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IZA DP No. 11391

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Mark Borgschulte
University of Illinois and IZA

Adriana Corredor-Waldron
University of Illinois

Guillermo Marshall
University of Illinois

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

A Path Out: Prescription Drug Abuse, Treatment, and Suicide*

In this paper we investigate the dual role of supply restrictions and drug treatment in combating the concurrent rise of opioid abuse and suicide in the United States over the last two decades. We find that supply-side interventions decrease suicides in places with strong addiction-help networks, implying that prescription drug abuse is associated with an inherent risk of suicide. Our findings support an important role for access to treatment services in policies designed to combat the opioid epidemic.

JEL Classification: I12, I18, D11, D12

Keywords: prescription drugs, drug abuse, drug addiction treatment, PDMP, suicide

Corresponding author:
Mark Borgschulte
214 David Kinley Hall
1407 W Gregory St
Urbana
IL 61801
USA

E-mail: markborg@illinois.edu

* This paper is forthcoming in the *Journal of Economic Behavior & Organization*. We thank Padmaja Ayyagari, Colleen Carey, Monica Deza, Carlos Dobkin, David Frisvold, Esteban Petruzzello, and seminar participants at University of Iowa, University of Illinois at Urbana-Champaign, University of Michigan (H2D2 Research Day), and the Population Association of America Annual Meet-ings for helpful comments and suggestions. Heather Grey and Sherry Green at NAMSDL provided use-ful background information. All errors and omissions are our own.

Over the past two decades, a prescription drug abuse epidemic has spread across the United States, driven primarily by the increased use and abuse of opioid medications.[1] Recent research attributes a reversal of the decades-long trend in falling mortality rates among middle-aged white non-Hispanics to the combined effects of drug and alcohol abuse, as well as a potentially related cause, suicide (Case and Deaton, 2015a). In tandem with the rise in prescription drug abuse has been an increase in reported pain, which is strongly associated with the age and geography of the rise in suicide.[2] However, despite these suggestive correlations, the causal links between the rise in deaths due to prescription drug abuse and suicide largely remain unexplored.

Responses to the prescription drug abuse epidemic must weigh the merits of policies targeting the supply or demand for prescription drugs. Traditional law enforcement approaches to combating drug abuse focus on reducing the supply of illegal or diverted drugs. However, economists and public health researchers have long been critical of an exclusive focus on supply-side measures, instead suggesting that demand-side interventions, particularly drug treatment, can be as or more effective in reducing mortality and other adverse outcomes.[3] Given the unsettled debate on the merits of supply versus demand-side policies, it is unsurprising that we know very little about interactions and potential complementaries between the two approaches.

In this paper, we examine the response of suicide to disruptions in the supply of prescription drugs, with a particular focus on the role of drug treatment in mediating the relationship between abuse and suicide. We identify supply shocks using the passage of state legislation that implements a Prescription Drug Monitoring Program (PDMPs), one of the primary policy tools used to combat the prescription drug abuse epidemic. PDMPs require pharmacies to report the names of both the patient and prescriber to a central database when dispensing potentially addictive prescription drugs, and have expanded from 12 to 49 states since 1999, reflecting their importance in the policy response to the epidemic. While early studies of PDMPs found mixed evidence for their efficacy, recent research has found their implementation to result in reductions in the prescribing of opioids with the highest potential for abuse (i.e. drugs classified in Schedule II), fewer prescriptions written to those receiving drugs from many doctors or dispensers, improvements in time required for drug

[1] The CDC and its researchers have issued regular reports on the rise in drug overdoses, as in Paulozzi et al. (2011), Jones et al. (2013), and Rudd et al. (2016). Maxwell (2011) reviews the literature.

[2] Volkow and McLellan (2016) reviews the literature on opioid abuse and the rise in chronic pain. Phillips (2014) reports on the rising trend in suicides. Case and Deaton (2015b) find a strong association between pain and suicide using data from the Gallup surveys; from their paper: "The suicide epidemic in middle age is the tip of an iceberg of mortality and morbidity, especially pain, among middle-aged Americans."

[3] The research on supply-side policies has generally found them to have, at best, temporary effects on prices and usage of illicit substances; for example, see DiNardo (1993) and Dobkin and Nicosia (2009). Swensen (2015) provides demand-side evidence and for further citations to the literature.

diversion investigations, and reductions in overdose deaths.[4] PDMPs vary in their details, and have been passed in standalone bills, as well as in legislation that includes measures to combat pill mills and doctor shopping, and regulate pain management clinics. We assume these programs, and related legislation, make it more difficult for addicts to maintain a regular supply of prescription drugs, acting as a negative supply shock to the market for diverted drugs. However, these supply-side restrictions on the availability of prescription drugs are not usually combined with demand-side expansions in treatment services. For example, we find no response in the number of treatment facilities at or around the time of PDMP implementation.[5] Thus, we hypothesize that these policy-induced supply shocks have the potential to lead to undesirable outcomes, such as suicide, in places where treatment services are unavailable to meet this new demand. In the remainder of the paper, we refer to these supply shocks as "PDMPs."

To better understand the response to these policies, we propose a dynamic model that describes how a supply shock affects an addict's choice between continued drug use, effort put towards quitting, and suicide. We model suicide as a rational choice (as in Hamermesh and Soss 1974, Cutler et al. 2000, and Koo and Cox 2008), within the constraints imposed by addiction. In the model, suicide occurs when the drug habit becomes unsustainable—for instance, due to restrictions on access to the drug—and also when the addict's non-withdrawal pain becomes intolerable—for instance, due to emotional pain or depression. In line with existing research, we assume the latter is beyond the control of a drug user and we call it *inherent risk*, as it is not necessarily related to having lost access to the drug.[6] Addicts also choose how much effort to exert towards recovery which, combined with the efficacy of drug addiction treatment, determines the rate of recovered addicts. Thus, addicts have two possible paths out of addiction: drug addiction treatment or suicide.

In the model, PDMPs reduce the frequency with which drugs arrive, which in turn reduces the value of using the drug, as the withdrawal symptoms are alleviated less frequently. The effect of PDMPs on the value of using the drug has two effects on suicides, reflecting the two paths out

[4] Buchmueller and Carey (2018) provides evidence on the reduction in supply to heavy users who are most likely to be addicts. See Reisman et al. (2009), Reifler et al. (2012), Finklea et al. (2014), Kilby (2015), Meara et al. (2016), Patrick et al. (2016), and Moyo et al. (2017) for further evidence on the effects of PDMPs. We address heterogeneity in PDMP legislation, specifically the role of mandatory access provisions, in the analysis. Missouri is the only state which has not passed a PDMP.

[5] In addition, Jones et al. (2013) reports that the number of patients treated at methadone clinics has not changed in the last decade. Anecdotal evidence in Vestal (2016) suggests that methadone-prescribing clinics have not expanded during the epidemic, and as a result, have long waiting lists and difficulty in keeping up with the demand for their services.

[6] Previous research in economics finds that the supply of drugs and alcohol can affect suicide rates (Carpenter 2004, Anderson et al. 2014). See Kuramoto et al. (2012) and Ilgen et al. (2016) for evidence showing an association between prescription drug abuse and suicidal attempts as well as Fischer et al. (2005) for evidence showing an association between prescription drug abuse and depression. These studies do not address causality.

of addiction. First, it causes some drug habits to become unsustainable, triggering an increase in the rate of suicides. Second, it makes recovery more attractive relative to using the drug, which increases the equilibrium levels of effort with which addicts seek recovery. More effort increases the likelihood of recovery, which reduces the number of people exposed to the inherent risk of using the drug. The model predicts that a greater drug treatment effectiveness or availability reduces the first effect, while it intensifies the second effect (i.e., it makes each unit of effort more productive). Together, these competing effects lead to the conclusion that suicides may increase following the introduction of PDMPs in places where drug treatment is unavailable (e.g., places fewer drug abuse treatment centers or limited availability of opioid-replacement therapy), while suicides may decrease with PDMPs where drug treatment is more effective. The net effect on suicides is ambiguous.

We evaluate the model in an empirical analysis, using variation generated by the introduction of PDMPs between 1999 and 2014. We focus the analysis on middle-aged white non-Hispanics, the group driving the trends in both drug overdose and suicide (see Figure 1), but also consider effects on the entire population and other subgroups. Identification comes from the timing of the passage of PDMPs, in conjunction with variation in the availability of treatment services at both the county and state level. We measure treatment availability by both the number of drug treatment facilities and by the frequency with which medication-assisted therapies are used. The data come from several sources, including deaths by overdose and suicide from the Vital Statistics System Multiple Causes of Death Microdata Files, prescription drug sales obtained through Freedom of Information Act requests to the US Drug Enforcement Administration, and drug treatment facilities information from the National Survey of Substance Abuse Treatment Services (N-SSATS) and County Business Patterns.

Our primary analysis examines how suicide responds to the passage of a state PDMP in counties with differing availability of treatment facilities. Consistent with the model, we find PDMPs reduce suicides in counties with high availability of drug addiction treatment facilities relative to counties with low levels of treatment facilities. The heterogeneous effects of PDMPs grow stronger when we consider only those reforms which included a mandatory access provision requiring doctors to check the state database before prescribing any monitored drug.[7] As the county-level analysis includes state by year fixed effects, the analysis controls for local trends in economic shocks, the availability of substitute drugs, and other concurrent state-level policy changes that are not associated with the penetration of treatment centers. A closely-related paper to ours, Swensen (2015),

[7] Buchmueller and Carey (2018) find mandatory access to be the most important feature of PDMPs in predicting a decrease in drug sales to the Medicare patients likely to be addicts.

finds that expansions of treatment services lowers mortality, including suicide. Taken together, the evidence points to an important role for treatment services in reducing mortality in this population.

We then turn to a parallel analysis of the mortality response to the passage of PDMPs in a state-quarter panel. This model uses almost entirely independent variation from the county-level analysis, and also allows us to extend the heterogeneity analysis to include interactions with measures of medication-assisted therapy. Medication-assisted therapy is the medically-recommended method of drug treatment; however, many states and treatment service providers mandate "cold-turkey" methods be used in publicly-funded clinics, which make up a majority of treatment facilities. Consistent with the county-level analysis, we find PDMPs decrease suicides in states with more facilities, as well as in states where doctors are more likely to prescribe the opiate replacements methadone and buprenorphine. These dimensions of heterogeneity (treatment facilities and opiate replacement prescribing rates) appear to be long-run characteristics of the states, rather than endogenous responses to the epidemic themselves. Thus, we conclude that the availability of these drugs influences suicide rates, and access to effective treatment services can complement supply-side restrictions.

Our study makes three primary contributions to the literature. First, we provide some of the first quasi-experimental evidence on the links between the concurrent rise in prescription drug abuse and suicides among white non-Hispanics. Suicide rates can show a persistent decrease following reductions in the supply of prescription drugs in places where addicts have a path out. Whether the decrease comes through changes in the behavior of addicts, as proposed in our model, or through the reduction in the number of addicts, the response implies there is an inherent risk of suicide associated with prescription drug abuse. Put another way, the concurrent rise in prescription drug abuse and suicides are causally associated. This finding has broad implications for theories that seek to explain one or both trends.[8]

Second, we contribute to the broader literature on drug policy by highlighting interactions of supply and demand in drug policy. Policy and research have long focused on supply-side measures, of which PDMPs are merely the latest example. Economists have criticized the focus on supply-side interventions as short-sighted, and likely to fail due to the role of demand for these products (Becker et al., 2004). Our findings demonstrate the complementarity between supply-side and demand-side policies in combating drug abuse. In this aspect, we believe our results are the first of their kind.

Third, we contribute to the literature on the economics of suicide. Our theoretical model ex-

[8] Although we argue that our evidence establishes a causal link, PDMPs have had only modest effects on the supply of drugs, limiting our ability to assess the total contribution of the rise in prescription drug abuse to the rise in suicide.

plains the puzzling decrease in suicides in places where drug treatment is more available or effective. Our empirical and theoretical results jointly suggest that drug users respond to incentives when choosing whether to seek drug treatment, as well as the importance of treatment effectiveness for the choices of drug users. If suicide can be taken as a measure of the welfare of drug addicts, our findings demonstrate that reductions in the supply of addictive drugs can, in some circumstances, increase the welfare of addicts.

The paper is organized as follows. Section 1 provides background on the prescription drug epidemic and policy responses to it as well as a description of the data. Section 2 presents a theoretical framework that shows how a supply shock interacted with a demand response may cause suicide to decline in places with strong addiction-help networks. Our econometric framework is discussed in Section 3. In Section 4, we present results that suggest that the supply shock created by PDMPs did cause suicide to decline in places with strong addiction-help networks, and prescription drug abuse is inherently risky. Lastly, in Section 5, we discuss broader implications of our findings and some limitations of our analysis.

