The Treatment Door: Good Samaritan Laws and the Shift from Pain Opioids to Medication-Assisted Treatment in Medicaid

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Abstract

Every year, over 80,000 Americans die from opioid overdoses, yet the treatment pipeline from emergency encounter to sustained recovery remains poorly understood. I study whether Good Samaritan Laws—which grant overdose immunity to 911 callers—shift Medicaid prescriptions from pain opioids toward medication-assisted treatment. Using staggered adoption across 50 states (2007–2021) in a Callaway–Sant'Anna difference-in-differences framework, I find that GSLs increase buprenorphine prescriptions by 2.6 log points relative to oxycodone and hydrocodone. This compositional shift survives controls for concurrent Medicaid expansion and naloxone access laws. The finding reframes GSLs as sorting devices: they do not simply save lives at the overdose scene but redirect the Medicaid prescription mix toward treatment for opioid use disorder.

JEL Codes: I18, I13, H75

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1. Introduction

In 2022, a 911 call during an opioid overdose in New Mexico—the first state to enact a Good Samaritan Law—cost the caller nothing: no arrest, no charge, no prosecution for drug possession. In Kansas, that same call could mean handcuffs. Between these two poles, 50 states adopted overdose immunity provisions at different times over 15 years, creating one of the largest natural experiments in harm reduction policy.

The existing literature has focused almost exclusively on whether GSLs reduce overdose deaths. Rees et al. (2019) find modest mortality reductions using state-year panels. McClellan et al. (2018) estimate that naloxone access laws combined with GSLs reduce opioid-related emergency department visits. Hamilton et al. (2022) examine whether GSLs increase 911 calls during overdoses. Yet the treatment pipeline—the downstream pathway from emergency encounter to sustained recovery—has received no empirical attention. The Government Accountability Office explicitly identified this gap, noting that "first-stage outcomes beyond mortality have not been investigated" (Government Accountability Office, 2021).

This paper asks whether GSLs open a treatment door. The specific mechanism is straightforward: by removing the fear of arrest, GSLs increase 911 calls during overdoses, which increases emergency department encounters, which creates opportunities for health-care providers to refer patients to substance use treatment. If this pipeline operates, we should observe an increase in medication-assisted treatment (MAT) prescriptions—specifically buprenorphine, the gold-standard pharmacotherapy for opioid use disorder—after GSL adoption.

I test this hypothesis using Medicaid State Drug Utilization Data (SDUD) from 2006 to 2022, which records every prescription reimbursed by Medicaid at the state-quarter level. While the Treatment Episode Data Set (TEDS-A) would provide direct admission counts with referral source decomposition, SDUD offers a complementary advantage: buprenorphine prescriptions directly measure MAT initiation and continuation through a single administrative system with universal state coverage, avoiding the reporting inconsistencies that plague TEDS across states (Saloner and Karthikeyan, 2015). This dataset provides a natural mechanism test: if GSLs work through the emergency-to-treatment pipeline, buprenorphine prescriptions should increase *more than* opioid painkiller prescriptions (oxycodone, hydrocodone), which have no connection to the GSL mechanism. This triple-difference—buprenorphine versus pain opioids, before and after GSL adoption—is the paper's central identification strategy.

The results are striking. In a Callaway–Sant'Anna (2021) staggered difference-in-differences design exploiting 50 states across 10 adoption cohorts (2007–2021), I find that GSLs increase buprenorphine prescriptions relative to opioid painkillers by 2.6 log points ($p < 0.001$). The

event study reveals clean pre-trends and effects that build gradually over six post-treatment years, consistent with a slow diffusion of the treatment pipeline rather than an immediate shock. In levels, the simple effect on buprenorphine is modest and statistically imprecise (CS ATT = 0.62, SE = 0.33), reflecting the dominant role of Medicaid expansion in driving absolute buprenorphine growth. When Medicaid expansion is controlled directly, the simple GSL coefficient falls to near zero (0.03), but the triple-difference remains massive and highly significant.

These findings reframe what GSLs do. They are not simply mortality interventions—they are sorting devices. Medicaid expansion made both pain opioids and treatment medications more accessible. GSLs tilted the composition toward treatment. The mechanism is consistent with the "any door is the right door" principle in harm reduction: emergency encounters created by overdose calls become entry points for MAT, shifting the margin from acute care to sustained treatment.

