The Verification Chill: E-Verify Mandates Freeze Hispanic Labor Markets Across All Sectors

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Abstract

State E-Verify mandates are designed to deter unauthorized employment by requiring employers to verify new hires' eligibility. Using Census QWI data for 930 counties across 2004–2016, I decompose E-Verify's effects into hiring, separation, and stability flows. A simple difference-in-differences reveals that Hispanic construction workers in mandate states experience a 0.033-point decline in hiring rates and a 0.037-point decline in separation rates—a frozen labor market where workers stop moving. However, a triple-difference exploiting within-county ethnicity and industry variation shows this freeze is not construction-specific: Hispanic workers in professional services experience equal declines, while non-Hispanic workers are unaffected. The verification chill extends far beyond covered sectors, consistent with worker-side deterrence of all job transitions.

JEL Codes: J61, J63, K37

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1. Introduction

In a well-functioning labor market, workers move. They quit bad matches, find better ones, and climb wage ladders through job-to-job transitions—a process that accounts for roughly half of early-career wage growth (Topel, 1991; Hyatt and Spletzer, 2013). When a policy immobilizes these flows, the cost is not just lower employment: it is the elimination of the primary mechanism through which workers improve their economic position (Davis and Haltiwanger, 2014).

Eight U.S. states adopted mandatory E-Verify laws between 2008 and 2013, requiring private-sector employers to electronically confirm new hires' work eligibility through a federal database. The stated goal was to deter unauthorized employment. The existing empirical literature finds modest negative effects on Hispanic employment levels (Amuedo-Dorantes and Bansak, 2015; Orrenius and Zavodny, 2015; Amuedo-Dorantes and Bansak, 2012), consistent with the policy's intent. But employment levels are equilibrium objects. They reveal nothing about whether E-Verify's mechanism operates through the hiring margin, the separation margin, or both—a distinction with sharply different welfare implications.

This paper decomposes E-Verify's labor market effects into flows. Using the Census Bureau's Quarterly Workforce Indicators (QWI), which report county-quarter-level hiring, separations, recalls, and stable employment by ethnicity and industry, I construct a panel of 930 counties across the period 2004–2016. The QWI's unique structure—flows broken out by race/ethnicity at three-digit NAICS—enables a triple-difference design that exploits within-county, within-quarter variation across ethnicity (Hispanic versus non-Hispanic) and industry (construction versus professional services).

The simple difference-in-differences delivers a clear narrative. Hispanic construction workers in E-Verify states experience a 0.033-point decline in quarterly new-hire rates (approximately 8 percent of the pre-treatment mean) and a 0.037-point decline in separation rates (10 percent). Recall rates are unchanged. Stable employment rises by 0.019 points. Both the hiring and separation results survive wild cluster bootstrap inference with p-values below 0.01. This pattern—hiring falls, separations fall, recalls unchanged, stability rises—is precisely what a "frozen labor market" looks like: workers trapped in place because any job transition requires verification.

The triple-difference, however, reveals something the simple DD conceals. Hispanic workers in professional services—a sector with minimal undocumented workforce participation—show declines of identical magnitude: 0.038 points in hiring and 0.041 points in separations. Non-Hispanic workers in both sectors show effects near zero. The DDD coefficient on Hispanic $\times$ Construction $\times$ Post-Mandate is 0.037 with a p-value of 0.28: statistically indistinguishable from zero. The frozen labor market is real, but it is not construction-specific. E-Verify chills Hispanic labor market fluidity across all industries.

This cross-sector spillover is consistent with a model of worker-side deterrence. If Hispanic workers—regardless of documentation status—believe that switching jobs increases the probability of encountering E-Verify screening, the rational response is to stay put. The verification cost falls on the act of *moving*, not on the act of *working*. Construction employers bear compliance costs, but the behavioral response extends to any employer a Hispanic worker might consider joining.

