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The Spillover Effects of Prescription Drug Monitoring Programs (PDMPs) Integration and Data Sharing on Opioids Prescribing Rate

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Short Paper

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Abstract

To reduce the supply of opioids to non-medical users in the U.S., many states have implemented Prescription Drug Monitoring Programs (PDMPs) to collect patients' opioids purchase history and provide physicians this information. We study the impact of two PDMP-enhancement policies: 1) within-state IS integration, which aims to integrate a state's PDMP into local hospitals' health information technologies (HITs), and 2) interstates IS data sharing, which facilitates the interoperability of PDMP data across states line. We construct a county-level panel dataset from 2006 to 2017. First, we do not find evidence that PDMP integration could reduce the focal state's regional opioids prescribing rate; instead, we find that a focal state's PDMP integration triggers doctor shopping phenomenon by increasing the opioids prescribing rate of counties located in neighboring states, suggesting the negative IT spillover effect. Second, we find nuanced evidence that PDMP interstate data sharing can mitigate this negative spillover effect, showing the positive information externality.

Keywords: Opioid crisis, health IT, information externality, PDMP

Introduction

Prescription opioids, such as OxyContin, can effectively alleviate acute pain when properly used. But non-medical or improper use would lead to severe health problems, such as addiction and even death. In December 2017, the Donald Trump Administration declared the opioids crisis in the U.S. as "national health emergency". According to the U.S. Department of Health and Human Resource (HHR), more than 130 people per day die due to opioid-related drug overdoses[1] (HHR, 2019).

The over-prescribing of opioids has been identified as one of the major factors contributing to the opioids epidemic. Basically, patients can seek opioids from two different channels: the legal channel where physicians make prescriptions, and the alternative channels, such as asking from a friend or relative and buying from the illegal market. Among the 11.5 million people who used pain relievers in 2016, only 36.8%

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[1] See at https://www.hhs.gov/opioids/, accessed on April 15, 2019.

of them obtained the drugs from a health care provider (NSDUH, 2017). Consistent with this fact, the physicians on average prescribed 20% to 46% more than the amount of opioids actually needed (Schnell, 2017). The excess of prescription opioids would easily be transferred via the alternative channels; 53.0% of pain relivers users obtained drugs from a friend or relative, and 9.4% bought from drug dealers or some other ways (NSDUH, 2017). Therefore, due to its importance in limiting excessive drug supply, reducing opioids prescribing rate could be one of the first steps to fight with the opioids crisis.

To respond to the increasing non-medical use opioids, many states have legislated and invested in state-run Prescription Drug Monitoring Programs (PDMPs), a health information system (IS) which collects and distributes data about the prescription and depensation of federally controlled substances. Each state PDMP records patients' opioids consumption information when they get prescription opioids from dispensers, and this information could be retrieved from the PDMP's web portal by authorized physicians. Therefore, PDMPs are supposed to provide physicians better knowledge of a patient's true health status and to evaluate whether to prescribe opioids and if yes, the proper dose to be prescribed. However, prior literature has found that PDMPs have on average little effect. One important reason is that many physicians regard it as a cumbersome and inefficient process to review patients' records.

In this paper, we focus on two complementary IS policies which aim to enhance the effectiveness of PDMPs in terms of reducing physicians' opioids prescribing rate, as shown in Figure 1. The first policy is to integrate state PDMPs into local Health Information Technologies (HITs) like Electronic Health Records (EHR), Health Information Exchanges (HIE) and/or Pharmacy Dispensing Systems (PDS). We refer it as "Integration Policy" which aims to integrate a sperate IS (PDMP) into local practitioners' clinic workflow, liberating physicians from significant search cost such as registration, logging into the state PDMP website, entering search inquiry and waiting long time for system responses. After integration, a physician can quickly or even automatically retrieve the PDMP data from EHR interface.

We argue that although the PDMP integration policy may help prescribers identify risky prescriptions easily and reduce the focal state's opioids prescribing rate, it could trigger patients' strategic response. Opioid-addicted patients may strategically visit doctors who are located in a neighboring state and thus have less information about their opioid usage history, so called the doctor shopping phenomenon. Because of the "information silo" problem, it could be easier for those patients to get drugs from doctors who are located in the different states. As a result, the PDMP integration policy in one state may lead to an increase in opioids prescribing rate of the neighboring states. The first goal of this paper is thus to empirically examine this negative externality of PDMP integration.

