Inheriting Risk: Theory and Evidence on Parental Substance Use, Child Outcomes, and PDMP Mandates

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Abstract

This paper examines whether strict mandatory-access Prescription Drug Monitoring Programs (PDMPs) affect primary caregivers' mental health and children's mental health and educational outcomes, and whether effects differ by household substance-use risk. We develop a theoretical model of parental health management under present bias, where PDMP constraints can reduce impulsive opioid use but may induce harmful substitutions and household stress. Using 2016–2023 National Survey of Children's Health data linked to state-level PDMP adoption, we estimate two-way fixed-effects and staggered-adoption event-study models. Household substance-use risk is large: any adult tobacco use, indoor smoking, or a caregiver alcohol/drug problem raises poor/fair caregiver mental health by 24, 21, and 36 percentage points (pp) and elevates child anxiety, low school engagement, and grade repetition. PDMPs reduce caregiver distress by 2.1 pp and low engagement by 1.1 pp. Treatment-effect heterogeneity by household risk shows mandates widen academic failure in high-risk homes: grade repetition increases by 1.6 pp (tobacco), 2.4 pp (indoor smoking), and 1.5 pp (caregiver substance problem), and behavior problems rise by 2.6 pp when a caregiver reports substance problems—concentrated among boys, younger children, and poorer families. Event studies confirm parallel pre-trends and reveal persistent post-mandate increases in grade repetition. Findings imply PDMPs deliver modest caregiver benefits but can magnify educational disparities.

Keywords: Prescription drug monitoring programs (PDMP); Parental substance use; Child mental health; Educational outcomes (JEL: I12, I18, I21, J13)

1 Introduction

In 2022, drug overdoses reached 107,941 deaths; opioids were implicated in 81,806 of them (largely illicit fentanyl) (Spencer et al., 2024). Annual costs were about $1.5 trillion in 2020, roughly 3% of GDP (Joint Economic Committee, 2022). By 2030, public systems linked to children affected by parental opioid use are projected to face nearly $400 billion in cumulative costs (United Hospital Fund, 2019). These losses may extend beyond mortality. Families can face unstable routines and income shocks. Children may experience stress at home and reduced

support for learning. The crisis may threaten human capital formation, not only current health. Understanding how parental risk might transmit to children is therefore central to policy design.

States responded to the crisis by building Prescription Drug Monitoring Programs (PDMPs). All states now operate one, but mandates differ. Voluntary checks changed little. Strict mandate rules require a PDMP query for every opioid prescription to reduce risky prescribing and doctor-shopping (Buchmueller & Carey, 2018). Scope and enforcement vary across states. We focus on strict mandates, which impose the strongest supply constraint. Supply control alone may not resolve pain, addiction, or stress. Households might adapt in ways that help or harm children. We examine these margins by linking mandate timing to caregiver well-being and to children's mental health and academic outcomes.

This study asks two major questions. First, do strict mandatory-access PDMPs change primary-caregiver mental health and children's mental health and educational outcomes? Second, are any policy effects larger for children living in households with substance-use risk? We answer these questions using nationally representative microdata from the National Survey of Children's Health (NSCH), linked to state-by-year strict mandate PDMP timing from 2016–2023.

In the theory, a parent with chronic pain chooses among pain management options, once-all-for-all-treatment, continued medication and health-promoting behaviors, and opioids. Opioids provide quick relief but carry later costs through tolerance and withdrawal. With tight budgets and limited self-control, a household can overweight immediate relief and overuse on opioids relative to options that would yield better long-run health. A strict monitoring rule can act as an upper limit on use. Under full rationality such a cap cannot improve outcomes because it narrows choices, yet with limited self-control it can reduce losses by curbing impulsive use. When

opioids are restricted, some households may shift toward smoking as a substitute. Smoking worsens pain through inflammation, impaired vascular function, and heightened sensitivity, and it is accompanied by deteriorating mental health, creating a pain–distress–smoking cycle. These choices spill over to children through secondhand exposure and reduced caregiving capacity, weakening attention, memory, and school engagement and raising the risk of repeating a grade.

This study estimates whether strict mandatory-access PDMPs change primary-caregiver mental health and child outcomes by exploiting state-level policy timing in a two-way fixed-effects difference-in-differences. We compare within state changes before and after mandate adoption to contemporaneous changes in never-treated or not-yet-treated states, with state and year fixed effects and the NSCH covariate set. Because adoption is staggered and effects may change over time, we also use the doubly robust inverse-probability-weighted event-study of Callaway and Sant'Anna (2021), which is valid under staggered timing and provides leads and lags to check pre-trends (Goodman-Bacon, 2021; Sun & Abraham, 2021).

This paper is structured as follows. Section 2 provides background on the U.S. opioid crisis and the evolution of strict-mandate PDMPs. Section 3 lays out the theoretical framework that motivates our hypotheses about parental risk, policy constraints, and child outcomes. Section 4 describes the NSCH data and key variables. Section 5 details the empirical methodology, including the difference-in-differences and staggered-adoption event-study approaches. Section 6 presents the main results and heterogeneity analyses. Section 7 discusses policy implications considering the prior literature. Section 8 concludes with a summary of study's contributions.

2 Background

2.1 Evolution and Societal Burden of the U.S. Opioid Crisis

The United States opioid crisis emerged over several decades through distinct waves driven by evolving patterns of pain management and drug use. In the late 1990s and early 2000s, healthcare providers dramatically increased opioid prescribing as part of an aggressive approach to pain treatment (Dowell et al., 2022). Prescription-opioid dispensing quadrupled between 1999 and 2010, contributing to a parallel surge in misuse and dependence; by 2012 dispensing peaked at roughly 255 million prescriptions, 81.3 per 100 residents (Guy et al., 2017). This oversupply precipitated the first wave of the epidemic, characterized by rising overdose deaths involving natural and semi-synthetic opioids such as oxycodone and hydrocodone (Spencer et al., 2024).

Policy and clinical practices tightened around 2010–2012. A pivotal event was the 2010 abuse-deterrent reformulation of OxyContin, which unintentionally spurred a surge in heroin use (Evans et al., 2019). Dependent patients, finding prescription opioids less accessible or effective, shifted to heroin as a cheaper, more available substitute (Evans et al., 2019), fueling the epidemic's second wave (Cicero & Ellis, 2015). Beginning in 2013, a third wave unfolded with the proliferation of illicitly manufactured fentanyl and other synthetic opioids, which are extraordinarily potent and often mixed into heroin or counterfeit pills (Spencer et al., 2024).

More than 564,000 Americans died from opioid-involved overdoses between 1999 and 2020 (Centers for Disease Control and Prevention, 2022). Annual U.S. overdose deaths surpassed 100,000 for the first time in 2021 and climbed to 107,941 in 2022. Opioids, especially illicit fentanyl, were implicated in 81,806 of those deaths. Although prescription-opioid fatalities have plateaued or declined modestly since 2017, deaths from illicit opioids remain at crisis levels (Spencer et al., 2024).

The economic burden is staggering. The Council of Economic Advisers (CEA, 2017) estimated that the epidemic cost the nation over $504 billion in 2015 after accounting for medical spending, lost productivity, criminal-justice involvement, and the statistical value of life. CDC economists later valued 2017 costs at $1.02 trillion (Luo et al., 2021). By 2020, the Joint Economic Committee put the annual cost near $1.5 trillion, roughly 3 percent of GDP (Joint Economic Committee, 2022). Intergenerational costs loom as well. United Hospital Fund (2019) projects that by 2030 the cumulative fiscal burden attributable to children affected by parental opioid use through healthcare, education, and child-welfare spending will approach $400 billion.

2.2 Strict PDMP Mandates: Policy Framework

Responding to the opioid crisis has required policy action spanning prevention, treatment, and harm reduction. Early supply-side measures targeted “pill mills” and tightened prescribing guidelines (Evans et al., 2019). One of the most widespread interventions is the Prescription Drug Monitoring Program (PDMP), a state-run electronic database that tracks controlled substance prescriptions and allows prescribers or pharmacists to view a patient’s fill history. PDMPs aim to curb “doctor shopping” and alert clinicians to potential misuse or diversion, thereby improving prescribing decisions (Haffajee et al., 2015).

PDMPs are statewide electronic databases that track prescriptions of controlled substances. Although all 50 states have operational PDMPs, the timing and scope of mandates requiring prescriber use vary substantially. Modern electronic PDMPs proliferated during the 2000s, and by 2010 most states had authorized a program, yet use was typically voluntary (Patrick et al., 2016). Provider query rates were low (Haffajee et al., 2015)—and studies found that voluntary PDMPs alone did little to change opioid-prescribing patterns (Buchmueller & Carey, 2018). Nevada in 2007 and Kentucky in 2012 was among the first to mandate PDMP

checks before most opioid prescriptions (Patrick et al., 2016). Since then, many states have enacted mandatory access provisions. Strict mandates compel prescribers to query the PDMP for essentially every opioid prescription, whereas partial mandates apply only under limited circumstances (Grecu et al., 2019).

The policy of interest is defined as a strict mandatory-access PDMP law, which compels prescribers to consult the PDMP before issuing any opioid or other Schedule II controlled substance prescription, with few exceptions. This contrasts with weaker mandates that apply only to initial prescriptions, prescriptions over a certain supply threshold, or new patients. Our focus follows the definition adopted by Dave et al. (2025), who restrict their treatment group to states that require prescriber use for all opioid prescriptions or at each refill, rather than under limited circumstances.

3 Theoretical Framework

3.1.1 Model of Rational Addiction in Health Management

This section considers a discrete time model based on Becker and Murphy's (1988) addiction theory. An economic agent lives *n* periods and faces the following maximization problem to manage her health at time t:

$$\max_{(A_i,B_i,O_i)_{i=t}^{n}} \sum_{i=t}^{n} \delta^{i-t}\ u_i((A_j,B_j,O_j)_{j=0}^{i})$$

$$s.t.\ P_A A_i + P_B B_i + P_O O_i \leq m \ \text{ for each } i \in \{t, t+1, ...\},$$

where A_i denote the once-and-for-all medical treatment at time *i*, such as surgery, vaccination, and physical therapy; B_i denote long-term medication and healthy behaviors at time *i*; O_i denote the use of opioids at time *i*, which involves non-negligible side effects and addiction risks. Their

economic prices are indexed by $P_A, P_B,$ and P_O respectively. m denotes the budget for health. δ is the subjective discounting factor.

The utility function is set to be

$$u_i((A_j, B_j, O_j)_{j=0}^{i}) = ln(max\{A_j\}_{j=0}^{i} + B_i + O_i - \sum_{k=0}^{i-1} \alpha^{i-k} O_k).$$

A_j is binary and takes value from $\{0, 1\}$. The maximization term $max\{A_j\}_{j=0}^{i}$ ensures that, once the agent chooses to buy A_j at any time *j,* she has no incentive to buy it again. The once-for-all treatment increases utility permanently.

$B_i \epsilon \mathbb{R}^+$ increases utility only at time *i*, as healthy behaviors (e.g. exercising, healthy diet) and long term medication (e.g. asthma spray, insulin) increase health temporarily.

$O_i \epsilon \mathbb{R}^+$ increases utility only at time *i*, as it is a temporary pain control medicine, while it creates long-term disutility in future periods.

$-\sum_{k=0}^{i-1} \alpha^{i-k} O_k$ captures the drug tolerance and withdrawal effect of past usage of opioids. It takes doses of opioids to maintain the previous level of utility $\alpha \in (0, 1)$ is the coefficient of negative impact of the past usage. Recent and larger dosage have more severe impact than long time ago and small dosage.