1 Background: Policy, Data and the Supply Shock

1.1 The Prescription Drug Epidemic and Policy Responses

Deaths from unintentional drug overdoses in the United States have risen by 500 percent since the early 1990s, and are now the second-leading cause of accidental death (Okie, 2010). According to the CDC, the trend in overdoses is largely explained by the rise in prescription drug use and abuse, and in particular, with the increase in the use of opioid analgesics (Rudd et al., 2016). By 2007, this class of drugs was responsible for more deaths by unintentional overdose than heroin and cocaine combined. The most affected demographic and age group is non-Hispanic whites between the ages of 20 and 64.[9]

The origins of the epidemic are multifaceted. While reported pain and the prevalence of chronic pain have been rising, the underlying causes of these trends are not clear (Case and Deaton, 2015b). A growing literature suggests the epidemic is related to the prescribing behavior of physicians. In the time series, the emergence of the epidemic is tied to the 1990s change in standards of care which expanded the use of heavy-dosage and often long-lasting opioid medication to a much wider class of patients.[10] Observational studies have found that patients prescribed higher doses are more

[9] Low-education and urban populations are also more affected. See Paulozzi et al. (2012) for details on demographic composition of overdoses.

[10] Remarkably, this change occurred despite a lack of evidence on the efficacy of long-term opiate medication for

likely to overdose (Bohnert et al., 2011). Despite suggestive evidence that the epidemic is at least partly iatrogenic or supply-driven, other evidence finds a strong association between the abuse of prescription drugs and other substance abuse disorders (McCabe et al., 2008). Recent research suggests that prescription drug abuse may be partly responsible for the rise in heroin overdose deaths (Lankenau et al. 2012, Peavy et al. 2012, Jones 2013, Alpert et al. 2017, Evans et al. 2017).

One of the most common state-level policy response to the epidemic has been the introduction of prescription drug monitoring programs.[11] PDMPs require dispensers to report the identity of the patient, prescribing health care provider and dispenser to a statewide system at the time a monitored drug is dispensed. The information then enters a statewide database, which can be accessed in several circumstances. The primary users of the database are prescribing physicians, who can check whether patients have received a monitored drug from another source. Law enforcement in most states can also access the database, speeding up investigations of drug diversion. Many, but not all, state databases are linked through a system of interstate sharing. The effect of PDMPs on the overall prescribing of regulated drugs is ambiguous, as it allows more precise targeting of drugs to non-addicts.[12] However, PDMPs are unambiguously designed to reduce the supply of prescriptions to drug addicts. We discuss evidence on the efficacy of PDMPs, below.

The specifics of PDMPs differ between states, and PDMP legislation may also include or coincide with other, related interventions. Other state-level policy responses include changes to the security of prescription forms, pain clinic laws, crackdowns on pill mills, increased regulation of pain management clinics, ID requirements, and drug courts. PDMPs have received the majority of the attention in the policy literature, and we know of no paper which attempts to account for the individual contribution of the full range of policy changes. For these reasons, we do not attempt to evaluate the effect of PDMPs per se, and instead focus on the interplay of supply shocks, suicide, and treatment, as emphasized by the model. We use the implementation of PDMPs from 1999 through 2015 to identify the timing of these supply shocks.

Several features of PDMPs and related legislation deserve mention, as they are important to our identification. First, the timing of PDMP implementation appears to be unrelated to recent trends in the severity of the epidemic, as measured by drug overdoses. Although they represent one of the major policy tools used to combat the epidemic, the exact timing of their passage has been determined by the status of previous (usually paper-based) programs, internet penetration (required

the treatment of chronic pain. Specifically, there is no randomized evidence from studies with follow-ups longer than 3 months (Chou et al., 2015).

[11] Heather Grey of NAMSDL provided some information that appears in the following paragraphs in personal communication. All errors and omissions are our own.

[12] Baehren et al. (2010) finds the introduction of the Ohio PDMP altered prescribing of opioids in 41 percent of emergency department cases, with significant shares of patients receiving either fewer or more opioid medication.

to run the electronic registration system), and state-level political developments. The apparent randomness in the timing of passage may be related to our exclusion of those states which pass laws before the analysis window, who presumably have the highest propensities to pass PDMPs. Second, PDMPs also appear to have little relationship with the availability of treatment services. PDMPs are supply-side interventions, and a review of PDMP legislation in the sample period has found none that included expanded funding for or access to treatment services. We further substantiate the lack of important coincident demand-side interventions by testing for an empirical relationship between the passage of PDMPs and the number of treatment centers in a state. We find no relationship between PDMP legislation and number of treatment centers, either before or after the legislation. Third, federal law prohibits the inclusion of treatment-based provision of drugs in state PDMPs. Thus, we do not worry that the passage of PDMPs directly affects the option to go to drug treatment.

The literature on the efficacy of PDMPs has proceeded from the measurement of total sales of regulated drugs and other aggregate outcomes, to more focused studies of the effects on heavy users and of key program characteristics. Most studies in the first category find mixed or no effect of PDMPs on aggregate outcomes. For example, a recent large scale study, Meara et al. (2016), finds weak evidence of effects of state laws, including PDMPs, on drug sales. Using Medicare data, Meara et al. (2016) finds no effect of the average state-level reform during the 2006-2012 period; suggestive evidence showing reductions in sales do not survive corrections for multiple hypothesis testing. These results contrast with Moyo et al. (2017), which finds significant reductions in the total volume of opioids dispensed to Medicare patients following implementation of PDMPs. These studies of aggregate outcomes may be misleading if there are changes in the composition of patients or prescribed drugs. For example, one of the more consistent findings in the recent literature is that PDMPs cause doctors to substitute away from Schedule II drugs, which have the highest potential for addiction.[13] If doctors continue prescribing opiates, but shift patients to drugs with lower value to addicts, PDMPs may affect the supply of diverted drugs more than average prescriptions and sales.

A second wave of studies has focused more closely on the groups targeted by PDMPs, and specific elements of the programs. One of the largest and most comprehensive studies of prescribing behavior, Buchmueller and Carey (2018), uses Medicare Part D data from 2007-2012 to examine patients' prescription histories. This paper finds that PDMPs have the intended effect on supply, reducing the percentage of enrollees who obtain prescriptions from five or more physicians by more than 8 percent and from five or more pharmacies by more than 15 percent, with no effect on

[13]For evidence on Schedule II prescriptions, see Bao et al. (2016), Moyo et al. (2017), and Wen et al. (2017).

the mean of the utilization distribution. The paper also finds an important role for the details of the programs, especially when prescribers are mandated to access the database before prescribing. Our approach to identifying the effect of PDMPs follows this paper closely. Consistent with the empirical strategy in Buchmueller and Carey (2018), Patrick et al. (2016) examines variation in overdose outcomes that result from the passage of PDMPs with differing characteristics. The evidence in this paper supports a broader effect of PDMPs, with reductions in overdoses associated with the passage of PDMPs with characteristics beyond mandatory access, such as the frequency with which the data is updated, and whether the state monitors four or more of the DEA drug schedules. Similarly, Pardo (2017) finds that more stringent PDMPs result in larger reductions in opioid overdoses in a 1999-2014 sample period, and that mandatory access is not the only program characteristic that matters. While these studies cover different sample periods and reach different conclusions on the key features of PDMPs, taken together, they provide strong evidence that PDMPs reduce in opiates available in the market for diverted drugs.

1.2 Data

To measure the impact of PDMPs and associated reforms on the supply of drugs and suicides we use a variety of data sources. The primary outcome of interest, suicides, is drawn from the National Vital Statistics System's (NVSS) Multiple Causes of Death Microdata that contain all certified deaths occurred in the US at the county level. The data report the manner of death and the underlying cause of death[14] as well as demographic information such as race, ethnicity, gender, age and education. We aggregate the data at the county–year or state–quarter level and restrict attention to years 1999 to 2014 for two reasons: availability of other data and changes in death diagnosis codes in 1999.

Information on the date of user access to PDMP is obtained from reports of the National Alliance for Model State Drug Laws (NAMSDL).[15] As in Kilby (2015), we only take states with programs implemented after the Model Prescription Monitoring Program Act of 2003 (a total of 38 states). This restricts attention to PDMPs that are comparable in terms of physician access to patient prescription information, as outlined in the Act's guidelines.

We use state and county-level measures to test the heterogeneity results implied by our theo-

[14]Suicides are identified as those records where manner of death is equal to suicide, regardless of the underlying cause of death. Opioid–related overdose are identified using the underlying and multiple cause of death information, and they correspond to those records where T40.2 ('Other opioids') is mentioned. Therefore our measure of suicide includes all possible underlying cause of death: drugs, firearm, suffocation, among others; while our overdose measure includes all manners of death: suicide, accidental, homicide, among others.

[15]See Table A1 in the Appendix for details on the dates of user access to PDMP.

retical model with respect to treatment availability. The first is the total number of substance abuse treatment facilities (private and public) in each state, which we gather from the annual reports of the Substance Abuse and Mental Health Services Administration (SAMHSA)[16] available through the Inter-university Consortium for Political and Social Research (ICPSR). The second are state-level measures of drug distribution for methadone and buprenorphine from Drug Enforcement Administration's (DEA) Automated Reports and Consolidated Orders System (ARCOS), which measure the availability of opioid-replacement therapy. Lastly, we use the U.S. Census Bureau's County Business Patterns (CBP) to collect county-level information on the number of substance abuse treatment centers.[17]

2 A Model of Drug Use, Treatment Effectiveness, and Suicide

In this section, we develop a dynamic model to understand how the supply shock caused by PDMPs affects an addict's choice between continued drug use, drug addiction treatment, and suicide. We analyze the choices made by an addict once an addict and assume that the entry of new addicts follows an exogenous process.[18] In the model, suicide is a choice caused by the pain created by the drug habit (e.g., withdrawal symptoms and emotional pain). Suicides arise when the drug habit becomes unsustainable—for instance, due to a drug supply shock—or when the addict's non-withdrawal pain escalates beyond tolerable levels (e.g., due to depression or emotional pain). We assume the latter is beyond the control of a drug addict and we call it *inherent risk*, as it is not necessarily related to having lost access to the drug. Addicts also choose how much effort to exert towards drug addiction recovery which, combined with treatment efficacy, determines the rate of recovered addicts.

The main results we test in the data are related to the effects of a drug supply shock on suicides. On the one hand, a drug supply shock causes some drug habits to become unsustainable, leading to an increase in the number of suicides. On the other hand, a drug supply shock makes using the drug less attractive, increasing the relative attractiveness of drug addiction recovery, in particular, in places with strong addiction-help networks. The second effect increases the effort devoted to recovery, reducing the number of people exposed to the inherent risk of the drug and, hence, the

[16] N-SSATS is a voluntary census of all known drug and alcohol abuse treatment facilities in the U.S. In 2015, around 95% of the existent facilities responded the survey. The facilities include outpatient, inpatient and clinics that provide drug and alcohol treatment. The survey excludes patients of solo practice and facilities treating incarcerated patients.

[17] Following Swensen (2015), we label all establishments with NACIS codes 621420 and 623220 as substance abuse treatment centers.

[18] Exogeneous entry and other assumptions are discussed in Subsection 3.3.

rate of suicides. This second effect, however, only arises where the addiction-help network is sufficiently strong, implying that the supply shock caused by PDMPs may increase the suicide rate in places where treatment is unavailable, while potentially reduce the suicide rate in places where effective treatment is widely available.

2.1 Baseline

Consider an infinite horizon continuous time model describing the behavior of an addict. At every instant in time, addicts continue using the drug unless they recover after drug addiction treatment or choose to commit suicide. Following Hamermesh and Soss (1974), Cutler et al. (2000), and Koo and Cox (2008), we assume that suicide is chosen when the value of using the drug falls bellow 0 (i.e., normalized value of suicide). Conditional on choosing to continue using the drug, the addict chooses how much effort to exert towards seeking drug addiction recovery.

An addict faces withdrawal symptoms, w, that are only alleviated with the arrival of a drug dose (and the utility of using the drug, u), which happens at an addict-specific Poisson rate, λ. In order for the habit to be sustainable, the rate of arrival of drug doses, λ, must be sufficiently high, otherwise, the benefits of using the drug are surpassed by pain. When the habit is unsustainable, the addict commits suicide. An addict chooses an effort level e with which to seek recovery, where effort combined with treatment efficacy (or strength of the addiction-help network), π, determine the likelihood of recovery. We assume that the value of being a recovered addict is given by R. Addicts face an inherent risk, as emotional pain escalates at Poisson rate α, making the value of using the drug fall below the value of suicide, leading drug users to commit suicide. It is important to note that this inherent risk is independent of drug consumption. These last assumptions are consistent with studies showing an association between prescription drug abuse and both suicidal thoughts and depression problems (Kuramoto et al. 2012, Ilgen et al. 2016, Fischer et al. 2005). Finally, addicts discount future payoffs at rate $r \geq 0$.[19]

We restrict the parameters of the model in two ways. The first restriction guarantees that drug addicts have incentives to recover from drug addiction in places where drug addiction treatment is effective. In absence of this restriction, our model would be unable to capture the fact that some drug addicts attempt to recover in real life. The second restriction guarantees that drug use exists in equilibrium. That is, under this restriction at least some drug users prefer to use the drug over committing suicide. These parameter restrictions are stated in Assumption 1.