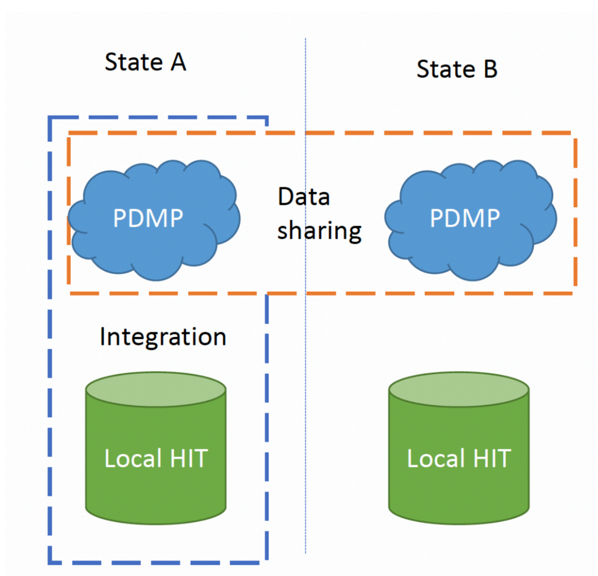

Figure 1. Within-state PDMP Integration with HITs and Interstate PDMP data sharing

The second policy of interest is to facilitate PDMP data sharing across different states. We refer it as "Data Sharing Policy". States implemented this policy by joining in a data sharing hub that allows for interoperability of PDMPs in the neighboring states. The policy authorizes the physicians in a focal state to retrieve data from PDMPs of partnered states, thus enabling them to identify potential patients at risk of overdose who come from other states. We argue that PDMP data sharing beyond geographical boundary is critical in preventing the patients' doctor shopping behavior. The second goal of this paper is thus to empirically examine if PDMP data sharing between two neighbor states can mitigate the negative spillover effect of the neighboring state's PDMP integration on the focal state's opioid prescription rate.

To examine the spillover effects of the two policies, we exploit the fact that the two PDMP-enhanced polices were implemented into different states over various time periods, thus creating a natural experiment setting. We construct county-level panel data containing all U.S counties (except for those located in Alaska and Hawaii) from 2006 to 2017. We run regressions of county-level opioid prescribing rate to estimate the effects of the two policies. To address the potential endogeneity of the state-led implementation of the two policies, we perform looking-ahead propensity scores matching (LA-PSM) using county-level features to construct the comparable treated and control counties.

The empirical results show that the effect of PDMP-HIT integration on the opioid prescription rate (about 0.96 prescription per 100 persons) of its affiliated counties is minimal, but it has a significant spillover effect on neighboring states; the PDMP integration in a neighboring state on average leads to an increase of about 2.1% in the focal state's opioid prescription rate (about 1.76 prescriptions per 100 persons). Interestingly, the PDMP data sharing between states can significantly mitigate the negative spillover effect of the PDMP integration. If two states share PDMP data, the PDMP integration in a neighboring state on average leads to a decrease of about 3.5% in the focal state's opioid prescription rate (about 2.95 prescriptions per 100 persons).

Our paper makes several theoretical contributions and policy implications. First, our work directly contributes to the specific stream of research on the relationship between PDMP use and physician behavior, and the literature on the general IT spillover effect. We add a new piece of causal evidence for whether PDMP can enable physicians to make less risky prescriptions. In contrast to the few prior studies that explore the relationship between PDMP enhancement and healthcare outcomes in same region, this paper is the among the first to demonstrate that health IS policy can impact physician behavior beyond the adopting state, that is, the spillover effect of PDMP integration. Second, prior literature on IT spillover effects usually evaluate only one specific IS or IS policy, investigating its impact beyond a focal firm, industry, or region. Our research framework accommodates two distinct but related IS policies, enabling us to explore how one IS policy could serve as the boundary condition of mitigating the other IS policy's spillover effect. Last but not least, our findings suggest important policy implications to federal health policy coordinators and state PDMP managers, including the untended consequences of PDMP integration on neighboring states, and the importance of joining in interstate PDMP data sharing hub to systematically fight with the opioid doctor shopping phenomenon.