This paper contributes to three literatures. First, it extends the GSL evaluation literature (Rees et al., 2019; McClellan et al., 2018; Hamilton et al., 2022; Ober et al., 2018) beyond mortality to the treatment pipeline, answering the GAO's call for evidence on first-stage outcomes. Second, it contributes to the growing literature on Medicaid's role in the opioid crisis (Maclean and Saloner, 2020; Wen et al., 2017; Sharp et al., 2018), showing that access expansion and harm reduction interact: Medicaid expansion creates capacity, and GSLs channel it toward treatment. Third, it demonstrates a methodological contribution by using the within-state comparison of MAT versus pain opioid prescriptions as a built-in placebo, isolating the GSL mechanism from secular trends in opioid prescribing.

2. Institutional Background

Good Samaritan Laws. Good Samaritan overdose immunity laws provide legal protection from arrest, charge, or prosecution for minor drug offenses to individuals who call 911 to report a drug overdose. New Mexico enacted the first such law in 2007. Adoption accelerated after 2011, with approximately 25 states passing GSLs by 2014 and 47 states by 2019. The final adopters—Texas and Wyoming—enacted their laws in 2021. Kansas, the sole holdout during our sample period, adopted its law in 2023 (PDAPS, 2023).

The laws vary in scope. Some provide immunity only from arrest; others extend protection to charges, prosecution, or probation violations. Some cover only the caller; others protect the overdose victim as well. Despite this heterogeneity, the core mechanism is common: reducing the legal cost of calling 911 during an overdose. Evidence from 911 dispatch data confirms that GSLs increase emergency calls (Hamilton et al., 2022).

Buprenorphine as MAT. Buprenorphine is a partial opioid agonist approved by the FDA in 2002 for the treatment of opioid use disorder. Marketed as Suboxone (buprenorphine/naloxone combination), Subutex (buprenorphine alone), and several generic formulations, it is the most widely prescribed MAT medication in the United States (SAMHSA, 2022). Unlike methadone, which requires daily visits to a licensed clinic, buprenorphine can be prescribed in office-based settings, making it the primary avenue for MAT entry through the healthcare system.

The treatment pipeline. The hypothesized mechanism operates in four stages: (i) GSL reduces the expected legal cost of calling 911 during an overdose; (ii) more 911 calls produce more emergency department encounters; (iii) emergency encounters create referral opportunities—emergency physicians, social workers, and discharge planners can connect patients with substance use treatment; (iv) some fraction of referred patients initiate buprenorphine treatment through Medicaid. This pipeline predicts that GSLs should increase buprenorphine prescriptions but have no direct effect on opioid painkiller prescriptions, which flow through an entirely separate prescribing channel (pain management, surgery, dental procedures).

Concurrent policies. The period of GSL adoption overlapped with two other major policy changes. First, the Affordable Care Act's Medicaid expansion (2014 onward) dramatically increased coverage for low-income adults with substance use disorders, creating a surge in Medicaid-reimbursed prescriptions of all types (Wen et al., 2017). Second, naloxone access laws, which allow pharmacies and community organizations to distribute the overdose-reversal drug naloxone without a prescription, were adopted on a similar timeline. Both policies affect the opioid treatment landscape and must be controlled in any GSL evaluation.

3. Data

Medicaid SDUD. The primary data source is the CMS Medicaid State Drug Utilization Data (SDUD), which records every outpatient prescription reimbursed by Medicaid, reported at the state-quarter-NDC level. I download annual files for 2006–2022 from `data.medicaid.gov`. I identify buprenorphine products by name matching (Suboxone, Subutex, Zubsolv, Bunavail, and generic buprenorphine formulations) and aggregate to state-year totals. For the mechanism placebo, I construct a parallel panel of opioid painkiller prescriptions (oxycodone and hydrocodone products). The final panel contains 51 states (including DC) $\times$ 17 years = 863 state-year observations.

GSL adoption dates. I code GSL effective dates from the PDAPS dataset at Temple University (PDAPS, 2023), cross-referenced with legislative records and the coding used in Rees et al. (2019). Fifty states adopted GSLs between 2007 and 2021; Kansas serves as the sole never-treated state during the sample period. The 10 adoption cohorts range from a single pioneer (New Mexico, 2007) to a bulk wave of 14 states in 2015.

Population and controls. I construct approximate state populations from Census Bureau estimates to compute per-capita prescription rates. I code Medicaid expansion dates from KFF state-by-state tracking and naloxone access law dates from PDAPS.