The logarithmic utility function takes $-\infty$ if the term inside the brackets is non-positive. It ensures the agent always has to do something with her health. Furthermore, if the agent has unfortunately accumulated large enough negative impacts from using opioids, with limited budget the utility will be $-\infty$A rational agent should try everything to avoid.

The settings with time-consistent preferences will serve as our benchmark model.

3.1.2 Necessary Conditions for Opioid Use

To restrict the attention to the usage of opioids, we make once-and-for-all medical treatment not affordable ($P_A > m$). The benchmark model is reduced to the following form:

$$\max_{(B_i,O_i)_{i=t}^n} \sum_{i=t}^{n} \delta^{i-t}\ u_i(B_i,(O_j)_{j=0}^i)$$

$$s.t.\ P_B B_i + P_O O_i \le m \quad \text{for each } i \in \{t, t+1, ...\}.$$

$$\text{where the utility function is } u_i(B_i,(O_j)_{j=0}^i) = ln(B_i + O_i - \sum_{k=0}^{i-1} \alpha^{i-k} O_k).$$

In the steady state, the mixed medical treatment plan can hardly exist.

$$(B_i^*, O_i^*) = \begin{cases} (0, \frac{m}{P_O}) & \text{if } \alpha\delta < 0.5, \text{ and } P_O < \frac{P_B(1-2\alpha\delta)}{1-\alpha\delta}; \\ (\{B_i, O_i | P_B B_i + P_O O_i = m\}, & \text{if } \alpha\delta < 0.5, \text{ and } P_O = \frac{P_B(1-2\alpha\delta)}{1-\alpha\delta}; \\ (\frac{m}{P_B}, 0) & \text{otherwise.} \end{cases}$$

For feasible once-for-all treatment condition, the solution follows similarly. The agent will buy the once-for-all treatment at the current time if efficient, namely

$$P_A < \frac{P_B}{1-\delta}$$

and the same solutions apply thereafter.

Opioids are used because they are cheap enough compared to other treatment options, even considering potential side effects. For policymakers, adjusting the coverage of health insurance and pricing of relevant medical treatments are the key to solving the opioids abuse problem.

We model the mandatory Prescription Drug Monitoring Programs (PDMP) as an constraint on the use of opioids.

$$O_i \le \bar{O}\ for\ each\ i \in \{t, t+1, ...\}$$

then clearly, imposing a upper limit constraint on opioids will never improve the health because of fewer treatment options. However, people are not always able to fully control their behaviors and maintain time consistency on addictive drugs.

3.2.1 Opioids Overdoes: Naive about Present Bias

This section utilizes present bias and naivety (O'Donoghue and Rabin, 1999) in behavioral economics to explain the reason for drug abuse. The quasi-hyperbolic utility (Phelps and Pollak 1968; Laibson 1997) streams $(u_i)_{i=t}^{n}$ starting from time *t* is

$$U_t = u_t + \beta(\sum_{i=t+1}^{n} \delta^{i-t}\ u_i),$$

where $\beta \in (0, 1]$ captures the present bias (figure A1), which is a tendency to overvalue present rewards but undervalue the long-term consequences. When a chronic patient suddenly suffers from pain, she will instinctively overlook the negative consequences of overuse of opioids in the future as a whole. δ is still the time discounting factor.

We consider a naive health agent. That is, she knows that there is a present bias at present time *t*, but does not realize the existence present bias in future periods. In other words, She is playing a game with her future selves, with ignorance of the future's present bias.

We apply a three-period model with $P_O < P_B$ to illustrate. In the first period, the agent decides her treatment plan:

$$\max_{(B_i,O_i)_{i=1}^{3}} u_1 + \beta\delta u_2 + \beta\delta^2 u_3,$$

or explicitly,

$$\max_{(B_i,O_i)_{i=1}^{3}} ln(B_1 + O_1) + \beta\delta ln(B_2 + O_2 - \alpha O_1) + \beta\delta^2 ln(B_3 + O_3 - \alpha^2 O_1 - \alpha O_2),$$

$$s.t.\ P_B B_i + P_O O_i \leq m \ \text{ for each } i \in \{1, 2, 3\}.$$

In the second period, her health treatment problem becomes

$$\max_{(B_i,O_i)_{i=2}^3} ln(B_2 + O_2 - \alpha O_1) + \beta\delta ln(B_3 + O_3 - \alpha^2 O_1 - \alpha O_2),$$

$$s.t.\ P_B B_i + P_O O_i \leq m \quad \text{for each } i \in \{2, 3\}.$$

Notice the time inconsistency by comparing the discounting factors of u_2 and u_3. In the first period, u_2 and u_3 are both "in future". Their time discounts differ by a δ. While in the second period, u_2 becomes "present", but u_3 is still "in future". Their time discounts differ by $\beta\delta$.

At time 1, the naive agent does not aware of the existence of present bias in the second period. She mistakenly thought she would have the following problem:

$$\max_{(B_i,O_i)_{i=2}^3} ln(B_2 + O_2 - \alpha O_1) + \delta ln(B_3 + O_3 - \alpha^2 O_1 - \alpha O_2),$$

The agent' third period health management problem is trivially

$$\max_{(B_3,O_3)} ln(B_3 + O_3 - \alpha^2 O_1 - \alpha O_2),$$

$$s.t.\ P_B B_3 + P_O O_3 \leq m.$$

3.2.1 Example:

To illustrate how the naive agent is inconsistent over time, we let $P_B = 1$, $P_O = 0.9$, $\alpha = 0.8$, $\beta = 0.01$, and $\delta = 0.9$. Her third-period optimal choice is $O_3^* = \frac{m}{P_O}$, since $P_O < P_B$. By backward induction, her second-period optimal solution is

$$(B_2^*, O_2^*) = \begin{cases} (0, \frac{m}{P_O}) & \text{if } (B_1, O_1) = (0, \frac{m}{P_O}), \\ (\frac{m}{P_B}, 0) & \text{if } (B_1, O_1) = (\frac{m}{P_B}, 0). \end{cases}$$

To interpret, when it comes to time 2, she would be addicted to opioids if she chose to consume only opioids in time 1, and vice versa. However, at time 1, the naive agent does not realize the existence of present bias. She mistakenly believes the following problem will appear in time 2:

$$\max_{(B_i,O_i)_{i=2}^3} ln(B_2 + O_2 - \alpha O_1) + \delta ln(\frac{m}{P_O} - \alpha^2 O_1 - \alpha O_2),$$

$$s.t.\ P_B B_i + P_O O_i \leq m \ \text{ for each } i \in \{2,3\}.$$

Notice the β vanishes in this hallucinated optimization problem. The solution to this wrongly expected problem is $(B_2^*, O_2^*) = \left(\frac{m}{P_B}, 0\right)$, which means she would buy only B_2 regardless of her first-period choice.

Backward to the first period, a sophisticated agent would realize it is a game playing with her future self, choosing between $\left(\left(0, \frac{m}{P_O}\right), \left(0, \frac{m}{P_O}\right)\left(0, \frac{m}{P_O}\right)\right)$ and $\left(\left(\frac{m}{P_B}, 0\right), \left(\frac{m}{P_B}, 0\right)\left(0, \frac{m}{P_O}\right)\right)$, where the later series prevails; while due to the negligence of present bias in future, a naive agent would wrongly believe she is making a decision between $\left(\left(0, \frac{m}{P_O}\right), \left(\frac{m}{P_B}, 0\right)\left(0, \frac{m}{P_O}\right)\right)$ and $\left(\left(\frac{m}{P_B}, 0\right), \left(\frac{m}{P_B}, 0\right)\left(0, \frac{m}{P_O}\right)\right)$, where the former series prevails, but not attainable. Because when it actually comes to time 2, the present bias appears again, forcing her to be addicted to opioids, namely, choosing $\left(\left(0, \frac{m}{P_O}\right), \left(0, \frac{m}{P_O}\right)\left(0, \frac{m}{P_O}\right)\right)$ eventually.

In this behavioral model, PDMP could serve as a commitment device that prevents naive patients from addicting to opioids. General closed-form necessary conditions can be found in Appendix

3.3.1 Substitutions

To address the findings in the empirical results, this subsection discusses the situation where substitutes exist. Suppose other than using opioids, smoking is as well available to the agent. We denote smoking at time *t* by S_i.

$$\max_{(B_i,O_i,S_i)_{i=t}^{\infty}} \sum_{i=t}^{\infty} \delta^{i-t}\ u_i(B_i,(O_j)_{j=0}^{i},(S_j)_{j=0}^{i})$$

$$s.t.\ P_B B_i + P_O O_i + S_i P_S \leq m \ \text{ for each } i \in \{t, t+1, ...\}.$$

$$\text{where } u_i(B_i,(O_j)_{j=0}^{i}) = ln(B_i + O_i - \sum_{k=0}^{i-1} \alpha^{i-k} O_k + S_i - \sum_{l=0}^{i-1} \gamma^{i-k} S_l).$$

The economic price for smoking is denoted by P_s, and the negative effect coefficient by γ.

If $\alpha\delta < 0.5$ and $P_O < \frac{P_B(1-2\alpha\delta)}{1-\alpha\delta}$, imposing an upper constraint on opioids use, $\bar{O} < \frac{m}{P_O}$ could potentially deviate the patient to seek for substitutes, as in this paper, smoking.

3.3.2 Smoking

Existing research demonstrates a bidirectional worsening relationship between smoking and chronic pain. Individuals with chronic pain exhibit significantly higher smoking rates (19.8%) compared to the general population (12.5%), while smoking exacerbates pain through multiple mechanisms: nicotine interferes with painkiller metabolism, increases inflammation, and impairs vascular function, heightening pain sensitivity (Patterson et al., 2012; Khan et al., 2019). This vicious cycle is often accompanied by deteriorating mental health, creating a "pain-psychological distress-smoking" triad (Vadivelu et al., 2017).

The intergenerational impact manifests through two key pathways:

Cognitive Development: Secondhand smoke exposure directly impairs children's neurodevelopment, reducing memory and attention capacity (Srivastava & Trinh, 2021), leading to poorer academic performance (Choi et al., 2020).

Family Functioning: Smoking parents with chronic pain show reduced caregiving capacity due to physical limitations and psychological distress, negatively affecting

children's school engagement and increasing grade repetition risks (Chen & Fish, 2013; Bortes et al., 2020).

Behavioral economics suggests this reflects risk-seeking individuals substituting opioids with cigarettes when access is restricted (Laibson, 1997; Becker & Murphy, 1988), creating unintended spillover effects on children (Fadlon & Nielsen, 2019). Policy interventions should therefore combine substance control with smoking cessation support to break this detrimental cycle.

4 Data

This study builds a balanced state-year panel from 2016 to 2023 by linking individual-level micro-data from the National Survey of Children's Health (NSCH) to each US state's enaction date of strict mandatory-access prescription-drug-monitoring program (PDMP). The NSCH is a nationally representative survey conducted annually by the U.S. Census Bureau on behalf of the Maternal and Child Health Bureau in all 50 states and the District of Columbia.