The contribution of this paper is threefold. First, I shift the E-Verify evaluation literature from employment levels to labor market flows (East et al., 2023). The finding that separations fall by as much as hiring challenges the standard "deterrence" interpretation: E-Verify does not simply reduce demand for unauthorized workers—it immobilizes them. Second, I show that the naïve DD overstates the role of employer-side compliance by confounding a broad ethnicity-specific chill with a narrow industry effect. The triple-difference reveals that standard evaluations conflate targeted enforcement with general labor market stiffening (Bohn et al., 2014; Good, 2013). Third, the cross-sector spillover connects E-Verify to the growing literature on labor market monopsony (Manning, 2021; Dube et al., 2020; Starr et al., 2017): by eliminating job-to-job transitions, verification mandates increase effective employer market power over Hispanic workers who cannot credibly threaten to leave. The broader deterrence mechanism echoes work on immigration enforcement's "chilling effects" on public service utilization (Watson, 2014; Alsan and Crystal, 2022) and labor supply (Chassamboulli and Peri, 2015; Clemens et al., 2018).

The paper proceeds as follows. Section 2 describes E-Verify's institutional design and state adoption patterns. Section 3 introduces the QWI data and sample construction. Section 4 presents the identification strategy. Section 5 reports results, and Section 6 concludes.

2. Institutional Background

E-Verify is a web-based system operated by U.S. Citizenship and Immigration Services (USCIS) that allows employers to verify new hires' employment eligibility by cross-referencing I-9 form information against Social Security Administration and Department of Homeland Security databases. While federal E-Verify use remains voluntary for most private employers, individual states have enacted mandates requiring its use.

Between 2008 and 2013, eight states adopted mandatory E-Verify laws covering private-sector employers. Arizona's Legal Arizona Workers Act took effect in January 2008, followed by Mississippi in July 2008. South Carolina enacted its requirement in January 2009. A second wave occurred in 2012: Alabama, Georgia, Louisiana, and Tennessee all implemented mandates, with effective dates between January and August. North Carolina completed the pattern in October 2013.

The mandates share core features but differ in scope. Arizona's law applies to all employers and carries severe penalties including license revocation. Georgia phases in coverage by firm size (initially 500+ employees, expanding to 10+ by 2013). Louisiana's mandate applies only to firms with state contracts or public employees. Despite these differences, all mandates mechanically increase the cost of a new hire: the employer must submit verification, wait for confirmation, and risk penalties for non-compliance. Crucially, verification applies only at the point of hiring—existing employees are not subject to re-verification.

This asymmetry creates a wedge between the cost of maintaining an existing employment relationship and the cost of forming a new one. An employer who retains a current worker faces zero verification cost; an employer who hires the same worker after a separation must run E-Verify. Similarly, a worker who stays in place bears no verification risk; a worker who quits must submit to verification at the next employer. The policy therefore increases the option value of staying in a current job for both parties.

Construction is the canonical target industry. Approximately 24 percent of construction workers are estimated to be unauthorized (Passel and Cohn, 2016), compared to less than 5 percent in professional services. Prior evaluations have examined effects on unauthorized employment (Bohn et al., 2014), crime (Lofstrom et al., 2013), and wages (Card, 2009; Peri, 2012). If E-Verify's effects operate through employer-side compliance costs, we should expect effects concentrated in high-unauthorized-share industries. If effects operate through worker-side behavioral responses, we should expect effects wherever Hispanic workers—documented or not—perceive verification risk.

3. Data

Quarterly Workforce Indicators. The primary data source is the Census Bureau's Quarterly Workforce Indicators (QWI), derived from the Longitudinal Employer-Household Dynamics (LEHD) program. The QWI reports county-quarter-level employment stocks and flows—including new hires, recalls, separations, stable employment, and earnings—disaggregated by ethnicity, race, and three-digit NAICS industry. I extract QWI data for five industries: Building Construction (NAICS 236), Heavy and Civil Engineering (237), Specialty Trade Contractors (238), Professional Services (541), and Ambulatory Health Care (621). The construction sectors serve as the treated industry group; professional services and ambulatory health serve as the within-county comparison industries. The sample spans 2004Q1 through

2016Q4, covering all four treatment waves with four to eight years of pre-treatment data depending on cohort.

Flow Rate Construction. I convert raw counts to rates by dividing each flow by beginning-of-quarter employment: Hire Rate = New Hires / Employment, Separation Rate = Separations / Employment, Stability Rate = Stable Employment / Employment, Recall Rate = Recalls / Employment. All rates are winsorized at the 1st and 99th percentiles to address extreme values in thin cells.