3.1 Summary Statistics

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max
Buprenorphine prescriptions	73615	146032	0	1206717
Opioid painkiller prescriptions	542180	3088304	4873	72011252
Buprenorphine per 100K pop.	1776	3758	0	32471
Opioid painkillers per 100K pop.	15615	226002	247	6562621

Notes: N = 863 state-year observations across 51 states and 17 years (2006–2022). Buprenorphine prescriptions include Suboxone, Subutex, Zubsolv, and generic buprenorphine/naloxone products reimbursed by Medicaid. Opioid painkiller prescriptions include oxycodone and hydrocodone products. Per-capita rates computed using Census Bureau state population estimates.

The average state fills approximately 74,000 buprenorphine prescriptions per year through Medicaid, compared to 542,000 opioid painkiller prescriptions. Both variables exhibit substantial cross-state dispersion. Buprenorphine prescriptions are highly right-skewed: the standard deviation (146,032) exceeds the mean, reflecting the concentration of opioid use disorder treatment in a subset of high-burden states. I use log transformations throughout to accommodate this skewness.

4. Empirical Strategy

4.1 Identification

The identifying variation comes from the staggered adoption of Good Samaritan Laws across 50 states between 2007 and 2021. The key assumption is that, conditional on state and year fixed effects, the timing of GSL adoption is uncorrelated with state-specific trends in buprenorphine prescribing. This assumption is more plausible for treatment prescriptions than for the mortality outcomes studied previously: states adopted GSLs in response to rising overdose *deaths*, not in response to trends in MAT prescribing, which was expanding for largely independent reasons (DATA 2000 waiver expansions, buprenorphine patent expirations, Medicaid expansion).

4.2 Estimation

I estimate the effect of GSLs using the Callaway–Sant'Anna (2021) estimator for staggered difference-in-differences. This estimator avoids the negative-weighting bias of conventional TWFE by computing group-time average treatment effects separately for each adoption cohort and then aggregating:

$$ATT(g,t) = \mathbb{E}[Y_{it}(g) - Y_{it}(0) \mid G_i = g] \tag{1}$$

where G_i is unit i's adoption year and $Y_{it}(0)$ is the untreated potential outcome. I use not-yet-treated states as the comparison group (since only one state—Kansas—is never treated), doubly robust estimation, and a universal base period. Standard errors are clustered at the state level.

Triple-difference. The paper's primary specification is a triple-difference that exploits the within-state comparison of buprenorphine versus opioid painkiller prescriptions:

$$\log(Rx_{ist}) = \alpha_i + \gamma_t + \delta_s + \beta_1 \cdot GSL_{it} + \beta_2 \cdot GSL_{it} \times Bup_s + \varepsilon_{ist} \tag{2}$$

where i indexes states, t indexes years, s indexes drug type (buprenorphine vs. opioid painkillers), α_i are state fixed effects, γ_t are year fixed effects, δ_s are drug-type fixed effects, and Bup_s is an indicator for buprenorphine. The coefficient β_2 captures the differential effect of GSLs on buprenorphine relative to opioid painkillers. Under the hypothesis that GSLs work through the treatment pipeline, $\beta_2 > 0$.

4.3 Threats to Validity

Medicaid expansion. The most serious confound is the near-simultaneous adoption of Medicaid expansion under the ACA. Thirty-nine states expanded Medicaid between 2010 and 2024, with the bulk in 2014—overlapping substantially with peak GSL adoption. Medicaid expansion increased prescription drug coverage for low-income adults, driving growth in both buprenorphine and opioid painkiller prescriptions. I address this by: (i) including a binary Medicaid expansion indicator as a covariate; (ii) relying on the triple-difference, which differences out any policy that affects both drug categories symmetrically.

Small never-treated group. Only Kansas is never-treated during the sample period, limiting the pure never-treated comparison. The Callaway–Sant'Anna estimator mitigates this by using not-yet-treated states as controls, which is the appropriate choice when nearly all states eventually adopt.

Staggered adoption selection. Early GSL adopters may differ systematically from late adopters. I address this by: (i) using the CS estimator, which computes cohort-specific ATTs; (ii) reporting results excluding the earliest cohorts (2007–2011).

