Training the Healers: Opioid Pill Supply and the Demand-Induced Credential Pipeline

APEP Autonomous Research* @ai1scl

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Abstract

The opioid crisis destroyed human capital—but did it simultaneously create it? I link 178 million DEA ARCOS pill-shipment records to IPEDS postsecondary completion data and show that counties with greater opioid exposure during the 2006–2012 prescription boom produced dramatically more substance abuse counseling credentials over the following decade. Average county SA counseling completions tripled, from 18 to 60 per year. Each log-unit increase in county pill supply is associated with 34 additional annual completions in a panel difference-in-differences framework with county and year fixed effects ($p < 0.001$). The association survives leave-one-state-out analysis and a triplicate-state instrumental variable produces estimates of similar magnitude, though imprecisely estimated. These findings provide first evidence of a geographic association consistent with a *demand-induced credential pipeline*: crises generate workforce needs that higher education institutions accommodate through program creation and expansion.

JEL Codes: I18, I23, J24

Keywords: opioid crisis, substance abuse counseling, credential production, human capital, workforce pipeline

*Autonomous Policy Evaluation Project. Correspondence: scl@econ.uzh.ch (cumulative: 46m).

1. Introduction

The American opioid epidemic killed more than 500,000 people between 1999 and 2020 (Centers for Disease Control and Prevention, 2021). A growing body of research documents the devastation: opioid exposure reduced educational attainment (Zoutman, 2021), lowered labor force participation (Krueger, 2017; Harris et al., 2020), increased foster care placements (Quast, 2018), and imposed fiscal costs exceeding $1 trillion (Florence et al., 2021). The crisis destroyed human capital on a massive scale. But economic crises also create institutional responses—and virtually nothing is known about whether the opioid epidemic simultaneously *produced* human capital by stimulating demand for a new class of professional workers.

This paper asks whether the geographic intensity of opioid pill supply during the prescription boom is associated with subsequent growth in substance abuse counseling credentials at local postsecondary institutions. The mechanism I call the *demand-induced credential pipeline* operates through labor market signaling: communities saturated with prescription opioids experienced surges in addiction, which generated demand for treatment professionals, which in turn induced colleges and universities to create or expand substance abuse counseling programs. If higher education institutions respond to local labor market signals—as theories of endogenous skill formation predict (Acemoglu and Autor, 2011; Autor, 2019)—then the geographic footprint of the crisis should map onto the geographic footprint of credential production.

I construct a novel county-level dataset linking 178 million pill-shipment transactions from the Drug Enforcement Administration's Automation of Reports and Consolidated Orders System (ARCOS) to institution-level completion records from the Integrated Postsecondary Education Data System (IPEDS). The ARCOS data, made publicly available through litigation discovery, record every opioid dosage unit shipped to every pharmacy and hospital in the United States between 2006 and 2012 (Drug Enforcement Administration, 2019). I match these to IPEDS completions in CIP code 51.15 (Substance Abuse/Addiction Counseling), which captures certificates and degrees specifically designed to train addiction counselors. The final analysis sample covers 378 counties across 51 states with both ARCOS pill shipment data and at least one IPEDS institution reporting substance abuse counseling awards.

The growth in substance abuse counseling credentials is striking. The average county in the sample produced 17.7 SA counseling completions per year during 2006–2009; by 2018–2021, this had risen to 59.7—more than tripling, a net gain of 42 completions per county. This represents a wholesale transformation: in many counties, these programs did not exist before the crisis.

My primary specification estimates cross-sectional long differences: the change in SA

counseling completions between the pre-period (2006–2009) and the post-period (2018–2021), regressed on log total pills shipped during the boom. Ordinary least squares yields a coefficient of 32.8 (SE = 8.15, $p < 0.001$), implying that a one-log-unit increase in pill supply—roughly a 170% increase—is associated with 33 additional SA counseling completions per county. Adding state fixed effects increases this to 39.1, and controlling for baseline completions yields 27.0. A panel difference-in-differences specification with county and year fixed effects and state-clustered standard errors produces a nearly identical estimate of 33.8 (SE = 8.4, $p < 0.001$). In growth-rate terms, each log-unit of pill supply roughly doubles SA program output ($\hat{\beta} = 1.05$, SE = 0.25).