Assumption 1.

[19] Our results hold for arbitrary values of r. That is, even when drug addicts heavily discount the future.

i) $R(\alpha+r) > -w+\lambda u$

ii) $-w+\lambda u+\pi^2 R^2/2 > 0.$

We focus on a stationary equilibrium by using a continuous time dynamic programming approach, where our assumptions guarantee a unique equilibrium. The value function of an addict must satisfy

$$rV = \max\left\{\max_e \; -w+\lambda u+e\pi(R-V)-c(e)-\alpha V, 0\right\}, \tag{1}$$

where the first value in the max operator is the flow value of an addict who chooses to continue using the drug, while the second, the (normalized) flow value of suicide.[20] Since the environment is stationary, we have that $V > 0$ as long as the rate of arrival of drug doses is sufficiently high, $\lambda > \lambda^*(\pi, R, u)$, where $\lambda^*(\pi, R, u)$ is characterized below. Addicts with $\lambda < \lambda^*(\pi, R, u)$ have drug habits that are unsustainable—i.e., the pain caused by the habit surpasses the utility gained from using the drug—leading them to choose to commit suicide.

To understand the flow value of an addict who chooses to continue using the drug, we have that the addict experiences withdrawal symptoms $-w$ at every instant of time; the addict finds a dose of the drug at Poisson rate λ and gains utility u from using the drug; the addict becomes a recovered addict at Poisson rate $e\pi$, earning the addict an incremental value $(R-V)$, where e is effort, π is a measure of drug addiction treatment efficacy, and R is the value of a recovered addict; the addict pays the effort cost of seeking recovery, $c(e) = e^2/2$; and faces the inherent risk at Poisson rate α, which leads to suicide and a change in value equal to $(0-V)$.

When $V > 0$, we have that the addict chooses effort according to

$$c'(e^*) = \pi(R-V) \quad \text{if} \quad R > V \tag{2}$$

and $e^* = 0$ if $R \leq V$. The equation shows that drug addicts equalize the marginal cost and marginal benefit of an extra unit of effort. The marginal benefit of seeking drug addiction recovery is the value increment gained when becoming recovered multiplied by the level of treatment effectiveness (π), where the level of treatment effectiveness can be thought of as the productivity of each unit of effort. Replacing (2) into (1), gives an implicit expression for the equilibrium value of V in an equilibrium with positive effort (i.e., $R-V > 0$)

$$rV = -w+\lambda u+\pi^2(R-V)^2/2-\alpha V. \tag{3}$$

[20] See the Online Appendix for details on the derivation of equation 1.

While equation (3) has two solutions, only one of the solutions is consistent with an equilibrium with positive effort (i.e., an equilibrium with $R > V$).[21] As well, V is positive as long as

$$\lambda > \frac{w - \pi^2 R^2/2}{u} \equiv \lambda^*(\pi, R, u), \tag{4}$$

which is guaranteed to hold under Assumption 1(ii).

The cumulative probability that an addict commits suicide by time t is given by

$$\Pr(\textit{suicide time} \leq t) = \frac{\alpha}{\alpha + e^*\pi}\left(1 - e^{-(\alpha + e^*\pi)t}\right),$$

where t is time measured from the moment when the addict became an addict. From the equation we can note that the long run probability of suicide for the individual is given by $\alpha/(\alpha + e^*\pi)$. The dynamics of the cumulative probability of suicide are illustrated in Figure 2 (curve A).

If at every instant of time there is a measure $\mu > 0$ of new addicts, with each addict drawing $\theta = \{\alpha, \lambda, w, u\}$ from a stationary distribution F, then the expected number of suicides at every instant of time is given by

$$E[\textit{suicides at } t] = \mu \int \frac{\alpha}{\alpha + e^*(\theta)} dF(\theta).$$

2.2 Supply Shocks, Treatment Effectiveness, and Suicides

Consider an exogenous change in the Poisson rate at which a drug user has access to the drug, λ. A decrease in λ reduces the value of using the drug, as withdrawal symptoms are alleviated less frequently. This change will have two effects. On the one hand, it may make the habit unsustainable for some addicts (i.e., λ may fall bellow λ^*), which would increase the number of suicides. On the other hand, by affecting the value of using the drug, it changes the incentives to exert effort towards seeking drug addiction recovery. Since effort is determined, in part, by the incremental value of becoming recovered, $R - V$, a lower value of V makes becoming recovered relatively more attractive, boosting incentives to exert effort. Implicit differentiation of (3) confirms this intuition

$$\frac{de^*}{d\lambda} = -\pi \frac{dV}{d\lambda} = -\frac{\pi u}{\alpha + r + \pi^2(R - V)} < 0.$$

How much the supply shock boosts incentives to exert effort depends also on treatment effec-

[21] Under Assumption 1, $R > V(e = 0) = (-w + \lambda u)/(r + \alpha)$. That is, the value of recovery exceeds the value of a drug user who sets $e = 0$. This rules out the possibility of $V > R$ and guarantees that $e^* > 0$ in equilibrium.

tiveness. The model implies that

$$\frac{d^2e^*}{d\lambda d\pi} = -\frac{u(r+\alpha)^2}{(\alpha+r+\pi^2(R-V))^3} < 0,$$

suggesting that a lower value of λ will create a higher effort response for greater values of π, as a greater value of π increases the productivity of those extra units of effort, providing further incentives to exert effort. These results are summarized in the following proposition.

Proposition 1 (Suicide rate and exogenous changes to drug access)**.** *An exogenous decrease in* λ *(i.e., drug access) has two effects on the suicide rate:*

i) Negative effect: It increases the effort devoted to seeking drug addiction recovery, which lowers the suicide rate by reducing the number of people exposed to the inherent risk of using the drug. (Curve B1 in Figure 2.)

ii) Positive effect: It causes addicts to fall below the habit sustainability threshold, λ^**, leading them to commit suicide. (Curve B2 in Figure 2.)*

A greater effectiveness or availability of drug addiction treatment, π, intensifies the negative effect and mitigates the positive effect on the suicide rate, leading to a potential overall decrease in the number of suicides when drug access is reduced. On the other hand, the negative effect is non-existent when drug addiction treatment is unavailable (i.e., $\pi = 0$), implying that a decrease in drug access will increase the suicide rate where treatment is ineffective.

Lastly, the model also makes predictions about the role played by treatment effectiveness on suicide rates. From (3), we can see that equilibrium effort increases with drug addiction treatment effectiveness

$$\frac{de^*}{d\pi} = (R-V) - \pi\frac{dV}{d\pi} = \frac{(r+\alpha)(R-V)}{r+\alpha+\pi^2(R-V)} > 0,$$

as an increase in π makes each unit of effort become more productive. The following proposition summarizes this result.

Proposition 2 (Suicides and treatment effectiveness)**.** *An increase in the effectiveness or availability of drug addiction treatment (i.e., an increase in* π*) increases equilibrium effort. Higher effort combined with higher drug addiction treatment effectiveness, increases the rate of recovery,* $e^*\pi$*, and, hence, lowers the number of suicides.*

2.3 Discussion

As discussed above, PDMPs may limit drug users' access to their drugs (i.e., lower value of λ). This is especially true for drug abusers who rely on several physicians or the illegal market to satisfy their needs. Proposition 1 implies that the effect of PDMPs on the suicide rate may be either negative or positive. Wherever there is a strong addiction-help network, PDMPs may create greater incentives to seek recovery, leading to a higher rate of recovered addicts which are no longer exposed to the inherent risk of using the drug. On the other hand, in places with a weak addiction-help network, PDMPs may make using the drug too painful and, without hope of recovery, lead to a greater suicide rate. The model illustrates how a supply shock combined with a consumer response may cause the suicide rate to decline in places where addicts have access to a strong help network.

Elements that are absent from the model include drug substitution, endogenous entry, and uncertainty about whether supply shocks will be reversed. One might think that when faced with a drug supply shock, addicts may choose to consume a substitute drug (e.g., heroin). While substitution caused by a supply shock is not formally present in the model, one may incorporate it into the model in reduced form by allowing the supply shock to have heterogeneous effects across individuals depending on how easily they can substitute to other drugs.[22] Substitution ease might be explained, for instance, by idiosyncratic physiological factors or heterogeneity in search technology. As long as substitution is less than perfect, the results above—while mitigated—still hold.

The model does not allow for a supply shock to change the rate of entry of new addicts. Since the PDMP supply shock is specific to prescription drugs, the value of abusing a prescription drug relative to the value of abusing a non-prescription drug (e.g., heroin) decreases with the policy intervention, which would endogenously increase entry into using non-prescription drugs. Under the plausible assumption that non-prescription drugs have a higher inherent risk, our results would still hold in a model with endogenous entry although a supply shock would make an increase in suicides likelier due to substitution towards more dangerous drugs. The effort channel however would still have to be present for one to see a decline in suicides after a supply shock.

Lastly, the model does not incorporate uncertainty about whether the drug supply shock caused by PDMPs will be reversed in the future. Both theoretical and empirical work have argued that uncertainty about the future can shape suicide decisions (Campaniello et al., 2017). In the Online Appendix, we present a version of the model that incorporates the possibility of a reversal of the drug supply shock. We show that our main results on the impact of a supply shock on the suicide rate still hold in presence of uncertainty, although they are mitigated when drug addicts believe

[22] Heterogeneous supply shocks can be captured by changes in λ that differ across individuals.

that the value of using drugs will improve in the future.

3 Empirical Strategy

Following the theoretical model, our empirical analysis has two parts. First, we study how PDMPs differentially impact suicide rates based on treatment availability at the county–year level. Second, we study the causal effect of the supply shock caused by PDMPs on suicides at the state–quarter level, allowing for heterogeneous effects along a drug treatment-efficacy dimension. Throughout the analysis, we date the introduction of PDMPs using the date the databases became accessible to prescribers.[23] We focus the analysis in the main text on the middle-aged and older white non-Hispanic population identified by Case and Deaton (2015a). This demographic group has some of the highest rates of prescription drug use and suicide in the population, which also serves to increase the power of our tests. We report results for all races and ages in the Appendix.

These exercises are based on the premise that drug users' suicide choices are affected by the supply shock caused by PDMPs (see Proposition 1).[24] To quantify the effect of PDMPs on suicides we use two approaches. The first is linear regressions where the dependent variable is the logarithm of the number of suicides and, the second is Poisson quasi-maximum likelihood estimators (QMLE) where the dependent variable is the number of suicides (Wedderburn 1974, McCullagh 1983, Gourieroux et al. 1984, Cameron and Trivedi 1986, Wooldridge 1997). For the Poisson models, we use a QMLE estimator instead of a maximum likelihood estimator (MLE) because the former does not impose the full structure of the Poisson distribution for estimation (i.e., the mean is not required to be equal to the variance), allowing for general variance structures which, for instance, can accommodate overdispersion as well as correlated error structures. Moreover, the QMLE only requires a correctly specified distribution mean for it to deliver consistent estimates for the mean, whereas alternative methods for count data (e.g., the negative binomial maximum likelihood estimator) require the full distribution to be correctly specified for consistency.

The first part of the analysis studies the differential impact of PDMPs by treatment center availability at the county–year level. The theoretical model predicts that a drug supply shock interacts with treatment availability in determining the impact of the supply shock on the suicide rate. To test this prediction in our empirical model, we allow for an interaction between PDMP indicators and the number (i.e. the level) of treatment centers in the county, which captures how the PDMPs' supply shocks differentially affect counties based on their treatment center availability. In

[23] See Table A1 in the Appendix for dates and other details.