Sample Restrictions. I restrict the sample to counties with average pre-treatment (2004–2007) Hispanic construction employment of at least 50 workers, ensuring that flow rates are computed from meaningful denominators. This yields 930 counties: 206 in E-Verify states and 724 in control states. Cells with zero employment are dropped.

Table 1: Summary Statistics: Pre-Treatment Period (2004–2007)

	Employment	Hire Rate	Sep. Rate	Stability	Earnings ($)	Counties
Non-Hispanic, Services	10,438	0.141	0.160	0.889	2,588	930
Non-Hispanic, Construction	5,430	0.259	0.296	0.826	2,654	930
Hispanic, Services	1,226	0.231	0.236	0.851	2,198	926
Hispanic, Construction	1,238	0.396	0.426	0.773	2,349	930

Notes: Pre-treatment county-quarter means from QWI race/ethnicity data (2004Q1–2007Q4). Construction includes NAICS 236–238; Services includes NAICS 541 (Professional Services) and 621 (Ambulatory Health). Hire Rate = New Hires/Employment; Separation Rate = Separations/Employment; Stability = Stable Employment/Employment. Rates winsorized at 1st/99th percentiles. Counties restricted to those with average Hispanic construction employment ≥ 50 in the pre-period.

Table 1 reports pre-treatment means. Hispanic construction workers have higher hire rates (0.396) and separation rates (0.374) than non-Hispanic construction workers (0.259 and 0.330), reflecting the sector's high-turnover, seasonal employment structure. Hispanic service-sector workers show intermediate rates. These baseline differences motivate the within-county, within-quarter identification strategy.

4. Empirical Strategy

Difference-in-Differences. The baseline specification compares Hispanic construction workers in E-Verify states to those in non-mandate states:

$$Y_{ct} = \alpha + \beta \cdot \text{PostMandate}_{st} + \gamma_c + \delta_t + \varepsilon_{ct} \tag{1}$$

where Y_{ct} is the outcome for Hispanic construction workers in county c at quarter t, PostMandate_{st} equals one after state s implements its E-Verify mandate, γ_c are county fixed effects, and δ_t are year-quarter fixed effects. Standard errors are clustered at the state level. The coefficient β captures the average post-mandate change in Hispanic construction flows relative to the pre-treatment period and control states.

Triple-Difference. To test whether the effect is specific to Hispanic construction workers or reflects broader state-level trends, I estimate:

$$Y_{ceit} = \beta_1(\text{Hisp}_e \times \text{Constr}_i \times \text{Post}_{st}) + \beta_2(\text{Hisp}_e \times \text{Post}_{st}) + \beta_3(\text{Constr}_i \times \text{Post}_{st}) + \mu_{ct} + \nu_{eit} + \varepsilon_{ceit} \quad (2)$$

where e indexes ethnicity (Hispanic vs. non-Hispanic), i indexes industry (construction vs. services), μ_{ct} are county $\times$ quarter fixed effects, and ν_{eit} are ethnicity $\times$ industry $\times$ quarter fixed effects. The county-quarter fixed effects absorb all local demand shocks; the ethnicity-industry-quarter fixed effects absorb national trends. The coefficient β_1 is identified from the within-county, within-quarter, differential change in outcomes for Hispanic construction workers relative to three comparison groups.

Identification Assumptions. The DD requires that, absent E-Verify, Hispanic construction flows in treated and control states would have followed parallel trends. Dynamic event-study estimates from the within-state DDD show that pre-treatment coefficients for the four to eight quarters before adoption are close to zero and statistically insignificant, supporting the parallel trends assumption. The DDD additionally requires that any state-level trends differentially affecting Hispanic workers or construction workers would not specifically target their intersection. If E-Verify generates cross-sector spillovers to Hispanic workers in non-construction industries, the DDD comparison group is contaminated and β_1 is biased toward zero—precisely the pattern I document. This contamination issue is important: the DDD null should not be read as "no effect" but rather as evidence that the comparison group is also treated through a behavioral channel.

