The complementarity of drug monitoring programs and health IT for reducing opioid-related mortality and morbidity

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Abstract
In response to the opioid crisis, each US state has implemented a prescription drug monitoring program (PDMP) to collect data on controlled substances prescribed and dispensed in the state. I study whether health information technology (HIT) complements patient prescription data in PDMPs to reduce opioid-related mortality and morbidity. A novel dataset is constructed that records state policies that integrate PDMP with HIT and facilitate interstate data sharing. Using difference-in-differences models, I find that PDMP-HIT integration policies reduce opioid-related inpatient morbidity. The reductions are substantial in states that established integration without ever mandating the use of a PDMP. A mechanism test suggests that PDMP integration works mainly through the hospital system while a mandate affects legal opioids prescription. The impacts from integration are strongest for the vulnerable groups—middle-aged, low-to middle-income patients, and those with public insurance. There is suggestive evidence that interstate data sharing further complements integration despite not having a significant impact independently. The results are robust to a set of tests using alternative specifications and measures. The total benefits from integration far exceed the associated costs.

Keywords
health information technology, opioid crisis, prescription drug monitoring, technology policy

1 | INTRODUCTION

Following a substantial long-term decline in mortality and morbidity rates since 1900, the United States has experienced a striking mortality and morbidity reversal for middle-aged white non-Hispanic Americans since the late 1990’s (Case & Deaton, 2015, 2017; Cutler et al., 2006). This deterioration in health is so substantial that overall mortality and morbidity rates have increased in recent years, with drug poisonings being a leading factor behind this health
deterioration (Case & Deaton, 2017). As the biggest cause of drug poisoning, the opioid-induced death rate more than tripled from 2000 to 2014 (Rudd et al., 2016). Moreover, most opioid-related deaths occur among those between the ages of 25 to 54, leading to large productivity losses and a future burden for Medicare (Centers for Disease Control, 2016). Opioid-related annual social costs are estimated to be between $294 billion and $622 billion (Council of Economic Advisers, 2017).

To reduce opioid-related poisonings, each US state has implemented a Prescription Drug Monitoring Program (PDMP, or PMP), and some states have mandated its use. The PDMPs are state-run electronic databases that provide prescription histories for controlled substances. Health care providers can use this database to identify drug-seeking behavior, avoid inappropriate prescribing, and conduct early interventions. Independently, the adoption of health information technologies (HITs) can reduce drug poisoning as part of general quality improvement. HITs are clinical software and systems that facilitate physicians’ clinical decisions by storing, processing, and analyzing patients’ medical services received. While both PDMP and HITs have drawn significant attention separately, their complementarity has been overlooked.

This paper studies policies that integrate PDMP and HITs to allow better data access and utilization within and across states. Until recent years, most states’ PDMPs were stand-alone web portals using technology standards different from those in clinical software. Exploring a patient’s medical history can be time-consuming and inaccurate without HITs; requesting opioid prescription history from a separate site that requires extra verification creates further hurdles. Moreover, some non-opioid prescription drugs that can interact dangerously with opioids are not recorded in a PDMP nor are they easy to identify or analyze without assistance from HITs. For instance, the class of psychoactive drugs, including benzodiazepines (benzos), are not always recorded in PDMPs, but are often prescribed to opioid users, and can result in dangerous interactions. Analytic functions embedded in HITs can help overcome these challenges.1

To reduce technological hurdles, the US Office of the National Coordinator for Health Information Technology (i.e., Office of the National Coordinator for Health Information Technology) collaborated with states and the private sector since 2011 to initiate pilot projects linking drug monitoring portals to medication histories within HITs.2 These PDMP-HIT integration pilots effectively reduced opioid prescriptions and improved associated treatment, and some of these projects were expanded into statewide programs (CDC, 2017). At the state-level, Nebraska and Maryland were aware of this issue up front and built PDMPs within their existing statewide HIT portals to create an integrated system. The impact of these statewide integration policies has not been studied systematically in the academic literature.

In addition, PDMPs are administered and managed independently by states, but patients with drug overdose histories frequently doctor-shop across state lines (McDonald & Carlson, 2014). Exchanging PDMP data across states is a challenging process. State privacy laws can impose barriers to the diffusion of interoperable technologies (Miller & Tucker, 2009). This legal barrier prevented New York and New Jersey from sharing PDMP data until April 2016 and restricted Florida’s attempts to integrate PDMP in 2012 even with a federal grant. Furthermore, a lack of funds can prevent PDMP data sharing as once occurred in North Carolina.3

This paper evaluates the impact of statewide PDMP-HIT integration policies, controlling for other PDMP policies and interstate data sharing. I link state integration policies to opioid-related hospital discharge rates and mortality rates. The policy data are collected from state legal and regulatory documents, press releases, and discussions with state HIT and PDMP agencies. The morbidity data include hospital discharges with diagnoses including poisoning by any types of opioids (prescription or illicit); the mortality data include deaths caused by any opioids and illicit opioids. Because states implemented integration policies at different dates, variation in when these policies were implemented is utilized to estimate difference-in-differences models for causal impacts. To my knowledge, this is the first paper examining the impact of PDMP-HIT integration, a design feature of PDMPs, on opioid-related outcomes.

Results show that PDMP-HIT integration effectively reduces opioid-related inpatient discharges in particular. The inpatient morbidity reductions from integration are about 13% of the mean of the total opioid-related inpatient rate during the sample period. The event studies confirm a lack of pre-trends in outcomes in states with integrated PDMPs relative to control states, and the post-period policy impacts are significant and build over time. Heterogeneity analyses reveal that the impacts are strongest for the most vulnerable groups, including middle-age patients, low-income patients, and patients with public insurance. All of these results, together with a mechanism test, suggest that integration works mainly in the hospitalization stage, by offering decision support for providers to identify risky patients for early intervention. Integration also allows insurers to make progress in helping enrollees during the opioid crisis.

Subsample results indicate that the inpatient morbidity reductions are substantial in states that integrated PDMPs without mandating the access during the sample period, suggesting that integration encourages effective utilization voluntarily. Although I am not able to test whether mandate and integration are complements due to data limitations, a mechanism test suggests that mandate and integration are more effective at different stages of the medical supply chain.
(i.e., prescription or treatment). In addition, the results are robust to controlling for different levels of confounding policies or demographics, placebo tests, drop-one-state test, and alternative policy measures. A Bacon decomposition is implemented to quantify the treatment heterogeneity stemmed from timing and treatment heterogeneity (Goodman-Bacon, 2018), and the results further validate the main results on integration in different treatment groups. Furthermore, there is suggestive evidence that interstate data sharing can complement PDMP integration despite the lack of a strong independent effect. A back-of-the-envelope calculation indicates that the total annual benefits that would be generated from a national integration policy are approximately $30-$60 billion per year, which far exceeds any plausible estimates of the associated costs.

This study contributes to two strands of the literature. First, I extend the literature on drug monitoring program evaluations with the new mechanism of PDMP-HIT integration. Although some studies show that PDMP is associated with reduced opioid prescriptions (Bao et al., 2016; Dowell et al., 2016; Kilby, 2016; Patrick et al., 2016), most find little impact on health outcomes, such as overdose mortality (Li et al., 2014; Meara et al., 2016). To increase the use of PDMPs, several states mandated that providers must access a PDMP before any new opioid prescription. Buchmueller and Carey (2018) find that opioid prescriptions declined among Medicare patients in states with a PDMP mandate, but they also show that a mandate does not reduce opioid poisoning and can drive up cross-state opioid doctor-shopping. Dave et al. (2017) find some evidence that mandates reduce opioid treatment program admission of young adults. Mandate is one of the most widely studied design feature of PDMPs.