Our empirical analysis focuses on six outcome variables that encompass caregiver well-being and child mental-health and educational outcomes. Primary-caregiver mental health is recorded on a five-point Likert scale that ranges from 1 (excellent) to 5 (poor). All child outcomes are binary indicators equal to 1 when a caregiver reports the presence of the condition within the past 12 months and 0 otherwise: depression, anxiety, behavioral problems, low school engagement, and grade repetition. The key policy regressor is a time-varying indicator that switches from 0 to 1 in the first calendar year a strict mandatory-access PDMP took effect in a child's state of residence and remains 1 thereafter. Figure 1

visually demonstrates such mandates: by 2023, 22 states (shaded blue) required a strict mandatory-access PDMP law, which compels prescribers to consult the PDMP before issuing

any opioid or other Schedule II controlled substance prescription, with few exceptions. This provides staggered treatment timing exploited in the difference-in-differences and event-study estimators.

Three variables describe the household substance-use environment. “Any household tobacco” identifies whether any adult residing with the child currently uses cigarettes, e-cigarettes, cigars, or smokeless tobacco. “Household smokes inside” flags the subset of tobacco-using homes that permit indoor smoking, while “Parental illicit drug exposure” marks households in which the primary caregiver self-reports an alcohol- or drug-related problem. These measures proxy for unobserved parental risk preferences and potential compliance responses to opioid prescribing restrictions. Standard sociodemographic covariates include child age in single years, sex, four race/ethnicity categories, household income-to-poverty-ratio split into the four NSCH brackets, current insurance status, and an indicator for living with two parents. All covariates are plausibly exogenous to the policy and jointly account for compositional changes in the child population over the sample period.

Table 1 summarizes the descriptive statistics for the sample, disaggregated into state-year observations without a strict mandatory-access prescription-drug-monitoring program (Panel A) and those after adoption (Panel B). Before mandates, the unconditional probability that a child currently has depression, anxiety, or behavioral problems is 0.80, 0.89, and 0.82, respectively. Roughly one fifth of school-aged children exhibit low engagement at school and 4 percent have ever repeated a grade. Caregivers report an average mental-health score of 2.01 on the 1 = excellent to 5 = poor scale. Exposure to household substance use is non-trivial: 12 percent of children live with at least one current tobacco user, 1.2 percent reside in homes where smoking occurs indoors, and 8.8 percent have a caregiver who self-reports an alcohol- or drug-related

problem. The average child is nine years old; just under half are male, 37 percent are teenagers (13-17 years), and 84 percent live with two parents.

Post-mandate means reveal modest compositional differences. Depression and anxiety rise marginally to 0.81 and 0.90, while behavioral problems edge up to 0.83. Low school engagement declines slightly to 0.20, yet grade repetition climbs to 6.7 percent, the largest unconditional change in the table. Caregiver mental health is essentially unchanged (mean = 2.00). The household risk environment shifts: prevalence of any tobacco use increases to 13.4 percent, and the share of homes that allow indoor smoking nearly doubles to 2.0 percent, whereas reported illicit drug problems fall modestly to 8.2 percent. Children in mandate state-years are fractionally more likely to be poor (13.7 percent vs 11.0 percent) and to live outside a two-parent household (18.4 percent vs 16.0 percent); their mean poverty-level category is 2.96 compared with 3.05 in pre-mandate observations.

Observation counts differ across variables because each child outcome is fielded only for the subset of children to whom the question is relevant and because the National Survey of Children's Health employs rotating topical modules. Mental-health and substance-use questions are asked of all interviewed households, so they approach the full sample size, whereas school-related items apply only to children who are enrolled in or have ever attended school, and the depression, anxiety, and behavioral-problem items are collected in alternating questionnaire modules across survey waves.

Figure 2 plots unadjusted annual means for the six study outcomes from 2016 through 2023. It contrasts states that never adopted a mandatory-access PDMP or are still in the pre-mandate period (solid blue) with the same states once the mandate is in force (dashed burgundy). In every panel the two series move almost in lockstep before mandate implementation, lending

visual support to the parallel-trends assumption. Thereafter modest divergences emerge. Caregiver mental-health scores, which rise steadily over the sample window, are consistently a few hundredths of a point lower in mandate years, indicating slightly better reported well-being relative to untreated observations. For child anxiety and behavior problems, both groups experience a gentle upward drift, but the post-mandate trajectory edges above the comparison series by 2023, suggesting a small increase in the prevalence of these conditions. Depression exhibits almost perfectly overlapping paths throughout, implying no clear descriptive association with the policy. By contrast, grade repetition shows the sharpest separation. Finally, low school engagement spikes in 2018 in both groups, flattens thereafter, and remains slightly lower in mandate years, hinting at a slight improvement in this dimension of educational engagement.

Several limitations are inherent in the data. First, all child outcomes and household risk factors are caregiver-reported and thus vulnerable to social-desirability bias; however, misclassification is likely non-differential with respect to PDMP timing and therefore attenuates estimated effects toward zero. Second, the policy indicator captures the presence of a legal requirement but not its enforcement intensity, which differs across states and over time. Third, the NSCH's cross-sectional design prevents tracking the same child before and after mandate adoption, although state and year fixed effects remove the most consequential sources of time-invariant heterogeneity.

5 Methodology

The empirical objective of this study is to determine whether the introduction of strict mandatory-access PDMP alters primary-caregiver mental health and child outcomes and, whether any such effects are larger for children living in households with evidence of substance-use risk. To address potential endogeneity in mandate policy responses, the analysis

combines (i) a two-way fixed effects (TWFE) difference-in-differences framework and (ii) an event-study estimator that is robust to staggered adoption. All specifications are estimated from the 2016-2023 National Survey of Children's Health (NSCH); standard errors are clustered at the state level.

Let Y_{ist} denote one of six binary outcomes for child i living in state s in survey year t: primary-caregiver poor/fair mental health, child depression, anxiety, behavior problems, low school engagement, or grade repetition. Then, our regression model would be –

$$Y_{ist} = \beta_0 + \beta_1 Risk_{ist} + \beta_2 PDMP_{st} + \beta_3 (Risk_{ist} \times PDMP_{st}) + X_{ist} + \eta_s + \lambda_t + \varepsilon_{ist} \quad (1)$$

In this equation, $Risk_{ist}$ is the three household substance-exposure indicators: any adult tobacco use, smoking inside the home, and a caregiver-reported alcohol- or drug-use problem. Policy treatment, $PDMP_{st} = 1$, when a strict mandate is in full force in state s (and remains 1 thereafter); it equals 0 for never-treated states and for not-yet-treated years in adopting states. X_{ist} is the set of control variables contain child age (years), sex, race/ethnicity (four categories), household income-to-poverty-ratio category (four levels), current insurance status, and a two-parent-household indicator. λ_t and η_s are respectively the year and state fixed effects to account for unobserved heterogeneity across time and states. In equation (1), the coefficient β_1 measures baseline gaps between risky and low-risk households prior to any mandate. The scalar β_2 captures the mandate's direct effect among low-risk households, while the interaction vector β_3 reveals whether the mandate magnifies or attenuates the risk gradient.

Equation (1) is estimated by weighted least squares using NSCH sample weights; heteroskedasticity-robust standard errors are clustered by state (Angrist & Pischke 2015). Because the dependent variables are binary, coefficients read directly as percentage-point changes. The model identifies causal effects if, conditional on controls, potential outcomes in

adopting and non-adopting states would have trended in parallel had the mandate never been enacted.

Policy spillovers may be larger for specific subpopulations. To uncover such effect modification, we extend the baseline model in (1) by interacting with the PDMP indicator with six binary stratifiers. Specifically, we examine parental substance exposure, household tobacco exposure, child sex, adolescence, poverty status and family structure.

$$Y_{ist} = \alpha + \delta PDMP_{st} + \theta H_{ist} + \psi(H_{ist} \times PDMP_{st}) + X_{ist} + \eta_s + \lambda_t + \varepsilon_{ist} \quad (2)$$

where H_{ist} denotes one of the six subgroup indicators introduced above. The coefficient δ captures the mandate's effect for the reference category ($H_{ist} = 0$), whereas ψ measures the incremental impact for the focal subgroup ($H_{ist} = 1$). Each dimension is analyzed in a separate regression to avoid multicollinearity and to facilitate a clear behavioral interpretation of ψ. All models retain the full vector of individual covariates, state fixed effects, and survey-year fixed effects, and standard errors remain clustered at the state level.

Since PDMP adoption years vary across states, TWFE estimators can be biased when treatment effects evolve over time (Goodman-Bacon 2021; Sun & Abraham 2021). We therefore also employ the doubly robust inverse-probability-weighted event-study estimator of Callaway & Sant'Anna (2021), which is valid under staggered adoption.

6 Results

6.1 Main Results: Effects of Household Substance Use and PDMP Adoption

Household substance-use environments exhibit large, adverse associations with both caregiver and child outcomes. Table 2A demonstrates living in a home where any adult uses tobacco, someone smokes indoors, or a caregiver has alcohol/drug problems raises the probability the primary caregiver reports poor or fair mental health by roughly 24, 21,

and 36 p.p., respectively, and substantially increases children's risks of anxiety, low school engagement, and grade repetition. PDMP adoption itself delivers modest direct benefits, a 2 p.p. reduction in caregiver mental distress and a 1 p.p. decline in low school engagement—but leaves other outcomes unchanged. Crucially, PDMPs amplify the link between household risk factors and academic failure: the interaction terms add 1.6 p.p. (tobacco), 2.4 p.p. (indoor smoking), and 1.5 p.p. (parental substance problem) to the baseline effect on grade repetition. The pattern extends to disruptive behavior: combining a caregiver alcohol/drug problem with a mandatory-access PDMP adds roughly 2.6 p.p. to the probability a child is reported with behavioral problems.

Table 2B illustrates, for both male and female children, tobacco use, indoor smoking, and parental alcohol/drug problems raise the likelihood that the primary caregiver reports poor mental health by roughly 23–24 p.p. and grade repetition by 1–4 p.p., with the largest gaps linked to indoor smoking (male children = 3.9 p.p.; female children = 2.3 p.p.). PDMP adoption on its own lowers caregiver distress for each sex and modestly improves boys' school engagement (-1.8 p.p.). The interaction terms show that grade repetition is the one outcome consistently exacerbated by PDMP in high-risk homes for both sexes, but the magnitude is larger for male children. Among male children, PDMP adds 1.7 p.p. to the tobacco effect, 3.5 p.p. to the indoor-smoking effect, and 1.9 p.p. to the parental-substance-problem effect. For female children, the corresponding excess risks are 1.3 p.p., 0.8 p.p. (not significant), and 1.2 p.p. Heterogeneity also emerges for child depression: PDMP intensifies the tobacco–depression link for male children by 8.8 p.p. but for female children by 3.9 p.p.

Table 2C shows, among children (age <12), tobacco use, indoor smoking, and parental substance problems raise caregiver poor-mental-health reports by 24–36 p.p. and increase grade

repetition by 0.7–2.3 p.p. PDMP by itself modestly lowers low school engagement (-1.7 p.p.) and is otherwise neutral, yet its interaction with each household risk factor adds a further 1.4–3.1 p.p. to the grade-repetition gap. Mental-health and behavioral outcomes show no statistically significant moderation. For teenagers (age 12-17) the pattern is more diffuse. Baseline risk effects remain large. Interaction terms still signal heightened grade-repetition risk (1.1 p.p. to 1.9 p.p.), yet these increments are lesser than those observed for younger children. Instead, PDMP moderation for teens surfaces in mental-health domains: the combination of parental substance problems and PDMP raises teen depression and anxiety by 1.9 and 1.7 p.p., respectively, while PDMP attenuates the indoor-smoking effect on behavioral problems (-6.0 p.p.).

