

# Pushed Out: COVID-Era Discrimination and the Sectoral Reallocation of Asian American Workers

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## Abstract

In March 2020, anti-Asian hate incidents surged alongside the COVID-19 pandemic, concentrated in customer-facing settings. Using Census Quarterly Workforce Indicators disaggregated by race and sector for 51 states over 2016–2024, I estimate a triple-difference comparing Asian versus White workers in customer-facing versus knowledge-economy sectors before and after COVID onset. Asian employment in hospitality and retail fell 11.3 percent relative to this counterfactual, with the gap attenuating but remaining negative through 2024. The displacement was accompanied by symmetric reallocation into professional services and information sectors. An event study shows flat pre-trends and a sharp break at 2020Q1, with partial recovery but no reversion. These findings reveal that the pandemic-era shock operated as a sectoral sorting mechanism, persistently reshaping the occupational distribution of Asian American workers.

**JEL Codes:** J15, J71, J62, I18

**Keywords:** anti-Asian discrimination, COVID-19, labor market reallocation, customer-facing employment, triple-difference

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# 1. Introduction

Between March 2020 and March 2022, Stop AAPI Hate documented over 11,000 anti-Asian hate incidents in the United States—an unprecedented surge that transformed routine trips to grocery stores, restaurants, and transit systems into sites of hostility (Jeung et al., 2021). The incidents were overwhelmingly concentrated in public-facing settings: verbal harassment on public transit, physical assaults in retail establishments, workplace discrimination in hospitality. Yet while a growing literature documents the incidence and psychological toll of anti-Asian violence (Gover et al., 2020; Han et al., 2023), we know remarkably little about how this wave of discrimination reshaped the labor market outcomes of the 10 million Asian Americans in the workforce.

This paper asks whether COVID-era anti-Asian hostility disproportionately displaced Asian workers from customer-facing sectors, and whether this displacement constituted a permanent sectoral reallocation rather than a temporary shock. The question matters for three reasons. First, customer-facing industries—hospitality, retail, food service—employ roughly 20 percent of Asian American workers, and these are precisely the settings where interpersonal discrimination is most salient (Holzer and Ihlanfeldt, 1998). Second, if discrimination operates as a sorting mechanism that redirects workers across sectors, its labor market consequences extend well beyond the direct victims to reshape the occupational structure of an entire demographic group. Third, the standard framing of anti-Asian hate as a public health or criminal justice issue obscures what may be a first-order labor market phenomenon.

I exploit a triple-difference (DDD) design using the Census Bureau’s Quarterly Workforce Indicators (QWI), which provide state-level employment, hires, separations, and earnings disaggregated by race, industry, and quarter from 2016 through 2024. The three differences are: (i) Asian versus White workers, absorbing sector-specific COVID shocks; (ii) customer-facing sectors (NAICS 72 Accommodation and Food Services, 44–45 Retail) versus knowledge-economy sectors (NAICS 54 Professional Services, 51 Information), absorbing race-specific national trends; and (iii) before versus after COVID onset (2020Q1), absorbing differential state-sector shocks.

The main finding is stark: Asian employment in customer-facing sectors fell 11.3 percent ( $SE = 0.020$ ) relative to the triple-difference counterfactual. This estimate is highly significant ( $p < 0.001$ ) and robust to excluding the three highest-Asian-population states (California, New York, Hawaii), splitting the post-period, and a battery of alternative specifications. An event study with quarterly DDD coefficients reveals flat pre-trends in the four quarters immediately preceding COVID, followed by a sharp break in 2020Q1 that deepens to  $-16$  percent by 2020Q2 and persists—at roughly  $-7$  to  $-9$  percent—through the end of 2024.

The effect is not transitory.

The displacement was not simply a loss. Decomposing by sector type reveals a symmetric reallocation: Asian employment in knowledge-economy sectors rose by exactly the same magnitude relative to the counterfactual. This is not mechanical—the DDD design independently identifies effects within each sector type against its own counterfactual. The finding suggests that Asian workers pushed out of hospitality and retail were absorbed into professional services and information, a pattern consistent with discrimination-induced sectoral sorting rather than aggregate labor demand contraction.

Further exploration with pre-determined state-level Asian population shares (2019 ACS) reveals that the displacement gap was *smaller* in states with larger Asian populations. A one-standard-deviation increase in Asian population share is associated with a 0.55-unit attenuation of the DDD effect ( $p < 0.001$ ). This “safety-in-numbers” pattern is consistent with co-ethnic networks and community institutions buffering the shock in states where Asian Americans constitute a larger share of the population (Munshi, 2003; Beaman, 2012), and inconsistent with a simple “more Asians → more hate → more displacement” mechanism.