[24] Our estimates are reduced form in that we do not directly observe the magnitude of the supply shock. See Buchmueller and Carey (2018), along with other citations in the introduction, for the effect of PDMPs on drug sales.

our linear regressions, the logarithm of suicides is modeled as

$$\log \text{suicides}_{c,t} = \theta_c + \gamma_{s(c),t} + \beta Facilities_{c,t-1} + \delta 1\{PDMP_{s(c),t}\} Facilities_{c,t-1} + \varepsilon_{c,t}, \quad (5)$$

while in our Poisson models, the county–year mean suicide count, $\mu_{c,t}$, is modeled as

$$\log \mu_{c,t} = \theta_c + \gamma_{s(c),t} + \beta Facilities_{c,t-1} + \delta 1\{PDMP_{s(c),t}\} Facilities_{c,t-1}, \quad (6)$$

where θ_c and $\gamma_{s(c),t}$ are county and state–year fixed effects; $1\{PDMP_{s(c),t}\}$ is an indicator variable that takes the value one if county c's state s had already implemented a PDMP by year t; and $Facilities_{c,t}$ is the number of substance abuse treatment facilities in county c in year t. To give a meaningful scale to this variable, we divide the raw number of facilities by the standard deviation weighted by population, 77.54 facilities. In these models, the coefficients of interest are δ and β. δ captures how PDMPs differentially impact suicide as a function of treatment availability; β captures the main effect of how treatment availability impacts the suicide rate. We also present an event study version of the linear model by interacting the PDMP indicator with a dummy for states with high or low availability of facilities. Proposition 1 predicts that after a supply shock, the suicide rate decreases by more in places with greater treatment availability (i.e., $\delta < 0$). Proposition 2 predicts $\beta < 0$, as greater treatment availability increases the productivity of each unit of effort, leading to a greater recovery rate (all else equal). We weight by the population to generate representative estimates and to increase efficiency. We report standard errors that are robust to within-state correlation in the error terms.

In the second part of the analysis, the unit of observation is a state–quarter combination. In our linear regressions, the logarithm of suicides is modeled as

$$\log \text{suicides}_{s,t} = \theta_s + \gamma_t + \delta_1 1\{PDMP_{s,t}\} + \delta_2 1\{PDMP_{s,t}\} X_{s,t-1} + \delta_3 X_{s,t-1} + \varepsilon_{s,t}, \quad (7)$$

while in our Poisson models, the state–quarter mean suicide count, $\mu_{s,t}$, is modeled as

$$\log \mu_{s,t} = \theta_s + \gamma_t + \delta_1 1\{PDMP_{s,t}\} + \delta_2 1\{PDMP_{s,t}\} X_{s,t-1} + \delta_3 X_{s,t-1}, \quad (8)$$

where θ_s and γ_t are state and quarter fixed effects; $1\{PDMP_{s,t}\}$ is an indicator variable that takes the value one if state s had already implemented a PDMP by year–quarter t; $X_{s,t-1}$ is the value of a covariate measuring the strength of the addiction help network for state s in $t-1$. The interaction term $1\{PDMP_{s,t}\} X_{s,t-1}$ allows for PDMPs to have a heterogeneous effect on suicides, allowing us to test the predictions that supply shocks may lower the suicide rate in places with greater treatment

availability. In these empirical models, the coefficients of interest are δ_1 and δ_2. Since both of these models are in logs, we can interpret $\delta_1 + \delta_2 X_{s,t-1}$ as the proportionate change in mean suicides as a consequence of the PDMP implementation. We again use population weights and cluster at the state level.

Crucially, the state–quarter and county–year strategies exploit entirely independent variation for identification. Identification in the state–quarter framework would be compromised by concurrent reforms in state policy that also affect suicide rates. To address this, the county–year model absorbs the state-level variation used to identify the state–quarter model, through the use of state–year fixed effects. Thus, the county-level model explicitly controls for state-level changes over time, greatly reducing the potential set of confounders. Similarly, the state-level model implicitly aggregates the data on the location of drug treatment centers, addressing any endogeneity between their within-state location and suicides. Thus, the two empirical approaches serve as independent tests on patterns predicted by the theoretical model.

4 Effects of PDMPs and Drug Treatment on Suicides

4.1 Trends and Descriptive Statistics

To illustrate the rapid increase in suicides among white non-Hispanics over 30 years old, we plot in Figure 1 the evolution of suicides by race, and suicides of white non-Hispanics by age group. As can be seen in Panel A, the rate of deaths per 100,000 residents[25] for white non-Hispanics is much larger than for other races, and has increased in 44 percent from 1999 to 2014. When we decompose the increase for white non-Hispanics by age group, we observe that the 45-54 age range are the most affected group, with a growth rate of 66 percent (Panel B). This group was highlighted in Case and Deaton (2015a). As for suicides of white non-Hispanics in other ages, there is an increase over the study period, but not as pronounced as for the mentioned group. Our main specification uses the aggregate of all white non-Hispanic over 30 years old.

Table 1 provides summary statistics of suicides[26], overdoses, access to opioids, and drug-treatment related variables. Panel A of the table shows that there are on average 9.8 suicides in a county–year. However, suicides committed by other means besides drugs are the main component of the total number of suicides, being the mean of non-overdose suicides 8.3 in a county–year.[27]

[25] Computed as the number of deaths per 100,000 population by race.

[26] Includes non-drug related suicides and drug related suicides.

[27] For example intentional self-harm by handgun, hanging or sharp objects. To compute this variable we remove from the total number of suicides those with codes X60-X64 which are related with drug use.

Likewise, the average rate of opioid overdose deaths is smaller than the average suicide rate, with a mean of 8.6 at the county–year level. As for the distribution of opiates, at the state level there were on average 135 milligrams morphine equivalent of oxycodone, a commonly abused prescription opiate, while of buprenorphine and methadone there were only 21.6mg and 2.4mg per person. With respect to drug treatment, counties have on average 5.9 facilities in the study period.

4.2 PDMPs and Suicides

The primary empirical results appear in Table 2, where we present county–year level estimates for the differential impact of PDMPs by treatment center availability. The first three columns present estimates for the linear model, and the last three present estimates for the Poisson model.[28] All the specifications include state by year fixed effects, which address a number of identification threats including local economic trends, the availability of substitute drugs, and other concurrent state-level policy changes (e.g., state budget for health care).[29] In a subset of the specifications, we interact the PDMP indicator with the number of treatment centers in each county (in standard deviations) to measure heterogeneity along the treatment availability dimension.[30]

Columns 1 and 4 (Table 2) show that a one standard deviation greater availability of treatment centers is associated with about a four to five percent decrease in suicides.[31] Columns 2 and 5 interact the number of facilities with PDMP indicators. The coefficients reveal that PDMPs have a more negative impact on suicides in places with a greater number of treatment centers. We estimate that an additional standard deviation in treatment centers is associated with about a 1.6 percent decrease in suicides after the passage of a PDMP. In Figure 3, we report the event study version of this specification. The difference between high and low states is driven by reductions in suicide in the high-facility states, which arrive in the year after PDMP implementation. This is consistent with the mechanisms in the model, and specifically, an inherent risk of suicide associated with drug addition. These estimates suggest that treatment availability interacted with a supply shock may boost drug addicts' incentives to recover and cause suicides to decline, which is in line with

[28] The first three columns include fewer observations as the log transformation drops county–year combinations with a zero suicide count.

[29] The state by year fixed effects also capture drug addicts' beliefs about whether the drug supply shock will be reversed in a given state. As argued in Section 3, the possibility of a reversal impacts drug addicts' incentives to commit suicide and exert effort towards drug addiction recovery.

[30] Figure A2 in the Appendix presents evidence suggesting that PDMPs did not impact the number of treatment facilities, and PDMPs were not passed in places that were experiencing an increase in the number of treatment facilities. This evidence further suggests that variation in treatment centers independent of the timing of PDMPs identifies our coefficients of interest.

[31] These results have the same order of magnitude than the results in Swensen (2015).

the predictions of the model.[32]

We have argued that PDMPs should reduce the supply of prescriptions to drug addicts but acknowledge that the specifics of PDMPs may differ between states, particularly the circumstances in which the database is accessed and the set of drugs that are covered by the program. Buchmueller and Carey (2018) present evidence suggesting that stricter programs—i.e., PDMPs where prescribers are mandated to access the database before prescribing—have a greater effect on measures of drug misuse than weaker programs. We leverage these differences to further test the implications of our model. Columns 3 and 6 (Table 2) restrict attention to "must-access" PDMPs.[33] The estimates suggest that an additional standard deviation in treatment centers is associated with a 9.9 to 12.4 percent decrease in suicides after the passage of these stricter PDMPs, which is larger than the effects in columns 2 and 5. These results leverage fewer reforms, and have correspondingly larger standard errors. In spite of this, these larger point estimates are in line with the prediction of the model that the addicts' incentives to recover are increasing in the size of the supply shock.

To measure differences in stringency across PDMPs, we also use a PDMP score constructed by the Trust for America's Health and The Robert Wood Johnson Foundation, who assessed 10 different policies that states have implemented in their PDMPs to combat prescription drug abuse.[34] The score takes values between 0 and 10, where greater values capture PDMPs with a stronger set of policies to combat abuse. In Table A3, we replace the PDMP dummy for the PDMP score in our usual specifications. We find that a stronger PDMP magnifies the interaction effect between treatment availability and PDMPs in reducing suicides. That is, for a given level of treatment availability, a stronger PDMP has a greater effect on suicides, as the model would predict. Importantly, we find no correlation between the stringency of the PDMP and the availability of drug treatment services (either facilities or use of medication-assisted therapy) in the state.

In Table 3, we present state–quarter level estimates for the mean effect of PDMPs on suicides and the heterogeneous effects by drug treatment and opioid availability. We report the linear and Poisson regression estimates in Panel A and Panel B, respectively.[35] In Column 1 (Panel A), PDMP legislation has no overall effect on suicides. Columns 2 through 4 (Panel A) report heterogeneity in the effect of PDMPs based on measures of the availability and effectiveness of treatment. The estimated coefficients suggest that the introduction of a PDMP in a state with 1% more drug addiction treatment facilities is estimated to cause a 0.02 percent decrease in suicides. The use of

[32] In Table A2 we present estimates using the logarithm of the number of facilities as opposed to the number of facilities (in standard deviations). The negative coefficients on the interaction term remain unchanged.

[33] See Table A1 in the Appendix for details on states with must-access PDMPs.

[34] For more information, please refer to Levy et al. (2013).

[35] In Table A4 we replicate Table 3 using the level of facilities instead of the logarithm of facilities. The results are qualitatively identical.

opioid-replacement therapy like methadone and buprenorphine have a negative effect on suicides, meaning that a state with 1% greater availability of methadone/buprenorphine is estimated to experience a decrease in suicides of 0.027 and 0.029 percent, respectively. Panel B shows Poisson regression estimates that are in line with those in Panel A. Although the effects are modest in the aggregate, the effect of PDMPs on dispensed drugs is similarly modest.[36]

In summary, the evidence in Table 2 and Table 3 provide support for the mechanism that we highlight in the model, where the supply shock incentivizes drug addicts to seek recovery and thus reduces suicide. This mechanism explains why the overall impact of PDMPs on suicides is only found to be negative in states with above average availability of treatment, which as argued above, are the states where exerting costly effort towards recovery is more productive. These results also provide support for the existence of the inherent risk of abusing drugs (Kuramoto et al. 2012, Ilgen et al. 2016, Fischer et al. 2005) because the effort of recovery channel can only explain a decline in suicides if using drugs is inherently risky.[37] The existence of an inherent risk of suicide associated with prescription drug abuse implies that the rise in suicides documented by Case and Deaton (2015a) and others can be attributed, at least in part, to the rise in prescription drug use.

Several interesting heterogeneity analyses appear in the Appendix. Women have been particularly affected by the rise in opiate abuse and suicide, and in Table A5 we separate the sample by gender and repeat our county–year Poisson regression analysis. The coefficients for women are consistently larger than those for men, both for the effect of treatment availability on its own, and when interacted with PDMPs. These results imply that the availability of treatment is particularly important for women. In Table A6 we repeat our county–year analysis including individuals of all races and all ages. The table shows that the effects are found in the larger population, though they are weaker, likely due to the low suicide rates in other demographic groups. Finally, in Table A8, we separate counties by large urban, medium/small urban, and rural, and repeat our county–year analysis. Table A8 suggests that the effect of PDMPs on suicides are greatest in large urban and rural areas.

Finally, it is important to note two limitations in the analysis. First, we cannot directly measure the size of the supply-shock to the market for diverted drugs caused by the introduction of a

[36]The estimates of Buchmueller and Carey (2018) imply that the strongest PDMPs reduce the supply of diverted drug by 8-15%, at the most. If we assume that PDMPs reduce the supply of diverted drugs by 10%, and that 20% of suicides are drug-related (nearly the entire increase since 2000), then we would arrive at an elasticity of 1 for the response of suicide to treatment following a reduction in the supply of diverted drugs.

[37]Our theoretical analysis does not model the process of becoming an addict. One might think that the decline in suicides in some states may be in part due to a more limited number of new addicts caused by the supply shock. Even if this is the case, however, the decline in suicides would still be explained by having fewer people exposed to the inherent risk of drug abuse.