Among families at or below the federal poverty line (≤ 100 % FPL), tobacco use, indoor smoking, and parental substance problems raise the probability the primary caregiver reports poor/fair mental health by 33–47 p.p. and increase grade repetition by 2–3 p.p in table 2D. PDMP brings no direct benefits here, and its interaction with household tobacco or parental-substance exposure adds a further 3.1 p.p. and 2.8 p.p., respectively, to the grade-repetition gap. A notable exception is indoor smoking: PDMP offsets its positive association with child depression (12.5 p.p.), hinting at some mental-health relief even for the poorest households. For lower-middle-income children (101–199 % FPL) the baseline risk effects shrink slightly and PDMP itself reduces anxiety (-4.9 p.p.) and grade repetition (-1.3 p.p.). Interaction terms are generally null. In the upper-middle tier (200–399 % FPL) baseline gaps contract further, yet PDMP begins to widen the academic divide again: interaction with household tobacco and indoor-smoking raise grade repetition by 1.0 and 3.3 p.p., respectively. At the top of the distribution (≥ 400 % FPL) substance-risk households still face sizeable disadvantages (substance use adds 31.6 p.p. to caregiver distress and 2.0 p.p. to grade repetition). PDMP directly lowers

caregiver distress (2.7 p.p.) and low engagement (1.5 p.p.), yet the parental-substance and PDMP interaction adds 2.1 p.p. to grade repetition.

Figure 3 plots dynamic average treatment effects, estimated with the Callaway-and-Sant'Anna doubly-robust inverse-probability weighting (DR-IPW) estimator. For each outcome the dots show the coefficient in a given event year relative to the mandate's start (year 0); vertical bars are 95 % confidence intervals. Years −5 to −1 (red) capture pretreatment differences, while years +1 to +3 (blue) trace post-mandate adjustments. All models include state and survey-year fixed effects plus the full child-level covariate set.

Across all six panels the pretreatment estimates hover tightly around zero with wide, overlapping confidence intervals, providing visual confirmation that mandate, and control states followed parallel trajectories before adoption. After mandates take effect, the trajectories diverge in ways that match the TWFE results. Primary-caregiver distress tends to fall after a mandate, with point estimates around –0.04 to –0.09, but none reaches 5 % significance. Child anxiety and behavior problems drift upward but never significantly exceed zero, mirroring the small, non-robust main effects. Low school engagement shows a mild increase that peaks in year +2 (+2.2 p.p.; $p = 0.013$) and drops back by year +3, underscoring the transitory nature of that coefficient in the baseline model. By contrast, grade repetition displays a clear and sustained rise: the effect is near zero at adoption but grows to +1.3 p.p. in year +2 and +2.0 p.p. in year +3 (both statistically significant at conventional levels), echoing the subgroup-specific penalties documented earlier. No post-period coefficient for depression differs from zero.

6.2 Appendix Results: Subgroup Analyses and Robustness Checks

Children who live with a caregiver reporting an alcohol- or drug-related problem fare markedly worse across four of the five outcomes in appendix table A1A. Relative to peers in

low-risk homes, their probabilities of depression, anxiety, low school engagement, and grade repetition are higher by 3.6, 1.9, 8.6, and 2.7 p.p., respectively. A strict mandatory-access PDMP on its own does not materially change these outcomes, but the interaction term shows that mandates worsen several gaps: depression (2.0 p.p.), behavior problems (2.6 p.p.), and grade repetition (2.0 p.p.). Wald tests of joint significance reject the null hypothesis that the coefficients on parental substance exposure, PDMP mandates, and their interaction are jointly zero for all variables, confirming that children in substance-affected households are systematically worse off and that PDMP adoption further widens the gaps for several outcomes.

Any adult tobacco use inside the home is associated with higher depression (2.4 p.p.), anxiety (1.5 p.p.), low engagement (4.8 p.p.), and grade repetition (2.1 p.p.), represented in table A1B. PDMP adoption slightly improves engagement for children in tobacco-free homes (-1.2 p.p.) but leaves other outcomes unchanged. Crucially, the Tobacco and PDMP interaction term adds a further 2.3 p.p. to grade repetition. Wald tests of joint significance reject the null hypothesis that the coefficients on tobacco use, PDMP adoption, and their interaction are jointly zero for depression, anxiety, and grade repetition, but not for low engagement. These tests confirm that the effect of PDMP adoption differs significantly between children in smoking versus non-smoking households for grade repetition.

Girls show substantially higher baseline internalizing symptoms than boys—depression by 5.3 p.p. and anxiety by 1.8 p.p., but lower grade repetition (-1.6 p.p.) in table A1C. PDMP adoption raises grade repetition among boys by 0.8 p.p.; the Female and PDMP interaction term is 1.4 p.p. None of the mental-health or engagement outcomes display sex-specific moderation. Wald test confirms that the interaction effect is jointly significant for grade repetition. In contrast,

none of the mental-health or engagement outcomes show statistically significant sex-specific moderation.

Adolescents (12–17) are less likely than younger children to exhibit behavior problems (-3.6 p.p.) but more likely to report low engagement (2.8 p.p.) which is illustrated in table A1D. PDMP rules reduce low engagement for both age groups (-1.4 p.p.) but do not otherwise benefit teens. Instead, the Teen × PDMP coefficient raises grade repetition by 0.9 p.p. ($p < 0.01$), confirming that mandates add an extra academic burden for adolescents while leaving mental-health gaps largely intact. Wald tests indicate that the effects are jointly significant for child behavior, low school engagement, and grade repetition, but not for depression or anxiety.

For children in poor households (≤ 100 % FPL) every adverse outcome is elevated depression by 4.7 p.p. and grade repetition by 3.4 p.p. in table A1E. PDMP adoption modestly lowers low engagement for non-poor children (-1.1 p.p.), yet has no other main-effect benefits. Among poor children, however, the mandate increases grade repetition by an additional 2.5 p.p. while slightly reducing anxiety (-1.6 p.p.). Wald tests confirm that the joint interaction of poverty and PDMP adoption is statistically significant for all variables, indicating that the effects of the mandate differ meaningfully by poverty status.

Children in two-parent families face lower low engagement (-2.8 p.p.) and grade repetition (-0.6 p.p.) than those in single-parent homes, demonstrated in table A1F. PDMP adoption raises grade repetition within single-parent households by 0.8 p.p. The interaction of two-parent household and PDMP has an opposite effect (–0.9 p.p.) here. Wald tests of joint significance reject the null hypothesis that the coefficients on two-parent households, PDMP adoption, and their interaction are jointly zero for low engagement and grade repetition, but not for other variables. These tests confirm that the effect of PDMP adoption differs significantly

between children in single- versus two-parent households for low engagement and grade repetition.

7 Discussion

Our findings indicate that strict mandatory-access Prescription Drug Monitoring Programs (PDMP) have complex impact. In broad terms, the evidence aligns with prior health economics research showing that "must-access" PDMP laws can curb opioid misuse and improve certain adult outcomes.

Buchmueller and Carey (2018) find that PDMP mandates led to significant reductions in opioid prescriptions and doctor-shopping in Medicare, a clear indication of supply-side restraint. Likewise, state-level analyses by Meinhofer (2018) and Grecu et al. (2019) report decreases in overall opioid dispensing and misuse following PDMP implementation. Consistent with these patterns, our study detects a small but meaningful improvement in caregiver mental health after PDMP adoption. This suggests that, on average, tightening prescription monitoring may relieve some strain on families. We also find a slight uptick in child school engagement in the post-PDMP period, hinting at potential benefits for family functioning. These direct gains resonate with evidence from the literature that PDMP mandates confer positive externalities, such as lower crime rates (Dave et al., 2021) and even reductions in foster care entries over time (Gihleb et al., 2022), presumably by mitigating the prevalence of opioid-related dysfunction in communities.

At the same time, a central contribution of this analysis is uncovering the heterogeneity behind those aggregate benefits. Our results show that PDMP effects are not distributed evenly across households. Mandatory PDMPs may exacerbate existing disparities in child outcomes linked to household substance use. Children living in homes with parental risk factors like

tobacco use, indoor smoking, or caregiver substance abuse, experienced worsened outcomes relative to their peers after PDMP implementation. Notably, we observe a gap in academic performance. PDMPs appear to widen the academic divide between children from stable versus unstable home environments. This unintended divergence echoes broader concerns in the literature that supply-side interventions, while curbing the targeted behavior, can induce adverse spillovers. An example is the reformulation of OxyContin in 2010, a supply shock which dramatically reduced misuse of that prescription opioid but inadvertently fueled a surge in heroin use and related overdose deaths (Alpert et al., 2018; Evans et al., 2019). Our findings suggest that when a parent with opioid dependency is suddenly constrained by a PDMP, the family may experience turbulence that manifests as poorer academic or behavioral outcomes for children.

Several behavioral mechanisms could explain why children in high-risk households fare worse under PDMP mandates. One mechanism is substitution: parents who lose access to prescription opioids might substitute toward other substances or behaviors. Prior research has noted that opioid users often turn to illicit opioids or other drugs if prescriptions become harder to obtain (Evans et al., 2019). Our subgroup evidence supports this possibility. This could imply that some opioid-using parents, once constrained by PDMPs, resorted to smoking more heavily at home, thereby exposing their children to more secondhand smoke and associated cognitive detriments. An increase in smoking due to opioid substitution could directly harm children's schooling.

Another plausible mechanism is household stress transmission. When a strict PDMP suddenly restricts a dependent parent's access to opioids, withdrawal symptoms or undertreated pain can elevate irritability and psychological strain inside the home. Parents under such strain may supervise children less effectively or respond more harshly, thereby increasing household

chaos and undermining children's sense of emotional security. Although our dataset cannot observe these dynamics directly, the idea of intra-household spillovers is consistent with evidence that an adult health shock prompts measurable behavior changes among other family members (Fadlon & Nielsen, 2019). In line with this channel, we find that PDMP enforcement in households already exhibiting caregiver substance problems is associated with higher rates of child depression and behavioral problems, suggesting the policy may amplify emotional stress in vulnerable families.

We also document differences by child age and gender that carry implications for understanding vulnerability. The adverse academic effects of PDMP exposure were concentrated among older children (especially adolescents). We found that mandatory PDMPs had a stronger association with grade repetition for teenagers than for younger children. One interpretation is that adolescents' educational progress is more sensitive to household stability. Teens typically have greater autonomy over school attendance and work, so if a parent's functioning deteriorates during the PDMP rollout, a teenager might be more likely to skip classes, fall behind, or even assume additional caregiving responsibilities for siblings, all of which can undermine their studies. For instance, Bullinger and Ward (2021) find that opioid overdose spikes in a community lead to more infants and grade-school kids being removed into foster care. Our results are not inconsistent with that: younger children in severe situations might be caught by the child welfare system (removing them from harm), whereas adolescents may be left in the risky home and exhibit their distress through poor educational performance. Over time, if PDMPs succeed in reducing parental opioid abuse, one would expect improvements for children of all ages; indeed, a recent study detected a decline in foster care entries about two years after PDMP mandates, indicating eventual benefits once parental recovery gains traction (Gihleb et

al., 2022). The short-run uptick in academic problems among teens that we observe highlights that those improvements may not be immediate for older children, and schools may need to pay special attention to adolescents in communities undergoing opioid policy transitions.