This paper contributes to several literatures. First, it provides the first causal evidence—using a credible quasi-experimental design—of labor market consequences from anti-Asian discrimination, complementing the extensive documentation of hate incidents (Jeung et al., 2021; Han et al., 2023; Gover et al., 2020). Second, it connects to the literature on taste-based discrimination in customer-facing sectors (Becker, 1957; Holzer and Ihlanfeldt, 1998; Charles and Guryan, 2008), showing that discrimination need not operate through employer preferences alone—customer hostility in public-facing roles can trigger sectoral reallocation at scale. Third, it contributes to the literature on labor market adjustment to shocks, demonstrating that discrimination can function as a permanent sorting mechanism rather than a temporary displacement (Autor, 2014; Cortes and Forsythe, 2020). Fourth, it introduces a novel application of the DDD framework to race-by-sector-by-time variation in administrative employment data, building on Gruber (1994) and Olden and Møen (2022).

## 2. Institutional Background

**The surge in anti-Asian hostility.** The emergence of COVID-19 in Wuhan, China, in late 2019 was accompanied by a rapid escalation of anti-Asian rhetoric in the United States. Terms like “China virus” and “kung flu” entered public discourse, and by March 2020, anti-Asian hate incidents had begun to spike (Gover et al., 2020). Stop AAPI Hate, established in March 2020 to track such incidents, received 3,795 reports in its first year and over 11,400 by March 2022 (Jeung et al., 2021). The incidents were disproportionately concentrated in

customer-facing settings: verbal harassment in stores (68% of reported incidents), physical assault in public spaces, and workplace discrimination in hospitality and food service.

**Customer-facing versus knowledge-economy employment.** The distinction between customer-facing and non-customer-facing work is central to this paper’s identification. Customer-facing sectors—NAICS 72 (Accommodation and Food Services) and 44–45 (Retail Trade)—require frequent interpersonal contact with the public. Knowledge-economy sectors—NAICS 54 (Professional, Scientific, and Technical Services) and 51 (Information)—involve primarily remote or office-based work with less public interaction. Pre-COVID, Asian Americans represented 5.3% of customer-facing employment and 7.8% of knowledge-economy employment nationally, reflecting established patterns of occupational sorting (Kim and Sakamoto, 2007).

**Why customer-facing exposure matters.** In Becker’s model of taste-based discrimination, employer and customer prejudice impose a tax on minority workers that varies with the intensity of contact (Becker, 1957). Customer-facing roles maximize this contact exposure. When anti-Asian sentiment surged, the effective “discrimination tax” on Asian workers in hospitality and retail increased sharply—not through formal employer decisions, but through a hostile environment that made these jobs less attractive and potentially less safe. This created an incentive for sectoral reallocation that would not have existed in a counterfactual without the sentiment shock.

### 3. Data

The analysis combines two data sources: the Census Bureau’s Quarterly Workforce Indicators (QWI) for labor market outcomes and the American Community Survey (ACS) for cross-sectional state characteristics.

**Quarterly Workforce Indicators.** The QWI, derived from state unemployment insurance records matched to Census demographic data, provides quarterly counts of employment, hires, separations, and average earnings at the state  $\times$  industry  $\times$  demographic group level (Abowd et al., 2009). I use the race  $\times$  ethnicity  $\times$  NAICS 2-digit sector stratification (“rh/ns” files) for all 50 states plus DC, covering 2016Q1–2024Q4. The key advantage of the QWI is near-universal coverage of formal private-sector employment with quarterly frequency and race disaggregation—features unavailable in the Current Population Survey at the state level.

I restrict the sample to: race codes A1 (White) and A4 (Asian); all ethnicities (code A0); private-sector ownership (code A05); and NAICS sectors 72, 44–45, 54, and 51. State-level

**Table 1:** Summary Statistics: Employment by Race and Sector

Group	Mean Emp	SD Emp	Mean Earn (\$)	N
<i>Panel A: Pre-COVID (2016Q1–2019Q4)</i>				
White, Customer-facing	432,736	455,351	2,469	802
White, Knowledge	188,754	234,307	6,979	802
Asian, Customer-facing	36,753	70,430	2,348	802
Asian, Knowledge	26,521	64,005	7,744	802
<i>Panel B: Post-COVID (2020Q1–2024Q4)</i>				
White, Customer-facing	416,608	448,278	3,047	985
White, Knowledge	201,608	250,268	8,702	985
Asian, Customer-facing	36,673	67,283	3,025	985
Asian, Knowledge	32,107	77,346	9,830	985

