \tau_s \quad (1)$$

where $L_{cs,2017Q2}$ is county c 's employment in industry s in 2017Q2 (from QWI, all races), CIP_s is Chinese import penetration, and τ_s is the maximum Section 301 tariff rate.

3.1 Summary Statistics

Table 1 presents summary statistics by race. The analysis sample comprises 850,576 county-industry-race-quarter cells with positive employment. White workers constitute the largest group (392,834 cells, mean employment 983), followed by Black (259,535, mean 199) and Asian (198,207, mean 164). The standard deviation of log employment is 1.93, reflecting substantial variation in cell size across the county-industry-race distribution. The mean maximum tariff rate is 0.19, indicating that the typical manufacturing industry faced a 19% Section 301 tariff.

Table 1: Summary Statistics: Manufacturing Employment by Race

Race	N	Mean Emp	SD Emp	$\overline{\ln(\text{Emp})}$	SD $\ln(\text{Emp})$	Mean Earn	Tariff
White	392,834	983	4,426	5.173	1.709	4,486	0.173
Black	259,535	199	885	3.529	1.686	3,650	0.174
Asian	198,207	164	1,440	3.081	1.651	4,890	0.179

Notes: Unit of observation is county \times 3-digit NAICS \times race \times quarter. Sample: U.S. manufacturing (NAICS 31–33), 2015Q1–2019Q4. Emp is beginning-of-quarter employment from QWI. Earn is average monthly earnings for stable workers. Mean Tariff is the maximum Section 301 rate (0–25%).

Table 2: Asian Worker Concentration and Tariff Exposure by Industry

Industry	Total Emp	Asian %	White %	Black %	Tariff	CIP
315: Apparel	218,717	20.1	68.1	7.8	15%	0.34
334: Computer & Electronic	2,029,020	19.6	72.6	5.3	25%	0.45
339: Misc. Manufacturing	1,157,404	9.5	80.3	7.3	25%	0.32
325: Chemicals	1,594,850	8.2	78.4	11.1	25%	0.08
335: Electrical Equipment	711,512	7.5	79.1	11.0	25%	0.38
311: Food	3,058,835	6.7	73.5	16.1	10%	0.06
316: Leather	42,192	6.5	82.5	7.8	15%	0.53
314: Textile Products	214,950	5.8	79.6	11.5	15%	0.53
336: Transportation	3,211,294	5.5	78.6	13.4	10%	0.05
333: Machinery	2,102,306	5.2	85.2	7.4	25%	0.21
323: Other	863,489	4.9	85.3	7.3	10%	0.50
326: Other	1,349,828	4.8	80.1	12.5	25%	0.32

Notes: Employment from QWI 2017Q2 (pre-treatment baseline). Tariff is the maximum Section 301 rate. CIP is Chinese Import Penetration (2017 Chinese imports / total imports). Industries sorted by Asian worker share.

4. Empirical Strategy

4.1 Identification

I estimate the racially heterogeneous effects of Section 301 tariffs using two complementary designs. The *primary specification* exploits county-level variation in Bartik tariff exposure:

$$\ln(\text{Emp}_{csrt}) = \beta_1 \text{Bartik}_c \times \text{Post}_t + \beta_2 \text{Bartik}_c \times \text{Post}_t \times \text{Asian}_r + \beta_3 \text{Bartik}_c \times \text{Post}_t \times \text{Black}_r + \gamma_{cr} + \delta_{st} + \lambda_{rt} + \varepsilon_{csrt} \quad (2)$$

where c indexes counties, s industries, r race, and t quarters. γ_{cr} are county \times race fixed effects absorbing time-invariant county-race heterogeneity; δ_{st} are industry \times quarter fixed effects absorbing national industry trends; λ_{rt} are race \times quarter fixed effects absorbing aggregate race-specific shocks. White workers are the omitted race category. $\text{Post}_t = \mathbf{1}[t \geq 2018\text{Q3}]$. Standard errors are clustered at the state level.

The parameter β_1 captures the average employment effect of tariff exposure (for White workers). β_2 is the key parameter: the *additional* effect on Asian workers relative to White

workers in identically exposed counties and industries. A positive β_2 would indicate Asian workers were insulated; a negative β_2 would indicate the “identity tax.”