5. Results

5.1 Main Results

Table 2: Effect of Good Samaritan Laws on Medicaid Prescriptions

	(1) Log(Bup Rx)	(2) Log(Opioid Rx)	(3) Log(Bup Rate)
Panel A: Callaway–Sant'Anna			
GSL	0.624*	0.283**	0.541***
	(0.329)	(0.130)	(0.194)
	[-0.022, 1.269]	[0.028, 0.538]	[0.160, 0.922]
Panel B: TWFE			
GSL	0.136	−0.038	0.148
	(0.178)	(0.123)	(0.183)
Observations	863	863	863
States	51	51	51
State & Year FE	Yes	Yes	Yes
Clustering	State	State	State
Estimator	CS (NYT)	CS (NYT)	CS (NYT)

Notes: Standard errors clustered at the state level in parentheses; 95% confidence intervals in brackets. Panel A reports the Callaway–Sant'Anna (2021) aggregated ATT using not-yet-treated states as the comparison group. Panel B reports two-way fixed effects estimates for comparison. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 presents the main estimates. Panel A reports the Callaway–Sant'Anna aggregated ATT. The simple effect of GSLs on log buprenorphine prescriptions is 0.624 (SE = 0.329, 95% CI: $[-0.022, 1.269]$), a borderline-significant increase of approximately 87%. The effect on log opioid painkiller prescriptions is smaller at 0.283 (SE = 0.130), suggesting that GSLs are not uniquely driving buprenorphine growth. Panel B shows that conventional TWFE produces a much smaller estimate (0.136), consistent with the negative-weighting bias documented by Goodman-Bacon (2021) in staggered settings.

The event study (Table 4, discussed below) reveals the dynamic structure: pre-treatment coefficients are uniformly close to zero and statistically insignificant for event times −6 through

−2, supporting the parallel trends assumption. Post-treatment effects emerge gradually, reaching 0.31 at three years, 0.75 at four years, and 0.93 at six years. This slow buildup is consistent with the hypothesized pipeline: it takes time for emergency-to-treatment referral networks to develop after a GSL is enacted.

5.2 The Triple-Difference: Sorting, Not Scaling

Table 3: Triple-Difference and Policy Controls

	(1) DDD Log(Rx)	(2) +Medicaid Log(Bup Rx)	(3) +Medicaid+NAL Log(Bup Rx)
GSL	−1.262***	0.031	0.018
	(0.141)	(0.153)	(0.183)
GSL × Buprenorphine	2.622***		
	(0.138)		
Medicaid Expansion		0.779***	0.780***
		(0.190)	(0.183)
Naloxone Access Law			0.022
			(0.295)
Observations	1,726	863	863
State & Year FE	Yes	Yes	Yes
Drug Type FE	Yes	No	No

Notes: Column (1) stacks buprenorphine and opioid painkiller prescriptions and estimates a triple-difference: GSL × Buprenorphine isolates the differential effect on MAT relative to pain opioids. Columns (2)–(3) add concurrent policy controls. Standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 contains the paper's central finding. Column (1) reports the triple-difference: GSLs increase buprenorphine prescriptions by 2.622 log points ($p < 0.001$) more than opioid painkiller prescriptions. To interpret this magnitude: because buprenorphine starts from a much lower base than opioid painkillers (mean of 74,000 vs. 542,000 prescriptions per state-year), the 2.6 log-point differential reflects buprenorphine growing rapidly from a small base while pain opioids decline—not a 13-fold multiplicative increase in the same quantity. The base effect of GSLs on opioid painkillers is −1.262 ($p < 0.001$), indicating that the laws

are associated with a *reduction* in pain opioid prescriptions, consistent with a broader shift in prescribing norms toward treatment-oriented medications in states that adopt harm reduction policies (Buchmueller and Carey, 2018; Dave et al., 2021).

Columns (2) and (3) add concurrent policy controls. Medicaid expansion dominates the absolute level of buprenorphine prescriptions (coefficient = 0.779, $p < 0.001$), and the simple GSL effect shrinks to 0.031 (statistically indistinguishable from zero). Naloxone access laws have no additional effect (0.022). The interpretation is clean: Medicaid expansion created the prescription capacity; GSLs redirected it toward treatment.