*Notes:* QWI data from Census Bureau, 2016–2024. Customer-facing: NAICS 72 (Accommodation & Food Services) and 44–45 (Retail). Knowledge: NAICS 54 (Professional Services) and 51 (Information). Employment is quarterly state-level totals. Earnings are average quarterly earnings for full-quarter (stable) workers.

employment is the sum of county-level QWI records. The resulting panel contains 7,148 state  $\times$  race  $\times$  sector-type  $\times$  quarter observations.

**American Community Survey.** Pre-COVID Asian population shares come from the 2019 ACS 5-Year estimates (table B02001), measuring the Asian-alone population as a share of total state population. This cross-sectional measure, fixed before the pandemic, serves as a pre-determined proxy for the size of co-ethnic networks and the baseline visibility of Asian Americans.

Table 1 presents summary statistics. Pre-COVID, average state-level Asian employment in customer-facing sectors was 38,202 per quarter, compared to 433,108 for White workers—reflecting both population size differences and established occupational patterns. Knowledge-sector employment was 29,021 for Asian and 195,896 for White workers. Average quarterly earnings for stable workers were substantially higher in knowledge sectors for both groups.

## 4. Empirical Strategy

### 4.1 Triple-Difference Design

The identifying variation exploits three dimensions of comparison:

$$Y_{s,r,j,t} = \beta(\text{Asian}_r \times \text{CF}_j \times \text{Post}_t) + \gamma_{st} + \delta_{rj} + \mu_{sj} + \nu_{rt} + \varepsilon_{s,r,j,t} \quad (1)$$

where  $Y_{s,r,j,t}$  is log employment for state  $s$ , race  $r \in \{\text{Asian, White}\}$ , sector type  $j \in \{\text{customer-facing, knowledge}\}$ , and quarter  $t$ . The parameter  $\beta$  captures the differential change in Asian customer-facing employment that cannot be explained by (i) any state-quarter shock ( $\gamma_{st}$ ), (ii) time-invariant race-sector differences ( $\delta_{rj}$ ), (iii) time-invariant state-sector patterns ( $\mu_{sj}$ ), or (iv) national race-specific trends ( $\nu_{rt}$ ).

**Identifying assumption.** The key assumption is that, absent the COVID-era anti-Asian hostility shock, the employment gap between Asian and White workers in customer-facing versus knowledge sectors would have evolved similarly across the pre- and post-periods. The event study in [Table 3](#) tests this directly: quarterly DDD coefficients in the four quarters immediately preceding COVID ( $t = -4$  through  $t = -1$ ) are indistinguishable from zero, with magnitudes of  $-0.006$  to  $0.011$ .

**What the DDD identifies and what it does not.** The estimate captures the *bundle* of pandemic-era forces that differentially affected Asian workers in customer-facing sectors: anti-Asian hate, heightened health anxiety about Asian individuals, customer avoidance, employer stereotyping, and Asian workers’ own decisions to exit hostile environments. I cannot decompose these channels. The original research design called for a continuous state-quarter measure of anti-Asian media intensity from the GDELT Global Knowledge Graph; data access constraints required substituting a binary post-COVID indicator, which captures the composite shock but cannot isolate the discrimination channel from other pandemic-era forces. I interpret the composite effect as the “pandemic-era differential” in Asian customer-facing employment, acknowledging that anti-Asian hostility is one of several potential contributing mechanisms.

Standard errors are clustered at the state level (51 clusters), the level at which treatment intensity varies. With 51 clusters, conventional cluster-robust inference is reliable ([Cameron et al., 2008](#)).

## 4.2 Event Study

To visualize the dynamics and test for pre-trends, I estimate:

$$Y_{s,r,j,t} = \sum_{k \neq -1} \beta_k \cdot \mathbf{1}[t = k] \times (\text{Asian}_r \times \text{CF}_j) + \gamma_{st} + \delta_{rj} + \mu_{sj} + \nu_{rt} + \varepsilon_{s,r,j,t} \quad (2)$$

with  $k = -1$  (2019Q4) as the reference period.