In contrast, this paper studies an alternative design to make PDMP user-friendly through HIT integration. Most physicians are aware of PDMPs but find them difficult to use (Fleming et al., 2014; Rutkow et al., 2015). The time-consuming data requests and frustrating cross-system data interpretation crowd-out treatment time, resulting in prescriber opposition and low compliance rates to mandates (Blum et al., 2016; Haffajee et al., 2015). PDMP-HIT integration can resolve these technology challenges and improve decision support.

Second, this paper contributes to studies on digitization in health care with an emphasis on complementary assets. Identifying and using complementary assets to improve health care is difficult but important (Dranove et al., 2014; McCullough et al., 2010, 2016). Although most drug-related poisonings in the past 2 decades have involved controlled substances, these drugs were not recorded nor analyzed by most HITs. Not surprisingly, there is little evidence that HITs independently reduce adverse drug events (Agha, 2014). In contrast, HITs can complement prescriber education to improve antibiotic use (Meeker et al., 2016) and substantially reduce opioid utilization in federally funded pilot projects when integrated with PDMPs (Centers for Disease Control, 2017). This paper provides systematic validation of these project results at the state-level and highlights the value of integrating complementary assets in an era with massive yet segmented patient data.

The paper proceeds as follows. Section 2 describes the background and data. Section 3 presents empirical strategies and results. Section 4 reports robustness checks. The final section concludes and discusses policy implications.

2  |  BACKGROUND AND DATA

2.1  |  Do physicians react to inter-connected PDMPs and HIT?

Anecdotal evidence suggests PDMP-HIT integration greatly increases PDMP utilization. For example, in a federally funded pilot hospital, the PDMP data requests increased 145-fold the year after integration, with a 22% decrease in hospital opioid prescriptions. During the same period, the PDMP data request rate increased by 28% statewide, with a 13% increase in hospital opioid prescriptions (CDC, 2017). In another example, two years after Kansas implemented interstate data sharing, the out-of-state data requests from in-state physicians increased from zero to 25.2% (CDC, 2017). Realizing these benefits, the Centers for Medicare & Medicaid Services (CMS) issued a letter in 2018 highlighting the importance of leveraging technology to combat the opioid crisis. Given the lack of detailed data on illicit opioid use that substitutes for opioid prescriptions, in this study I focus on patient health outcomes rather than prescription volume.

2.2  |  Legal coding on PDMPs

State-quarter level indicators are coded for whether an operational PDMP is available in a state, whether a further modernized PDMP has been implemented (Horwitz et al., 2018), and whether a state has a mandate requiring providers
to access the PDMP before writing a new opioid prescription. A PDMP is defined as operational when its core functionality as electronic data of controlled substances becomes available to authorized users. Some states mandate that all eligible providers must access PDMP for each new patient. Others encourage voluntary access.

Three data sources are cross-checked to code PDMP-related operational and mandate dates. First, I obtained PDMP regulatory data provided by the National Alliance for Model State Drug Laws (NAMSDL), a federally funded non-profit institution that works in coordination with the Office of National Drug Control Policy. Second, I acquired legislative data collected by Legal Science, LLC in the Prescription Drug Abuse Policy System (PDAPS), using grants from the National Institute on Drug Abuse. Third, I used the resources and state profiles stored in the Prescription Drug Monitoring Program Training and Technical Assistance Center (PDMP TTAC) managed by Brandeis University. In addition, when a PDMP became “modern system operational” is controlled for using data from Horwitz et al. (2018).

2.3 PDMP-HIT integration, PDMP interstate data sharing, and HIT adoption rates

State autonomy in PDMP database design results in many PDMP data formats that are often incompatible with clinical data standards. In contrast, most HITs are developed following industry standards to transfer clinical data securely and confidentially. The timings of integration are plausibly exogenous given the multilateral coordination of agencies involved.

Integration is defined as a policy integrating PDMP into HITs to streamline access and analysis with clinical data. Such an integration can facilitate statewide access to PDMP within HITs without an external login. Data are collected from multiple sources. First, I collected reports from federally funded integration pilot projects that document progress and whether/when integration extends to the state-level. Second, I checked PDMP websites and training documents to ascertain timing and, when necessary, discussed particular details with state PDMP and/or HIT managers. Third, I searched press media releases from stakeholders involved in the integration. For example, Appriss Health releases states’ contracting status with their data solution products. Each state is checked concerning whether it had an integration or experienced barriers to integration during the sample period. A PDMP is always considered to be integrated if a state built the PDMP directly into the state health information exchange.

Interstate sharing is defined as cross-state PDMP data exchange through the national hub—“PMP InterConnect.” The hub links the participating states’ PDMPs via secured, encrypted channels. State PDMPs need a single memorandum of understanding (MoU) to join the hub instead of negotiating bilateral MoUs with each participating state. The National Association of Boards of Pharmacy provided the date a state “goes live” and starts interstate data sharing via the hub. This measure is superior for identifying when cross-state PDMPs become connected to alternative measures that record the date when a state allows PDMP data sharing. The lack of restrictions on PDMP sharing can have little relationship to actual sharing implementation, as the details are subject to legal interpretation. Table 1 reports the policy implementation dates.

In addition, state HIT levels are controlled for to account for changes in health care quality through channels independent of opioid-related treatments, such as a timely process of regular medical data and clinical decision support. HIT adoption has risen dramatically in recent decades independent from substance control as most states had not included PDMP integration into their performance measures (“meaningful use” criteria) during my sample period. The best available proxy measure for states’ HIT levels is states’ adoption rates for electronic health records (EHR, the most universally used HITs), which is also most relevant to hospital diagnostic and treatment that are closely associated with health outcomes. Data are obtained from the American Hospital Association Annual Survey IT database.