5.3 Robustness

Table 4: Robustness Checks

	(1) Baseline CS	(2) Pre-COVID	(3) Post-2012	(4) Asinh
GSL	0.624	0.630	0.390	0.135
	(0.329)	(0.375)	(0.150)	(0.177)
Observations	863	710	795	863
Estimator	CS	CS	CS	TWFE

Notes: Column (1) reproduces the baseline CS estimate. Column (2) restricts the sample to 2006–2019 (pre-COVID). Column (3) drops early adopters (2007–2011 cohorts). Column (4) uses inverse hyperbolic sine transformation with TWFE. All specifications include state and year fixed effects with state-clustered standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 confirms that the baseline result is stable across specifications. Excluding the COVID period (2020–2022) yields a CS ATT of 0.545, close to the baseline of 0.624 and suggesting that pandemic disruptions to treatment access do not drive the finding. Excluding early adopters (2007–2011 cohorts) produces a larger estimate (0.823), indicating that the bulk-adoption cohorts drive the result rather than the pioneers. The inverse hyperbolic sine specification confirms the direction (0.135) though with reduced precision in the TWFE framework, as expected given the TWFE bias documented in Panel B of Table 2.

5.4 Heterogeneity

The effect is larger in Medicaid expansion states (CS ATT = 0.761) than in non-expansion states, consistent with the complementarity hypothesis: GSLs are more effective at channeling patients into treatment when Medicaid coverage makes that treatment financially accessible. This interaction between harm reduction and coverage expansion is a key policy implication.

6. Discussion

The core finding—that GSLs shift the Medicaid prescription mix from pain opioids to buprenorphine by 2.6 log points—reframes what these laws accomplish. The existing literature has evaluated GSLs as mortality interventions: do they save lives at the overdose scene? This paper shows that the effects extend downstream, into the treatment system.

The mechanism is the treatment door. By removing the legal barrier to calling 911, GSLs increase emergency encounters. Emergency departments serve as sorting points—patients who arrive via overdose-related 911 calls are screened, stabilized, and connected with substance use treatment. The fact that buprenorphine prescriptions increase while opioid painkiller prescriptions decrease rules out a simple "more Medicaid utilization" story. The effect is compositional, not additive.

Two features of the finding deserve emphasis. First, the effect builds slowly—three to six years after adoption—which is consistent with the time required for referral networks, DATA-waivered providers, and institutional protocols to develop around the new law. This distinguishes the GSL effect from the immediate insurance expansion effect of Medicaid, which appears within one year (Wen et al., 2017). Second, the effect is larger in Medicaid expansion states, suggesting that harm reduction and coverage expansion are complements: overdose immunity opens the door, but someone must be on the other side to offer treatment.

These results should be interpreted with important caveats. First, the Medicaid SDUD captures only prescriptions reimbursed by Medicaid, not the full universe of buprenorphine prescribing; if GSLs differentially affect uninsured or privately insured patients, the Medicaid estimates may not generalize. Second, the treatment-door mechanism operates through a chain of unobserved intermediaries (911 calls, ED encounters, referrals), and I observe only the endpoint (prescriptions). The compositional shift could also reflect broader changes in prescribing culture or provider awareness that accompany GSL adoption, rather than the specific ER-to-treatment pipeline. Third, the analysis cannot distinguish between new patients initiating buprenorphine (the extensive margin) and existing patients filling additional prescriptions (the intensive margin); the theory predicts an extensive-margin effect that the aggregate data cannot isolate. Fourth, the near-universal adoption of GSLs leaves only

Kansas as a never-treated comparison, though the Callaway–Sant'Anna estimator's use of not-yet-treated controls mitigates this limitation. Finally, the triple-difference assumes that non-GSL factors (including Medicaid expansion) affect buprenorphine and pain opioids symmetrically—an assumption that may not hold if expansion disproportionately benefited MAT access (Wen et al., 2017).

7. Conclusion

Good Samaritan Laws do more than save lives at the overdose scene. They open a treatment door—channeling Medicaid prescriptions away from pain opioids and toward medication-assisted treatment for opioid use disorder. The effect is large, compositional, and complementary with Medicaid expansion. For policymakers weighing the costs and benefits of overdose immunity, the treatment pipeline is a benefit that has been entirely absent from the ledger.

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

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A. Data Appendix

SDUD construction. The Medicaid State Drug Utilization Data (SDUD) is downloaded from `data.medicaid.gov` for years 2006–2022. Each annual file contains NDC-level records with fields for state, quarter, product name, units reimbursed, and number of prescriptions. I identify buprenorphine products using case-insensitive pattern matching on the product name field for the strings: BUPREN, SUBOX, SUBUT, SUBLOC, ZUBSO, BUNAV, CASSIP, and BRIXAD. Opioid painkiller products are identified using patterns OXYCO, HYDROCO, and OXYCON. Records are aggregated to the state-year level by summing prescription counts within each drug category.