PDMP. Evidence from Buchmueller and Carey (2018) suggests the "first-stage" effect is modest, in the range of a 10-15 percent reduction in sales to the heaviest users, implying that the local average treatment effects may be large. Second, we do not exploit a quasi-experimental source of exogenous variation in drug treatment center concentrations and the availability of medication-assisted therapies. As a result, these variables serve as proxies for the availability and efficacy of treatment within the state or county, and may themselves be correlated with one another and other measures of treatment network efficacy. For these two reasons, we interpret the evidence as supportive of the model's mechanism and consistent with an important role for access to drug treatment and opioid-replacement therapy in reducing suicides associated with prescription drug abuse.

4.3 Robustness

We present a range of robustness checks in the Appendix. We test for pre-trends using an event study design in Appendix Figures A1 and 3. The individual estimates are noisy, however, we find no statistically significant evidence for pre-trends, and the point estimates are inconsistent with a gradual roll out of demand-side interventions that are timed with the PDMPs.

We also consider robustness to alternative specifications and measurement issues. We allow the county-level model to drop counties with zero suicides in the period. In Appendix Tables A14 and A15, we show the results are very similar when we instead focus on counties with suicides in every period, or replace the zeros in the data with ones. In our analysis, we have restricted the sample to states that have implemented PDMPs after 2003. In Table A9, we repeat our analysis using all the states, and we find that the estimates remain qualitatively identical. We also find similar results when replicating Table 2 with time-varying demographic and economic condition controls at the county–year level (see Tables A10 to A12).

Lastly, we also note that our dependent variable—the number of suicides—differs from our ideal dependent variable—the number of suicides motivated by addiction problems. Our data separate suicides between drug overdoses and suicides by means other than drugs, however, this does not necessarily help us build a measure closer to our ideal dependent variable—in the sense that not all overdoses are by addicts and not all addicts commit suicide by overdosing (and likewise for suicides by means other than drugs). While we prefer using the overall number of suicides as our dependent variable, this suicide breakdown provides us with alternative measures to test our hypotheses. In Table A13, we repeat our analysis using suicides by means other than drugs and find that the results are qualitatively similar (though noisier in the former case).[38]

[38] See Patrick et al. (2016) for a discussion on PDMPs and drug overdose deaths.

5 Discussion and Conclusion

The prescription drug epidemic and the concurrent increase in suicides among middle-aged non-Hispanic whites in the US have raised questions about the forces driving these trends. In this paper, we investigate the link between supply shocks to the market for diverted drugs, identified by the implementation of PDMPs, and suicides. We find only minimal evidence that the introduction of PDMPs affected suicide rates. However, we do find important heterogeneity in the response to PDMPs: states with strong addiction help networks, measured by the number of drug treatment facilities and likelihood of prescribing medication-assisted therapy, saw relative declines in suicide rates after the implementation of PDMPs. Most surprisingly, the heterogeneity seems to be driven by absolute decreases in suicide in states with strong addiction help networks.

Our primary analysis makes use of PDMPs as a generic supply shock, however, the magnitude of the estimated effects has implications for aggregate mortality. To quantify the role of drug treatment on suicide prevention, we calculate the counterfactual number of suicides if all states would have had the same logged number of facilities as California (or Washington) when passing their PDMPs. We estimate that this expansion in drug treatment availability would have reduced the expected number of suicides by 18,232.[39] That is a 4.7 percent decrease in the expected number of suicides over the course of our sample period. The modest effects of PDMPs on dispensed drugs estimated in other studies suggests that larger supply changes could explain an important share of the rise in suicide in places with weak addiction-help networks.

Our results have immediate implications for the current response of policy to the prescription drug epidemic and concurrent rise in suicides. Although these programs have reduced access to prescription opioids, unintended consequences could neutralize the expected positive effect. Put simply, addicts need a path out of addiction. Our findings suggest that attempts to reduce the supply of diverted drugs should be accompanied with expansions of drug treatment options, as the combination of reductions in the supply of prescription drugs in conjunction with readily available drug treatment can reduce suicide rates. As well, our results suggest that opiate-assisted therapies are effective in reducing suicide rates of those in drug treatment. We believe these are the first quasi-experimental results demonstrating the role of drug treatment and medication-assisted therapies in mitigating drug-abuse related suicides.

Our study also makes a contribution to the economic analysis of suicide. We propose a new model of suicide, which incorporates the inherent risks of drug abuse. The model allows us to rationalize several elements of our findings. First, explicitly modeling the effort of addicts to

[39] For this exercise, we make use of the estimates in Table 3 (Column 2).

quit using provides a force that can decreases suicides in the aftermath of a supply shock. The economics behind this effect is that using becomes less attractive relative to recovery when addicts find it costlier to access the drug, which increases the addicts' incentives to exert effort and recover. However, increased incentives to exert effort only arise where effort is productive, that is, where drug addiction treatment is available. Our findings—i.e., a reduction in suicides in places with drug addiction treatment availability—present evidence in favor of both the existence of the inherent risk of drug abuse and the mechanism proposed by our model. As compared to classical economic models of suicide, an inherent risk suggests a role for instantaneous utility, or a heavily discounted lifetime utility function. We know of one other paper, Carpenter (2004), which finds an apparent role for substance use and instantaneous utility in suicide rates. It is perhaps unsurprising that this evidence of an inherent risk comes from a setting with addiction, given the importance of addictive behavior in motivating the behavioral economics literature.

We conclude by noting the broader implications of our findings for the debate on the underlying causes of the recent increase in both prescription drug abuse and suicide among white non-Hispanics. While a narrative in the media and academic discourse has tied these troubling patterns in mortality to trends in inequality, income growth, divorce, the decline in manufacturing employment and intergenerational mobility, a separate literature has identified dramatic changes in prescribing behavior as a fundamental cause of the rise in prescription drug abuse and overdose deaths. However, prior to this paper, the literature has been largely silent on the underlying causes of rising suicide. Our findings suggest a full accounting of the effects of prescription drug use and abuse on suicide is needed, along with investigations into deeper social trends that may explain the apparent misery of so many Americans.

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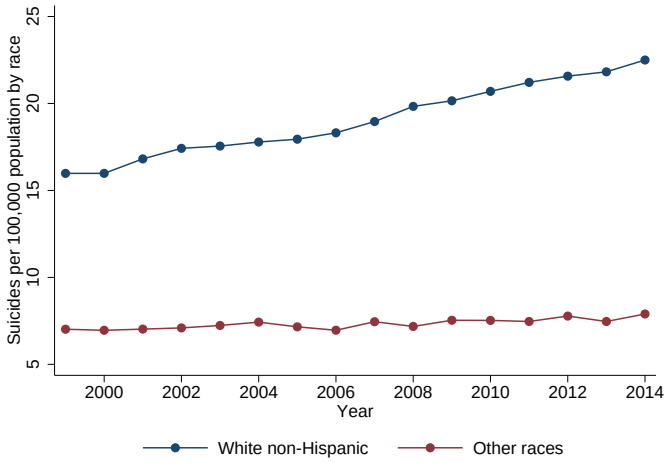
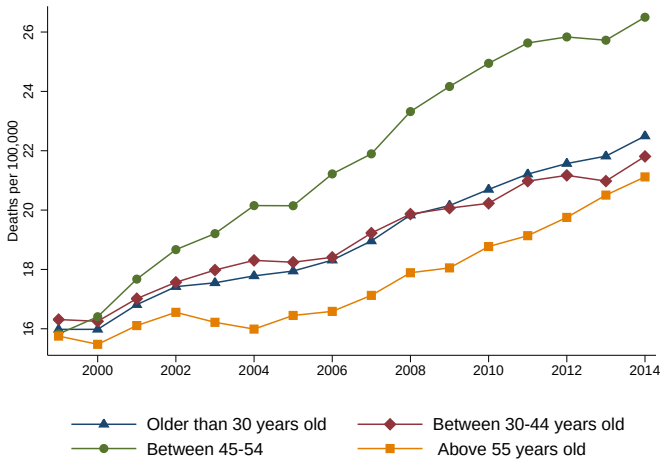
Figures and Tables

Figure 1: Evolution of Suicides by Race and Age Group

(a) White non-Hispanic and other races



(b) White non-Hispanic by age group



Note: Trends are computed from (NVSS) Multiple Causes of Death Microdata (1999-2014), and correspond to all deaths of individuals over 30 years old, including states without a PDMP implemented after 1999.

Figure 2: The Dynamics of the Cumulative Probability of Suicide

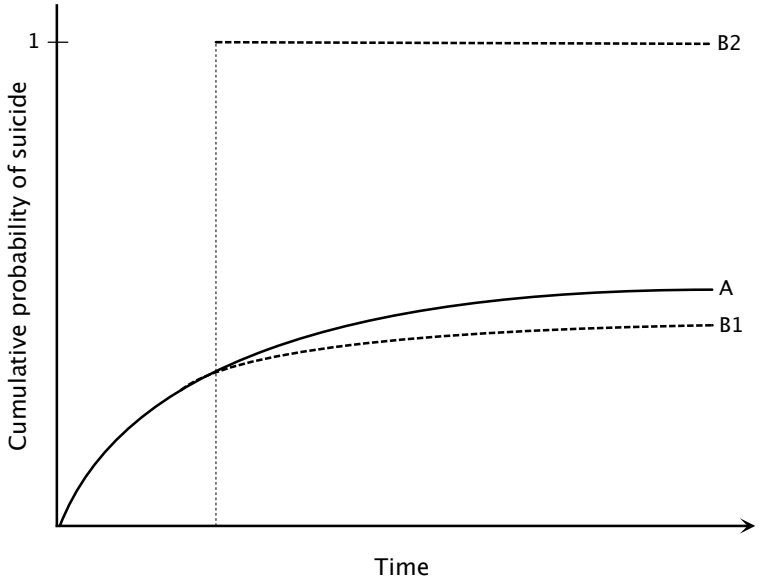
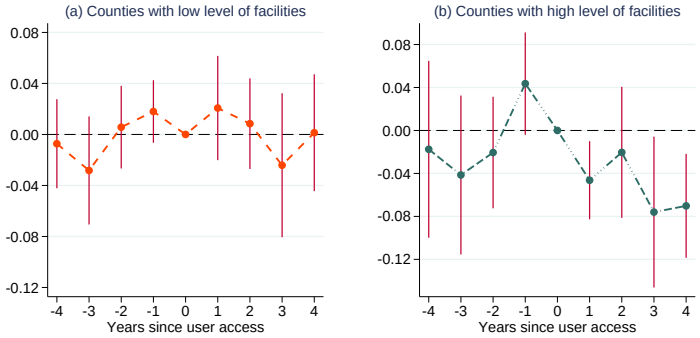


Figure 3: Suicides and PDMP Implementation by level of treatment facilities



Note: The figure shows coefficients and associated clustered standard errors from an event study in which log number of suicides is the dependent variable, and the year of PDMP implementation is the baseline year ($t = 0$). The counties were divided by their standardized level of facilities. Counties with facilities above 0.8 standard deviations are classified as High. This regression is run at the county–year level, and includes county FE and year FE.

Table 1: Summary Statistics

	Mean	Standard deviation	Minimum	Median	Maximum
A. Cause of death for White non-Hispanic over 30 years old					
Unit: count deaths (county–year)					
Suicides	9.82	21.84	0	4	499
Opioid–related overdose[a]	2.19	7.18	0	0	142
Overdose	8.62	23.09	0	2	469
Unit: count deaths (state–quarter)					
Suicides	113.41	116.51	0	83	734
Opioid–related overdose[a]	25.11	35.53	0	13	238
Overdose	98.72	119.02	0	61	734
B. Distribution of opiates and opiod-replacement therapy (state–quarter)					
Unit: Morphine Equivalent Milligrams (MME) per person and Milligrams per person (MP)					
Total opiates[b](MME)	182.81	93.22	37.25	172.48	773.31
Oxycodone (MME)	135.01	76.70	23.40	123.44	700.04
Methadone (MP)	21.60	18.70	0.62	16.11	122.88
Buprenorphine (MP)	2.39	2.45	0	1.61	12.0
C. Treatment related variables					
Unit: count centers (county–year)					
Facilities	5.95	17.58	0	5.09	563
Unit: count centers (state–quarter)					
Facilities	251.45	278.33	33	201.50	1820

Note: The table reports unweighted summary statistics for key variables in the 38 states included in our sample. Panel A displays the number of deaths by two underlying causes of death: suicide and overdose. The information was obtained from NVSS. Data spans years 1999 to 2014. Panel B presents the MME and MP for opiates and opiod-replacement substances. The data source is the DEA and the information is at the state–quarter level for the period 2000-2013. Panel C displays on the number of facilities, and this information comes from County of Business Pattern and N-SSATS.