2.4 Outcome data: opioid-related morbidity, mortality, and prescription

Morbidity measures include opioid-related inpatient stays and emergency room visits at the state-quarter level and available from the Healthcare Cost and Utilization Project (HCUP) Fast Stats opioid topic. The data are also stratified by age group, community income quartiles, patient location, and expected payers. The underlying data are all discharges diagnosed with any opioid-related illnesses in the State Inpatient Databases and State Emergency Department Databases that record hospital inpatient discharges and hospital-affiliated emergency department discharges. The data do not distinguish between prescription and illicit opioids (including synthetic opioids, e.g., fentanyl) and are intended to capture all opioid-related diagnoses. My sample is an unbalanced panel from 2005 to 2016. Table A1 reports detailed data availability.
| State name   | State | PDMP     | Mandate | Integrate | Interstate share |
|--------------|-------|----------|---------|-----------|------------------|
| Alabama      | AL    | 2006q2   | 2017q3  | 2017q1    |                  |
| Alaska       | AK    | 2011q3   | 2017q3  | 2016q1    |                  |
| Arizona      | AZ    | 2008q4   | 2017q4  | 2017q2    | 2012q2           |
| Arkansas     | AR    | 2013q1   | 2015q3  | 2013q4    |                  |
| California   | CA    | Pre-2005 | 2017q1  |           |                  |
| Colorado     | CO    | 2007q3   | 2015q3  | 2013q2    |                  |
| Connecticut  | CT    | 2008q3   | 2015q4  | 2012q1    |                  |
| Delaware     | DE    | 2012q3   | 2012q3  | 2013q4    |                  |
| District of Columbia | DC | 2016q3   |        | 2017q4    |                  |
| Florida      | FL    | 2011q3   |         |           |                  |
| Georgia      | GA    | 2013q3   |         | 2016q3    |                  |
| Hawaii       | HI    | Pre-2005 |         |           |                  |
| Idaho        | ID    | Pre-2005 |         | 2014q2    | 2014q1           |
| Illinois     | IL    | Pre-2005 |         | 2013q1    |                  |
| Indiana      | IN    | Pre-2005 | 2014q3  | 2011q3    |                  |
| Iowa         | IA    | 2009q1   |         | 2015q2    |                  |
| Kansas       | KS    | 2011q1   |         | 2012q2    |                  |
| Kentucky     | KY    | Pre-2005 | 2012q3  | 2013q1    |                  |
| Louisiana    | LA    | 2008q1   | 2014q3  | 2013q1    |                  |
| Maine        | ME    | Pre-2005 | 2017q1  | 2017q2    |                  |
| Maryland     | MD    | 2013q4   | 2018q3  | 2015q2    |                  |
| Massachusetts| MA    | Pre-2005 | 2014q3  | 2016q1    | 2016q3           |
| Michigan     | MI    | Pre-2005 |         | 2017q2    | 2012q1           |
| Minnesota    | MN    | 2010q1   |         | 2013q4    |                  |
| Mississippi  | MS    | 2006q2   |         | 2013q2    |                  |
| Missouri     | MO    |          |         |           |                  |
| Montana      | MT    | 2012q1   |         | 2017q1    |                  |
| Nebraska     | NE    | 2011q2   |         | 2011q2    |                  |
| Nevada       | NV    | Pre-2005 | 2015q4  | 2015q1    | 2014q1           |
| New Hampshire| NH    | 2014q3   | 2016q1  |           | 2016q4           |
| New Jersey   | NJ    | 2011q3   | 2015q4  |           | 2014q2           |
| New Mexico   | NM    | 2005q1   | 2012q3  | 2015q2    | 2012q3           |
| New York     | NY    | Pre-2005 | 2013q3  | 2016q1    | 2016q2           |
| North Carolina| NC | 2007q3   |         |           |                  |
| North Dakota | ND    | 2007q3   | 2014q4  | 2014q2    | 2012q1           |
| Ohio         | OH    | 2006q3   | 2015q4  | 2011q3    | 2011q3           |
| Oklahoma     | OK    | Pre-2005 | 2015q4  | 2014q2    | 2015q1           |
| Oregon       | OR    | 2011q2   |         | 2017q3    |                  |

(Continues)
State-quarter level mortality data are retrieved from the Wide-ranging Online Data for Epidemiologic Research (CDC WONDER) administered by the Centers for Disease Control and Prevention. Raw data come from the death certificates of US residents, where each contains a broad single underlying cause of death and up to 20 detailed multiple causes (including the contributing ones). I focus on deaths where drug- and opioid-induced poisonings are recorded as contributing causes. The death rates per 100,000 population are calculated with supplementary population data from the Surveillance, Epidemiology, and End Results Program.

As additional outcomes to test mechanisms, opioid prescription data are obtained from the Automated Reports and Consolidated Ordering System (ARCOS), reported by manufacturers and distributors to the Drug Enforcement Administration (DEA). The ARCOS Retail Drug Summary Reports are frequently used to measure opioid prescription (Evans et al., 2018). Specifically, the data record state-level drug distribution in gram weight per 100,000 population by quarter. Nine opioids are consistently reported for all years in my sample period: codeine, buprenorphine, oxycodone, hydromorphone, hydrocodone, meperidine (pethidine), methadone, morphine, fentanyl base. Morphine milligram equivalents (MME) conversion factors are applied when calculating aggregate retail volume for legally prescribed opioids.

### 2.5 | Descriptive statistics

The pairwise correlations between PDMP, mandate, integration, and interstate sharing are all below 0.5. Identifying variation comes from differences in which states implemented policies and when these policies became effective. Figure 1 depicts the policy variation. Many PDMPs became operational before 2005, yet most of the other policies started after 2010. Figure 2 shows the rapid increase of integration policy adoption and states’ entry into the sharing hub. By the end of my sample period in 2016, a total of 26 states had implemented PDMP-HIT integration. In addition, 37 states are making growing efforts in interstate PDMP data sharing.

Table 2 reports summary statistics for the outcome variables at the state-quarter level. During the sample period, the overall opioid-related discharge morbidity rates are, on average, 200 per 100,000 in inpatient stays and 145 in emergency room (ER) visits. For stratified outcomes, opioid-related inpatient discharge rates are always much higher than those of emergency department visits. In both the inpatient and ER data, the highest opioid-related morbidity rates occur among 25- to 44-year-old patients followed by those between the ages of 45 and 64. Stratified by community income, the opioid-related morbidity rates are highest among low-to-middle-income populations in the first and second quartiles. Patients
with Medicare and Medicaid as expected payers have higher inpatient morbidity rates among insured patients. The means of all opioid-induced and illicit opioid-induced mortality rates are 2.23 and 1.10 per 100,000, respectively. The morbidity data set is an unbalanced panel with inpatient data from the 46 states and ER data from the 35 states that ever participated in the HCUP data project during the sample period. Because states participated in different years, an empirical test is used to check whether there are policy-relevant differences in state-quarters with missing data versus those without. The results suggest that the missing data are not policy-relevant and are likely missing at random. The suppressed mortality data cover all 50 states and the District of Columbia.

3 | **EMPIRICAL ANALYSIS & RESULTS**

3.1 | **Empirical strategies**

The primary analysis evaluates the impact of state policies on state-quarter aggregates of opioid-related mortality and hospital discharges in inpatient and ER settings. A PDMP is likely more effective when data can be accessed and
analyzed within HIT, which allows providers to access PDMP data more quickly and thus effectively analyze patients’ disease history and drug interactions involving opioids (within a PDMP) and other drugs (within HITs). Because states implemented integration at different dates, I exploit within-state changes in health outcomes and cross-state variation in when policies were implemented to estimate difference-in-differences models. The regression model is:

$$y_{st} = \delta_s + \delta_t + \alpha PDM P_{st} + \beta \text{integration}_{st} + \gamma \text{mandate}_{st} + \eta X_{st} + \varepsilon_{st}$$ (1)

where $y_{st}$ is a state-quarter-level outcome variable. $PDM P_{st}$ indicates whether state $s$ in quarter $t$ has implemented a PDMP. The key variable of interest, $\text{integration}_{st}$, indicates whether a state at time $t$ has implemented PDMP-HIT integration. $\text{mandate}_{st}$ controls for whether a state requires providers to access PDMP data in a year. $X_{st}$ is a set of