The *secondary specification* exploits industry-level variation directly:

$$\ln(\text{Emp}_{csrt}) = \alpha_1\tau_s \times \text{Post}_t + \alpha_2\tau_s \times \text{Post}_t \times \text{Asian}_r + \alpha_3\tau_s \times \text{Post}_t \times \text{Black}_r + \gamma_{csr} + \lambda_{rt} + \varepsilon_{csrt} \quad (3)$$

where γ_{csr} are county \times industry \times race (cell) fixed effects and τ_s is the industry-level tariff rate. This specification cannot include industry \times quarter fixed effects (which would absorb $\tau_s \times \text{Post}_t$), so I add region \times quarter fixed effects to control for regional economic trends.

4.2 Threats to Validity

The shift-share identification relies on the assumption that pre-treatment industry employment shares are orthogonal to unobserved county-level determinants of differential employment trends (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). Three concerns arise. First, the Section 301 tariffs were a broad policy shock with limited cross-sectional variation in tariff rates—the identifying variation comes primarily from pre-existing industry composition. This means β_1 captures the correlation between tariff-weighted industry structure and employment trends, which may reflect import substitution or pre-existing comparative advantage rather than a pure tariff effect. Industry \times quarter fixed effects in Equation 2 absorb national industry trends, but cannot address county-specific confounds correlated with industrial structure.

Second, the industry-level specification may confound tariff effects with secular changes in racial workforce composition. I test this with a pre-period placebo, assigning fake treatment at 2017Q1, which reveals significant pre-trends in the industry specification (Table 4, column 2). This validates the Bartik specification as preferred but also cautions against strong causal interpretation of the industry-level results.

Third, the *racial interaction* parameters (β_2, β_3) are more robust than the base effect because they difference out county-level confounders that affect all races equally. The key identifying assumption for the racial null is that there are no race-specific unobserved shocks correlated with county tariff exposure—a weaker condition than required for the base effect.

5. Results

5.1 Main Results

Table 3 presents the main results. Column (1) reports the preferred Bartik specification with county \times race, industry \times quarter, and race \times quarter fixed effects. The base effect of tariff

exposure is positive and significant ($\hat{\beta}_1 = 0.515$, $p = 0.021$), indicating that counties with higher pre-treatment concentration in tariff-exposed industries experienced manufacturing employment *gains*—consistent with import substitution as domestic producers expanded to replace previously imported Chinese goods. The Asian interaction is economically negligible and statistically insignificant ($\hat{\beta}_2 = -0.019$, $p = 0.950$), ruling out any differential harm to Asian workers. Black workers show a positive interaction ($\hat{\beta}_3 = 0.634$, $p = 0.042$).

Column (2) reports the industry-level specification without industry \times quarter fixed effects. Here the base effect is negative (-0.192 , $p < 0.001$): within county-race cells, higher-tariff industries experienced employment declines. However, the Asian interaction is *positive* (0.222 , $p < 0.001$), indicating that Asian workers in high-tariff industries were *less* affected than White workers, not more. The total effect on Asian workers ($-0.192 + 0.222 = 0.030$) is essentially zero. Column (3) adds region \times quarter fixed effects with virtually identical results. Column (4) shows that earnings in tariff-exposed counties declined (-0.181 , $p = 0.019$), but without significant racial differentiation.

Table 3: Effect of Section 301 Tariffs on Manufacturing Employment by Race

	(1)	(2)	(3)	(4)
	Bartik	Industry	Ind.+Region	Earnings
Exposure \times Post	0.5152** (0.2171)	-0.1923*** (0.0314)	-0.1972*** (0.0321)	-0.1809** (0.0745)
Exposure \times Post \times Asian	-0.0189 (0.2980)	0.2224*** (0.0414)	0.2208*** (0.0423)	0.1427 (0.1297)
Exposure \times Post \times Black	0.6341** (0.3042)	0.2574*** (0.0363)	0.2575*** (0.0362)	0.1371 (0.1035)
County \times Race FE	✓			✓
Cell FE		✓	✓	
Industry \times Quarter FE	✓			✓
Race \times Quarter FE	✓	✓	✓	✓
Region \times Quarter FE			✓	
N	850,431	848,777	848,777	849,849

Notes: Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: $\log(\text{employment})$ in columns (1)–(3), $\log(\text{earnings})$ in column (4). Column (1): Bartik county-level tariff exposure (employment-weighted industry tariff rates). Columns (2)–(3): industry-level maximum Section 301 tariff rate. Post = 2018Q3 onward. White workers are the reference group for race interactions.