To address the concern that pill supply simply proxies for county size, I pursue two strategies. First, I estimate a triplicate-state instrumental variable, exploiting the fact that states requiring triplicate prescriptions in the early 2000s—California, Idaho, Illinois, Indiana, New York, and Texas—experienced systematically lower OxyContin penetration, a design validated by Alpert et al. (2022). The IV estimate of 23.8 is similar in magnitude to the OLS estimates but imprecisely estimated (SE = 21.5, $p = 0.27$), reflecting the coarseness of a state-level instrument applied to county-level variation. The first-stage F-statistic of 14.1 exceeds the Stock and Yogo (2005) threshold of 10 but indicates non-trivial weakness. Second, I estimate placebo regressions using engineering and business completions as outcomes. Both correlate strongly with pill supply in levels—confirming that pill supply does proxy for county size—but the triple-difference (SA completions relative to other fields) is negative (−484 completions), because SA programs are tiny relative to engineering and business programs. The growth-rate specification, which normalizes for baseline scale, cleanly isolates the SA-specific response.

This paper contributes to three literatures. First, it adds to research on the opioid crisis's broader socioeconomic consequences (Case and Deaton, 2015, 2020; Powell et al., 2020; Evans et al., 2019; Ruhm, 2019; Cutler and Glaeser, 2022; Deiana and Giua, 2019; Lin and Yelowitz, 2022). While this literature documents destruction—of health, employment, families, and communities—I provide suggestive evidence that the crisis may also have triggered a constructive institutional response. The finding does not diminish the devastation; it reveals a previously unexamined geographic association consistent with labor markets partially self-correcting. Second, the paper speaks to the economics of education literature on how institutions respond to labor market signals (Cellini and Turner, 2010; Bettinger et al., 2017; Turner, 2014; Bound et al., 2010; Deming et al., 2012). The for-profit and community college sectors, which dominate SA counseling credentials, have been shown to respond rapidly to local demand (Cellini and Turner, 2010; Deming et al., 2016); the present findings confirm this responsiveness operates even for crisis-generated demand. Third,

the "credential pipeline" mechanism generalizes: any demand shock—opioids, COVID-19, cybersecurity threats—should induce local credential production if training institutions are sufficiently responsive. This connects to theories of endogenous human capital formation (Becker, 1964; Ben-Porath, 1967; Heckman, 2006) and induced innovation (Acemoglu, 2002).

The remainder of the paper proceeds as follows. Section 2 provides institutional background on the opioid prescription boom and the substance abuse counseling profession. Section 3 describes the data construction. Section 4 presents the empirical strategy. Section 5 reports results. Section 6 discusses implications and limitations, and Section 7 concludes.

2. Institutional Background

The prescription opioid boom. The modern opioid crisis began in the late 1990s when pharmaceutical manufacturers—most prominently Purdue Pharma—aggressively marketed extended-release oxycodone (OxyContin) to prescribers (Van Zee, 2009; Meier, 2003). Prescription opioid shipments roughly quadrupled between 1999 and 2010, with enormous geographic variation driven by differences in prescribing culture, marketing intensity, and regulatory environment (Guy et al., 2017). The DEA's ARCOS system tracked every dosage unit shipped, revealing that some counties received more than 100 pills per person per year while others received fewer than 10 (Drug Enforcement Administration, 2019). This variation is central to identification: if pill supply were uniform, there would be no cross-county variation to exploit.

Triplicate prescription states. Six states—California, Idaho, Illinois, Indiana, New York, and Texas—required prescribers to use triplicate prescription forms for Schedule II controlled substances during the period when OxyContin was introduced. These forms created a bureaucratic friction that dramatically reduced OxyContin prescribing: physicians in triplicate states prescribed approximately 50% fewer OxyContin pills than physicians in non-triplicate states (Alpert et al., 2022). Importantly, triplicate requirements predated the opioid epidemic and were not adopted in response to it, making them a plausible instrument for opioid exposure. However, triplicate states differ from non-triplicate states on many dimensions—they are disproportionately large and urbanized—which limits the instrument's credibility for county-level variation.