| Variables | Obs. | Mean | Std. dev. | Min | Max |
|-----------|------|------|-----------|-----|-----|
| Opioid-related inpatient stays (per 100,000 population) | | | | | |
| Total inpatient stays | 2052 | 200 | 97 | 40 | 562 |
| Age group: 25–44 | 2047 | 289 | 173 | 30 | 1058 |
| Age group: 45–64 | 2046 | 275 | 164 | 48 | 1470 |
| Age group: 65+ | 2018 | 228 | 109 | 34 | 808 |
| Community income quartile 1 | 1833 | 320 | 286 | 43 | 2067 |
| Community income quartile 2 | 1892 | 219 | 135 | 46 | 929 |
| Community income quartile 3 | 1890 | 180 | 90 | 36 | 613 |
| Community income quartile 4 | 1660 | 138 | 60 | 27 | 513 |
| Expected payer: Medicare | 1972 | 94 | 40 | 23 | 263 |
| Expected payer: Medicaid | 1927 | 99 | 79 | 12 | 523 |
| Expected payer: Private | 1977 | 16 | 6 | 4 | 35 |

| Opioid-related emergency room visits (per 100,000 population) | | | | | |
|-----------------|----------|------|-------------|-----|-----|
| Total emergency visits | 1424 | 145 | 93 | 16 | 608 |
| Age group: 25–44 | 1409 | 279 | 218 | 26 | 1520 |
| Age group: 45–64 | 1390 | 149 | 100 | 25 | 953 |
| Age group: 65+ | 1214 | 61 | 38 | 9 | 271 |
| Community income quartile 1 | 1253 | 242 | 207 | 31 | 2052 |
| Community income quartile 2 | 1307 | 174 | 134 | 22 | 916 |
| Community income quartile 3 | 1292 | 138 | 93 | 20 | 669 |
| Community income quartile 4 | 1129 | 103 | 59 | 21 | 392 |
| Expected payer: Medicare | 1268 | 37 | 21 | 7 | 128 |
| Expected payer: Medicaid | 1242 | 72 | 61 | 8 | 450 |
| Expected payer: Private | 1293 | 11 | 5 | 2 | 33 |

| Opioid-induced mortality rates (per 100,000 population) | | | | | |
|-----------------|----------|------|-------------|-----|-----|
| All opioid deaths | 2282 | 2.23 | 1.37 | 0.14 | 10.98 |
| Illicit opioid deaths | 1712 | 1.10 | 1.14 | 0.06 | 9.03 |

Notes: Each observation is a crude rate at the state-quarter level. Healthcare Cost and Utilization Project-provided opioid-related morbidity outcomes are only available in counts when stratified by expected payer, so the rates are calculated by dividing these discharge counts by the number of people covered by each expected payer. Since there are more unclear discharges in terms of expected payers (the missing appears to be random), outcome stratified by expected payers are overall much smaller than other stratified measures.
control variables including PDMP interstate sharing, baseline HIT adoption levels measured as the share of hospitals that adopted any EHR system,\textsuperscript{24} whether a modern PDMP is implemented, and other policies studied in the literature, including unemployment rate, large pill mill bill, naloxone access laws, Good Samaritan overdose prevention laws, medical marijuana laws and dispensaries, and Medicaid expansion (Doleac & Mukherjee, 2017; Hollingsworth et al., 2017; Horwitz et al., 2018; Mallat, 2018; Powell et al., 2015; Rees et al., 2017; Wen et al., 2020). Fixed effects for states ($\delta_s$) and year-quarters ($\delta_t$) are included to account for fixed differences between states and year-quarters, respectively. Standard errors are clustered at the state-level.\textsuperscript{25} For the main results, the more conservative wild cluster bootstrap percentile-t $p$-values are also reported (Cameron et al., 2008).

There are two identifying assumptions: common trends and a lack of common shocks. The assumptions are evaluated within an event study framework for two reasons. First, this framework helps assess the validity of the assumption that the trend in control group (state-quarters without integrated PDMPs yet) is a valid counterfactual for the treated group (state-quarters with integrated PDMPs). Differential trends of outcomes between the treatment and control groups in the pre-treatment periods would suggest policy endogeneity or correlation with other shocks. Event studies with zero coefficients on event indicators prior to a policy provide evidence in support of the identifying assumptions. Second, the event study measures the dynamic responses of outcomes to policies. The integration policy could improve over time through more effective treatment, or it may have an instantaneous impact that diminishes over time as patients switch to illicit opioids. The event study estimates the following equation:

$$y_{st} = \delta_s + \delta_t + \alphaPDMP_{st} + \sum_{j \in [-12,12]} \beta_j \left\{ \begin{array}{ll} \text{integration} & \\
\text{event time} & \\
\end{array} \right\}_{st} + \gamma mandate_{st}^{PMP} + \eta X_{st} + \varepsilon_{st}$$

(2)

where $\beta_j$ denotes the difference between treatment and control units in the period $j$ quarters relative to when an integration was implemented. The period before implementation, $j = -1$, is omitted as the reference period. The event window is specified to be 12 quarters before and 8 quarters after the event.\textsuperscript{26} Sample sizes are small outside of this range.

### 3.2 Baseline results

Table 3 reports the results of the difference-in-difference estimation. The inpatient morbidity rates are the main outcomes, and the estimated policy impacts are discussed in detail. Then, hypotheses are formed for inpatient morbidity results in stratified sub-populations. Results for overall ER visits and mortality are reported at the end of the table and are discussed later.

For overall morbidity, the integration estimate is about 26 fewer hospital discharges per 100,000 for opioid-related inpatient stays and is statistically significant at the 5% level. The inference is unaffected by the wild cluster bootstrap procedure. The associated event study (Figure 3) supports the lack of a pre-trend for treated and control groups, and the post-period reductions occur quickly and build over time. Intuitively, admitted patients are usually severely ill and require substantial treatment. For doctors treating these patients, integrated PDMPs can be particularly helpful in providing opioid-related data and decision support functions via HITs.

Results from stratified opioid-related inpatient morbidity rates are reported in Table 3. Groups are examined where there is a plausible hypothesis for why the policy effects might differ: adult age groups, community-income quartiles, and patients with different types of insurance. These measures are closely related to patients’ socioeconomic status, and thus might isolate vulnerable sub-populations. Due to data availability issues, I lack state-quarter mortality rates stratified by demographics, so I am not able to provide a stratified mortality analysis.\textsuperscript{27}

Across adult patient age groups, middle-to old-aged patients can benefit more from an integrated policy presumably because they require greater treatment intensity and use more hospital resources. Specifically, patients of working age (the 25–64 age groups) are most vulnerable based on mean inpatient morbidity rates, and old-age patients are less time-constrained for inpatient treatment. From the regression results, the integration coefficient point estimates are 26, 35, and 46 fewer inpatient discharges per 100,000 for patients aged 25–44, 45–64, and 65 and older, respectively (corresponding to 9%, 13%, and 20% of mean morbidity rate). Event studies (Figure 4) reveal no significant pre-period differences between the treated and control groups and post-period policy effects build over time. The noise in pre-period differences likely undermined the estimated policy effects for age groups 25–44. Although the pre-trend for patients between ages 45–64 are slightly above zero, the relative differences hold fixed in pre-periods, and clearly diverge...
downward in post-period estimates. The effect for the elderly clearly grows in the post-policy periods, despite the noisy pre-periods that suggest an overestimation.