Related Literature

Impact of PDMP on the Opioid Epidemic

Except for Missouri, every state has run its own PDMP. Ideally, PDMPs are supposed to help physicians quickly detect risky controlled substance prescribing. Some literature has evaluated its effectiveness on the supply and demand sides of opioid prescription. Overall, existing literature shows mixed and inconclusive findings (Haegerich et al. 2014). On the demand side, earlier studies tend to indicate that PDMPs have no effect or little effect, in terms of lower opioid consumption or opioid related mortality, misuse rate (Paulozzi et al. 2011: Reifler et al. 2012). Another study uses a sample of disability enrollees from 2006 to 2012 and finds no relationship between PDMP implementation and reduction in high-risk opioids or treatment for prescription opioid use (Meara et al. 2016). More recent articles find that operational PDMP is associated with positive consequences, including reduction in opioids-related death rate, risk of prescription opioid-related poisoning, (Patrick et al. 2016; Pauly et al. 2018;). On the supply side, physicians' prescribing decision can be affected by PDMP intervention. For example, Bao et al. (2016) finds that implementation of PDMP is associated with reduction in the prescription rate of Schedule II opioids. Chang et al. (2016)

finds that in Florida, the impact of PDMP on reducing opioid prescriptions concentrates on high-risk prescribers.

Organizational adoption of health IS does not necessarily guarantee individual adoption or actual use (Lin et al. 2019). The effectiveness of PDMP seems to be contingent on complementary policies that technically or legislatively enhance its use. For example, several studies find that states having implemented PDMP mandates for prescribers, delegation laws, PDMP integration into EHRs, or interoperability of interstate data exchange, saw a reduction in opioids prescribed to Medicaid enrollees, opioid-related mortality and morbidity, high-risk opioid prescriptions (Wen et al. 2017; Bao et al. 2018; Pauly et al. 2018; Wang 2019). However, those existing studies do not consider the fact that opioid-addicted patients could shop over physicians outside the adopting state as strategic response, and thus neglect the possibility that PDMP enhancement policies may have untended effects beyond the adopting states. Our work fills in this research gap by providing empirical evidences of the spillover effects of a focal state's PDMP policies on geographically bordering states.

IT Spillover effects in Healthcare

The IS field has been traditionally interested in IT spillover effects in business settings, especially supply chain management and IT productivity. Scholars have accumulated a large body of evidence on this research stream (e.g. Cheng and Nault 2012; Tambe and Hitt 2014). In the context of healthcare, solid empirical evidence for IT spillover effect is not too much. Several studies have found that health IT adopted by a focal hospital could generate spillover benefits to other hospitals through forming information sharing network. For instances, Ayabakan (et al. 2017) find that health information sharing can significantly reduce duplicate testing rate in the Texas's hospital network. Atosay et al. (2018) find that although EHR investment increases the cost of the adopting hospital, it can reduce the cost of neighboring hospitals. Both the two studies suggest that information sharing is one of the main mechanisms driving health IT's spillover effect.

As the empirical research on information externality of health IT is rather limited, we contribute to this niche topic by showing that not all health providers can benefit equally from health IT. In our research setting, physicians make prescribing decisions based on their beliefs about a patient' health status. However, these beliefs are not always formed precisely due to information asymmetry. While PDMP integration can update a physician's knowledge of a patient's opioid use information within that state, physicians working in other states can never obtain this information from their own PDMP if there is no interstate PDMP data sharing. Anticipating this situation, strategic patients may visit physicians who are in a neighboring state and have little information about their opioids use history. Thus, PMDP integration can trigger doctor shopping and interstate PDMP data sharing can mitigating this externality. The two health IS enhancement policies can have opposite spillover effects and are complimentary to each other.

Data and Measurements

We constructed a longitudinal dataset from multiple sources. We collected state and county level prescription rate from Centers for Diseases Control and Prevention (CDC). CDC's website provides U.S. opioid prescribing rate maps, portraying these rates of U.S. states and counties for a given year from 2006-2017[2]. Opioid prescribing rate is defined as retail opioid prescriptions dispensed per 100 persons per year in a state or county. The unit of analysis is at county level, as the sample size is large compared to state level analysis and allows for more heterogeneity with fixed effect econometric specifications.