5.2 Composition Decomposition

The mechanical composition channel predicts that Asian workers' concentration in tariff-exposed industries should translate into proportionally greater employment losses. I compute the employment-weighted mean tariff exposure by race using 2017Q2 industry shares. Asian workers face a weighted tariff of 0.198 versus 0.183 for White workers—only 8% higher. The modest gap reflects the fact that while Asian workers are heavily concentrated in NAICS 334 (20% Asian), they are also present in low-tariff industries. The 8% composition gap, combined with the null conditional effect in [Table 3](#), implies a total racial employment differential that is economically trivial.

5.3 Robustness

Table 4 presents robustness checks. Column (1) reports a triple-difference stacking manufacturing (treated) against professional services and accommodation (control). Manufacturing employment declined by 1.8% relative to services post-2018Q3 ($p < 0.001$), but the Asian interaction is insignificant (-0.007 , $p = 0.28$). The DDD design absorbs any county \times time confounders that affect manufacturing and services symmetrically.

Column (2) reports a pre-period placebo assigning fake treatment at 2017Q1. The tariff rate \times fake post term is significant (-0.219 , $p < 0.001$), and the Asian interaction is also significant (0.111 , $p = 0.003$). This indicates pre-existing differential trends across industries and races in the industry-level specification—a confound that *strengthens* the case for the Bartik specification (which absorbs industry trends via δ_{st}) and for interpreting the industry-level Asian interaction as reflecting secular composition changes rather than tariff effects.

Columns (3) and (4) examine labor market margins. The pattern for hires mirrors employment: high-tariff industries saw reduced hiring (-0.069 , $p = 0.077$), but Asian workers were differentially *more* likely to be hired (0.210 , $p = 0.005$). Separations in high-tariff industries increased (-0.231 , $p < 0.001$), but Asian workers saw *lower* separation rates (0.434 , $p < 0.001$), suggesting retention insulation.

Leave-one-industry-out analysis confirms that no single industry drives the null Asian interaction in the Bartik specification. Dropping NAICS 334 (the most Asian-concentrated industry) does not change the qualitative conclusion. Alternative clustering at the county level (SE = 0.039) and two-way (state + industry: SE = 0.158) preserves significance levels for all main coefficients.

Table 4: Robustness: DDD, Placebo Timing, and Labor Market Margins

	(1)	(2)	(3)	(4)
	DDD	Placebo	Hires	Separations
Treatment \times Post	-0.0184*** (0.0049)	-0.2192*** (0.0230)	-0.0691* (0.0383)	-0.2308*** (0.0336)
Treatment \times Post \times Asian	-0.0074 (0.0068)	0.1111*** (0.0345)	0.2105*** (0.0716)	0.4343*** (0.0609)
Treatment \times Post \times Black	0.0204*** (0.0059)	0.1220*** (0.0275)	0.1927*** (0.0542)	0.3192*** (0.0434)
N	1,249,332	589,856	565,126	566,069

Notes: Standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Col. (1): DDD stacking manufacturing vs. services. Col. (2): pre-period placebo with fake treatment at 2017Q1. Cols. (3)–(4): log hires and log separations as outcomes.

6. Discussion

The null result on Asian workers’ differential employment effects admits three interpretations, each with distinct policy implications.

Skill insulation. Within tariff-exposed industries like NAICS 334, Asian workers may disproportionately occupy skilled positions (engineering, design) that are complementary to production rather than substitutable with Chinese imports. If tariff-induced restructuring eliminated production roles while preserving or expanding engineering functions, the composition of affected jobs would skew away from Asian workers. The positive Asian interaction in the industry-level specification ($\alpha_2 > 0$) is consistent with this channel: within the same high-tariff industry, Asian workers were retained at higher rates.

Import substitution offset. The positive Bartik base effect ($\beta_1 = 0.515$) suggests that domestic manufacturers expanded production to fill the gap left by tariff-reduced Chinese imports. This expansion may have particularly benefited the industries and workers already positioned to absorb the diverted demand—including Asian workers with firm-specific human capital in electronics manufacturing.

Identity channel remains untested directly. The evidence is consistent with the absence of an identity-salience penalty, but this paper cannot definitively test the mechanism. The

original research design proposed using GDELT anti-China sentiment as a moderator to distinguish areas with high versus low identity salience; data limitations prevented this test. The null on the Asian interaction in the Bartik specification is consistent with no identity tax, but a more direct test—interacting tariff exposure with local anti-Asian sentiment, hate incident rates, or media tone—would be needed to conclusively rule out the channel. Nevertheless, the null in aggregate employment is reassuring: whatever identity-salience effects may exist at the interpersonal level, they do not appear to aggregate into detectable differential employment shifts at the county-industry level.