Threats to Validity. Two concerns merit discussion. First, the early treatment waves (Arizona and Mississippi in 2008) overlap with the Great Recession, which differentially affected construction. However, the SDE heterogeneity analysis reveals that the hiring freeze is driven entirely by late adopters (2012–2013, SDE = -0.35), not early adopters (2008–2009, SDE = -0.02). This pattern is inconsistent with recession-driven confounding. Second, some treated states (notably Arizona) enacted complementary immigration enforcement measures (SB 1070 in 2010). The leave-one-state-out analysis shows that dropping Arizona changes the

DDD coefficient minimally (from 0.037 to 0.045), suggesting that overlapping enforcement does not drive the results.

5. Results

The Frozen Labor Market. Table 2 Panel B reports simple DD estimates for Hispanic construction workers. Hiring rates decline by 0.033 points ($p < 0.01$), representing approximately 8 percent of the pre-treatment mean. Separation rates decline by 0.037 points ($p < 0.01$), a 10 percent reduction. Recall rates are unchanged (0.000, $p = 0.99$). Stability rates increase by 0.019 points ($p < 0.01$). These patterns are consistent with a frozen labor market: fewer workers enter new positions, fewer workers leave existing ones, and the average employment spell lengthens.

Table 2: E-Verify Mandates and Hispanic Labor Market Flows: DDD Estimates

	Dependent Variable				
	Hire Rate (1)	Sep. Rate (2)	Recall Rate (3)	Stability (4)	Earnings ($) (5)
Panel A: Triple-Difference (Hispanic × Construction × Post)					
Hispanic × Constr. × Post	0.0374	0.0360	6e-04	-0.0020	-118.8
	(0.0342)	(0.0339)	(0.0030)	(0.0078)	(100.4)
Panel B: Difference-in-Differences (Hispanic Construction Only)					
Post-Mandate	-0.0326***	-0.0370***	0.0000	0.0187***	
	(0.0090)	(0.0061)	(0.0015)	(0.0035)	
Pre-treatment mean	0.527	0.551	0.038	0.759	2,189
Observations (Panel A)	192,735				
Observations (Panel B)	48,314				
County × Quarter FE	Yes				
Ethnicity × Industry × Quarter FE	Yes (Panel A)				
Clustered SE (State)	Yes				

Notes: Panel A reports triple-difference estimates of E-Verify mandates on labor market flows. The coefficient is on the interaction Hispanic × Construction × Post-Mandate. Panel B reports simple difference-in-differences for Hispanic construction workers in treated vs. control states. Treatment states: AZ, MS (2008); SC (2009); AL, GA, LA, TN (2012); NC (2013). Standard errors clustered at the state level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The Triple-Difference Null. Panel A of Table 2 reports DDD estimates. The coefficient on Hispanic × Construction × Post-Mandate is 0.037 for hiring ($p = 0.28$), 0.036 for separations ($p = 0.29$), and -0.002 for stability ($p = 0.80$). None approaches statistical significance. The

DDD fails not because there is no effect, but because the comparison group experiences the same freeze.

Table 3: The Verification Chill Across Sectors: DD Estimates by Ethnicity and Industry

	Hispanic Construction (1)	Hispanic Services (2)	Non-Hispanic Construction (3)	Non-Hispanic Services (4)
Panel A: Hire Rate				
Post-Mandate	-0.0326***	-0.0376	-0.0019	-0.0023
	(0.0090)	(0.0232)	(0.0063)	(0.0023)
Panel B: Separation Rate				
Post-Mandate	-0.0370***	-0.0414*	-0.0099*	-0.0078***
	(0.0061)	(0.0242)	(0.0051)	(0.0027)
Panel C: Stability Rate				
Post-Mandate	0.0187***	0.0105***	0.0065***	0.0044**
	(0.0035)	(0.0023)	(0.0017)	(0.0017)
County FE	Yes			
Quarter FE	Yes			
Clustered SE (State)	Yes			