To define PDMP integration, we use a time-varying dummy variable to indicate whether a focal state has integrated its PDMP into local HITs in a given year. We search this information from each state PDMP's website, reports of PDMP enhancement projects sponsored by federal health administrative sectors such as Substance Abuse and Mental Health Services Administration (SAMHSA), CDC, and cross validate with existing literature (Wang 2019).

[2] See CDC's Opioids Overdose website at https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html.

To define PDMP data sharing, we create two distinct but related measurements. The first measurement is following Wang's (2019) definition as "exchange of PMP data across state boundaries through the only following national hub —PMP InterConnect".[3] So a PDMP data sharing dummy will equal to 1 if a focal state has joined in the hub in a given year; and 0, otherwise. An obvious drawback of the measurement is that it only captures a focal state's unilateral efforts, but fails to reflect the bilateral relationship between bordering states. We noticed the fact that PMP Interconnect is directly governed by the representatives of PDMPs participating in the hub. Each state member of the PMP InterConnect maintains complete autonomy over which state can access to its PDMP through the hub. When practitioners wish to get PDMP data other states, they should firstly retrieve from their home-state PDMP and only if their own PDMP had been granted access, the relevant data could be obtained. Therefore, we argue that it would be more meaningful to develop a new bilateral measurement. For a focal state in a given year, we assign a new interstate data sharing dummy to be 1 if at least one of its bordering states has become the focal state's data sharing partners before the end of that year, conditional on both the focal state and the parterner state having joined in PMP InterConnect hub. We use the Interstate Data Sharing Partners report released by the PDMP Training and Technical Assistance Center (PDMP TTAC) to predict this variable[4].

In the empirical analysis, we adopt the second measure for estimation. It is worthy noted that the two variables are highly correlated (0.88). When using the first unilateral measurement, the empirical results remain qualitatively similar. One possible concern is that for a focal state, its first state to implement PDMP integration may not be the first state to become its data sharing partner. If there are many states to be this case, it would be difficult to estimate the moderating effect of data sharing due to measurement error. Checking our sample set, we find that only one state is in this situation (Nebraska did integration in 2011 but hadn't done data sharing during our sample period), and other states usually tend to firstly form data sharing partnership with neighbor states adopting PDMP integration.

To account for potential confounding variables that may affect opioid prescribing rate at each county, we controlled some PDMP-related dummies and demographic and socioeconomic factors. We controlled two dummies indicating whether a focal state in a given year has implemented PDMP or not, and whether that state has legislatively mandated PDMP use for practitioners. These data were collected from policy reports released by PDMP TTAC and PDMP Center for Excellence at Brandeis University. Besides, population size, employment, average personal income data were obtained from the regional database of Bureau of Economic Analysis (BEA). Age and ethnicity portion data were retrieved from the Surveillance Epidemiology and End Results (SEER) database. Following Chan and Ghose (2014), we calculated the proportions of 15-24 age group, 25-34 age group, and the portions of white American, as age and ethnicity composition may influence the frequency of seeking risky fun among population.

The summary statistics of our dataset are provided in Table 1. The panel data contains observations of 2772 counties located in 48 states and the District of Columbia from 2006-2017.

Table 1. Summury Statistics

Variable	N	Mean	St. Dev.	Min	Max
Prescribing_Rate	28,850	84.09	44.25	0.00	437.20
Integration	28,850	0.11	0.31	0	1
Sharing	28,850	0.22	0.42	0	1

[3] Here PMP is an abbreviation equivalent to PDMP. The official website of PMP InterConnect can be visited at https://nabp.pharmacy/initiatives/pmp-interconnect/.

[4] The report released by the Brandeis University is available at TTAC website: http://www.pdmpassist.org/pdf/Interstate_Data_Sharing_Partners_20180904.pdf. Besides, our predictions need one additional assumption that state PDMP managers tend to prioritize data sharing with their neighbor states. We believe that it is quite reasonable assumption, as that's the primary motivation why the PDMP directors required to develop and participate in PMP InterConnect.