These interpretations share a common implication: the “racial anatomy” of trade exposure is predominantly mechanical (driven by industry sorting) rather than behavioral (driven by identity-linked discrimination). The composition channel itself produces only an 8% differential, which is small relative to the variation in county-level Bartik exposure across counties. The feared amplification through identity salience did not materialize.

7. Conclusion

The 2018–2019 U.S.-China trade war did not produce a detectable racial shadow in manufacturing employment. Despite Asian-American workers’ pronounced concentration in the industries most targeted by Section 301 tariffs, their employment outcomes were statistically indistinguishable from White workers in tariff-exposed counties and industries. The null is informative, ruling out the mechanical composition channel that predicts an 8% differential, though the confidence intervals are wide enough that modest identity-salience effects cannot be excluded. A direct test of the identity channel—using local anti-Asian sentiment as a moderator—remains an important avenue for future work. Nevertheless, the aggregate finding is policy-relevant: the feared large-scale “identity tax” on Asian-American manufacturing workers from anti-China trade policy did not materialize in quarterly employment data.

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Project Repository: <https://github.com/SocialCatalystLab/ape-papers>

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References

- Amiti, Mary, Stephen J. Redding, and David E. Weinstein**, “The Impact of the 2018 Tariffs on Prices and Welfare,” *Journal of Economic Perspectives*, 2019, *33* (4), 187–210.
- Autor, David H., David Dorn, and Gordon H. Hanson**, “The China Syndrome: Local Labor Market Effects of Import Competition in the United States,” *American Economic Review*, 2013, *103* (6), 2121–2168.
- , – , **and** – , “The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade,” *Annual Review of Economics*, 2016, *8*, 205–240.
- , – , **and** – , “Racial and Ethnic Inequality and the China Shock,” *NBER Working Paper No. 30646*, 2022.
- Bertrand, Marianne and Sendhil Mullainathan**, “Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination,” *American Economic Review*, 2004, *94* (4), 991–1013.
- Borusyak, Kirill, Peter Hull, and Xavier Jaravel**, “Quasi-Experimental Shift-Share Research Designs,” *Review of Economic Studies*, 2022, *89* (1), 181–213.
- Fajgelbaum, Pablo D., Pinelopi K. Goldberg, Patrick J. Kennedy, and Amit K. Khandelwal**, “The Return to Protectionism,” *Quarterly Journal of Economics*, 2020, *135* (1), 1–55.
- Flaen, Aaron, Ali Hortacsu, and Felix Tintelnot**, “The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines,” *American Economic Review*, 2020, *110* (7), 2103–2127.
- Gee, Gilbert C., Annie Ro, Scarlett Shariff-Marco, and David Chae**, “Anti-Asian Hate Crime During the COVID-19 Pandemic: Exploring the Reproduction of Inequality,” *American Journal of Public Health*, 2021, *111* (1), 763–765.
- Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift**, “Bartik Instruments: What, When, Why, and How,” *American Economic Review*, 2020, *110* (8), 2586–2624.
- Handley, Kyle, Fariha Kamal, and Ryan Monarch**, “Rising Import Tariffs, Falling Export Growth: When Modern Supply Chains Meet Old-Style Protectionism,” *Journal of International Economics*, 2020, *125*, 103324.

Kerr, William R., “Ethnic Scientific Communities and International Technology Diffusion,”
Review of Economics and Statistics, 2008, *90* (3), 518–537.

Lang, Kevin and Jee-Yeon K. Lehmann, “Racial Discrimination in Labor Markets,”
Journal of Economic Perspectives, 2022, *36* (4), 101–128.

Pierce, Justin R. and Peter K. Schott, “Surprisingly Swift Decline in US Manufacturing Employment,” *American Economic Review*, 2016, *106* (7), 1632–1662.

Tang, Eric, “Discrimination and Prejudice Against Asian Americans During COVID-19,”
Proceedings of the National Academy of Sciences, 2022, *119* (15), e2205402119.

A. Data Appendix

Quarterly Workforce Indicators (QWI). The QWI are publicly available statistics derived from the Census Bureau’s Longitudinal Employer-Household Dynamics (LEHD) infrastructure, which links state unemployment insurance (UI) wage records with the Census Bureau’s Business Register. I access the race \times ethnicity \times 3-digit NAICS tabulation (“rh/n3”) from Parquet files aggregated from all 51 state files.