Across community-level income quartiles, patients from low- and middle-income communities have the highest opioid inpatient rates and might be most responsive to PDMP integration. Patients from high-income communities, on the other hand, have more resources to travel across states and might therefore be more impacted by cross-state data sharing. In fact, patients from the two lowest community-income quartiles have the largest responses to the integration policy, with estimates of about 49 and 22 fewer inpatient discharges per 100,000. The estimate for patients in the third income quartile is 16 fewer discharges. Patients in the highest income quartile have about 12 fewer discharges per 100,000 (8% of the mean) from integration and experience nine fewer discharges associated with interstate sharing. The upward trending, statistically insignificant point estimates in the pre-period of the event study for this elderly group suggest that the integration estimate is conservative. Event studies for all other groups show lack of pre-trends and post-period integration effects that grow over time.

### TABLE 3  Baseline regression results

| Outcomes | Inpatient rate, by age group | Inpatient rate, by expected payer |
|----------|-----------------------------|----------------------------------|
|          | Overall 25–44 45–64 65+     | Medicare Medicaid Private        |
| Pres PDP | 5.053 (9.106) −2.903 6.619 (11.50) 11.62 (11.04) | 3.022 (4.478) 9.981 (9.759) 0.559 (0.727) |
| Mandate  | 20.01** (8.773) 59.96*** (18.70) 19.92* (11.69) 0.837 (10.78) | 8.291 (4.377) 25.01** (10.14) −0.0242 (0.664) |
| Integration | −25.88** (10.11) −25.84 −35.41*** (12.06) −46.07*** (14.00) | −16.46*** (5.408) −24.10** (10.15) −0.0964 (0.913) |
| Interstate | −6.716 (7.047) −9.049 −14.78 −14.39 (10.01) (8.958) | −4.245 (3.373) −1.319 (7.083) −0.699 (0.735) |
| LHS mean  | 200 289 275 228 94 99 16 94 99 228 | 1972 1927 1977 1972 1927 1977 |
| N        | 2052 2047 2046 2018 | 1972 1927 1977 |

| BS wc p-val | 0.029 | 0.229 | 0.011 | 0.007 | 0.020 | 0.058 | 0.920S |
|-------------|-------|-------|-------|-------|-------|-------|--------|
| Outcomes    | Inpatient rate, by income quartile | ER visits | Mortality rate |
|             | Q1   | Q2   | Q3   | Q4    | Q1   | Q2   | Q3   | Q4    | Overall | Illicit/syn. |
| PDMP        | −14.13 (19.07) −12.20 (12.49) 7.471 (8.157) 7.481 (5.639) | −21.52** (10.60) | −0.115 (0.196) | −0.038 (0.213) |
| Mandate     | 28.88 (17.87) 29.38*** (10.68) 19.95** (7.995) 1.483 (5.451) | 32.10** (12.19) | 0.566*** (0.210) | 0.520** (0.217) |
| Integration | −49.02** (22.07) −22.32* (11.84) −16.02* (8.232) −12.20** (4.715) | 13.57 (10.58) | 0.128 (0.211) | 0.111 (0.235) |
| Interstate  | −15.63 (14.19) −6.036 (8.476) −9.992 (6.160) −8.709** (3.391) | −2.308 (8.601) | −0.103 (0.159) | −0.191 (0.152) |
| LHS mean    | 320 219 180 138 145 2.23 1.10 2.23 1.10 1712 | 1833 1892 1890 1660 1424 2282 1712 |
| BS wc p-val | 0.038 | 0.121 | 0.095 | 0.039 | 0.243 | 0.574 | 0.687 |

Notes: This table reports the results of the baseline model using Equation (1). Each column name represents a dependent variable in a separate regression. Fixed effects for states and year-quarters are included. Wild cluster bootstrap percentile-t p-values are reported in the last row (bolded for significant cases). Robust standard errors (in parentheses) are clustered at the state level. Abbreviation: LHS, left-hand side. Robust p-values: ***p < 0.01, **p < 0.05, *p < 0.1.
A patient’s insurance status may capture both provider’s treatment incentives and personal characteristics that affect the health production function. Specifically, Medicare and Medicaid patients may over-use opioids under lenient reimbursement policies but can also benefit more from integrated PDMPs when e-billing data can be used to detect overuse. Combining results from regressions and event studies, Medicare and Medicaid patients are estimated to have the largest responses to the integration policy: −16 and −24 fewer inpatient discharges, respectively. However, these two estimates should be interpreted with caution given the weak pre-trends. In contrast, estimates for privately insured patients are imprecise, but are likely an underestimate given the clear trend reversal. Overall, results from expected payers are probably conservative given that morbidity rates calculated for this subset has smaller magnitudes compared to other stratified outcomes in the raw data.

The robustness of these main results are tested in a drop-one state analysis where one of the 26 implementing states are removed from the sample in each test. Figure A1 reports the summary results for all inpatient outcomes. The red line represents the overall estimates, and each estimate drops the state denoted on the x-axis, which are ordered by implementation date. Finding that removing a state significantly changes estimated policy impact would suggest that specific circumstances in that state drive the results. Instead, all point estimates share similar economic magnitudes with 95% confidence intervals all below zero.

Results from other outcomes, including opioid-related ER visits and mortality rates, are imprecise and inconclusive. None of the integration coefficients is significantly different from zero, and the associated event studies indicate a lack of statistical power and lack of clear impact in all these cases. Intuitively, ER visits are less responsive to policies probably because ER physicians are usually exempted from PDMP use (Blum et al., 2016). In addition, the data availability is more limited in ER than in inpatient settings (Table A1). The lack of impact in mortality results is understandable as deaths are extreme outcomes and suppressed in my data.

The above results altogether suggest that PDMP-related policies may work effectively at different stages in the medical supply chain. Given the complexity and evolving nature of the opioid crisis, a policy not significantly affecting some health outcomes may work effectively through another mechanism. For example, mandates may not have sufficient impact in time-sensitive inpatient treatment if not integrated with clinical systems, but a mandate can be easily implemented and thus deter prescription of legal opioids.28 To test the hypothesis, I repeat the main analysis on opioid prescription outcomes and find that mandates effectively reduce opioid use via the prescription channel (Table A3), especially for commonly used opioids—oxycodone and hydrocodone. All integration estimates are still negative but not statistically significant. The different results about integration and mandate indicates the value of a combination of PDMP-related policies to curb the evolving opioid crisis through different mechanisms.29

There are a few supporting results. First, although the interstate sharing coefficients are not statistically significant in most regressions, all of these estimates are negative, as expected, and sizable. Most states participated in interstate sharing before implementing integration, and the impact of sharing is not likely to reach its full potential without
FIGURE 4  Event Studies: Integration on Opioid-Related Inpatient Morbidity, Stratified. Notes: These figures report event coefficient estimates using Equation (2). Outcomes are hospital inpatient discharge per 100,000, stratified by adult age group, community-level income quartile, and expected payer. The dots are point estimates of differences in outcomes between treatment and control groups 12 quarters before and 6 quarters after implementation. The whiskers present 95% confidence intervals.
integration. Second, I test the hypothesis that integration matters more in states with higher EHR penetration by interacting integration and EHR adoption rates rather than including the two variables separately. All the main results hold, and the integration estimates are larger than the baseline estimates, confirming the hypothesis (Table A2). Third, stratified analyses across rural-urban classifications suggest that rural and median-sized metropolitan residents are most responsive to integration. Fourth, specification tests incorporating different levels of fixed effects reveal that the estimates are stronger after accounting for unobserved differences across states and year-quarters (Table A5).