These results enrich the growing literature evaluating opioid policies by highlighting intergenerational dimensions. They confirm that strict PDMP mandates – which prior studies credit with reducing opioid prescriptions, misuse, and even overdose deaths (Buchmueller & Carey, 2018; Meinhofer, 2018; Grecu et al., 2019) – can indeed translate into better outcomes for some families (less caregiver distress, improved student engagement). At the same time, we uncover evidence of collateral stress in vulnerable households, worsened child mental health and academic performance in the short run. These dual findings underscore a key point emphasized in policy discussions: supply-side interventions like PDMPs are a crucial tool to combat the opioid crisis, but they are not a panacea when used in isolation (Haffajee et al., 2015). If the underlying demand for opioids (driven by addiction or untreated pain) is not addressed, simply constricting the prescription supply may displace the problem rather than fully resolve it.

8 Conclusion

Strict mandatory-access PDMPs yield modest average gains, improved caregiver mental well-being and slightly better school engagement. In homes with tobacco exposure, indoor smoking, or caregiver substance problems, mandates coincide with worsening academic progression and, when substance problems are present, there are more behavioral difficulties. The policy takeaway is straightforward: PDMPs are necessary but insufficient. Pairing monitoring with accessible non-opioid pain care, medications for opioid use disorder, and smoking-cessation support, and proactively routing academic and pediatric services to high-risk families can preserve public-health gains while protecting children. Future research should track

longer-run trajectories, directly measure substitution and home exposure, and evaluate integrated PDMP with supportive services.

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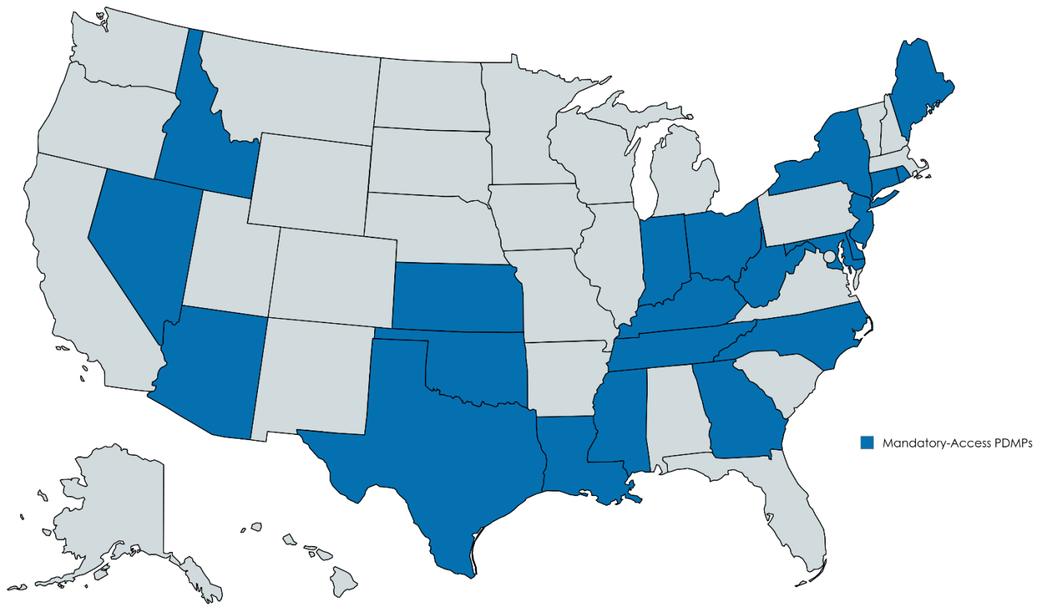
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Figures and Tables

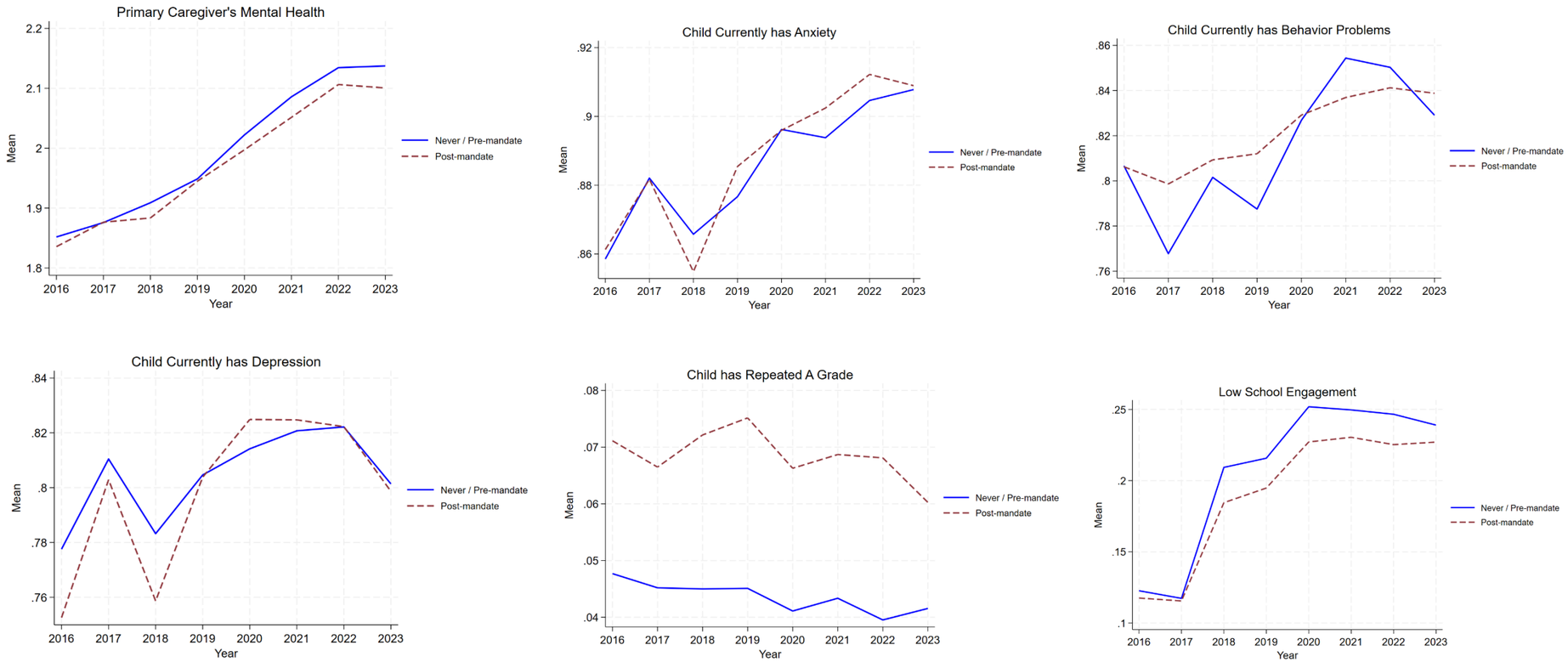
Figures

Figure 1 – Strict Mandatory-Access Prescription Drug Monitoring Programs (PDMPs) Policy in the United States



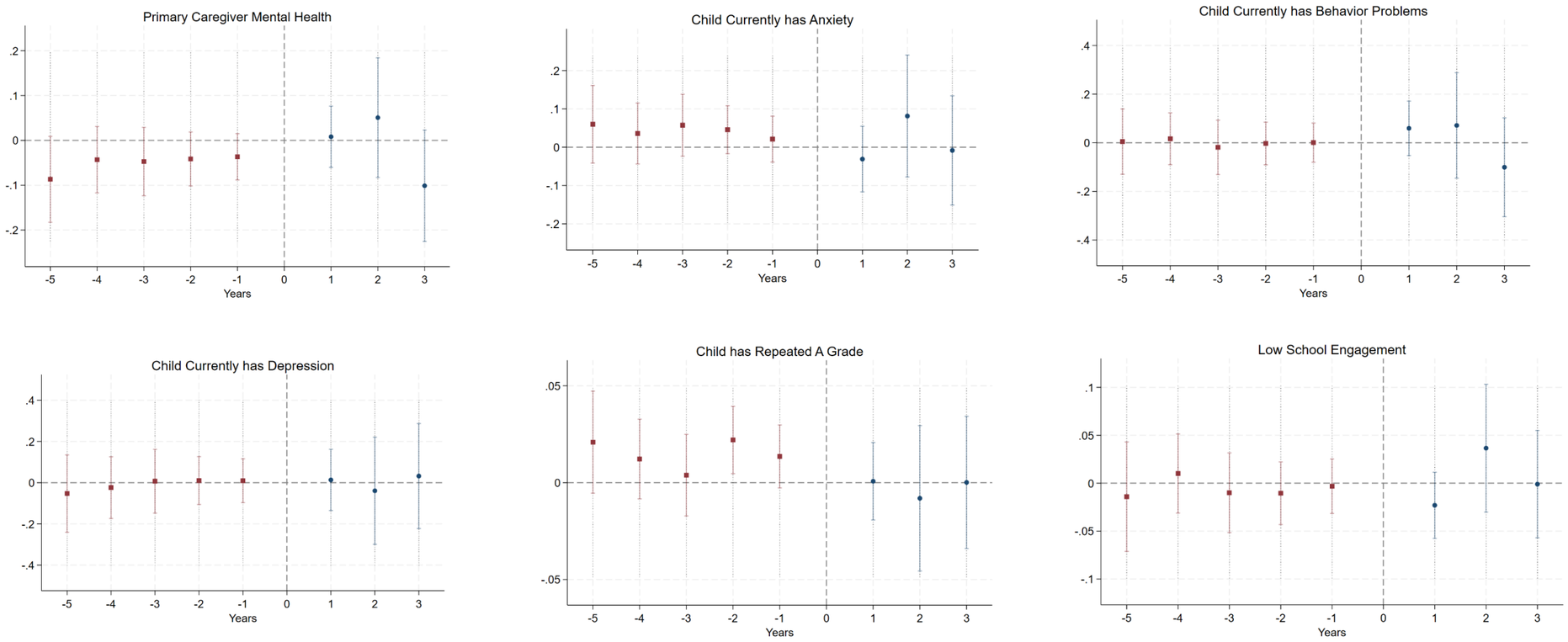
Notes: This map highlights US states that have adopted strict mandatory-access prescription drug monitoring programs (PDMPs). States shaded in blue have such laws in force, with coverage spanning large portions of the South, Midwest, and Northeast, as well as several western states; those in gray have not enacted these mandates.

Figure 2 – Unadjusted Outcome Trends by Mandatory-Access Prescription-Drug-Monitoring-Program (PDMP) Mandate Status (2016 – 2023)



Notes: Each panel traces yearly mean for the indicated outcome, contrasting states that never adopted a mandate/are still pre-mandate (solid blue) with states after mandatory-access PDMP adoption (dashed burgundy). The two trajectories move roughly in tandem before mandate exposure, lending support to the parallel-trends assumption for primary-caregiver mental health and the five child outcomes—anxiety, behavior problems, depression, grade repetition, and low school engagement.

Figure 3 – Event-Study Estimates of Mandatory-Access Prescription-Drug-Monitoring-Program (PDMP) Mandates on Caregiver and Child Outcomes



Notes: Each panel plots the average treatment effect on the treated with 95% confidence intervals from Callaway-and-Sant'Anna event-study regressions. The horizontal axis shows event time in years relative to a state's first strict mandatory-access PDMP (year 0, vertical dashed line); the vertical axis reports coefficient magnitudes (baseline = 0). Red markers represent pre-mandate leads and blue markers represent post-mandate lags. Estimates are net of covariates and weighted by inverse-propensity scores; confidence intervals are clustered at the state level.