Neighbor Integration	28,850	0.27	0.44	0	1
PDMP	28,850	0.77	0.42	0	1
PDMP Mandate	28,850	0.11	0.31	0	1
Log(employment)	28,850	9.75	1.37	6.59	15.54
Log(population size)	28,850	10.46	1.31	7.08	16.09
Log(income)	28,850	10.47	0.24	9.62	12.36
White American Portion	28,850	0.87	0.15	0.10	1.00
Age 15-24 Portion	28,850	0.13	0.03	0.04	0.42
Age 25-34 Portion	28,850	0.12	0.02	0.05	0.28

Table 1. Summary Statistics

Empirical Methodology and Preliminary Results

To fulfill the goal of evaluating the impact of PDMP integration and interstate data sharing on regional opioid prescribing rate, we exploit the fact that the two policies were implemented into different states over various period to conduct difference-in-differences (DID) estimator. This identification strategy has been adopted by prior IS literature (e.g., Chan and Ghose 2014; Greenwood and Agarwal 2016). We specify a reduced-form econometric model as the following form

$$y_{it} = \beta_1 Integration_{it} + \beta_2 Sharing_{it} + \beta_3 Neighbor\_Integration_{it} + \beta_4 Neighbor\_Integration_{it} * Sharing_{it} + \theta_1 PDMP_{it} + \theta_2 PDMP\_mandate_{it} + \theta_3 PDMP\_mandate_{it} * Integration_{it} + \boldsymbol{A_i} + \boldsymbol{B_t} + \boldsymbol{X_{it}\delta} + \epsilon_{it} . \quad (1)$$

Subscript i and t index county and year respectively. The dependent variable y_{it} is the opioid prescribing rate of county i in year t. We don't log transform it as its distribution shows no dispersion. $Integration_{it}$ is a binary variable for a focal county's PDMP integration. $Integration_{it}$ = 1, if in a particular year, a focal county is located in a state that having implemented PMDP integration before the year; otherwise, $Integration_{it}$ = 0. Similarly, $Sharing_{it}$ is a binary variable denoting for whether a focal county affiliated to a state that has formed PDMP data exchange partnership with at least one of its geographically bordering states. $Neighbor\_Integration_{it}$ is a dummy indicating whether in given year at least one of neighbor states has implemented PDMP integration. The coefficient β_4 on the interaction term captures the moderating effect of PDMP data sharing on the association between neighbor states' integration on the focal county's opioid prescribing rate. We also include two confounding PDMP-related dummies. $PDMP_{it}$ denotes whether a focal state has operational PDMP, and $PDMP\_mandate_{it}$ denotes whether that state has legislatively mandated PDMP use for practitioners before they make prescribing decisions. The interaction term of PDMP mandate use with Integration is added, as prior literature has found their amplifying effects to each other (Bao et al. 2018; Wang 2019). $\boldsymbol{A_i}$ and $\boldsymbol{B_t}$ are vectors of county fixed effects and year fixed effects. $\boldsymbol{X_{it}}$ is a vector of demographic and socioeconomic factors, capturing time-varying heterogeneity across counties. These control variables include population size, employment, average personal income, ethnicity portion of white American people, age 15 to 24 portion indicating teenager population and age 25 to 34 indicating working class population.

Our preliminary results are offered in Table 2, with clustered standard error at county level. In Model 1 and Model 2, we show regression results using the full sample. In Model 3 and 4, we run regressions combined with the looking-ahead propensity scores matching (LA-PSM) technique. The LA-PSM technique is used for addressing potential endogeneity issues by matching a unit treated in time t with control units who have not been treated at that time but would be treat in a future time. This method has been used in prior IS literature (e.g., Burtch, Carnahan and Greenwood, 2018). While Model 1 and 3 are baseline regressions that does not include the variables of interests, results of Model 2 and 4 are full models. Across all models, the estimated coefficients of Integration is insignificantly negatively, suggesting that the effect of PDMP integration in reducing a focal state's regional opioid prescribing rate is minimal. The estimated coefficients of Neighbor Integration in Models 2 and 4 are positive and significant, suggesting a negative spillover effect of a neighboring state's PDMP integration on a focal county's prescribing rate. Taken together, the results show that PDMP integration triggers 2.8 pieces increase in a near state's opioid prescribing rate. Besides, consistent with our conjuncture, interstate PDMP data sharing plays a key role in mitigating the negative externality of integration. The large magnitude of coefficient on the interaction term of neighbor integration with sharing indicates that interstate data sharing can invert the externality of integration to be positive. We also noticed the inconsistent signs of coefficient of Sharing among the four models, implying omitted variables bias.