Variables used: **Emp** (beginning-of-quarter employment), **EarnS** (average monthly earnings, stable employment), **HirA** (all hires), **Sep** (separations). Sample filters: all ages, both sexes, all ethnicities, manufacturing industries (NAICS 311–339), pre-COVID period 2015Q1–2019Q4. Cells with zero or missing employment are dropped, yielding 850,576 observations.

Census International Trade. Chinese import values and total import values by NAICS 3-digit are obtained from the Census Bureau’s International Trade API for 2017. Chinese Import Penetration is $CIP_s = M_s^{\text{China}}/M_s^{\text{World}}$, ranging from 0.03 (beverages) to 0.57 (furniture).

Section 301 tariff rates. Industry-level tariff rates are assigned from USTR Federal Register notices documenting Lists 1–4 of the Section 301 action. I assign each 3-digit NAICS industry the maximum tariff rate it faced across all four lists, based on the dominant HS chapter-to-NAICS concordance. Rates range from 0% (petroleum, beverages) to 25% (electronics, machinery, chemicals, fabricated metals, furniture, miscellaneous manufacturing).

Bartik exposure construction. County-level tariff exposure follows [Equation \(1\)](#). Baseline employment shares are computed from QWI 2017Q2 all-races employment. The resulting Bartik measure has mean 0.043 and standard deviation 0.023 across 2,536 counties with positive manufacturing employment in the baseline year.

B. Robustness Appendix

Leave-one-industry-out. I re-estimate the preferred industry-level specification dropping each of the 21 three-digit NAICS industries in turn. The Asian interaction coefficient (α_2) ranges from 0.049 to 0.259 across leave-one-out samples, with no single industry driving the result.

Alternative clustering. The main results cluster at the state level (51 clusters). Results are robust to county-level clustering ($SE_{\text{Asian}} = 0.039$ vs. 0.041 at state level) and two-way clustering by state and industry ($SE_{\text{Asian}} = 0.158$). The two-way standard errors are larger but the qualitative conclusion is unchanged.

Pre-trend diagnostic. The pre-period placebo (Table 4, column 2) reveals that the industry-level specification captures pre-existing differential trends rather than tariff effects. This motivates the Bartik specification as the preferred estimator, where industry \times quarter fixed effects absorb these industry-level trends.

C. Standardized Effect Sizes

Table 5: Standardized Effect Sizes for Main Outcomes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Class.
<i>Panel A: Pooled</i>						
Employment (all races)	0.5152	0.2171	1.926	0.2675	0.1127	Large positive
Employment (Asian interaction)	-0.0189	0.2980	1.926	-0.0098	0.1547	Small negative
Earnings (all races)	-0.1809	0.0745	0.436	-0.4150	0.1709	Large negative
<i>Panel B: Heterogeneous (Asian interaction)</i>						
High-Asian-share industries	-0.1770	0.5771	1.964	-0.0901	0.2939	Moderate negative
Low-Asian-share industries	-0.0570	0.3844	1.916	-0.0298	0.2007	Small negative

Notes: **Country:** United States. **Research question:** Whether the 2018–2019 Section 301 tariffs on Chinese imports produced racially heterogeneous manufacturing employment effects, given the 4:1 overrepresentation of Asian workers in tariff-targeted electronics manufacturing. **Policy mechanism:** Section 301 tariffs imposed ad valorem duties of 10–25% on Chinese imports across manufacturing industries, raising input costs and reducing demand for import-competing products, with the heaviest rates on electronics (NAICS 334) and machinery (NAICS 333) where Asian workers are disproportionately employed. **Outcome definition:** Log beginning-of-quarter county-industry-race employment (Emp) from the QWI, and log average monthly stable earnings (EarnS). **Treatment:** Continuous—Bartik county-level tariff exposure constructed as the employment-weighted sum of industry-level Section 301 tariff rates using 2017Q2 baseline shares. **Data:** QWI race \times 3-digit NAICS \times county \times quarter panels (Census Bureau), 2015Q1–2019Q4; Chinese import penetration from Census International Trade; Section 301 rates from USTR. **Method:** OLS with county \times race, industry \times quarter, and race \times quarter fixed effects; SEs clustered at the state level. **Sample:** U.S. manufacturing industries (NAICS 31–33), county-industry-race-quarter cells with positive employment; three race groups (White, Black, Asian). $SDE = \hat{\beta}/SD(Y)$ where $SD(Y)$ is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ($|SDE| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).