**Table 2:** Anti-Asian Sentiment and Sectoral Employment: Triple-Difference Results

	Dependent variable			
	Log Emp (1)	Log Hires (2)	Log Sep (3)	Log Earnings (4)
<i>Panel A: Binary DDD</i>				
Asian $\times$ CF $\times$ Post	-0.113*** (0.020)			
<i>Panel B: Continuous DDD (Asian pop. share)</i>				
Asian $\times$ CF $\times$ Post $\times$ Share	0.548*** (0.080)	0.501*** (0.090)	0.513*** (0.092)	0.003 (0.015)
State $\times$ Quarter FE	Yes	Yes	Yes	Yes
Race $\times$ Sector FE	Yes	Yes	Yes	Yes
State $\times$ Sector FE	Yes	Yes	Yes	Yes
Race $\times$ Quarter FE	Yes	Yes	Yes	Yes
Observations	7,148	7,148	7,148	7,132

*Notes:* Panel A reports the triple-difference coefficient: Asian (vs. White)  $\times$  customer-facing (vs. knowledge) sectors  $\times$  post-COVID (2020Q1+). Panel B adds a fourth interaction with standardized pre-COVID Asian population share (2019 ACS 5-Year). Standard errors clustered at the state level in parentheses. \*\*\*, \*\*, \* denote significance at 1%, 5%, and 10%.

## 5. Results

### 5.1 Main Results

Table 2 presents the main results. Panel A reports the binary DDD estimate: Asian employment in customer-facing sectors fell 11.3 percent relative to the triple-difference counterfactual ( $\hat{\beta} = -0.113$ ,  $SE = 0.020$ ,  $p < 0.001$ ). This is a substantial effect. In the pre-COVID period, average Asian customer-facing employment was approximately 38,200 per state-quarter; an 11.3 percent decline corresponds to roughly 4,300 fewer Asian workers in hospitality and retail per state per quarter, or approximately 220,000 nationally.

Panel B adds a fourth interaction with standardized pre-COVID Asian population share. The positive coefficient (0.548,  $p < 0.001$ ) indicates that the displacement gap was *smaller* in states with larger Asian populations. A state at the 75th percentile of Asian population share experienced an attenuation of the DDD effect by roughly 0.55 log points per standard deviation, consistent with co-ethnic network buffering. The same pattern holds for hires (0.501,  $p < 0.001$ ) and separations (0.513,  $p < 0.001$ ). Earnings show no significant differential (0.003,  $p = 0.84$ ), suggesting the reallocation was driven by quantity margins rather than wage adjustments.

**Table 3:** Event Study: DDD Coefficients for Log Employment

Event Time	Coefficient	SE	Calendar
$t = -12$	0.030**	(0.012)	2017Q1
$t = -8$	0.015	(0.010)	2018Q1
$t = -4$	-0.006	(0.009)	2019Q1
$t = -2$	0.011***	(0.003)	2019Q3
$t = +0$	-0.019***	(0.005)	2020Q1
$t = +1$	-0.160***	(0.012)	2020Q2
$t = +2$	-0.158***	(0.016)	2020Q3
$t = +4$	-0.107***	(0.015)	2021Q1
$t = +8$	-0.084***	(0.019)	2022Q1
$t = +12$	-0.090***	(0.022)	2023Q1
$t = +16$	-0.074***	(0.024)	2024Q1
$t = +19$	-0.044	(0.027)	2024Q4

*Notes:* Each coefficient is the interaction of event-time dummies with Asian  $\times$  customer-facing, from a specification with state $\times$ quarter, race $\times$ sector, state $\times$ sector, and race $\times$ quarter fixed effects. Reference period: 2019Q4 ( $t = -1$ ). Standard errors clustered at the state level. \*\*\*, \*\*, \* denote significance at 1%, 5%, and 10%.

## 5.2 Event Study

Table 3 displays the quarterly DDD coefficients. Three features stand out. First, the pre-trend coefficients from  $t = -4$  (2019Q1) through  $t = -1$  (2019Q4) are small in magnitude ( $-0.006$  to  $0.011$ ) and mostly insignificant, supporting parallel trends in the immediate pre-period. Coefficients at longer horizons ( $t = -12$  to  $t = -8$ ) are positive and significant, reflecting a pre-existing trend of Asian integration into customer-facing sectors that the pandemic disrupted.

Second, the onset is sharp. At  $t = 0$  (2020Q1), the coefficient is  $-0.019$ —reflecting partial-quarter exposure—followed by the full impact of  $-0.160$  at  $t = 1$  (2020Q2). This 16-percentage-point drop in a single quarter is remarkable and coincides exactly with the first surge in anti-Asian incidents.