[a] Drug poisoning deaths include injury deaths of any intent (unintentional, suicide, homicide, or undetermined) in which an opioid drug was mentioned.

[b] Morphine equivalent sum of oxycodone, fentanyl, hydromorphone, meperidine, and morphine.

[c] Information obtained from TEDS–A.

Table 2: Effects of County-Level Treatment Facilities by PDMP Status

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log suicides			Dependent variable: suicide count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Facilities(t-1)	-0.044***	-0.030***	-0.043***	-0.048***	-0.032***	-0.048***
	(0.007)	(0.007)	(0.007)	(0.004)	(0.005)	(0.004)
PDMP*Facilities(t-1)		-0.016***	-0.099**		-0.016***	-0.124***
		(0.003)	(0.040)		(0.002)	(0.025)
Mean	50.21	50.21	50.21	49.23	49.23	49.23
Unweighted mean	10.85	10.85	10.85	9.34	9.34	9.34
Observations	22477	22477	22477	25785	25785	25785
Counties	1714	1714	1714	1720	1720	1720
Clusters	37	37	37	38	38	38

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* $\times$ *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* $\times$ *year* (in weighted standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effects of PDMPs by State-Level Treatment Availability

	(1)	(2)	(3)	(4)
Panel A. Dependent variable: log suicides. OLS regressions.				
PDMP	-0.003	0.001	0.008	0.003
	(0.013)	(0.012)	(0.012)	(0.012)
(PDMP)*Log(Facilities(t-1))		-0.025***		
		(0.009)		
(PDMP)*Log(Methadone(t-1))			-0.017***	
			(0.005)	
(PDMP)*Log(Buprenorphine(t-1))				-0.010
				(0.006)
Panel B. Dependent variable: suicide count. Poisson regressions.				
PDMP	-0.022***	-0.005	0.005	-0.000
	(0.008)	(0.010)	(0.011)	(0.009)
(PDMP)*Log(Facilities(t-1))		-0.021***		
		(0.007)		
(PDMP)*Log(Methadone(t-1))			-0.016***	
			(0.006)	
(PDMP)*Log(Buprenorphine(t-1))				-0.011**
				(0.006)
Mean	206.31	210.50	213.71	218.49
Unweighted mean	107.73	111.43	113.77	115.06
Observations	2430	1698	1356	1254
States	38	38	38	38

Note: The table reports parameter estimates from two types of models. Panel A corresponds to OLS models where the dependent variable is the logarithm of suicides in a $state \times quarter$. Panel B shows the results for Poisson models where the dependent variable is the number of suicides in a $state \times quarter$. The independent variables are in logs, and all the regressions control for state FE and quarter FE. Standard errors are in parentheses and are clustered by state. The regressions are weighted by the white non-Hispanic population over 30 years old in each state. The weighted mean ('Mean') and unweighted mean were computed in the pre-period.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ONLINE APPENDIX: NOT FOR PUBLICATION

A Path Out: Prescription Drug Abuse, Treatment, and Suicide

Mark Borgschulte, Adriana Corredor-Waldron, and Guillermo Marshall

Model: Omitted Details

Value Functions

To derive equation (1), it is useful to first write down the value function of an addict, V, in a discrete time model where each period is of length Δ. For ease of exposition, assume that λ is large so that the suicide condition is non-binding, and the addict chooses effort level e. We then have that

$$V = \Delta(-w - c(e)) + \lambda\Delta u + \frac{(1-\alpha\Delta)(1-e\pi\Delta)}{1+r\Delta}V + \frac{e\pi\Delta}{1+r\Delta}R + \frac{\alpha\Delta(1-e\pi\Delta)}{1+r\Delta}0,$$

where $\lambda\Delta$, $e\pi\Delta$, and $\alpha\Delta$ are the probabilities that the addict, in a period of length Δ, finds a dose, recovers, and faces extreme pain (and commits suicide), respectively, while $1/(1+r\Delta)$ is the discount factor. The addict's continuation payoff when recovered is R, while in case of suicide, 0.

We can rewrite the equation above as

$$\begin{aligned}
(1+r\Delta)V &= \Delta(1+r\Delta)(-w-c(e)) + \lambda\Delta(1+r\Delta)u + (1-\alpha\Delta)(1-e\pi\Delta)V + e\pi\Delta R, \\
(1/\Delta+r)V &= (1+r\Delta)(-w-c(e)) + \lambda(1+r\Delta)u + (1/\Delta - e\pi - \alpha + e\pi\alpha\Delta)V + e\pi R, \\
rV &= (1+r\Delta)(-w-c(e)) + \lambda(1+r\Delta)u + (-\alpha + e\pi\alpha\Delta)V + e\pi(R-V).
\end{aligned}$$

Taking the limit as $\Delta \to 0$,

$$rV = -w - c(e) + \lambda u - \alpha V + e\pi(R-V),$$

which is analogous to equation (1).

Uncertainty

Both theoretical and empirical work have argued that uncertainty about the future can shape suicide decisions (Campaniello et al., 2017). In our context, beliefs about future improvements in the value of using a drug may mitigate the impact of short-run drug supply shocks and prevent suicides. In this subsection, we provide an overview of an extension of the model, which incorporates uncertainty in the rate of arrival of drug doses. Using this version of the model, we examine how uncertainty about whether a drug supply shock will be reversed impacts drug addicts' choices.

We consider the case with two states: low and high. Drug users are initially in the "low" state, which has a low rate of arrival of drug doses as a consequence of the policy intervention. At a Poisson rate β, the drug users switch to the "high" state, in which drug users face a greater rate

of arrival of drug doses. For simplicity, we assume that the high state is an absorbing state. The possibility of switching to the high state gives drug users hope that their utility flow will improve in the future, and therefore affects incentives to exert effort and commit suicide.

The value functions in each state must satisfy

$$rV_l = \max\left\{\max_e \; -w + \lambda_l u + e\pi(R - V_l) - c(e) - \alpha V_l + \beta(V_h - V_l), 0\right\}, \tag{9}$$

$$rV_h = \max\left\{\max_e \; -w + \lambda_h u + e\pi(R - V_h) - c(e) - \alpha V_h, 0\right\}, \tag{10}$$

where the interpretation of the equations is analogous to that of equation (1). We assume that $\lambda_l < \lambda_h$, which captures that the rate of arrival of drug doses is greater in the high state.

The following properties of the equilibrium value functions hold true:

Lemma 1.

1. $V_h > V_l$.[40]
2. $\lambda_l^* = (w - \pi^2 R^2/2 - \beta V_h)/u$ *is the lower bound for the set of values of* λ_l *which guarantee that* $V_l \geq 0$.
3. $\dfrac{dV_h}{d\lambda_h} = \dfrac{u}{\alpha + r + \pi^2(R - V_h)} > 0, \; \dfrac{dV_h}{d\pi} = \dfrac{\pi(R - V_h)^2}{\alpha + r + \pi^2(R - V_h)} > 0.$
4. $\dfrac{dV_l}{d\lambda_l} = \dfrac{u}{\alpha + r + \beta + \pi^2(R - V_l)} > 0, \; \dfrac{dV_l}{d\pi} = \dfrac{\pi(R - V_l)^2 + \beta dV_h/d\pi}{\alpha + r + \beta + \pi^2(R - V_l)} > 0.$

These properties resemble the analysis in the main text. That is, a greater rate of arrival of drug doses improves the value of using the drug, and a greater productivity of each unit of effort does as well.

Based on these properties, we can establish that our main results on how a drug supply shock impacts the suicide rate (1 and 2) hold true even in presence of uncertainty.

Proposition 3.

i) An exogenous decrease in λ_l *causes addicts to fall below the habit sustainability threshold* λ_l^* *(see Lemma 1).*

[40] We prove this result by contradiction. We take the difference between the equations that implicitly define V_h and V_l, and obtain $(\alpha + \beta + r)(V_h - V_l) = u(\lambda_h - \lambda_l) + \pi^2/2((R - V_h)^2 - (R - V_l)^2)$. If we suppose $V_l > V_h$, we reach a contradiction since $\lambda_h > \lambda_l$ in conjunction with the equilibrium conditions imply $V_h > V_l$.

ii) An exogenous decrease in λ_l increases the effort devoted to seeking drug addiction recovery:

$$\frac{de_l}{d\lambda_l} = \frac{-\pi u}{\alpha + r + \beta + \pi^2(R - V_l)} < 0.$$

iii) An exogenous decrease in λ_l increases the effort devoted to seeking drug addiction recovery by more in places with a greater value of π (i.e., places with greater effectiveness or availability of drug addiction treatment).

$$\frac{d^2 e_l}{d\lambda_l d\pi} = \frac{-u}{\alpha + r + \beta + \pi^2(R - V_l)} + \frac{-\pi u}{(\alpha + r + \beta + \pi^2(R - V_l))^2} \times \Gamma < 0,$$

with $\Gamma > 0$.[41]

As in our baseline analysis in the main text, Proposition 3 shows that a drug supply shock has a negative and positive effect on the suicide rate. The positive effect comes from the drug habit becoming unsustainable for some drug addicts. The negative effect comes from increased incentives to exert effort, with the effort channel being stronger in places with greater availability/effectiveness of drug addiction treatment.

With respect to how uncertainty in the arrival rate of drug doses impacts these results, we can establish the following results.

Proposition 4.

i) The drug habit sustainability threshold λ_l^* is decreasing in β.

ii) An exogenous decrease in λ_l increases the effort devoted to seeking drug addiction recovery by less in places with a greater value of β (i.e., places where future improvements in the value of using the drug are likelier):

$$\frac{d^2 e_l}{d\lambda_l d\beta} = \frac{\pi u(\alpha + r + \beta + \pi^2(R - V_h))}{(\alpha + r + \beta + \pi^2(R - V_l))^2} > 0.$$

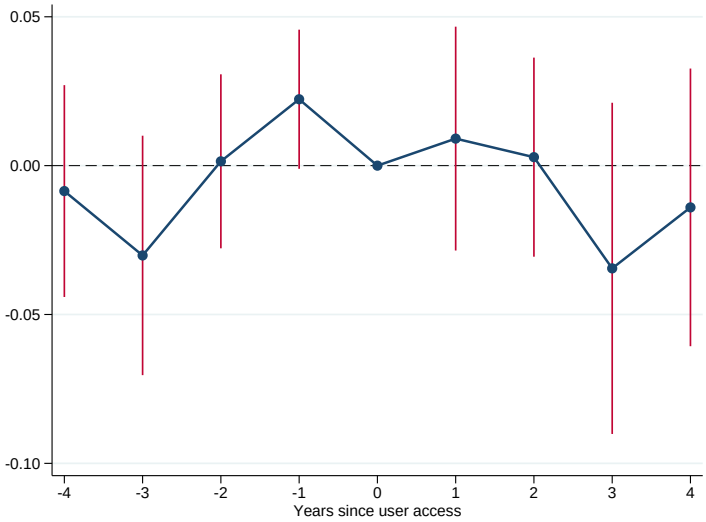
While Proposition 3 shows that our main results hold in presence of uncertainty, Proposition 4 shows that uncertainty impacts the extent of these results. Proposition 4 shows that the positive and negative effects of a drug supply shock on the suicide rate are mitigated in places with a greater likelihood of future improvements in the arrival rate of drug doses (i.e., greater β). On the one

[41] $\Gamma = \frac{(\alpha+r+\beta+\pi^2(R-V_h))(\pi^3(R-V_l)^2+2\pi(R-V_l)(\alpha+r))+2\beta\pi(R-V_l)(\alpha+r)+\beta\pi^3(R-V_h)(2(R-V_l)-(R-V_h))}{(\alpha+r+\beta+\pi^2(R-V_h))(\alpha+r+\pi^2(R-V_l))} > 0$, where we use $R > V_h > V_l$ to establish the inequality.

hand, a greater value of β decreases the drug habit sustainability threshold λ_l^*, which captures that drug addicts are more willing to wait before committing suicide when they perceive that the value of using the drug may improve in the future. On the other hand, the likelihood of an improvement in the value of using the drug increases the discounted value of using the drug, which decreases the incentives to exert effort towards rehabilitation.