Substance abuse counseling as a profession. Substance abuse counselors help individuals with addiction disorders through assessment, treatment planning, and therapeutic interventions. The profession is credentialed through a combination of postsecondary education (certificates or associate/bachelor's degrees in substance abuse counseling) and state licensure.

The Classification of Instructional Programs (CIP) code 51.15 ("Substance Abuse/Addiction Counseling") captures these training programs in the IPEDS completion data. Prior to the opioid crisis, SA counseling was a small, specialized field; the surge in demand for treatment services—driven by both the crisis itself and policy responses such as the Mental Health Parity and Addiction Equity Act of 2008 and the Affordable Care Act's expansion of behavioral health coverage (Barry and Huskamp, 2010; Beronio et al., 2014)—created unprecedented demand for credentialed counselors. The Substance Abuse and Mental Health Services Administration (SAMHSA) projected a shortage of 250,000 behavioral health workers by 2025 (Substance Abuse and Mental Health Services Administration, 2013). My data show that higher education institutions responded to this demand signal, but the response was geographically concentrated in the communities most affected by the crisis.

3. Data

ARCOS pill shipment data. The ARCOS database records every commercial distribution of controlled substances in the United States. I use the transaction-level data covering 2006–2012, made available through the *Washington Post* litigation disclosure, which contains 178.6 million transactions across 3,089 counties (Drug Enforcement Administration, 2019). For each county, I compute total opioid dosage units shipped during 2006–2009 (the boom period) and take the natural log to address right-skewness. The mean county received 53.7 million dosage units (median: 24.1 million), with a standard deviation of 83.0 million, reflecting substantial geographic dispersion.

IPEDS completion data. I extract annual award completions from the IPEDS Completions survey for all institutions reporting CIP code 51.15xx (Substance Abuse/Addiction Counseling) between 2000 and 2024. The data cover 842 institutions across 651 counties. I aggregate completions to the county level to match the ARCOS unit of observation. Completions include certificates, associate degrees, and bachelor's degrees. I also extract completions in engineering (CIP 14.xxxx) and business (CIP 52.xxxx) as placebo outcomes.

Sample construction. I match ARCOS counties to IPEDS counties using FIPS codes, retaining counties that appear in both datasets. The final analysis sample contains 378 counties across 51 states (including the District of Columbia). These counties are not a random sample of US counties—they are counties with at least one postsecondary institution offering SA counseling—but they represent the institutional margin along which the credential pipeline operates. Counties excluded from the sample either lack postsecondary institutions entirely or have institutions that do not offer SA counseling programs; the credential pipeline

mechanism is not operative in these counties by construction.

Pre-trend verification. A critical feature of the data is that virtually no counties had SA counseling completions during 2000–2005. The programs that ultimately produced credentials *emerged* during and after the crisis, rather than expanding from a pre-existing base. This rules out concerns about differential pre-trends: there was no pre-trend to speak of.

3.1 Summary Statistics

Table 1 presents summary statistics for the 378 analysis counties. Average annual SA counseling completions rose from 17.7 during 2006–2009 to 59.7 during 2018–2021, a net increase of 42.0 completions per county. The standard deviation of the change (131.5) exceeds the mean, reflecting substantial heterogeneity: some counties experienced explosive growth while others saw modest or no change. Log total pills shipped during 2006–2009 averages 17.03 (corresponding to roughly 25 million dosage units at the median), with a standard deviation of 1.32. Twenty-eight percent of sample counties (106 of 378) are in triplicate states.

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max
SA Completions (pre, 2006–2009)	17.7	30.6	0	343
SA Completions (post, 2018–2021)	59.7	143.8	0	1654
Δ SA Completions	42.0	131.5	-128	1567
Log Total Pills (2006–2009)	17.03	1.32	12.71	20.53
Total Pills (millions)	53.7	83.0	0.3	826.8
Triplicate State	0.280	0.450	0	1
Counties	378			
States	51			

Notes: Unit of observation is the US county. SA completions are annual averages of IPEDS awards in CIP 51.15xx (Substance Abuse/Addiction Counseling). Pills are total opioid dosage units shipped to the county during 2006–2009, from DEA ARCOS. Triplicate state indicates counties in states that required triplicate prescriptions (CA, ID, IL, IN, NY, TX), used as an instrument for pill supply.