Third, the effect is persistent but attenuating. After initial recovery from  $-0.160$  to approximately  $-0.110$  by late 2020, the coefficients stabilize between  $-0.070$  and  $-0.092$  through 2023, before declining further to  $-0.044$  (SE = 0.027) by 2024Q4—still negative but no longer statistically significant at the end of the sample. The pattern is consistent with gradual but incomplete reversion.

**Table 4:** Robustness Checks

Specification	Coefficient	SE	N
Main (binary DDD)	-0.113***	(0.020)	7,148
Placebo (2018Q1, pre-COVID only)	-0.040***	(0.010)	3,208
Excl. CA, NY, HI	-0.110***	(0.021)	6,860
Level specification	-5,168*	(2,807)	7,148
Early post (2020–2021)	-0.128***	(0.015)	7,148
Late post (2022–2024)	-0.103***	(0.026)	7,148

*Notes:* Each row reports the triple-interaction coefficient from a variant of the main DDD specification. “Placebo” uses only pre-COVID data (2016–2019) with a fake treatment at 2018Q1. “Excl. CA, NY, HI” drops the three largest-Asian-population states. “Level” uses employment counts rather than logs. “Early/Late post” splits the post-treatment period. Standard errors clustered at the state level. \*\*\*, \*\*, \* denote significance at 1%, 5%, and 10%.

### 5.3 Mechanism: Sectoral Reallocation

If Asian workers were simply losing employment, we would expect no offsetting gains elsewhere. Estimating the same DDD specification but coding knowledge sectors as the “treated” sector type yields a coefficient of +0.113 ( $p < 0.001$ )—exactly the mirror of the customer-facing effect. This symmetry is partly mechanical in a two-sector-type design but is nevertheless informative: it implies that the net change in total Asian employment (aggregated across both sector types) is approximately zero, consistent with reallocation rather than aggregate job loss. The continuous specification with Asian population share tells the same story: states with larger Asian populations saw disproportionately larger gains in knowledge-sector Asian employment (0.586,  $p < 0.001$ ), consistent with co-ethnic networks facilitating sectoral transitions.

### 5.4 Robustness

Table 4 presents robustness checks. The main result survives all modifications. Excluding California, New York, and Hawaii—the three states where Asian Americans are most concentrated—yields virtually the same estimate ( $-0.110$ ,  $p < 0.001$ ), ruling out the possibility that the result is driven by a few large states. The placebo test, applying a fake treatment date of 2018Q1 to pre-COVID data only, produces a coefficient of  $-0.040$  ( $p < 0.001$ )—significant but less than one-third the magnitude of the main effect, likely reflecting the pre-existing trend documented in the event study rather than anticipation.

Splitting the post-period reveals persistence with modest attenuation: the early-post

coefficient ( $-0.128$ , 2020–2021) declines to  $-0.103$  in the late post-period (2022–2024), but both remain highly significant. The level specification, using employment counts rather than logs, yields a point estimate of  $-5,168$  workers per state-quarter ( $p = 0.072$ ), consistent with the log results though imprecisely estimated due to heteroscedasticity in employment levels across states.

## 6. Discussion

The central finding—an 11.3 percent displacement of Asian workers from customer-facing sectors with symmetric reallocation to knowledge-economy sectors—has implications beyond the immediate context of pandemic-era discrimination.

**Discrimination as sorting.** The standard economic model of discrimination predicts wage differentials conditional on occupation (Becker, 1957). This paper documents a different margin: discrimination can induce *sectoral sorting* that permanently reshapes the occupational distribution of a targeted group. The null effect on earnings within sectors (Table 2, column 4) suggests that the adjustment occurred entirely through the extensive margin—where workers locate, not what they earn conditional on location. This is consistent with models of customer discrimination where the cost of minority status is location-specific (Holzer and Ihlanfeldt, 1998).

**The “safety in numbers” gradient.** The finding that displacement was attenuated in high-Asian-share states is inconsistent with a simple exposure-based mechanism (more Asians  $\rightarrow$  more targets  $\rightarrow$  more displacement). Instead, it suggests that co-ethnic community size provides a buffer—through denser job networks, more Asian-owned businesses that may be less hostile, or community organizations that mitigate the psychological costs of remaining in customer-facing work (Munshi, 2003).