Tables

Table 1 – Descriptive Statistics

Panel A. States/Years without a Mandate (PDMP = 0)

Variables	Observations	Mean	SD	Min	Max
Child Depression	10979	0.8044	0.3966	0	1
Child Anxiety	22587	0.8906	0.3121	0	1
Child Behavioral Problems	16884	0.8198	0.3844	0	1
Low School Engagement	121070	0.2037	0.4028	0	1
Grade Repetition	139961	0.0419	0.2003	0	1
Caregiver's Mental Health	207368	2.0093	0.8928	1	5
Any Household Tobacco	213322	0.121	0.3261	0	1
Household Smokes Inside	213322	0.0123	0.1103	0	1
Parental Illicit Drug Exposure	213322	0.0883	0.2837	0	1
Child Age (years)	213322	8.9163	5.2879	0	17
Child Sex (=2 Male)	213322	1.4829	0.4997	1	2
Teen (13–17 yrs)	213322	0.3741	0.4839	0	1
Race	213322	2.1957	0.8433	1	4
Poverty level	213322	3.0523	1.0094	1	4
Currently insured	212395	1.0406	0.1972	1	2
Two-parent Household	213322	0.8397	0.3669	0	1
Poor Household	213322	0.1096	0.3124	0	1

Panel B. States/Years with a Mandate (PDMP = 1)

Variable	Observations	Mean	SD	Min	Max
Child Depression	5972	0.8081	0.3938	0	1
Child Anxiety	13238	0.8962	0.305	0	1
Child Behavioral Problems	10039	0.8277	0.3777	0	1
Low School Engagement	68130	0.1978	0.3984	0	1
Grade Repetition	79448	0.0671	0.2502	0	1
Caregiver's Mental Health	117271	2.0042	0.902	1	5
Any Household Tobacco	121386	0.1343	0.341	0	1
Household Smokes Inside	121386	0.0197	0.139	0	1
Parental Illicit Drug Exposure	121386	0.0824	0.275	0	1
Child Age (years)	121386	8.9536	5.2808	0	17
Child Sex (=2 Male)	121386	1.4842	0.4998	1	2
Teen (13–17 yrs)	121386	0.3771	0.4847	0	1
Race	121386	2.2109	0.8204	1	4
Poverty level	121386	2.9551	1.0553	1	4
Currently insured	120761	1.0466	0.2107	1	2
Two-parent Household	121386	0.8156	0.3878	0	1
Poor Household	121386	0.1369	0.3437	0	1

Notes: Summary statistics are using the National Survey of Children's Health 2016–2023. Panel A refers to state-year observations before a strict mandatory-access prescription-drug-monitoring-program (PDMP) took effect; Panel B covers state-years after adoption.

Table 2A – Baseline TWFE Estimates: Household Substance-Use Environments, PDMP Mandates, and Child Outcomes

Variables	Caregiver's Mental Health	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any Adult Uses Tobacco	0.235***	0.013	0.010*	0.009	0.033***	0.014***
	(0.008)	(0.010)	(0.006)	(0.008)	(0.003)	(0.002)
Someone Smokes Inside Home	0.214***	0.036*	0.012	0.027	0.047***	0.032***
	(0.027)	(0.020)	(0.012)	(0.016)	(0.009)	(0.007)
Caregiver has Alcohol/Drug Problem	0.360***	0.034***	0.017***	0.006	0.080***	0.024***
	(0.009)	(0.006)	(0.005)	(0.007)	(0.004)	(0.003)
Mandatory-access PDMP	-0.021**	-0.010	-0.003	-0.006	-0.011*	-0.003
	(0.009)	(0.014)	(0.011)	(0.010)	(0.005)	(0.003)
Tobacco × PDMP	-0.005	0.017	0.003	0.009	0.005	0.016***
	(0.012)	(0.015)	(0.010)	(0.013)	(0.007)	(0.004)
Indoor Smoking × PDMP	0.006	-0.017	-0.008	-0.023	-0.019	0.024**
	(0.032)	(0.025)	(0.020)	(0.024)	(0.013)	(0.009)
Alcohol/Drug × PDMP	-0.000	0.018	0.008	0.026**	-0.011	0.015***
	(0.017)	(0.011)	(0.007)	(0.011)	(0.007)	(0.005)
Observations	323,722	16,879	35,700	26,811	188,649	218,904
R-squared	0.064	0.018	0.010	0.036	0.044	0.035

Notes: Each column reports two-way fixed-effects (TWFE) estimates of the indicated outcome using data from the 2016–2023 National Survey of Children's Health. Explanatory variables capture household substance-use environments—any adult tobacco use, indoor smoking, and whether the primary caregiver reports alcohol or drug problems—and a state-year indicator for the presence of a strict mandatory-access prescription-drug-monitoring program (PDMP). Interaction terms test whether PDMP adoption moderates the relationship between household risk factors and child or caregiver outcomes. All regressions include child age (years), sex, race/ethnicity, poverty status, health-insurance coverage, and two-parent household indicators. State fixed effects and survey-year fixed effects are included in every specification. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2B.1 – Gender-Stratified TWFE Estimates: Male Children

Variables	Caregiver's Mental Health	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any Adult Uses Tobacco	0.229***	-0.013	0.017*	0.017*	0.040***	0.018***
	(0.011)	(0.016)	(0.010)	(0.009)	(0.005)	(0.003)
Someone Smokes Inside Home	0.207***	0.048	0.011	0.033*	0.069***	0.039***
	(0.032)	(0.036)	(0.019)	(0.019)	(0.014)	(0.011)
Caregiver has Alcohol/Drug Problem	0.355***	0.034**	0.022**	0.004	0.082***	0.025***
	(0.011)	(0.014)	(0.009)	(0.009)	(0.007)	(0.003)
Mandatory-access PDMP	-0.014*	-0.018	0.020	-0.007	-0.018**	0.002
	(0.008)	(0.026)	(0.017)	(0.014)	(0.007)	(0.003)
Tobacco × PDMP	-0.010	0.088***	0.002	0.003	0.001	0.017***
	(0.015)	(0.028)	(0.014)	(0.015)	(0.010)	(0.006)
Indoor Smoking × PDMP	0.032	-0.072	-0.023	-0.034	-0.038*	0.035**
	(0.043)	(0.046)	(0.028)	(0.029)	(0.020)	(0.016)
Alcohol/Drug × PDMP	-0.006	0.027	0.012	0.027*	-0.001	0.019***
	(0.020)	(0.022)	(0.013)	(0.013)	(0.012)	(0.006)
Observations	167,203	7,202	16,432	18,907	93,126	113,354
R-squared	0.063	0.022	0.014	0.041	0.038	0.040

Notes: Each column reports two-way fixed-effects (TWFE) estimates for the male children subsample of the indicated outcome using data from the 2016–2023 National Survey of Children's Health. Explanatory variables capture household substance-use environments—any adult tobacco use, indoor smoking, and whether the primary caregiver reports alcohol or drug problems—and a state-year indicator for the presence of a strict mandatory-access prescription-drug-monitoring program (PDMP). Interaction terms test whether PDMP adoption moderates the relationship between household risk factors and child or caregiver outcomes. All regressions include child age (years), sex, race/ethnicity, poverty status, health-insurance coverage, and two-parent household indicators. State fixed effects and survey-year fixed effects are included in every specification. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2B.2 – Gender-Stratified TWFE Estimates: Female Children

Variables	Caregiver's Mental Health	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any Adult Uses Tobacco	0.242***	0.032***	0.004	-0.008	0.026***	0.011***
	(0.010)	(0.012)	(0.009)	(0.014)	(0.004)	(0.002)
Someone Smokes Inside Home	0.222***	0.024	0.014	0.011	0.027*	0.023**
	(0.031)	(0.019)	(0.018)	(0.030)	(0.014)	(0.009)
Caregiver has Alcohol/Drug Problem	0.366***	0.034***	0.013**	0.009	0.079***	0.022***
	(0.013)	(0.011)	(0.005)	(0.010)	(0.006)	(0.004)
Mandatory-access PDMP	-0.030**	-0.006	-0.021	-0.005	-0.003	-0.008*
	(0.014)	(0.019)	(0.015)	(0.023)	(0.005)	(0.004)
Tobacco × PDMP	0.001	-0.039*	0.004	0.022	0.007	0.013***
	(0.017)	(0.022)	(0.014)	(0.027)	(0.008)	(0.004)
Indoor Smoking × PDMP	-0.024	0.028	0.003	0.007	0.000	0.008
	(0.037)	(0.029)	(0.024)	(0.044)	(0.022)	(0.015)
Alcohol/Drug × PDMP	0.005	0.012	0.007	0.024*	-0.020**	0.012*
	(0.023)	(0.018)	(0.009)	(0.014)	(0.009)	(0.006)
Observations	156,519	9,677	19,268	7,904	95,523	105,550
R-squared	0.066	0.015	0.011	0.030	0.030	0.026

Notes: Each column reports two-way fixed-effects (TWFE) estimates for the female children subsample of the indicated outcome using data from the 2016–2023 National Survey of Children's Health. Explanatory variables capture household substance-use environments—any adult tobacco use, indoor smoking, and whether the primary caregiver reports alcohol or drug problems—and a state-year indicator for the presence of a strict mandatory-access prescription-drug-monitoring program (PDMP). Interaction terms test whether PDMP adoption moderates the relationship between household risk factors and child or caregiver outcomes. All regressions include child age (years), sex, race/ethnicity, poverty status, health-insurance coverage, and two-parent household indicators. State fixed effects and survey-year fixed effects are included in every specification. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2C.1 – Age-Stratified TWFE Estimates: Younger Children (< 12 years)

Variables	Caregiver's Mental Health	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any Adult Uses Tobacco	0.242***	-0.012	-0.010	0.008	0.020***	0.007**
	(0.009)	(0.025)	(0.010)	(0.009)	(0.004)	(0.003)
Someone Smokes Inside Home	0.225***	0.102**	0.028	-0.014	0.051**	0.023**
	(0.034)	(0.042)	(0.023)	(0.026)	(0.019)	(0.011)
Caregiver has Alcohol/Drug Problem	0.362***	0.022	0.020**	0.004	0.074***	0.014***
	(0.011)	(0.016)	(0.008)	(0.010)	(0.007)	(0.003)
Mandatory-access PDMP	-0.021	0.010	-0.007	0.004	-0.017*	-0.004
	(0.014)	(0.029)	(0.016)	(0.014)	(0.009)	(0.005)
Tobacco × PDMP	-0.008	0.066	0.027	0.000	0.004	0.014***
	(0.016)	(0.044)	(0.019)	(0.015)	(0.008)	(0.005)
Indoor Smoking × PDMP	0.028	-0.094	-0.043	0.021	-0.026	0.031**
	(0.046)	(0.072)	(0.030)	(0.032)	(0.024)	(0.015)
Alcohol/Drug × PDMP	-0.019	0.009	-0.010	0.009	-0.014	0.020***
	(0.020)	(0.029)	(0.012)	(0.015)	(0.013)	(0.007)
Observations	202,145	2,619	12,293	14,662	85,452	95,944
R-squared	0.058	0.047	0.014	0.014	0.034	0.028