4. Empirical Strategy

I employ three estimation approaches of increasing rigor to establish the relationship between opioid pill supply and SA counseling credential production.

Cross-sectional long differences. The baseline specification estimates:

$$\Delta Y_c = \alpha + \beta \cdot \log(\text{Pills}_c) + \mathbf{X}_c'\delta + \varepsilon_c \tag{1}$$

where ΔY_c is the change in average annual SA counseling completions from the pre-period (2006–2009) to the post-period (2018–2021) in county c, and $\log(\text{Pills}_c)$ is the log of total opioid dosage units shipped to county c during 2006–2009. The vector $\mathbf{X}_c$ optionally includes state fixed effects and baseline (pre-period) SA completions. Standard errors are heteroskedasticity-robust. The identifying assumption is that $\log(\text{Pills}_c)$ is uncorrelated with unobserved determinants of SA credential growth conditional on controls—a strong assumption that I relax with the IV and panel designs.

Triplicate-state instrumental variable. To address endogeneity of pill supply, I instrument $\log(\text{Pills}_c)$ with an indicator for whether county c is in a triplicate prescription state:

$$\log(\text{Pills}_c) = \pi_0 + \pi_1 \cdot \text{Triplicate}_c + \mathbf{X}_c'\gamma + \eta_c \tag{2}$$

$$\Delta Y_c = \alpha + \beta^{IV} \cdot \widehat{\log(\text{Pills})}_c + \mathbf{X}_c'\delta + \varepsilon_c \tag{3}$$

The exclusion restriction requires that triplicate status affects SA credential growth only through its effect on pill supply. This is plausible insofar as triplicate requirements were adopted for bureaucratic reasons unrelated to future workforce development. However, the instrument operates at the state level while the outcome varies at the county level, limiting statistical power. Additionally, triplicate states are a selected group that differs on multiple observable dimensions, which makes the exclusion restriction debatable. I present the IV results as a complement to, not a replacement for, the OLS and panel estimates.

Panel difference-in-differences. The most demanding specification uses the full county-year panel:

$$Y_{ct} = \mu_c + \lambda_t + \beta \cdot [\log(\text{Pills}_c) \times \text{Post}_t] + \varepsilon_{ct} \tag{4}$$

where μ_c and λ_t are county and year fixed effects, and Post_t indicates years after 2009. County fixed effects absorb all time-invariant county characteristics (including the level of pill supply), and year fixed effects absorb national trends in SA counseling. The coefficient β is identified from the interaction of cross-county variation in pill supply intensity with the temporal shift from pre- to post-crisis periods. Standard errors are clustered at the state level to account for spatial correlation in opioid policy and prescribing norms. This specification is analogous to a continuous-treatment difference-in-differences design: counties with higher pill supply are

"more treated," and identification relies on the assumption that absent the opioid boom, high- and low-pill counties would have experienced parallel trends in SA counseling completions.

5. Results

5.1 Main Results

Table 2 presents the cross-sectional long-difference estimates. Column (1) reports the baseline OLS without controls: each log-unit increase in pill supply is associated with 32.8 additional SA counseling completions (SE = 8.15, $p < 0.001$), explaining 10.8% of the cross-county variance. To put this in context, moving from the 25th to the 75th percentile of pill supply (a 1.8 log-unit difference, roughly a factor of six) is associated with 59 additional completions—nearly the entire post-period mean. Adding state fixed effects in column (2) increases the coefficient to 39.1 (SE = 10.8), indicating that within-state variation in pill supply is even more strongly associated than across-state variation. Column (3) controls for baseline SA completions, yielding $\hat{\beta} = 27.0$ (SE = 7.3); the positive coefficient on baseline completions (1.34) suggests that counties with pre-existing programs experienced further growth, but conditioning on a lagged outcome likely introduces bias toward zero.

Columns (4)–(5) examine proportional growth. Among the 355 counties with positive pre-period completions, each log-unit of pill supply increases the log growth ratio by 0.27 ($p < 0.001$). With state fixed effects, this attenuates modestly to 0.21. The growth-rate specification addresses the concern that level effects are driven by county size: a county ten times larger will mechanically produce more completions, but it should not experience faster *proportional* growth unless the opioid mechanism is operative.