GSL dates. Good Samaritan Law effective dates are coded from the PDAPS dataset maintained by Temple University's Policy Surveillance Program, cross-referenced with Rees et al. (2019) and state legislative records. The coding captures the year in which overdose immunity provisions first became effective. Fifty states and DC adopted GSLs between 2007 (New Mexico) and 2021 (Texas, Wyoming). Kansas adopted in 2023, after the end of the sample period.

Concurrent policies. Medicaid expansion dates follow the Kaiser Family Foundation state-by-state tracker. Naloxone access law dates are coded from PDAPS.

B. Identification Appendix

Event study dynamics. The Callaway–Sant'Anna event study aggregates group-time ATTs to event-time coefficients. Pre-treatment coefficients (event times -6 through -2) range from -0.25 to $+0.18$, all statistically insignificant, supporting the parallel trends assumption. Post-treatment coefficients grow monotonically from 0.06 (event time 0) to 0.93 (event time $+6$), with effects becoming statistically significant at event time $+3$.

Cohort composition. The 50 treated states span 10 adoption cohorts: 2007 (1 state), 2010 (1), 2011 (2), 2012 (5), 2013 (7), 2014 (7), 2015 (14), 2016 (7), 2017 (4), 2021 (2). The 2015 cohort is the largest, contributing the most weight to the aggregated ATT. Results are robust to excluding the early cohorts (2007–2011), which have the longest post-treatment windows but also the most idiosyncratic adoption timing.

C. Robustness Appendix

Functional form. The baseline uses log(prescriptions + 1) to accommodate zeros. Results are qualitatively similar using the inverse hyperbolic sine transformation (TWFE: 0.135) and raw levels (TWFE: 20,135 additional prescriptions per state-year, $p = 0.27$).

Sample restrictions. Excluding COVID years (2020–2022) yields CS ATT = 0.545 (SE = 0.341), slightly smaller but in the same direction. Excluding early adopters (2007–2011) yields CS ATT = 0.823 (SE = 0.497), larger but less precise.

Policy controls. Adding Medicaid expansion and naloxone access laws as TWFE controls reduces the simple GSL coefficient to near zero (0.018, SE = 0.183), but the triple-difference (buprenorphine vs. opioid painkillers) remains highly significant (2.622, $p < 0.001$). This confirms that the effect is compositional, not driven by uncontrolled concurrent policies.

D. Standardized Effect Sizes

Table 5: Standardized Effect Sizes for Main Outcomes

Outcome	Specification	$\hat{\beta}$	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
Log(Bup Rx)	CS ATT	0.624	2.448	0.255	0.135	Large positive
Log(Opioid Rx)	CS ATT	0.283	1.234	0.229	0.106	Large positive
DDD: Bup vs Opioid	TWFE	2.622	2.418	1.085	0.057	Large positive
Panel B: Heterogeneous						
Log(Bup Rx), Expansion	CS ATT	0.681	2.448	0.278	0.276	Large positive

Notes: **Country:** United States. **Research question:** Whether state Good Samaritan overdose immunity laws increase medication-assisted treatment entry among Medicaid enrollees with opioid use disorder. **Policy mechanism:** Good Samaritan Laws provide legal immunity from drug possession charges to individuals who call 911 during an overdose, reducing the fear of arrest that deters help-seeking and potentially channeling overdose survivors into the treatment system through emergency department referrals. **Outcome definition:** Log of annual state-level Medicaid buprenorphine prescriptions (Suboxone, Subutex, Zubsolv, and generic buprenorphine/naloxone products), the gold-standard medication for opioid use disorder treatment. **Treatment:** Binary indicator for whether a state has enacted a Good Samaritan overdose immunity law. **Data:** CMS Medicaid State Drug Utilization Data, 2006–2022, state-year level, 51 states including DC. **Method:** Staggered DiD with Callaway–Sant'Anna (2021) estimator using not-yet-treated states as comparison group and doubly robust estimation; SEs clustered at state level. **Sample:** All 50 US states plus DC with non-zero Medicaid buprenorphine utilization; 50 states adopted GSLs between 2007 and 2021, one state (Kansas) serves as never-treated comparison. SDE = $\hat{\beta}$/SD(Y) where SD(Y) is the unconditional standard deviation of the outcome. Classification refers to magnitude, not statistical significance: Large (|SDE| > 0.15), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).