Notes: Each column reports two-way fixed-effects (TWFE) estimates for children younger than 12 of the indicated outcome using data from the 2016–2023 National Survey of Children's Health. Explanatory variables capture household substance-use environments—any adult tobacco use, indoor smoking, and whether the primary caregiver reports alcohol or drug problems—and a state-year indicator for the presence of a strict mandatory-access prescription-drug-monitoring program (PDMP). Interaction terms test whether PDMP adoption moderates the relationship between household risk factors and child or caregiver outcomes. All regressions include child age (years), sex, race/ethnicity, poverty status, health-insurance coverage, and two-parent household indicators. State fixed effects and survey-year fixed effects are included in every specification. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2C.2 – Age-Stratified TWFE Estimates: Teen (12 – 17 years)

Variables	Caregiver's Mental Health	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any Adult Uses Tobacco	0.228***	0.017*	0.022***	0.012	0.044***	0.021***
	(0.012)	(0.010)	(0.008)	(0.015)	(0.006)	(0.003)
Someone Smokes Inside Home	0.199***	0.022	0.003	0.055**	0.041***	0.033***
	(0.032)	(0.021)	(0.015)	(0.024)	(0.012)	(0.009)
Caregiver has Alcohol/Drug Problem	0.360***	0.036***	0.016**	0.011	0.084***	0.030***
	(0.012)	(0.007)	(0.006)	(0.011)	(0.005)	(0.004)
Mandatory-access PDMP	-0.019	-0.011	-0.001	-0.019	-0.006	-0.002
	(0.016)	(0.016)	(0.016)	(0.021)	(0.009)	(0.004)
Tobacco × PDMP	0.001	0.007	-0.010	0.021	0.005	0.016***
	(0.020)	(0.015)	(0.012)	(0.023)	(0.010)	(0.005)
Indoor Smoking × PDMP	-0.020	0.002	0.007	-0.060*	-0.013	0.019*
	(0.044)	(0.028)	(0.023)	(0.035)	(0.022)	(0.011)
Alcohol/Drug × PDMP	0.012	0.019*	0.017*	0.035**	-0.011	0.011*
	(0.020)	(0.011)	(0.009)	(0.016)	(0.009)	(0.006)
Observations	121,577	14,260	23,407	12,149	103,197	122,960
R-squared	0.079	0.018	0.012	0.031	0.046	0.038

Notes: Each column reports two-way fixed-effects (TWFE) estimates for children between 12 and 17 of the indicated outcome using data from the 2016–2023 National Survey of Children's Health. Explanatory variables capture household substance-use environments—any adult tobacco use, indoor smoking, and whether the primary caregiver reports alcohol or drug problems—and a state-year indicator for the presence of a strict mandatory-access prescription-drug-monitoring program (PDMP). Interaction terms test whether PDMP adoption moderates the relationship between household risk factors and child or caregiver outcomes. All regressions include child age (years), sex, race/ethnicity, poverty status, health-insurance coverage, and two-parent household indicators. State fixed effects and survey-year fixed effects are included in every specification. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2D.1 – Income-Stratified TWFE Estimates: Households ≤ 100 % Federal Poverty Line

Variables	Caregiver's Mental Health	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any Adult Uses Tobacco	0.330***	-0.006	0.014	0.009	0.022**	0.023***
	(0.020)	(0.024)	(0.014)	(0.016)	(0.008)	(0.007)
Someone Smokes Inside Home	0.248***	0.100***	-0.000	0.022	0.073***	0.028*
	(0.045)	(0.030)	(0.018)	(0.026)	(0.019)	(0.015)
Caregiver has Alcohol/Drug Problem	0.466***	0.034*	0.020	-0.012	0.070***	0.028***
	(0.022)	(0.018)	(0.015)	(0.018)	(0.012)	(0.005)
Mandatory-access PDMP	-0.033	-0.013	-0.033*	-0.032	-0.007	-0.008
	(0.023)	(0.034)	(0.020)	(0.029)	(0.018)	(0.011)
Tobacco × PDMP	-0.034	0.063	0.009	0.025	0.018	0.031***
	(0.028)	(0.040)	(0.020)	(0.027)	(0.020)	(0.011)
Indoor Smoking × PDMP	0.032	-0.125***	0.002	-0.040	-0.036	0.000
	(0.059)	(0.046)	(0.029)	(0.036)	(0.028)	(0.023)
Alcohol/Drug × PDMP	-0.056	0.022	0.013	0.019	0.003	0.028***
	(0.039)	(0.028)	(0.019)	(0.021)	(0.018)	(0.010)
Observations	37,646	2,662	4,665	4,594	21,362	26,233
R-squared	0.072	0.034	0.027	0.032	0.037	0.049

Notes: Each column reports two-way fixed-effects (TWFE) estimates for households at or below 100 % of the federal poverty line (FPL) of the indicated outcome using data from the 2016–2023 National Survey of Children's Health. Explanatory variables capture household substance-use environments—any adult tobacco use, indoor smoking, and whether the primary caregiver reports alcohol or drug problems—and a state-year indicator for the presence of a strict mandatory-access prescription-drug-monitoring program (PDMP). Interaction terms test whether PDMP adoption moderates the relationship between household risk factors and child or caregiver outcomes. All regressions include child age (years), sex, race/ethnicity, poverty status, health-insurance coverage, and two-parent household indicators. State fixed effects and survey-year fixed effects are included in every specification. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2D.2 – Income-Stratified TWFE Estimates: Households (101-199) % Federal Poverty Line

Variables	Caregiver's Mental Health	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any Adult Uses Tobacco	0.259***	0.026	-0.015	0.029*	0.025**	0.017***
	(0.015)	(0.017)	(0.012)	(0.016)	(0.010)	(0.006)
Someone Smokes Inside Home	0.148***	0.006	0.050***	-0.014	0.037*	0.027*
	(0.035)	(0.038)	(0.018)	(0.033)	(0.020)	(0.014)
Caregiver has Alcohol/Drug Problem	0.370***	0.032*	0.026*	-0.000	0.074***	0.026***
	(0.020)	(0.019)	(0.013)	(0.010)	(0.010)	(0.006)
Mandatory-access PDMP	-0.009	-0.011	-0.049**	-0.034	-0.009	-0.013**
	(0.030)	(0.059)	(0.023)	(0.022)	(0.013)	(0.006)
Tobacco × PDMP	0.007	-0.023	0.037*	-0.001	0.012	0.015
	(0.023)	(0.038)	(0.020)	(0.021)	(0.014)	(0.010)
Indoor Smoking × PDMP	-0.069	0.030	-0.004	-0.002	-0.045	0.015
	(0.054)	(0.056)	(0.027)	(0.048)	(0.027)	(0.022)
Alcohol/Drug × PDMP	0.029	0.026	-0.022	0.031	-0.018	0.002
	(0.036)	(0.030)	(0.019)	(0.024)	(0.015)	(0.011)
Observations	51,458	3,328	6,207	5,489	29,299	35,578
R-squared	0.056	0.027	0.024	0.029	0.042	0.032

Notes: Each column reports two-way fixed-effects (TWFE) estimates for households between (101-199) % of the federal poverty line (FPL) of the indicated outcome using data from the 2016–2023 National Survey of Children's Health. Explanatory variables capture household substance-use environments—any adult tobacco use, indoor smoking, and whether the primary caregiver reports alcohol or drug problems—and a state-year indicator for the presence of a strict mandatory-access prescription-drug-monitoring program (PDMP). Interaction terms test whether PDMP adoption moderates the relationship between household risk factors and child or caregiver outcomes. All regressions include child age (years), sex, race/ethnicity, poverty status, health-insurance coverage, and two-parent household indicators. State fixed effects and survey-year fixed effects are included in every specification. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2D.3 – Income-Stratified TWFE Estimates: Households (200-399) % Federal Poverty Line

Variables	Caregiver's Mental Health	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any Adult Uses Tobacco	0.197***	-0.003	0.023**	0.011	0.044***	0.017***
	(0.011)	(0.017)	(0.009)	(0.015)	(0.006)	(0.003)
Someone Smokes Inside Home	0.148***	0.016	-0.053	0.031	0.043	0.018
	(0.032)	(0.036)	(0.035)	(0.039)	(0.026)	(0.012)
Caregiver has Alcohol/Drug Problem	0.338***	0.021	0.010	0.013	0.093***	0.026***
	(0.008)	(0.016)	(0.010)	(0.013)	(0.007)	(0.004)
Mandatory-access PDMP	-0.005	0.013	0.035*	-0.010	-0.003	0.005
	(0.018)	(0.034)	(0.019)	(0.026)	(0.010)	(0.005)
Tobacco × PDMP	0.004	0.047	-0.026	-0.021	-0.008	0.010*
	(0.021)	(0.029)	(0.018)	(0.029)	(0.010)	(0.006)
Indoor Smoking × PDMP	0.020	0.029	0.022	0.048	0.009	0.033*
	(0.049)	(0.060)	(0.048)	(0.051)	(0.037)	(0.017)
Alcohol/Drug × PDMP	-0.017	0.009	0.021	0.026	-0.031**	0.006
	(0.023)	(0.024)	(0.014)	(0.019)	(0.013)	(0.007)
Observations	98,547	5,094	10,777	7,957	56,309	65,945
R-squared	0.044	0.025	0.015	0.045	0.046	0.024

Notes: Each column reports two-way fixed-effects (TWFE) estimates for households between (200-399) % of the federal poverty line (FPL) of the indicated outcome using data from the 2016–2023 National Survey of Children's Health. Explanatory variables capture household substance-use environments—any adult tobacco use, indoor smoking, and whether the primary caregiver reports alcohol or drug problems—and a state-year indicator for the presence of a strict mandatory-access prescription-drug-monitoring program (PDMP). Interaction terms test whether PDMP adoption moderates the relationship between household risk factors and child or caregiver outcomes. All regressions include child age (years), sex, race/ethnicity, poverty status, health-insurance coverage, and two-parent household indicators. State fixed effects and survey-year fixed effects are included in every specification. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

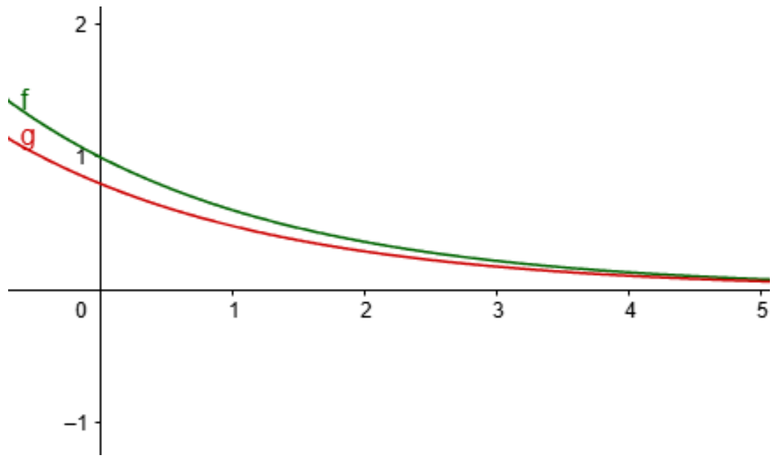
Table 2D.4 – Income-Stratified TWFE Estimates: Households above 400% Federal Poverty Line