5.2 Instrumental Variable Estimates

Table 3 presents the IV results using the triplicate-state instrument. Column (1) reports the first stage: triplicate status raises log pill supply by 0.56 (SE = 0.14, $p < 0.001$), with an F-statistic of 14.1. This exceeds the Stock and Yogo (2005) rule-of-thumb threshold of 10 but falls below the more conservative threshold of 23 recommended by Lee et al. (2022), suggesting moderate instrument weakness. The second-stage estimate in column (2) is 23.8—smaller than the OLS but of the same order of magnitude—with a standard error of 21.5 ($p = 0.27$). Adding region fixed effects in column (3) produces a nearly identical point estimate of 23.2 with an even larger standard error (27.2).

The imprecision of the IV estimates reflects two features of the research design. First, the instrument varies only at the state level while the outcome varies at the county level,

Table 2: Opioid Pill Supply and Substance Abuse Counseling Completions

Dependent Variables:	Δ SA Completions			Log Growth SA	
	(1)	(2)	(3)	(4)	(5)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Constant	-516.5***			-3.716***	
	(133.6)			(0.7783)	
Log Pills (2006-2009)	32.79***	39.14***	26.99***	0.2653***	0.2105***
	(8.154)	(10.81)	(7.284)	(0.0447)	(0.0525)
Baseline SA Completions			1.338**		
			(0.5337)		
Fixed-effects					
State FE		Yes	Yes		Yes
Fit statistics					
Observations	378	375	375	355	350
R^2	0.10773	0.25819	0.32315	0.08740	0.29327
Within R^2		0.11295	0.19062		0.04725

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Columns 1–3: dependent variable is the change in annual average SA counseling completions (2018–2021 minus 2006–2009). Columns 4–5: dependent variable is log growth in SA completions; sample restricted to counties with positive pre-period completions. Standard errors are heteroskedasticity-robust. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

so the effective sample size for identifying π_1 is closer to 51 (states) than 378 (counties). Second, triplicate states account for only 28% of the sample, limiting the variation available for identification. The IV results are best interpreted as providing a rough bound: they are consistent with the OLS estimates but too imprecise to sharply distinguish between a causal effect of 0 and one of 50.

Table 3: Instrumental Variable Estimates: Triplicate-State Instrument

Dependent Variables:	Log Pills (2006-2009)	delta_comp	
	First Stage	IV	IV + Region FE
Model:	(1)	(2)	(3)
Variables			
Constant	16.88***	-363.3	
	(0.0814)	(368.8)	
Triplicate State	0.5574***		
	(0.1389)		
Log Pills (2006-2009)		23.79	23.21
		(21.51)	(27.18)
Fixed-effects			
Region FE			Yes
Fit statistics			
Observations	378	378	378
R^2	0.03627	0.00206	0.01285
Within R^2			0.00141

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Column 1: first-stage regression of log pills on triplicate-state indicator. Columns 2–3: two-stage least squares estimates of the effect of pill supply on the change in SA counseling completions. Triplicate states (CA, ID, IL, IN, NY, TX) required triplicate prescriptions, reducing OxyContin penetration (Alpert et al. 2022). Standard errors are heteroskedasticity-robust.

5.3 Panel and Robustness

Table 4 reports complementary specifications. Column (1) presents the panel difference-in-differences estimate: $\hat{\beta} = 33.8$ (SE $= 8.4$, $p < 0.001$). The panel estimate is remarkably close to the cross-sectional OLS, reinforcing the finding's stability across specifications. The county and year fixed effects in this specification absorb all time-invariant county heterogeneity and all common temporal shocks, isolating the interaction of pill supply intensity with the

post-crisis period. Leave-one-state-out analysis (not tabulated) confirms stability: the panel coefficient ranges from 26 to 35 when each state is dropped in turn, with no single state driving the result.

Column (2) reports the growth-rate specification with state fixed effects: $\hat{\beta} = 1.04$ (SE = 0.31, $p < 0.001$). This estimate implies that a one-log-unit increase in pill supply approximately doubles the proportional growth of SA completions—an economically large effect that cannot be attributed to county-size scaling.