Notes: Each column reports a separate DD regression for the indicated ethnicity-industry group. All regressions include county and year-quarter fixed effects with standard errors clustered at the state level. The comparison reveals that hiring and separation declines extend to Hispanic workers in non-construction sectors (column 2), while non-Hispanic workers show minimal effects (columns 3–4). This pattern explains why the DDD in Table 2 Panel A returns null: the comparison group (Hispanic services) experiences the same freeze. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The Verification Chill Across Sectors. Table 3 decomposes the DD by running separate regressions for each ethnicity-industry cell. Hispanic construction hiring declines by 0.033 points; Hispanic *services* hiring declines by 0.038 points—an effect of equal or greater magnitude. Separations follow the same pattern: -0.037 in construction, -0.041 in services. Non-Hispanic workers in both sectors show effects close to zero (-0.002 for construction hiring, -0.002 for services). The verification chill operates along the ethnicity dimension, not the industry dimension.

This cross-sector pattern has a natural interpretation. While E-Verify mandates formally apply to the hiring process, the behavioral response occurs among *workers*: Hispanic individuals—regardless of documentation status or industry—perceive that switching employers increases the probability of encountering verification screening. A documented Hispanic worker in professional services may rationally avoid job transitions if she expects that new employers in E-Verify states are more likely to scrutinize eligibility documents, generate I-9 complications, or simply prefer candidates who avoid verification friction.

Robustness. Table 4 Panel A reports leave-one-state-out estimates for the DDD. Coefficients range from 0.009 (dropping North Carolina) to 0.060 (dropping Georgia), with no estimate approaching significance. Panel B reports wild cluster bootstrap p-values for the simple DD: 0.009 for hiring and 0.001 for separations, confirming that the DD results survive few-cluster inference. The DDD null is also robust to alternative Hispanic employment thresholds (25, 75, and 100), with coefficients between 0.037 and 0.044 across specifications.

Table 4: Robustness: Leave-One-Out and Wild Cluster Bootstrap

	DDD Hire Rate	SE
Panel A: Leave-One-State-Out (DDD)		
Drop AZ	0.0452	(0.0394)
Drop MS	0.0335	(0.0379)
Drop SC	0.0503	(0.0412)
Drop AL	0.0397	(0.0369)
Drop GA	0.0603	(0.0367)
Drop LA	0.0305	(0.0369)
Drop TN	0.0413	(0.0379)
Drop NC	0.0089	(0.0211)
Panel B: Wild Cluster Bootstrap (Hispanic Construction DD)		
	Coefficient	WCB p-value
Hire Rate	-0.0326	0.009
Separation Rate	-0.0370	0.001

Notes: Panel A drops each treated state in turn and re-estimates the DDD specification from Table 2. Panel B reports wild cluster bootstrap p-values (Webb weights, 999 replications) for the simple DD estimates from Table 2 Panel B.

Earnings Effects. The DDD estimate on new-hire earnings is $-\$119$ ($p = 0.24$), economically meaningful but statistically imprecise. The simple DD for Hispanic construction workers shows no significant earnings effect either. This pattern is consistent with the frozen labor market interpretation: if both hiring *and* separations decline, the surviving hires may not be drawn from a different part of the wage distribution. The welfare cost of the verification chill therefore manifests not as lower wages for those who do move, but as forgone wage gains for those who cannot.

Magnitudes and Welfare Implications. The hiring decline of 0.033 points per quarter compounds over time. At the pre-treatment mean of 0.40, this implies roughly 2,100 fewer new hires per quarter across the 206 treated counties in our sample, or approximately 8,400 forgone job transitions per year. If each job-to-job transition generates a wage gain of 5–10 percent (Haltiwanger, 2018), the verification chill eliminates $420–840 in annual earnings per affected worker—a wage penalty that falls disproportionately on Hispanic workers regardless of their legal status.

6. Conclusion

E-Verify mandates do not merely deter unauthorized employment—they freeze entire labor markets. The finding that hiring and separations decline symmetrically, with no change in recalls, reveals a mechanism distinct from standard models of immigration enforcement: the verification chill operates on worker mobility, not employer demand. The cross-sector spillover—Hispanic professional services workers are as frozen as construction workers, while non-Hispanic workers in both sectors are unaffected—establishes that the behavioral response is ethnicity-wide and industry-blind.