Variables	Caregiver's Mental Health	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any Adult Uses Tobacco	0.203***	0.041**	0.010	-0.018	0.026***	0.008***
	(0.011)	(0.020)	(0.013)	(0.020)	(0.006)	(0.003)
Someone Smokes Inside Home	0.113*	-0.023	0.057	0.074	0.020	0.057***
	(0.058)	(0.066)	(0.037)	(0.071)	(0.034)	(0.017)
Caregiver has Alcohol/Drug Problem	0.316***	0.051***	0.015	0.018	0.072***	0.020***
	(0.015)	(0.013)	(0.009)	(0.011)	(0.008)	(0.004)
Mandatory-access PDMP	-0.027**	-0.028	0.001	0.028	-0.015**	-0.001
	(0.012)	(0.038)	(0.023)	(0.024)	(0.006)	(0.004)
Tobacco × PDMP	-0.015	-0.033	0.010	0.049	0.010	0.002
	(0.019)	(0.034)	(0.019)	(0.031)	(0.011)	(0.005)
Indoor Smoking × PDMP	0.035	0.159	-0.106*	-0.129	-0.005	0.017
	(0.090)	(0.100)	(0.061)	(0.117)	(0.049)	(0.031)
Alcohol/Drug × PDMP	0.011	0.014	0.014	0.030*	0.007	0.021***
	(0.021)	(0.029)	(0.013)	(0.017)	(0.016)	(0.006)
Observations	136,071	5,795	14,051	8,771	81,679	91,148
R-squared	0.040	0.020	0.011	0.038	0.048	0.016

Notes: Each column reports two-way fixed-effects (TWFE) estimates for households above 400% of the federal poverty line (FPL) of the indicated outcome using data from the 2016–2023 National Survey of Children's Health. Explanatory variables capture household substance-use environments—any adult tobacco use, indoor smoking, and whether the primary caregiver reports alcohol or drug problems—and a state-year indicator for the presence of a strict mandatory-access prescription-drug-monitoring program (PDMP). Interaction terms test whether PDMP adoption moderates the relationship between household risk factors and child or caregiver outcomes. All regressions include child age (years), sex, race/ethnicity, poverty status, health-insurance coverage, and two-parent household indicators. State fixed effects and survey-year fixed effects are included in every specification. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix (Figures and Tables)

Figure A1 – Exponential Versus Quasi-hyperbolic discounting



Notes: The green curve (exponential) applies a constant discount rate over time. The red curve (quasi-hyperbolic, with $\beta = 0.8$, $\delta = 0.6$) shows present bias.

Table A1A – Heterogeneous Impacts of PDMP Mandates Conditional on Parental Alcohol/Drug Problems

Variables	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Caregiver has Alcohol/Drug Problem	0.036***	0.019***	0.008	0.086***	0.027***
	(0.006)	(0.005)	(0.007)	(0.004)	(0.003)
Mandatory-access PDMP	-0.009	-0.003	-0.005	-0.010*	-0.001
	(0.014)	(0.011)	(0.010)	(0.005)	(0.003)
Alcohol/Drug × PDMP	0.020*	0.009	0.026**	-0.010	0.020***
	(0.011)	(0.007)	(0.011)	(0.007)	(0.005)
Observations	16,879	35,700	26,811	188,649	218,904
R-squared	0.017	0.010	0.035	0.043	0.033

Notes: Each column reports two-way fixed-effects (TWFE) estimates examining whether a caregiver's alcohol/drug problem and a state's strict mandatory-access prescription-drug-monitoring program (PDMP) jointly affect child outcomes in the 2016–2023 National Survey of Children's Health. Regressions include child age (years), sex, race/ethnicity, poverty-level category, and health-insurance status, plus state fixed effects and survey-year fixed effects. Standard errors clustered at the state level are in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A1B – Heterogeneous Impacts of PDMP Mandates Conditional on Household Tobacco Exposure

Variables	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Any adult uses tobacco	0.024***	0.015**	0.014*	0.048***	0.021***
	(0.008)	(0.006)	(0.008)	(0.004)	(0.002)
Mandatory-access PDMP	-0.004	-0.001	-0.001	-0.012**	-0.002
	(0.014)	(0.011)	(0.010)	(0.005)	(0.003)
Tobacco × PDMP	0.017	0.003	0.009	0.002	0.023***
	(0.014)	(0.009)	(0.012)	(0.007)	(0.005)
Observations	16,879	35,700	26,811	188,649	218,904
R-squared	0.015	0.009	0.035	0.041	0.033

Notes: Each column reports two-way fixed-effects (TWFE) estimates whether the effect of strict mandatory-access prescription-drug-monitoring programs (PDMPs) differs for children living in households where any adult uses tobacco, using the 2016–2023 National Survey of Children's Health. The binary indicator "Any adult uses tobacco" equals 1 when at least one household member uses tobacco (tobacco-free households are the reference group). Consequently, the PDMP coefficient captures the mandate's impact for tobacco-free households, while the interaction term (Tobacco × PDMP) shows the differential effect when a child is exposed to household tobacco use. All regressions control for child age (years), sex, race/ethnicity, poverty-level category, health-insurance status, two-parent household, and include state and survey-year fixed effects. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A1C – Heterogeneous Impacts of PDMP Mandates by Child Sex

Variables	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Female Child	0.053***	0.018***	0.022***	-0.092***	-0.016***
	(0.006)	(0.004)	(0.006)	(0.003)	(0.002)
Mandatory-access PDMP	0.002	-0.000	-0.002	-0.014**	0.008**
	(0.017)	(0.011)	(0.010)	(0.006)	(0.004)
Female × PDMP	-0.006	-0.001	0.008	0.006	-0.014***
	(0.011)	(0.007)	(0.010)	(0.004)	(0.004)
Observations	16,879	35,700	26,811	188,649	218,904
R-squared	0.014	0.009	0.035	0.039	0.030

Notes: Each column reports two-way fixed-effects (TWFE) estimates whether the effect of strict mandatory-access prescription-drug-monitoring programs (PDMPs) varies by child sex in the 2016–2023 National Survey of Children's Health. "Female child" equals 1 for girls (boys are the reference group). The PDMP coefficient reflects the mandate's impact for boys; the interaction term shows the differential effect for girls. All regressions control for child age (years), race/ethnicity, poverty-level category, health-insurance status, and two-parent household, and include state and survey-year fixed effects. Standard errors, clustered at the state level, appear in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A1D – Heterogeneous Impacts of PDMP Mandates for Adolescents (Ages 12–17)

Variables	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Teen (12-17 years)	-0.004	-0.004	-0.036***	0.028***	-0.007***
	(0.016)	(0.006)	(0.009)	(0.004)	(0.002)
Mandatory-access PDMP	0.010	-0.003	-0.005	-0.014**	-0.004
	(0.021)	(0.012)	(0.011)	(0.007)	(0.004)
Teen × PDMP	-0.015	0.003	0.011	0.005	0.009***
	(0.017)	(0.007)	(0.011)	(0.006)	(0.003)
Observations	16,879	35,700	26,811	188,649	218,904
R-squared	0.014	0.009	0.035	0.040	0.030

Notes: Each column presents two-way fixed-effects (TWFE) estimates whether the effect of strict mandatory-access prescription-drug-monitoring programs (PDMPs) differs for adolescents (ages 12–17) relative to younger children, using data from the 2016–2023 National Survey of Children's Health. The binary indicator "Teen" equals 1 for children aged 12–17 (younger children serve as the reference group). Consequently, the PDMP coefficient captures the mandate's impact for younger children, while the interaction term (Teen × PDMP) gives the additional effect for adolescents. All regressions control for child sex, race/ethnicity, poverty-level category, health-insurance status, two-parent household, and child age in years, and include state and survey-year fixed effects. Standard errors, clustered at the state level, are in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A1E – Heterogeneous Impacts of PDMP Mandates by Household Poverty Status

Variables	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Poor household (≤ 100 % FPL)	0.047***	0.025***	0.051***	0.009**	0.034***
	(0.009)	(0.005)	(0.008)	(0.004)	(0.004)
Mandatory-access PDMP	0.001	0.001	0.002	-0.011**	-0.002
	(0.016)	(0.011)	(0.010)	(0.005)	(0.003)
Poverty × PDMP	-0.012	-0.016**	-0.009	-0.007	0.025***
	(0.013)	(0.007)	(0.011)	(0.008)	(0.007)
Observations	16,879	35,700	26,811	188,649	218,904
R-squared	0.013	0.009	0.032	0.038	0.028

Notes: Each column reports two-way fixed-effects (TWFE) estimates whether the effect of strict mandatory-access prescription-drug-monitoring programs (PDMPs) varies by household poverty status in the 2016–2023 National Survey of Children's Health. "Poor household" equals 1 when family income is at or below the federal poverty line (≤ 100 % FPL); non-poor children form the reference group. The PDMP coefficient therefore reflects the mandate's impact for non-poor children, while the interaction term shows the differential effect for poor children. All regressions control for child age (years), sex, race/ethnicity, poverty-level category, health-insurance status, and two-parent household, and include state and survey-year fixed effects. Standard errors, clustered at the state level, are in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A1F – Heterogeneous Impacts of PDMP Mandates by Household Structure (Two- vs. One-Parent Homes)

Variables	Child Depression	Child Anxiety	Child Behavioral Problems	Low School Engagement	Grade Repetition
Two-parent household	-0.001	-0.004	0.008	-0.028***	-0.006***
	(0.007)	(0.005)	(0.007)	(0.003)	(0.002)
Mandatory-access PDMP	-0.000	-0.002	-0.001	-0.013*	0.008*
	(0.019)	(0.012)	(0.012)	(0.007)	(0.004)
Two-parent × PDMP	-0.002	0.001	0.001	0.002	-0.009**
	(0.014)	(0.007)	(0.011)	(0.006)	(0.004)
Observations	16,879	35,700	26,811	188,649	218,904
R-squared	0.014	0.009	0.035	0.040	0.030

Notes: Each column reports two-way fixed-effects (TWFE) estimates whether the impact of strict mandatory-access prescription-drug-monitoring programs (PDMPs) differs for children living in two-parent households versus those in single-parent homes, using data from the 2016–2023 National Survey of Children's Health. The binary indicator "Two-parent household" equals 1 when the child resides with two parents (single-parent households are the reference group). Hence, the PDMP coefficient captures the mandate's effect for single-parent families, while the interaction term (Two-parent × PDMP) gives the differential effect for two-parent households. All regressions control for child age (years), sex, race/ethnicity, poverty-level category, health-insurance status, and include state and survey-year fixed effects. Standard errors, clustered at the state level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix (Theory)

3.2.1 Opioids Overdoes: Naive about Present Bias

3.2.1.1 Preference Condition:

$$U_1(O_1, B_2, O_3) > U_1(B_1, B_2, O_3) : ln\frac{P_B}{P_O} + \beta\delta ln(1 - \alpha\frac{P_B}{P_O}) + \beta\delta^2 ln(1 - \alpha^2) > 0. \quad (1)$$

$$U_1(B_1, B_2, O_3) > U_1(O_1, O_2, O_3) : ln\frac{P_O}{P_B} > \frac{\beta\delta ln(1 - \alpha) + \beta\delta^2 ln(1 - \alpha - \alpha^2)}{1 + \beta\delta}. \quad (2)$$

3.2.1.2 Optimal Solution Conditions:

$$(B_2^*, O_2^*)_{\text{sophisticated}} : P_B < 1 + \alpha\beta\delta, \quad \text{and} \quad (3)$$

$$\frac{P_O}{P_B} < \frac{1 - \alpha(1 + \beta\delta) - \alpha^2(1 + \beta\delta)}{1 - \alpha - \alpha^2}. \quad (4)$$

$$(B_2^*, O_2^*)_{\text{naive}} : \frac{1 - \frac{P_O}{P_B}}{\frac{P_O}{P_B} - \alpha} < \frac{\alpha\delta}{1 - \alpha^2}. \quad (5)$$