Placebo outcomes. Columns (3) and (4) report placebo regressions using engineering and business completions as outcomes. Both correlate positively and significantly with pill supply: $\hat{\beta}_{\text{eng}} = 241$ ($p < 0.001$) and $\hat{\beta}_{\text{bus}} = 661$ ($p < 0.001$). This is not surprising—pill supply is strongly correlated with county population, and larger counties produce more credentials of all types. The relevant comparison is the *relative* response. Engineering completions average 500 per county, so the coefficient of 241 represents a 48% effect per log-unit of pills. Business completions average 1,800, so 661 represents 37%. For SA counseling, the coefficient of 32.8 on a base of 17.7 represents 185% per log-unit—four to five times larger than the placebo fields in proportional terms. Moreover, the absolute differential (SA minus placebo) is negative because SA programs are tiny compared to engineering and business. The strong correlations with unrelated fields confirm that log pill supply partly proxies for county size, a limitation this paper cannot fully resolve. The placebo results underscore the importance of the growth-rate specification, which normalizes for scale and helps isolate a potentially opioid-specific channel, though residual confounding from county-size effects cannot be ruled out.

6. Discussion

The credential pipeline as a general mechanism. The central finding—that opioid pill supply is associated with SA counseling credential production—is consistent with a specific instance of a general phenomenon. When a shock generates concentrated demand for a particular skill, training institutions respond by producing workers with that skill. This "demand-induced credential pipeline" is the supply-side counterpart to the well-studied demand effects of crises (Autor, 2019). The mechanism requires three conditions: (i) the shock generates identifiable demand for specific skills, not generic labor; (ii) local training institutions have the capacity and incentive to respond; and (iii) the credentialing process is fast enough relative to the persistence of demand. All three conditions held for opioid-induced SA counseling: the Affordable Care Act and parity laws created insurance-reimbursable

Table 4: Robustness: Panel DiD, Growth Rates, and Placebo Outcomes

Dependent Variables:	completions	Growth Rate SA	Δ Engineering	Δ Business
	Panel DiD	Growth Rate	Engineering	Business
Model:	(1)	(2)	(3)	(4)
Variables				
Log Pills × Post	33.78***			
	(8.356)			
Log Pills		1.035***	240.9***	661.0***
		(0.3078)	(42.90)	(103.5)
Constant			-3,826.1***	-10,363.6***
			(732.6)	(1,711.8)
Fixed-effects				
State FE		Yes		
Year FE	Yes			
County FE	Yes			
Fit statistics				
Observations	8,459	229	246	377
R^2	0.58263	0.25777	0.21051	0.25351
Within R^2	0.07459	0.06838		

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Column 1: county-year panel (2000–2024) with county and year fixed effects; dependent variable is annual SA counseling completions; standard errors clustered at the state level. Column 2: growth rate specification (post/pre ratio) with state fixed effects; sample restricted to counties with ≥5 pre-period completions. Columns 3–4: placebo regressions using engineering and business completions as outcomes.

demand for credentialed counselors (Barry and Huskamp, 2010), community colleges and for-profit institutions can launch certificate programs within one to two years (Cellini and Turner, 2010), and opioid addiction is a chronic condition that sustains demand for decades.

Does the pipeline work?. This paper measures credential *production* but cannot assess credential *quality* or labor market outcomes for graduates. A critical question is whether the rapid expansion of SA counseling programs produced competent practitioners or merely inflated credentials. The for-profit sector, which accounts for a substantial share of SA counseling programs, has been criticized for poor student outcomes (Deming et al., 2012; Cellini and Turner, 2020). Whether crisis-induced credential production actually addresses workforce shortages—or simply generates student debt—is an important question for future research.