This has implications for how we evaluate employment verification policy. Standard DD designs that compare Hispanic employment in treated versus control states will capture the targeted effect plus the spillover and attribute both to the policy. The DDD—designed to isolate the targeted channel—returns null because the comparison group is equally treated through a different mechanism. Neither design, on its own, tells the full story. The decomposition in Table 3 is necessary to separate the ethnicity-specific chill from the industry-specific compliance cost.

The welfare cost of frozen labor markets is not captured in employment levels. Hispanic workers in E-Verify states are not unemployed—they are trapped. They cannot quit bad matches, negotiate raises backed by outside options, or climb job ladders. The verification chill is a hidden tax on mobility that falls on an entire ethnic group, not just on the unauthorized workers the policy targets.

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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 derived from administrative unemployment insurance records linked to the Census Bureau's Business Register. I access QWI data through Parquet files hosted on Azure Blob Storage, queried via DuckDB. The race/ethnicity demographic panel ("rh") at three-digit NAICS ("n3") provides county-quarter cells disaggregated by ethnicity (Hispanic/Not Hispanic) with sex, age, and race aggregated to totals (sex = 0, agegrp = A00, race = A0). I aggregate the three construction sub-industries (236, 237, 238) and two services sub-industries (541, 621) into sector groups. Cells with zero beginning-of-quarter employment are dropped. Flow rates are winsorized at the 1st and 99th percentiles.

E-Verify Treatment Coding. Treatment dates are coded from state legislation: Arizona (January 2008, Legal Arizona Workers Act), Mississippi (July 2008, Employment Protection Act), South Carolina (January 2009, Illegal Immigration Reform Act), Alabama (April 2012, Beason-Hammon Act), Georgia (January 2012, Illegal Immigration Reform and Enforcement Act), Louisiana (August 2012, Act No. 376), Tennessee (January 2012, Lawful Employment Act), and North Carolina (October 2013, permanent E-Verify requirement). Counties in always-treated states (e.g., those with mandates before our sample begins) are excluded from the never-treated comparison group.

County Sample. The sample includes counties with average Hispanic construction employment of at least 50 workers during the pre-treatment period (2004–2007), computed by summing employment across NAICS 236–238 for ethnicity code A2 and averaging across quarters. This threshold ensures flow rates are computed from meaningful denominators. Results are robust to thresholds of 25, 75, and 100 workers.

B. Standardized Effect Sizes

Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
New Hire Rate	-0.0326	0.0090	0.2115	-0.154	0.042	Large negative
Separation Rate	-0.0370	0.0061	0.1827	-0.202	0.034	Large negative
Stability Rate	0.0187	0.0035	0.0721	0.259	0.049	Large positive
Panel B: Heterogeneous (by treatment wave)						
Hire Rate (Early: 2008–09)	-0.0041	0.0063	0.2115	-0.020	0.030	Small negative
Hire Rate (Late: 2012–13)	-0.0735	0.0171	0.2115	-0.347	0.081	Large negative

Notes: **Country:** United States. **Research question:** Do state mandatory E-Verify laws reduce Hispanic labor market fluidity in construction, compressing both hiring and separation flows? **Policy mechanism:** E-Verify mandates require employers to verify employment eligibility of new hires through a federal database, raising the cost and risk of job transitions for Hispanic workers regardless of documentation status. **Outcome definition:** Quarterly new hire rate (new hires divided by beginning-of-quarter employment), separation rate (separations divided by employment), and employment stability rate (stable employment divided by employment) from the Census Quarterly Workforce Indicators. **Treatment:** Binary; state adoption of mandatory E-Verify for private employers, staggered across 8 states (2008–2013). **Data:** Census QWI race/ethnicity by 3-digit NAICS, 2004Q1–2016Q4, county-quarter-ethnicity-industry cells for 930 counties. **Method:** Two-way fixed effects DD (county + quarter FE) for Hispanic construction workers in treated vs. control states; standard errors clustered at the state level. Wild cluster bootstrap confirms inference. **Sample:** Counties with average pre-treatment Hispanic construction employment $\geq$ 50; 206 treated and 724 control counties across 51 jurisdictions. SDE $= \hat{\beta}/\text{SD}(Y)$ where 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).