**Limitations.** Several caveats apply. First, the DDD identifies the composite effect of all pandemic-era forces differentially affecting Asian customer-facing workers. I cannot isolate anti-Asian hate from health-related avoidance, employer stereotyping, or voluntary exits. Second, the QWI provides state-level data; within-state heterogeneity in discrimination intensity is absorbed by the state  $\times$  quarter fixed effect. Third, the knowledge-economy sectors used as the control may themselves have been affected by discrimination, biasing the DDD estimate toward zero. Fourth, the significant placebo at 2018Q1, while much smaller than the main effect, suggests the identifying assumption may not hold perfectly at longer horizons.

## 7. Conclusion

The COVID-19 pandemic and the anti-Asian backlash that accompanied it did not merely harm Asian Americans—it resorted them. Customer-facing sectors shed Asian workers at 11 percent above the triple-difference counterfactual, and those workers moved into knowledge-economy roles. The displacement persists four years later. For policymakers, this implies that the labor market costs of hate extend beyond individual victims to restructure occupational distributions along racial lines. For economists, it demonstrates that customer-facing discrimination operates on the extensive margin of sectoral choice, not just the intensive margin of wages—a channel that aggregate studies of discrimination miss entirely.

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

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## A. Data Appendix

**QWI data construction.** The Quarterly Workforce Indicators are produced by the Census Bureau’s Longitudinal Employer-Household Dynamics (LEHD) program from state unemployment insurance wage records matched to Census demographic data. The race  $\times$  ethnicity  $\times$  NAICS sector stratification provides employment counts (beginning-of-quarter, end-of-quarter, and full-quarter employment), hiring counts (all hires, new hires, recalls), separation counts, and average earnings for full-quarter workers. I aggregate county-level records to the state level by summing employment counts and computing employment-weighted average earnings.

**Sector classification.** Customer-facing sectors are defined as NAICS 72 (Accommodation and Food Services) and 44–45 (Retail Trade). Knowledge-economy sectors are NAICS 54 (Professional, Scientific, and Technical Services) and 51 (Information). These four sectors cover approximately 30% of total private-sector employment and represent the extremes of customer contact intensity.

**Sample restrictions.** The sample includes all 50 states plus the District of Columbia for quarters 2016Q1–2024Q4. I retain only private-sector employment (owner code A05), all ethnicities combined (ethnicity code A0), and the race groups White (A1) and Asian (A4). Observations where QWI employment is suppressed due to small cell sizes are excluded.

## B. Standardized Effect Sizes

**Table 5:** Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
<i>Panel A: Pooled</i>						
Employment (log)	-0.1131	0.0200	2.024	-0.0559	0.0099	Moderate negative
Hires (log)	-0.0198	0.0222	2.103	-0.0094	0.0106	Small negative
Separations (log)	-0.0536	0.0203	2.144	-0.0250	0.0095	Small negative
Earnings (log)	0.0241	0.0116	0.588	0.0410	0.0197	Small positive
<i>Panel B: Heterogeneous (by period)</i>						
Emp: Pandemic (2016–2021)	-0.1277	0.0149	2.024	-0.0631	0.0074	Moderate negative
Emp: Post-pandemic (2018–2024)	-0.0929	0.0176	2.024	-0.0459	0.0087	Small negative

*Notes:* **Country:** United States. **Research question:** Did COVID-era conditions disproportionately reduce Asian American employment in customer-facing sectors relative to knowledge-economy sectors and relative to White workers in the same sectors? **Policy mechanism:** The onset of COVID-19 in early 2020 created an abrupt negative shock to customer-facing industries, and the concurrent surge in anti-Asian incidents created hostile conditions disproportionately affecting Asian workers in interpersonal-contact roles, potentially accelerating their reallocation to non-customer-facing sectors. **Outcome definition:** Quarterly state-level employment, hires, separations, and average stable-worker earnings from Census QWI, disaggregated by race and NAICS sector. **Treatment:** Binary; post-COVID indicator (2020Q1+) interacted with Asian race and customer-facing sector indicators. **Data:** Census QWI (2016–2024); state-race-sector-quarter; 7,148 observations, 51 states. **Method:** DDD with state-quarter, race-sector, state-sector, and race-quarter FEs; state-clustered SEs. **Sample:** 50 states plus DC, Asian (A4) and White (A1) workers in customer-facing (NAICS 72, 44–45) and knowledge (NAICS 54, 51) sectors. SDE =  $\hat{\beta} / \text{SD}(Y)$  where  $\text{SD}(Y)$  is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ( $|\text{SDE}| > 0.15$ ), Moderate (0.05–0.15), Small (0.005–0.05), Null ( $< 0.005$ ).