Table 2. County-level analysis of impact of PDMP integration and data sharing				
	Dependent Variable: Opioid Prescribing Rate			
Variables	OLS		LA-PSM + OLS	
	Model 1	Model 2	Model 3	Model 4
Integration	-1.579 (0.875)	-1.807 (1.250)	-1.213 (0.845)	-0.404 (1.123)
Sharing	-1.077* (0.543)	1.570** (0.572)	0.417 (0.698)	1.957** (0.685)
Neighbor Integration		1.760** (0.597)		2.799*** (0.780)
Neighbor Integration * Sharing		-4.717*** (0.766)		-4.132*** (0.923)
PDMP	0.671 (0.536)	0.583 (0.539)	1.713* (0.851)	1.702* (0.861)
PDMP Mandate	-9.196*** (1.041)	-9.394*** (1.040)	-2.562** (0.859)	-4.105*** (0.979)
PDMP Mandate * Integration	4.066** (1.402)	4.218** (1.434)	-2.176 (1.112)	-0.777 (1.219)
Integration * Sharing		0.765 (1.456)		-0.698 (1.381)
Other Control Variables	YES	YES	YES	YES
Two-way Fixed Effects	YES	YES	YES	YES
Observations	28,850	28,850	15,883	15,833
R^2	0.024	0.024	0.011	0.016

Note: Standard errors are reported in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2. County-level analysis of impact of PDMP integration and data sharing

Discussions and Policy Implications

The present results do not find enough evidences to find a significant correlation of a state's own PDMP integration and local opioid prescribing rate, while the negative externality on neighbouring state's opioid prescribing rate is consistent under various econometric specifications. One interesting point is why we cannot find the "local" impact of PDMP. Readers may have concern about the variation of actual PDMP usage by physicians after the PDMP-enhancement policies. Although we have no access to nationwide statistics about PDMP usage by physicians, some policy reports suggest that after implementations of PDMP integration or data sharing in certain pilot hospitals or states, the numbers of PDMP data requests for in-state or out-of state patients can increase enormously (CDC, 2017).

The positive correlation between PDMP data sharing and prescribing rate is also counter-intuition. One possible reason may be that some omitted variable should have been included. For example, an area with high intensity of hospitals may have larger incentives to join in the data sharing hub, and more hospitals could be associated with higher demand for prescription drugs.

Our work can generate timely policy implications. As the integration and data sharing policies used to be implemented in some states separatedly. The negative spillover effects of PDMP integration evident in the present work can point out the dark side of health IT policy under certain conditions and emphasize the importance of health information sharing. To systematically fight with the opioid crisis, the U.S. federal government should actively coordinate the state-level health sectors to create information network of monitoring prescription drugs. Until 2019, there are still several states or regions that have not joined in the PMP InterConnect platform due to privacy, administrative and legislative concerns. A nation-wide information network is the key to prevent addicted patients' doctor shopping behaviors.

Conclusions

This paper empirically investigated whether PDMP integration with local HITs can impact physicians' opioid prescribing decisions beyond the adopting state and if yes, how could PDMP data sharing across states can moderating this spillover effect of health IT. Using a 12-years county-level panel data, we found that a neighbouring state's adopting PDMP integration can increase a focal state's opioid regional prescribing rate, if the two states have not shared PDMP data access. We also found that this negative externality of integration can be reversed if the two states have become PDMP data sharing parterners.

In future study, we need to improve the issues related to measurement errors. First, our measurement for interstate sharing is not exactly accurate. We will collect more pairwise data to improve the measurement error. Second, if continuous variable about aggregated individual behavioural data could be obtained, it could provide more granular evidence supporting for our causal inferences. For example, it would be relevant to check whether PDMP enhancement can increase physicians' actual usage of PDMP, or whether patients indeed reveal doctor shopping behavior (e.g., visiting a doctor in neighbouring states more frequently) as response to PDMP integration.

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