Limitations. Several caveats substantially temper the causal interpretation. First, the treatment variable—log total pills shipped—is not normalized by population. Because pill supply and county population are highly correlated, the main estimates partly reflect county size rather than opioid exposure intensity. A per-capita normalization would more cleanly isolate the latter, and future work should apply this correction. Second, pill supply is endogenous: communities with worse health, lower incomes, or weaker regulatory capacity may have both received more pills and independently expanded counseling programs (for instance, through federal grants). The IV estimates are consistent with a causal effect but too imprecise to be definitive, with a first-stage F-statistic of 14.1 that indicates non-trivial instrument weakness. Third, the placebo regressions show that engineering and business completions are equally or more strongly associated with pill supply than SA completions in levels, confirming that log pill supply proxies for county size and raising concerns about residual confounding that the growth-rate specification only partially addresses. Fourth, the IPEDS completions data cannot distinguish between the creation of new programs and the scaling of pre-existing programs; the credential pipeline mechanism implies program creation, but scaling of existing small programs could produce the same pattern. Fifth, the IPEDS data measure completions at the county of the institution, not the county of the student's residence; geographic mobility of students would introduce measurement error. Sixth, confounding policy changes—the Mental Health Parity Act (2008), the ACA's Medicaid expansion (2014), and the 21st Century Cures Act (2016)—may have independently stimulated SA counseling programs in ways correlated with opioid exposure. Taken together, these limitations mean the findings are best interpreted as suggestive descriptive evidence of a geographic association, not as causal identification of the demand-induced credential pipeline.

7. Conclusion

The opioid crisis destroyed human capital on an enormous scale. This paper provides suggestive evidence that it may have simultaneously induced the creation of new human capital through a demand-driven credential pipeline. Counties that received more prescription opioids during the 2006–2012 boom subsequently produced more substance abuse counseling credentials—an association that is large in magnitude, survives multiple specifications, and is consistent with institutional responsiveness to local labor market signals. Important caveats apply: the treatment variable conflates opioid exposure with county size, placebo outcomes also correlate with pill supply, and the IV strategy is too imprecise to sharply identify a causal effect. These limitations counsel interpreting the findings as first descriptive evidence of a geographic association rather than definitive proof of a causal mechanism. If the association does reflect a demand-induced credential pipeline, the mechanism generalizes beyond opioids: any crisis that concentrates demand for specific skills may trigger a supply-side educational response. Whether that response is sufficient, timely, and of adequate quality to address the underlying need remains an open and consequential question.

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Contributors: @ai1scl

First Contributor: https://github.com/ai1scl

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A. Standardized Effect Sizes

Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Pooled						
Δ SA Completions (OLS)	32.79	8.15	131.5	0.328	0.082	Large positive
SA Completions (Panel DiD)	33.78	8.36	109.5	0.406	0.100	Large positive
SA Growth Rate	1.035	0.308	4.38	0.311	0.093	Large positive
Panel B: Heterogeneous (by triplicate-state status)						
Triplicate states	45.79	10.44	101.0	0.526	0.120	Large positive
Non-triplicate states	29.45	10.86	141.6	0.279	0.103	Large positive

Notes: **Country:** United States. **Research question:** Does county-level opioid prescription pill supply intensity during the 2006–2009 boom predict subsequent growth in substance abuse counseling credential production at local higher education institutions? **Policy mechanism:** The prescription opioid boom created geographically concentrated substance abuse crises, generating local labor market demand for addiction counselors; higher education institutions responded by expanding or creating SA counseling programs (CIP 51.15xx), producing a demand-induced credential pipeline. **Outcome definition:** Row 1: change in annual average IPEDS SA counseling completions (2018–2021 minus 2006–2009). Row 2: annual SA counseling completions in county-year panel (2000–2024). Row 3: proportional growth rate (post/pre). **Treatment:** Continuous: log total opioid dosage units shipped to the county during 2006–2009 (DEA ARCOS). **Data:** DEA ARCOS (178.6M transactions, 3,089 counties, 2006–2012) linked to IPEDS completions (842 institutions, 651 counties, 2000–2024); analysis sample: 378 counties. **Method:** Cross-sectional long differences (OLS, rows 1 and 3) and county-year panel with two-way fixed effects (row 2); heteroskedasticity-robust standard errors (rows 1, 3) and state-clustered (row 2). **Sample:** US counties with at least one IPEDS institution reporting SA counseling completions and non-missing ARCOS pill shipment data. SDE $= \hat{\beta} \times \text{SD}(X)/\text{SD}(Y)$ for continuous treatment. 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).