Overall, I find that PDMP-HIT integration can improve opioid-related health outcomes, particularly among vulnerable populations with high morbidity rates. The lack of pre-trends supports the identifying assumption that the integration policies are exogenous; the policy on average takes two to three periods to materialize and its impact gradually builds over time.

3.3 Subsample analysis in states without a PDMP mandate

By the end of 2016, 26 states had implemented integrated PDMPs, 37 states had joined the national interstate sharing hub, and 23 states had issued PDMP user mandates. I repeat the previous analysis in subsamples of states that had never issued a mandate during my sample period to isolate the effects of integration in the absence of a PDMP mandate.

Theoretically, mandate and integration policies can facilitate PDMP utilization through different mechanisms. Mandate requires providers to access the PDMP data (with penalties for non-compliance) and can deter opioid prescription. However, the compliance rates of mandate policies are found to be under 50% in both survey and administrative data (Blum et al., 2016; Carey et al., 2021), raising questions on the effective use of non-integrated PDMP in treatment decisions. In contrast, integration can incentivize PDMP voluntarily in cases where the data are most needed. An integrated PDMP is easier to use and can harness the power of both a PDMP and HIT, especially in high risk inpatient cases where HIT analytics can be used to generate automatic alerts and analyze patient data. Most states started with one or the other policy but eventually moved towards adopting both a mandate and integration. Hence, states likely realized the value of both policies in curbing the opioid crisis at different stages.

Empirically, I cannot directly quantify the exact relationship between mandate and integration given the lack of sufficient independent variation during my sample period. Therefore, I report the results in subsamples of states without PDMP mandates to isolate the effects of integration (Table 4). In mortality regressions, none of the negative integration estimates are statistically significant at the 5% level. For opioid-related total inpatient morbidity, the integration estimate indicates 44 fewer opioid-related inpatient stays per 100,000, corresponding to about 23% of mean morbidity. Across stratified inpatient outcomes, the estimates indicate that integration policies work well for most of the subpopulations in states that never mandated PDMP use during my sample period. All of the integration estimates are negative and most of them are statistically significant at the 5% or 1% levels. Across results from stratified regressions in this subsample, most of the integration estimates range from about 15%–25% of the associated means.

The hypotheses across stratified populations follow the same idea as discussed in the previous section: at-risk populations should benefit more from a well-integrated system under the PDMP-HIT integration policy. Indeed, the reductions are most substantial among the most vulnerable groups: middle-age patients (especially those in prime working age), patients from low-to middle-income communities, and publicly insured patients. Per 100,000 population, patients in the 25–44 and 45–64 age groups have 61 and 46 fewer inpatient discharges; patients in income quartiles 1, 2, and 4 have 83, 32, and 18 fewer discharges, respectively. Patients in income quartiles 3 and 4 are also estimated to have fewer discharges associated with interstate sharing at 1% and 10% levels, respectively. Integration policies are estimated to reduce inpatient discharges of Medicare and Medicaid patients by about 19 and 37 per 100,000. The magnitudes of these estimates are larger than the counterparts in the main specifications (Figure A3).

I also ran an alternative test using the sample of all states without observations in post-mandate state-quarters and find consistent results. Prior studies suggest no systematic differences between pre-mandate period outcomes in states that ever or never issued a PDMP mandate (Buchmueller & Carey, 2018; Dave et al., 2017). Thus, this exercise aims to provide estimates for integration effects net of the post-mandate effects while maintaining a larger sample with more state-quarters. The pattern of integration estimates is similar to that in the subsample results, and the magnitudes of these estimates are between those in the no-mandate subsample and the baseline. Results are available upon request.

In the context of the existing literature, my results complement Buchmueller and Carey (2018), who mention the importance of integration, but were not able to measure it explicitly due to the lack of data in their earlier time periods. Their finding that mandate can drive up prescription shopping in neighboring states also suggest the importance of
integration and interstate sharing. My results are also consistent with Alpert et al. (2018) in the sense that supply-side policies alone can have unintended consequences in the presence of illicit substitutes to prescription opioids. The unintended consequences of PDMPs are substantial when accounting for heroin‐related crimes (Mallatt, 2018). Quantifying the exact effect of each policy across markets is beyond the scope of this paper.

Meanwhile, technology‐based policies can mitigate these concerns by improving treatment and prevention to help close the gap between supply‐side policies and demand‐side patient behavior adjustments.

3.4 | Alternative measures: complementarity between integration & interstate sharing

Integration and interstate sharing are technology‐based designs to improve PDMPs. While integration lowers the costs of accessing and analyzing PDMP data, interstate sharing improves PDMP data quality. The impacts from integration and interstate sharing are likely larger when implemented together. The state‐quarter level correlation between PDMP integration and interstate data sharing participation is about 0.38, and both gradually rolled out as shown in Figure 2. Since most of the integrations are implemented relatively late compared to the relatively widely participated interstate sharing, there is some state‐quarter level variation for a test on the relationship between these two technology‐based PDMP designs.

To do so, three mutually exclusive variables are included to replace the integration and interstate sharing variables in the baseline model: “integration & interstate,” “integration only,” and “interstate only.” Table 5 reports the results and suggests that there is some complementarity between integration and interstate sharing. The overall pattern of the results is similar to that of the baseline analysis, except now much of the effects are captured by the coefficient “integration & interstate,” while “integration only” has smaller independent effects. These results provide suggestive evidence that integration could work better with high‐quality data shared from other states, but these results need to be interpreted with caution because the test is more correlational than causal in nature.

### TABLE 4 Subsample analysis in states without prescription drug monitoring program (PDMP) mandates

| Outcomes | Inpatient rate, by age group | Inpatient rate, by expected payer | ER visits | Mortality rate |
|----------|-----------------------------|---------------------------------|-----------|---------------|
|          | Overall 25–44 45–64 65+ Medicare Medicaid Private | Overall Q1 Q2 Q3 Q4 | Overall illicit/syn. |
| Integration | −43.69*** −61.46** −46.12*** −49.94*** −19.18*** −36.55*** −0.934 | (13.33) (22.11) (15.28) (16.10) (6.824) (12.11) (1.417) | 5.373 0.150 0.183 |
| Interstate | −11.70 −10.37 −25.38* −25.99* −5.784 −3.632 −0.360 | (9.601) (16.58) (14.42) (13.81) (4.214) (9.979) (1.326) | 0.624 −0.116 −0.0736 |
| LHS mean | 187 242 274 249 97 94 15 | | 1.8 0.89 |
| N | 1108 1103 1102 1078 1076 1031 1086 | | 961 1012 1010 862 804 1237 818 |

Notes: This table reports the results of subsample regressions of Equation (1) in states that did not mandated PDMP access during my sample period. Only coefficients of interest are reported for simplicity. Each column name represents a dependent variable in a separate regression. Fixed effects for states and year‐quarters are always included. Robust standard errors are clustered at the state level and are reported in parentheses.

Abbreviation: LHS, left‐hand side.