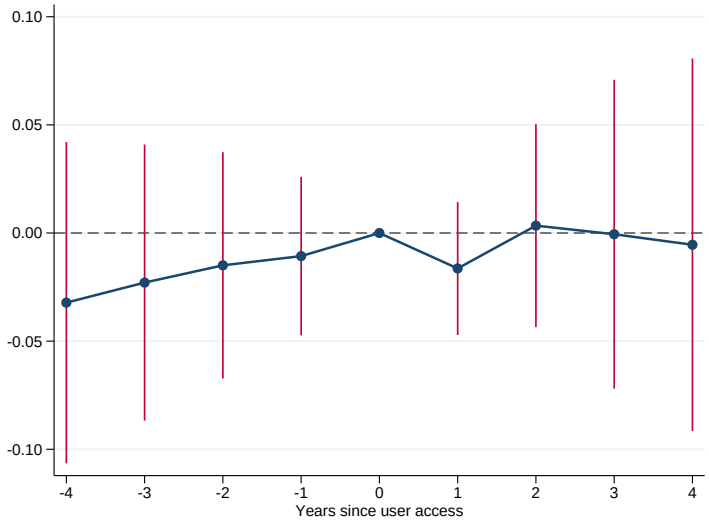
Tables and Figures

Figure A1: Suicides and PDMP Implementation



Note: The figure shows coefficients and associated clustered standard errors from an event study in which log number of suicides is the dependent variable, and the year of PDMP implementation is the baseline year ($t = 0$). This regression is run at the county–year level, and includes county FE and year FE.

Figure A2: Number of Facilities and PDMP Implementation



Note: The figure shows coefficients and associated clustered standard errors from an event study in which log number of facilities is the dependent variable, and the year of PDMP implementation is the baseline year ($t = 0$). This regression is run at the county–year level, and includes county FE and year FE.

Table A1: Date of PDMP Implementation by State

State	PDMP Date of user access	PDMP Mandatory[a]	Source Date of user access
Alabama	Aug-07		NAMSDL[b]
Alaska	Jan-12		NAMSDL
Arizona	Dec-08		NAMSDL
Arkansas	Mar-13		NAMSDL
California	Jan-09		NAMSDL
Colorado	Feb-08		NAMSDL
Connecticut	Mar-09		State PDMP administrator[c]
Delaware	Aug-12	Yes	NAMSDL
Florida	Oct-11		NAMSDL
Georgia	Jul-13		NAMSDL
Indiana	Jan-07		NAMSDL
Iowa	Mar-09		NAMSDL
Kansas	Apr-11		NAMSDL
Louisiana	Jan-09	Yes	NAMSDL
Maine	Jan-05		NAMSDL
Maryland	Jan-14		NAMSDL
Massachusetts	Dec-10		State PDMP administrator
Minnesota	Apr-10		NAMSDL
Mississippi	Dec-05		NAMSDL
Montana	Oct-12		NAMSDL
New Jersey	Jan-12		NAMSDL
New Mexico	Aug-05		NAMSDL
North Carolina	Oct-07		NAMSDL
North Dakota	Sep-07		State PDMP administrator
Ohio	Oct-06	Yes	NAMSDL
Oklahoma	Jul-06	Yes	NAMSDL
Oregon	Sep-11		NAMSDL
South Carolina	Jun-08		NAMSDL
South Dakota	Mar-12		NAMSDL
Vermont	Apr-09		NAMSDL
Washington	Jan-12		NAMSDL
Wisconsin	May-13		NAMSDL
Wyoming	Jan-04		NAMSDL

States without an operational PDMP or legislation to modernize the program after the Model Prescription Monitoring Program Act

Nebraska[d]
Pennsylvania[e]
New Hampshire[f]
Missouri[g]
DC[g]

Note: This table reports the date that providers and other users had access to PDMP information, in states that enacted their PDMP legislation after the PDMP Model Act of 2003.

[a] The information on states with mandatory access was obtained from Buchmueller and Carey (2018). There are in total six states with PDMP mandatory (DE, KY, LA, NV, OH and OK), however two of them implemented a PDMP before the Model Prescription Monitoring Program Act.

[b] Find more details in http://www.namsdl.org/library/580225E9-E469-AFA9-50E7579C1D738E71/.

[c] Contact information is available at http://www.namsdl.org/library/CBF7383C-EA1E-69E4-E15A9FC9F0C68F1C

[d] Participation by patients and physicians is voluntary. PDMP will be mandatory starting on Jan. 1, 2017.

[e] PDMP will be available for query starting on Aug. 25, 2016.

[f] Became operational at the end of the study period.

[g] MO has not enacted a PDMP, and DC's PDMP became operational in July 01, 2016.

Table A2: Effects of County-Level Treatment Facilities using the Logarithm of Facilities

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log suicides			Dependent variable: suicide count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Log(Facilities(t-1))	0.017	0.023**	0.019*	-0.014	0.003	-0.012
	(0.011)	(0.010)	(0.010)	(0.021)	(0.017)	(0.021)
PDMP*Log(Facilities(t-1))		-0.016	-0.033**		-0.042***	-0.042***
		(0.010)	(0.012)		(0.007)	(0.012)
Mean	52.88	52.88	52.88	52.21	52.21	52.21
Unweighted mean	12.83	12.83	12.83	11.44	11.44	11.44
Observations	17563	17563	17563	19587	19587	19587
Counties	1639	1639	1639	1712	1712	1712
Clusters	37	37	37	38	38	38

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* $\times$ *year* level, and the independent variable is the lag of the log of the number of treatment facilities in each *county* $\times$ *year*. The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effects of County-Level Treatment Facilities using PDMP Score

	(1)	(2)	(3)	(4)
	OLS		Poisson	
	Dependent variable: log suicides		Dependent variable: suicide count	
		PDMP: All		PDMP: All
Facilities(t-1)	-0.044***	-0.030***	-0.048***	-0.032***
	(0.007)	(0.007)	(0.004)	(0.005)
Score*Facilities(t-1)		-0.002***		-0.002***
		(0.000)		(0.000)
Mean	50.21	50.21	49.23	49.23
Unweighted mean	10.85	10.85	9.34	9.34
Observations	22477	22477	25785	25785
Counties	1714	1714	1720	1720
Clusters	37	37	38	38

Note: The table reports parameter estimates from linear models in columns 1 and 2, and Poisson models in the rest. The dependent variable is at the *county* $\times$ *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* $\times$ *year* (in weighted standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effects of PDMPs by State-Level Treatment Availability using Standardized Independent Variables

	(1)	(2)	(3)	(4)
Panel A. Dependent variable: log suicides. OLS regressions.				
PDMP	-0.003	-0.010	-0.011	-0.011
	(0.013)	(0.012)	(0.012)	(0.012)
(PDMP)*Facilities(t-1)		-0.016**		
		(0.006)		
(PDMP)*Methadone(t-1)			-0.016**	
			(0.006)	
(PDMP)*Buprenorphine(t-1)				-0.018***
				(0.006)
Panel B. Dependent variable: suicide count. Poisson regressions.				
PDMP	-0.022***	-0.022***	-0.023***	-0.025***
	(0.008)	(0.008)	(0.007)	(0.007)
(PDMP)*Facilities(t-1)		-0.040***		
		(0.010)		
(PDMP)*Methadone(t-1)			-0.039***	
			(0.014)	
(PDMP)*Buprenorphine(t-1)				-0.034***
				(0.013)
Mean	206.31	206.31	206.31	206.31
Unweighted Mean	107.73	107.73	107.73	107.73
Observations	2430	2430	2430	2430
States	38	38	38	38

Note: The table reports parameter estimates from two types of models. Panel A corresponds to OLS models where the dependent variable is the logarithm of suicides in a $state \times quarter$. Panel B shows the results for Poisson models where the dependent variable is the number of suicides in a $state \times quarter$. The independent variables are standardized, and all the regressions control for state FE and quarter FE. Standard errors are in parentheses and are clustered by state. The regressions are weighted by the white non-Hispanic population over 30 years old in each state. The weighted mean ('Mean') and unweighted mean were computed in the pre-period.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Effects of County-Level Treatment Facilities by PDMP Status and across Gender

	(1)	(2)	(3)
	Dependent variable: suicide count		
	All	Female	Male
Panel A: Facilities			
Facilities(t-1)	-0.048***	-0.075***	-0.040***
	(0.004)	(0.003)	(0.006)
Panel B: PDMP: All			
Facilities(t-1)	-0.032***	-0.058***	-0.024***
	(0.005)	(0.004)	(0.007)
PDMP*Facilities(t-1)	-0.016***	-0.017***	-0.016***
	(0.002)	(0.001)	(0.002)
Panel C: PDMP: Mandatory			
Facilities(t-1)	-0.048***	-0.074***	-0.040***
	(0.004)	(0.003)	(0.006)
PDMP*Facilities(t-1)	-0.124***	-0.306***	-0.077**
	(0.025)	(0.013)	(0.030)
Mean	49.23	11.64	37.82
Unweighted mean	9.34	2.05	7.29
Observations	25785	25785	25785
Counties	1720	1720	1720
Clusters	38	38	38

Note: The table reports parameter estimates from Poisson models where the dependent variable is the number of suicides of white non-Hispanic by gender. The observations are at the *county* $\times$ *year* level. The independent variable is the lag of the number of treatment facilities in each *county* $\times$ *year* (in weighted standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). Each of the panels correspond to separate regressions for each of the interaction variables. All the regressions control for county and state–year FE. Standard errors are in parentheses and are clustered by state. The regressions are weighted by the white non-Hispanic population in each gender and county.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Effects of County-Level Treatment Facilities by PDMP Status. All Races and All Ages.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log suicides			Dependent variable: suicide count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Facilities(t-1)	-0.066***	-0.051***	-0.065***	-0.048**	-0.025	-0.048**
	(0.004)	(0.005)	(0.004)	(0.023)	(0.030)	(0.023)
PDMP*Facilities(t-1)		-0.016***	-0.087**		-0.022***	-0.108***
		(0.002)	(0.032)		(0.007)	(0.028)
Mean	98.84	98.84	98.84	97.49	97.49	97.49
Unweighted mean	14.72	14.72	14.72	13.36	13.36	13.36
Observations	23620	23620	23620	25785	25785	25785
Counties	1717	1717	1717	1720	1720	1720
Clusters	37	37	37	38	38	38

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* $\times$ *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* $\times$ *year* (in weighted standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by population in each county, and clustered at the state level. All the regressions include county and state–year FE.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Effects of PDMPs by State-Level Treatment Availability. All races and All Ages

	(1)	(2)	(3)	(4)
Panel A. Dependent variable: log suicides. OLS regressions.				
PDMP	0.001	0.001	0.001	0.001
	(0.012)	(0.011)	(0.011)	(0.010)
(PDMP)*Facilities(t-1)		-0.010		
		(0.007)		
(PDMP)*Methadone(t-1)			-0.005	
			(0.008)	
(PDMP)*Buprenorphine(t-1)				-0.006
				(0.007)
Panel B. Dependent variable: suicide count. Poisson regressions.				
PDMP	-0.015	-0.005	-0.011	-0.014
	(0.010)	(0.012)	(0.015)	(0.012)
(PDMP)*Facilities(t-1)		-0.015**		
		(0.008)		
(PDMP)*Methadone(t-1)			-0.006	
			(0.011)	
(PDMP)*Buprenorphine(t-1)				-0.002
				(0.008)
Mean	325.29	325.29	325.29	325.29
Unweighted mean	107.73	107.73	107.73	107.73
Observations	2432	2432	2432	2176
States	38	38	38	38

Note: The table reports parameter estimates from two types of models. Panel A corresponds to OLS models where the dependent variable is the logarithm of suicides in a $state \times quarter$. Panel B shows the results for Poisson models where the dependent variable is the number of suicides in a $state \times quarter$. The independent variables are in logs, and all the regressions control for state FE and quarter FE. Standard errors are in parentheses and are clustered by state. The regressions are weighted by population in each state. The weighted mean ('Mean') and unweighted mean were computed in the pre-period.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Effects of County-Level Treatment Facilities by PDMP Status and across Rural and Urban Counties

	(1)	(2)	(3)	(4)
	Dependent variable: suicide count			
	All	Large urban	Medium/Small urban	Rural
Panel A: Facilities				
Facilities (t-1)	-0.048***	-0.049***	0.077*	0.109
	(0.004)	(0.004)	(0.041)	(0.143)
Panel B: PDMP: All				
Facilities (t-1)	-0.032***	-0.033***	0.137**	0.119
	(0.005)	(0.006)	(0.058)	(0.290)
PDMP*Facilities(t-1)	-0.016***	-0.016***	-0.078**	-0.015
	(0.002)	(0.002)	(0.039)	(0.342)
Panel C: PDMP: Mandatory				
Facilities (t-1)	-0.048***	-0.049***	0.081*	0.114
	(0.004)	(0.005)	(0.041)	(0.147)
PDMP*Facilities(t-1)	-0.124***	-0.230***	-0.118***	-0.139
	(0.025)	(0.005)	(0.045)	(0.109)
Mean	49.23	81.15	26.34	5.61
Unweighted mean	9.34	28.51	13.41	3.05
Observations	25785	3666	6324	15795
Counties	1720	245	422	1052
Clusters	38	28	37	36

Note: The table reports parameter estimates from Poisson models where the dependent variable is the number of suicides of white non-Hispanic in the age profile. The dependent variable is at the *county* × *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* × *year* (in weighted standard deviations). Each of the panels correspond to separate regressions for each of the interaction variables. All the regressions control for county and state–year FE. Standard errors are in parentheses and are clustered by state. The regressions are weighted by the white non-Hispanic population in each age profile and state.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Effects of County-Level Treatment Facilities by PDMP Status and using All States

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log suicides			Dependent variable: suicide count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Facilities (t-1)	-0.059***	-0.045***	-0.059***	-0.052***	-0.038***	-0.052***
	(0.016)	(0.015)	(0.016)	(0.007)	(0.007)	(0.007)
PDMP*Facilities (t-1)		-0.016***	-0.062		-0.015***	-0.086*
		(0.004)	(0.051)		(0.002)	(0.045)
Mean	49.90	49.90	49.90	48.92	48.92	48.92
Unweighted mean	10.74	10.74	10.74	9.24	9.24	9.24
Observations	32965	32965	32965	37601	37601	37601
Counties	2499	2499	2499	2508	2508	2508
Clusters	50	50	50	51	51	51

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* $\times$ *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* $\times$ *year* (in standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions include all the states, even those that implemented a PDMP before the PDMP Model Act of 2003. The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Effects of County-Level Treatment Facilities by PDMP Status after including Demographic and Economic Covariates. OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: suicide rate per 100,000 population					
	PDMP: All					
Facilities(t-1)	-0.044	-0.046	-0.045	-0.048	-0.044	-0.055
	(0.072)	(0.064)	(0.072)	(0.069)	(0.070)	(0.058)
PDMP*Facilities(t-1)	-0.071***	-0.070***	-0.071***	-0.077***	-0.079***	-0.087***
	(0.013)	(0.014)	(0.013)	(0.012)	(0.014)	(0.013)
%White(t-1)		-0.035				-0.059
		(0.037)				(0.041)
%Black(t-1)		-0.019				-0.036
		(0.063)				(0.063)
%Male(t-1)			-0.045			-0.068
			(0.062)			(0.070)
%Under 18 age(t-1)				0.009		-0.012
				(0.030)		(0.029)
%18–64 years old(t-1)				0.038		0.044
				(0.037)		(0.041)
ln(Per–capita income(t-1))					0.798	0.933
					(0.717)	(0.667)
%Unemployment(t-1)					0.050**	0.053**
					(0.022)	(0.019)
Mean	4.66	4.66	4.66	4.66	4.66	4.66
Unweighted mean	5.53	5.53	5.53	5.53	5.53	5.53
Observations	22477	22477	22477	22477	22463	22463
Counties	1714	1714	1714	1714	1714	1714
Clusters	37	37	37	37	37	37

Note: The table reports parameter estimates from linear models. The dependent variable is at the *county* × *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* × *year* (in weighted standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE, and control variables such as the fraction of the county population that is white, the fraction that is black and the fraction that is male. Also, county–level economic conditions (unemployment rate and per–capita income) where included. The total number of observation decreases in the last two columns because some counties dont' have information on per–capita income for all the years.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Effects of County-Level Treatment Facilities by PDMP Status after including Demographic and Economic Covariates. OLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: log suicides rate					
	PDMP: All					
Facilities(t-1)	-0.009	-0.010	-0.010	-0.008	-0.009	-0.011
	(0.016)	(0.012)	(0.016)	(0.016)	(0.015)	(0.013)
PDMP*Facilities(t-1)	-0.012***	-0.011***	-0.012***	-0.010***	-0.011***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
%White(t-1)		-0.020***				-0.022***
		(0.006)				(0.006)
%Black(t-1)		-0.014				-0.016*
		(0.009)				(0.009)
%Male(t-1)			-0.041***			-0.029*
			(0.012)			(0.014)
%Under 18 age(t-1)				0.000		-0.011
				(0.007)		(0.007)
%18–64 years old(t-1)				-0.010		-0.004
				(0.006)		(0.007)
ln(Per–capita income(t-1))					-0.065	-0.001
					(0.079)	(0.076)
%Unemployment(t-1)					0.004	0.005
					(0.004)	(0.004)
Mean	4.66	4.66	4.66	4.66	4.66	4.66
Unweighted mean	5.53	5.53	5.53	5.53	5.53	5.53
Observations	22477	22477	22477	22477	22463	22463
Counties	1714	1714	1714	1714	1714	1714
Clusters	37	37	37	37	37	37

Note: The table reports parameter estimates from linear models. The dependent variable is at the *county* × *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* × *year* (in weighted standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE, and control variables such as the fraction of the county population that is white, the fraction that is black and the fraction that is male. Also, county–level economic conditions (unemployment rate and per–capita income) where included. The total number of observation decreases in the last two columns because some counties dont' have information on per–capita income for all the years.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Effects of County-Level Treatment Facilities by PDMP Status after including Demographic and Economic Covariates. Poisson

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: suicides					
	PDMP: All					
Facilities(t-1)	0.005	0.004	0.005	0.006	0.005	0.003
	(0.030)	(0.028)	(0.030)	(0.031)	(0.030)	(0.029)
PDMP*Facilities(t-1)	-0.013**	-0.013**	-0.013**	-0.012**	-0.014**	-0.014***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
%White(t-1)		-0.017***				-0.021***
		(0.006)				(0.008)
%Black(t-1)		-0.018**				-0.020**
		(0.008)				(0.008)
%Male(t-1)			-0.019			-0.013
			(0.012)			(0.013)
%Under 18 age(t-1)				-0.005		-0.011**
				(0.005)		(0.005)
%18–64 years old(t-1)				-0.006		-0.005
				(0.006)		(0.006)
ln(Per–capita income(t-1))					0.111	0.144
					(0.124)	(0.124)
%Unemployment(t-1)					0.003	0.004
					(0.005)	(0.005)
Mean	49.23	49.23	49.23	49.23	49.23	49.23
Unweighted mean	9.34	9.34	9.34	9.34	9.34	9.34
Observations	25785	25785	25785	25785	25750	25750
Counties	1720	1720	1720	1720	1719	1719
Clusters	38	38	38	38	38	38

Note: The table reports parameter estimates from poisson models where population is used as an offset variable. The dependent variable is at the *county* $\times$ *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* $\times$ *year* (in weighted standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE, and control variables such as the fraction of the county population that is white, the fraction that is black and the fraction that is male. Also, county–level economic conditions (unemployment rate and per–capita income) where included. The total number of observation decreases in the last two columns because some counties dont' have information on per–capita income for all the years.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Effects of County-Level Treatment Facilities by PDMP Status and using Suicides committed by other Means Besides Drugs

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log suicides			Dependent variable: suicide count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Facilities (t-1)	-0.027***	-0.014**	-0.026***	-0.024***	-0.010*	-0.023***
	(0.006)	(0.006)	(0.006)	(0.004)	(0.005)	(0.004)
PDMP*Facilities (t-1)		-0.014***	-0.122**		-0.014***	-0.153***
		(0.003)	(0.056)		(0.002)	(0.032)
Mean	41.68	41.68	41.68	40.74	40.74	40.74
Unweighted mean	9.39	9.39	9.39	7.94	7.94	7.94
Observations	22115	22115	22115	25785	25785	25785
Counties	1712	1712	1712	1720	1720	1720
Clusters	37	37	37	38	38	38

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* × *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* × *year* (in standard deviations). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Effects of County-Level Treatment Facilities by PDMP Status in Counties with Suicides in Every Period.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log suicides			Dependent variable: suicide count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Facilities(t-1)	-0.047***	-0.032***	-0.046***	-0.052***	-0.037***	-0.051***
	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
PDMP*Facilities(t-1)		-0.016***	-0.113***		-0.015***	-0.124***
		(0.003)	(0.031)		(0.001)	(0.025)
Mean	53.93	53.93	53.93	53.93	53.93	53.93
Unweighted mean	16.36	16.36	16.36	16.36	16.36	16.36
Observations	13533	13533	13533	13548	13548	13548
Counties	903	903	903	904	904	904
Clusters	37	37	37	38	38	38

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* × *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* × *year* (in weighted standard deviations). The difference in number of observations between the linear and Poisson model is due to the exclusion of District of Columbia (DC) in the the linear model with fixed effects, because DC is a group with only one member. The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE. The regressions only include counties with positive counts of suicides for all years.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Effects of County-Level Treatment Facilities by PDMP Status taking suicides+1.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log(suicides+1)			Dependent variable: (suicide+1) count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Facilities(t-1)	-0.001	0.020	-0.001	-0.047***	-0.031***	-0.047***
	(0.051)	(0.062)	(0.052)	(0.005)	(0.006)	(0.005)
PDMP*Facilities(t-1)		-0.024*	-0.072		-0.015***	-0.107***
		(0.014)	(0.046)		(0.002)	(0.028)
Mean	50.23	50.23	50.23	50.23	50.23	50.23
Unweighted mean	10.34	10.34	10.34	10.34	10.34	10.34
Observations	25770	25770	25770	25785	25785	25785
Counties	1719	1719	1719	1720	1720	1720
Clusters	37	37	37	38	38	38

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* × *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* × *year* (in weighted standard deviations). For all the specifications we add one to suicides, so all the observations use in the Poisson model should be use in the logarithm specification. However, the 15 observations from District of Columbia (DC) are excluded from the linear model with fixed effects, because DC is a group with only one member. The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A16: Effects of County-Level Treatment Facilities by PDMP Status. Unweighted

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log suicides			Dependent variable: suicide count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Facilities(t-1)	0.003	0.004	0.004	-0.008**	-0.004	-0.008**
	(0.009)	(0.008)	(0.009)	(0.003)	(0.004)	(0.003)
PDMP*Facilities(t-1)		-0.001	-0.008		-0.004***	-0.021**
		(0.005)	(0.036)		(0.001)	(0.010)
Mean	50.21	50.21	50.21	49.23	49.23	49.23
Unweighted mean	10.85	10.85	10.85	9.34	9.34	9.34
Observations	22477	22477	22477	25785	25785	25785
Counties	1714	1714	1714	1720	1720	1720
Clusters	37	37	37	38	38	38

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* × *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* × *year* (in weighted standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are clustered at the state level. All the regressions include county and state–year FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A17: Effects of County-Level Treatment Facilities by PDMP Status. Unweighted for Counties with Suicides in All Periods.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log suicides			Dependent variable: suicide count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Facilities(t-1)	-0.005	0.001	-0.004	-0.013***	-0.009***	-0.013***
	(0.008)	(0.007)	(0.008)	(0.002)	(0.002)	(0.002)
PDMP*Facilities(t-1)		-0.007	-0.041**		-0.004***	-0.028**
		(0.005)	(0.017)		(0.001)	(0.012)
Mean	53.93	53.93	53.93	53.93	53.93	53.93
Unweighted mean	16.36	16.36	16.36	16.36	16.36	16.36
Observations	13533	13533	13533	13548	13548	13548
Counties	903	903	903	904	904	904
Clusters	37	37	37	38	38	38

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* × *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* × *year* (in weighted standard deviations). The difference in the number of observations between the linear and Poisson model is due to the exclusion of District of Columbia (DC) in the the linear model with fixed effects, because DC is a group with only one member. The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are clustered at the state level. All the regressions include county and state–year FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A18: Effects of County-Level Treatment Facilities by PDMP Status Clustering at the County Level

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Poisson		
	Dependent variable: log suicides			Dependent variable: suicide count		
		PDMP: All	PDMP: Mandatory		PDMP: All	PDMP: Mandatory
Facilities(t-1)	-0.044***	-0.030***	-0.043***	-0.048***	-0.032***	-0.048***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
PDMP*Facilities(t-1)		-0.016***	-0.099*		-0.016***	-0.124***
		(0.004)	(0.052)		(0.003)	(0.046)
Mean	50.21	50.21	50.21	49.23	49.23	49.23
Unweighted mean	10.85	10.85	10.85	9.34	9.34	9.34
Observations	22477	22477	22477	25785	25785	25785
Counties	1714	1714	1714	1720	1720	1720
Clusters	1714	1714	1714	1720	1720	1720

Note: The table reports parameter estimates from linear models in columns 1 to 3, and Poisson models in columns 4 to 6. The dependent variable is at the *county* × *year* level, and the independent variable is the lag of the number of treatment facilities in each *county* × *year* (in weighted standard deviations). The information of facilities at the county level comes from the U.S. Census Bureau's County Business Patterns (CBP). The regressions are weighted by the white non-Hispanic population over 30 years old in each county, and clustered at the state level. All the regressions include county and state–year FE.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$