Robust p‐values: ***p < 0.01, **p < 0.05, *p < 0.1.
## Limitations

The use of an aggregate, stratified hospital discharge dataset provides clear advantages in capturing overall opioid-related morbidity that incorporates the substitution between different types of opioids, but it also has some limitations. Because the underlying data are at the discharge-level instead of the patient-level, I cannot distinguish between reduced hospital visits among patients with an opioid use history versus fewer opioid initiations. Also, due to patient privacy protection, outcomes are aggregated at the state level without individual identifiers, so the precise amount of reductions in cross-state doctor-shopping are not estimated. Finally, the integration policy indicates when a state implements any infrastructure for providers to use PDMPs within any HITs in their workflow. Detailed data on the heterogeneity of what type of HIT system is integrated with the PDMP and the extent of integration are not available.

## ROBUSTNESS CHECKS

### 4.1 Testing confounding policies & demographic controls

An assumption in the empirical analysis is that the integration variable is not capturing impacts generated by other related policies implemented concurrently. This assumption is justified both qualitatively and quantitatively. State regulations on health and technology were searched but no other policies were found that would create similar
mechanisms as defined by “integration” in this paper. This investigation was confirmed with legal experts and state PDMP/HIT managers. The pairwise correlations between integration and other policies (mentioned in Section 3.1) are all below 0.34, suggesting these policies work through different mechanisms at different times. Besides, the main results stay similar without demographic controls, despite changes in age structure during the sample period that may be associated with opioid use.

To empirically test the sensitivity of the main results, three sets of specifications with much simplified observable controls are tested and reported in Table A4. These specifications include only main PDMP and HIT controls, added only potential confounding policy controls, or added only demographic factors as observables. The estimated results are not much different from those of the main specification. This test supports the idea that other concurrent policies or changes in demographic factors are not driving the results for integration.

4.2 | Placebo tests

A set of placebo regressions are estimated to test for the effect of PDMP-HIT integration on a set of morbidity rates for a few common types of reasons: total inpatient stays not involving opioids, total inpatient stays caused by injuries not involving opioids, inpatient stays for non-opioid-related mental health and substance use, and inpatient stays for surgery. The rationale is that if the integration policy is somehow correlated with general trends in morbidity, then I might incorrectly attribute the change in health outcomes to the integration policy. Thus, the placebo outcomes should be health conditions not directly related to controlled substances that usually do not require advanced treatments where PDMP-HIT integration can generate spillover effects. When the analyses are repeated on the placebo outcomes, none of the integration estimates is similar to those found in main results (Table A6).

4.3 | Treatment heterogeneity: Bacon decomposition analysis

In this setting, as in many other contexts, the treatment is staggered over time in a multi-treatment group difference-in-differences setting (Goodman-Bacon, 2018). States that implemented integration later serve as control states for states that implemented integration earlier, and states that never had an integration during the sample period can serve as control groups. In my case, there are no “always integrated” states. The Bacon decomposition helps disentangle how much of the treatment effect is a result from timing and these different control states (“Timing Groups”) as compared to a simple, “clean” control state where integration was never implemented over the entire sample period (“Never vs. Timing”). As shown in Table A7 and Figure A2 most of the estimated treatment effects (about 65%) stem from a comparison of treated states with never-treated states, with treatment magnitudes similar to the average treatment effect estimates. Integration effects from differential treatment timing account for a much smaller share (about 28%). The “within” variation derived from changing observables contributes to much smaller effects (<10%), suggesting that including or excluding observable controls would not substantially alter the coefficient estimates. The specific weights for each estimation vary to a small extent, mainly reflecting differences in data availability across outcome variables.

4.4 | Alternative PDMP operational dates

In the main specification, both regular PDMP operational dates and PDMP “modern system operational” dates (Horwitz et al., 2018) are controlled. As a robustness test, Table A8 reports estimating the main results using different coding of PDMP operational dates following definitions used by various sources: using only one of the two main operational dates, or using only dates defined and provided by NAMSDL, PDAPS, and Brandies TTAC, respectively. All coefficient estimates in terms of magnitudes and significance levels remain very similar to the estimates in the main results. Table A9, Table A10.

5 | CONCLUSION & DISCUSSION

This paper finds strong evidence that policies enabling PDMP-HIT integration effectively reduce opioid-related inpatient morbidity rates. The estimated overall morbidity reduction is about 13% of average opioid-related inpatient rates
and are robust to stratified analyses. A mechanism test suggests that integration mainly affects the hospitalization stage by providing better use of data for inpatient treatment. The morbidity reductions are substantial in states with integrated PDMPs and without mandated PDMP access. In addition, the impacts are strongest among the high-risk, vulnerable groups in this crisis: middle-aged patients, people residing in low-to middle-income communities, and patients with public insurance. Since concurrent policies are implemented and demographics changed during the sample period, robustness tests indicate that the results are robust to excluding some or all of these policy and demographic controls. The estimates are not driven by results from a few states and stay similar when decomposed to different subgroups in a treatment heterogeneity analysis.

Although many states have demonstrated significant effort in integrating PDMPs with HITs, there are substantial lags in some states. Meanwhile, the estimated annual social cost of the opioid crisis ranges from $293.3 billion to $622.1 billion, using a wide range of statistical values of life (CEA, 2017). Consequently, a 10% reduction in mean inpatient morbidity may generate annual savings of $29.3-62.2 billion. Even an exaggerated $500 million/state investment to implement integration suggests that such implementation would generate savings far exceeding the associated costs.

This paper suggests that a PDMP can be more effective when combined with technology-oriented designs including integration. States that proactively implemented PDMP integration benefited from morbidity reductions. More research and data are needed to systematically evaluate the best practices and strategies in improving PDMPs with technology. Practitioners, engineers, and policymakers may want to consider collaborating to improve PDMP designs to enhance the overall impact. Once PDMPs become more user friendly and fully integrated into clinical workflow, providers may voluntarily use it more frequently and effectively; therefore, the compliance rates for other PDMP-related policies may also increase. All of these can help providers to make more informed decisions quickly for patients with opioid-related issues.

Beyond the focus on PDMP-HIT integration in this paper that can streamline physicians' data access and analysis, other innovations in digital health can help mitigate the opioid crisis in broader dimensions, such as electronic prescription of controlled substances and direct-to-consumer behavioral nudges through mobile applications. These promising innovations mostly came after my sample period, and thus are not included in this paper. In addition, individual providers can further design their HIT analytics to use integrated PDMPs more effectively. Overall, the potential of leveraging health IT to combat the opioid crisis is substantial and thus deserves more practical investments and academic investigation.

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CONFLICT OF INTEREST
The Author has no conflict of interest to disclose.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon request.

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ENDNOTES

1. Benzos are Schedule IV drugs. Some prescription drug monitoring programs (PDMPs) do not record Schedule III–V drugs. As of 2013, Pennsylvania monitors Schedule II drugs only and Rhode Island monitors Schedules II and III (source: https://www.bja.gov/Publications/PDMP_PPR_Jan-Dec13.pdf). Even when benzo and opioids are both recorded, it is not easy to use multi-drug records for a patient without health information technology (HIT) analytics (Zaman et al., 2018).

2. Pilot projects involve extensive collaboration with electronic health record vendors, such as Appriss Health, Epic, Dr. First, and NextGen. Project details are available via https://www.healthit.gov/PDMP.

3. The legislative information is collected from a combination of public sources, numerous phone calls, and email communications with legal experts and state PDMP/HIT agencies.

4. Electronic Prescription for Controlled Substances (EPCS) has been legal only since June 2010, when the Drug Enforcement Agency revised the rules (DEA, 2010). According to Surescripts', fewer than 1% of physicians enabled EPCS by the end of 2015 in most states. I abstract away from this issue in this study.

5. A quote from a physician was reported on healthIT.gov: “I have to say that this is probably one of the more genius moves of the 21st century...having easy access to [the PDMP] without going to a totally different website and have it pop up instantly has taken a lot of time off of decision making for me.”

6. Source: https://www.medicaid.gov/federal-policy-guidance/downloads/smd18006.pdf

7. Mandates are coded under “broad circumstances” as in Buchmueller and Carey (2018). The Delaware mandate date is recoded to its operational date, as the mandate was issued before PDMP operated there.

8. Due to differences in raw data sources and definitions, there are inconsistencies in the policy dates, and many records are at the year level. For each inconsistency, I researched statutes, administrative codes, state documents, and consulted legal experts and state PDMP managers to improve coding accuracy.

9. PDMP is defined as operational when the core functionality of the electronic PDMP database becomes available to users (in line with main sources and the view of practitioners/providers). The definition in Horwitz et al. (2018) often includes sophisticated system updates and expansion in access methods to existing PDMPs. Both aspects are important conceptually and thus controlled in the baseline. Table A8 shows robust results controlling for one of the dates or other alternative PDMP dates.

10. I do not distinguish between specific HIT intermediaries utilized across states in the integration. The ability to integrate data into the HITs is an informative measure of the extensive margin of integration.

11. Anecdotes indicate that the time of doctors’ data access can be reduced from 5 to 10 min to 2 s with their technology. https://app.brainshark.com/appriss/vu?pi=zf0zuhID0zUwYDz0knodesktopflash=1

12. This definition does not include narrow integration, such as pilot integrations that were limited to a set of EHR users (e.g., Kentucky), or a program that became problematic and was suspended (e.g., Indiana).

13. The PMP InterConnect is also referred to as PDMPi Hub—the earliest and only national hub started in 2011. There is an alternative RxCheck Hub with only three non-bordering participating states by the end of 2015 (AL, KY, and ME); KY also joined the PMP InterConnect. I do not have data on this hub. Their collective data exchange is minimal in scale, and my results are robust to dropping these three states.

14. The state must have transferred data with at least one hub-participating state once it went live; this does not ensure data transfer between all bordering states. The timings of pairwise sharings are not available.

15. The rates are linearly interpolated to the quarter-level. Basic EHRs are the most widely used HITs, and basic EHR adoption rates are most representative of HIT levels in terms of clinical support. Advanced HITs that add business functions are less relevant in my case. The results are robust to alternative measures such as EHR incentive payments to hospitals, with data available from the CMS (Table A9).

16. The expected payer-specific measures are only available in counts instead of rates from HCUP. I calculated the denominators using the insurance coverage data by insurance type from the Census’ Current Population Survey (2005–2012) and American Community Survey (2013–2016).

17. The ER data captures hospital visits that do not result in admissions, and those ER visits result in inpatient admissions are recorded in the inpatient data (i.e., patients with more severe conditions).

18. The Healthcare Cost and Utilization Project (HCUP) decided it is impossible to extract illicit opioid morbidity in most diagnosis code series.

19. Opioid-induced death (multiple causes of death using ICD10 codes: T36-T50). These ICD codes are constructed following CDC and Case-Deaton (2017). CDC WONDER would suppress data when case counts are less than 10. Due to data access issues, I cannot use the restricted-access US death certificates directly. Mortality results should be interpreted with caution and as supplementary outcomes.

20. Quarterly population are linearly interpolated from the annual SEER data, as in Evans et al. (2018).

21. Conversion factors follow Piper et al. (2018) and CMS recommendation: codeine 0.15, buprenorphine 10, oxycodone 1.5, hydromorphone 4, hydrocodone 1, meperidine 0.1, fentanyl base 75. The conversion factor for methadone depends on the range of daily doses; both 12 and 8 are used for robustness checks.

22. An indicator variable on observation-level missing status is generated for each outcome, which is then regressed on policy variables and fixed effects. None of the coefficients is significant. The data provider stated that the pattern of missing data stems from the completeness of the data provided by the states.

23. In all of the specifications, I run the analysis on both the full sample and on the sample excluding states without an operational PDMP during the sample period. All states except Missouri had enacted PDMPs by the end of 2016, and the District of Columbia started operating...
its PDMP in late 2016. The results are similar in both samples and are reported for the full sample for simplicity and with a larger sample size.

24 EHR is the most common type of HIT adopted and is often used to represent the broad scope of HITs used in clinical settings. This is also the only consistently measured HIT variable in the AHA IT sample.

25 The standard error estimates are likely conservative for the mortality analysis according to new methodology that emphasizes design-based approaches to clustering (Abadie et al., 2017).

26 Data more than three years before and more than two years after an event are recoded to $j = -12$ and $j = 6$, respectively. The results are similar if data outside of the event window are dropped from the coding.

27 There is no clear hypothesis concerning stratified ER outcomes, and note that the coefficient estimate is not statistically significant for opioid-related total ER visits. The regression results and associated event studies using stratified ER outcomes are reported in Table A10 and Figure A3.

28 For example, if a patient were admitted to the hospital due to an illicit opioid overdose, doctors would not find prescriptions in a non-integrated PDMP, undermining the impact of a mandate. Meanwhile, an integrated PDMP records the patient’s disease and treatment history, making it easier for doctors to detect a potential illicit use and analyze drug interactions in treatment design and future prevention.

29 The results also reflect institutional features that make inpatient settings most likely to benefit from integration. Inpatient settings often require extensive documentation of care parameters (Office of the National Coordinator, 2020). Practitioners advocate for integration to inform comprehensive, coordinated, and effective treatment plans by utilizing data from patient admission, discharge, and transfer (National Governors Association, 2020). Mandating a non-integrated PDMP is found to be non-effective and inefficient in outpatient settings (Stucke et al., 2018).

30 This specification assumes a linear effect of percentage EHR adoption. Appendix Table A2 reports the results. Equation (1) reminds the preferred specification with weaker and more standard assumptions.

31 22 states have both PDMP integration and interstate sharing, and integration is typically the later one implemented. Among the 34 states with either integration or a mandate, 11 of them had integration without a mandate, eight had a mandate without integration, and 15 states had both integration and a mandate - among those, seven states implemented integration at the same time or before a mandate.

32 In the absence of detailed morbidity data, I cannot examine how integration affects morbidity related to drug switching/shopping behaviors. I also tried a two-layered event study to estimate a mandate-integration interaction beyond the two baseline policies, but the sample does not provide enough power.

33 By the end of 2016, 22 states implemented both integration and interstate sharing, four states only have integration without interstate sharing, and 15 states have only interstate sharing without integration.

34 Some limitations may be overcome with hospital-level data in a given state as in McKenna et al. (2018).

35 Data are aggregated from HCUP Fast Stats State Trends in Hospital Use (Inpatient Stay). Ideally, the placebo outcomes may also have similar incidences as opioid-related outcomes. However, the opioid crisis is unique and no other diseases are creating a problem with comparable magnitude.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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