The Negative Spillover Effect of Electronic Prescribing for Controlled Substances (EPCS) on Opioid Epidemic

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Short Paper

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Abstract

The opioid epidemic is a widespread societal problem. Electronic Prescription of Controlled Substances (EPCS) was introduced to reduce opioid overdose by enabling prescribers to detect doctor shoppers through patients' comprehensive prescription history. However, there is potential that limited access to opioids after EPCS mandates may cause drug users to travel to other locations without EPCS. Using a US county-level dataset from 2010 to 2020 with a difference-in-difference model, we find that EPCS mandate in a neighboring county is associated with increased opioid-related mortality and opioid dispensing rate in the focal county without EPCS. We offer relevant policy implications, demonstrating that insurance coverage moderates the effect of EPCS mandates, underscoring the importance of aligning health insurance initiatives with electronic prescribing policies. By identifying the negative spillover effect of EPCS, our work enriches discussions on the societal impacts of information sharing, prompting further research exploration.

Keywords: Spillover effect, health IT, societal impact, opioid overdose, Electronic Prescribing for Controlled Substances (EPCS)

Introduction

Opioid[1] overdose is a global crisis, causing about 0.5 million drug-related deaths annually, with over 70% attributed to opioids and 30% due to overdose (WHO). Yet, fewer than 10% of those needing treatment receive it. Naloxone, an effective medication, can avert overdose fatalities if administered promptly (WHO, 2020). Europe, notably the UK, saw a surge in prescription opioid use from 2010 to 2018, while France also witnessed an opioid overdose increase over two decades (Pierce et al., 2021; Natali et al., 2023). The escalating use of opioids has triggered critical societal issues, such as rising crime rates, increased HIV transmission, and higher job losses (Hodder et al., 2021; Winkelman et al., 2018). In US specifically, 18%

[1] Natural, synthetic, or semi-synthetic chemicals that interact with opioid receptors on nerve cells in the body and brain, and reduce the intensity of pain signals and feelings of pain. Prescription opioids include oxycodone, hydrocodone, codeine, morphine, etc. See at https://www.cdc.gov/opioids/basics/terms.html, accessed on May 4, 2023.

of individuals aged 12 and above used illicit drug or misused prescription medication[2] in 2017 (NIH, 2023). Over-prescription of opioids is a key contributor to opioid overdose and misuse, affecting not only addicts but also patients with chronic pain (Banta-Green et al., 2009), as 25% of long-term opioid therapy patients in US primary care settings face these risks.

To combat opioid epidemic, policymakers have taken Electronic Prescription of Controlled Substances (EPCS). EPCS, established in the US, is a state-level mandate to require prescribers to transmit prescriptions into electronic systems. The system stores and transmits all prescribing records, allowing doctors to access and review patient opioid prescription history in real time, enhancing interoperability and curbing fraudulent prescriptions. This feature could enable doctors to identify doctor shoppers and reducing opioid overuse. As a result, several studies have reported a positive effect of EPCS on preventing opioid abuse (Everson et al., 2020; Thomas et al., 2012).

However, on the other hand, such EPCS mandates may enable drug users and doctor shoppers to travel to other locations where the policy has not been adopted. According to the Rational Choice Theory (Clarke & Cornish, 1985), drug users may find it easier and less risky to obtain prescription drugs from prescribers in neighboring areas without EPCS. Studies shows potential of travel to seek opioid. For example, on average, drug seekers are willing to travel up to 1.8 miles to obtain prescription drugs (Johnson et al., 2013), and those with access to transportation may be able to communicate with prescribers located even further away (Young et al., 2014). In this regard, we aim to empirically measure the negative spillover effect of EPCS. Specifically, our research questions are:

RQ1: Does EPCS mandates of the focal county increase opioid prescription and opioid overdose death in the neighboring county without EPCS? (i.e., negative spillover effect)?

RQ2: In the presence of a negative spillover effect, do certain moderating factors contribute to the observed impact?

To answer these questions, we structure a US county-level panel dataset, leveraging EPCS mandates entering different states at different times between 2010 and 2020, and execute a difference-in-differences (DID) estimation with coarsened exact matching (CEM). Our sample includes approximately 20,000 observations, with control variables such as population, age, sex, race, employment, health insurance rate and Hepatitis C Virus death rate. We identify the treatment group as counties without an EPCS mandate in their own state but with a mandate in their neighboring state. The control group consists of counties without any influence of EPCS mandate geographically. We adopt CEM to improve the comparability of the treatment and control groups.

Our results suggest that, after EPCS has been mandated in the focal county, this increases the dispensing rate and opioid-related mortality in a neighboring county where EPCS is not mandated, suggesting a negative spillover effect. Specifically, after EPCS was mandated, the death rate increased by 17.0 %, and the opioid dispensing rate increased by 9.23% in the neighboring county without ECPS, located in the EPCS-mandated county. As for further analysis and robustness checks, we replicate our estimation using the relative time model (Greenwood et al., 2017).

We aim to contribute to both literature and practice. Firstly, it sheds light on the spillover effects of health information technology (HIT) and information systems (IS) on societal well-being. Previous research has explored negative IT spillover effects in healthcare, focusing on issues like information disclosure and security breaches (Kim & Kwon, 2019, Angst & Agarwal, 2009, Mishra et al., 2012). While insightful, the majority of them focus on service efficiency and cost reduction (Eftekhari et al., 2017; Lammers et al., 2014). Our study uniquely extends this exploration to patient health, particularly opioid overdose. By analyzing the implications of the EPCS mandate on overdose cases, we enrich the literature on policy impacts on public health (Chan & Ghose, 2012; Greenwood & Agarwal, 2016). Moreover, we advocate federal health policymakers and state coordinators to consider negative spillovers when implementing EPCS across state borders. Our findings reveal that areas with robust health insurance coverage experience fewer negative spillovers of EPCS on opioid overdoses, suggesting the potential of combining insurance initiatives with electronic prescribing policies for a more comprehensive opioid crisis response.

[2] See at https://nida.nih.gov/research-topics/trends-statistics/overdose-death-rates, accessed on May 4, 2023.

Related Literature

The Positive and Negative Spillover Effect of IT

IS researcher pays much attention to the positive spillover effects of IT, and the majority of them focuses on firm context. Studies found that IT can spread its benefits across the supply chain via better coordination and efficiency. Cheng and Nault (2007) found that upstream industries pass their gains from IT investment down to downstream industries, and customer firms' IT investments can spill over to suppliers with enhanced exchange of more accurate information (Cheng & Nault, 2012). IT productivity spillovers have also been observed among firms that involve labor mobility, as knowledge related to IT investments can be transferred from firms that hire labor from other firms (Tambe and Hitt, 2014). Additionally, the increasing prevalence of the platform economy has prompted discussion on demand spillovers from customers. retailers are more likely to form partnerships with third-party sellers (Song et al., 2021). Lee et al. (2022) further demonstrate that positive spillovers occur within the platform, with backward spillovers onto existing apps adopted before popular app adoption and forward spillovers onto new apps to be adopted after favored apps.

In the healthcare context, positive spillover effects of IT have been reported in the organization (i.e., hospital) level. In the hospital level, for example, Eftekhari et al. (2017) conducted a study on the effect of health information exchanges on reducing repetitive medical tests and services. Atasoy et al. (2018) found that HIT adoption reduced costs for neighboring hospitals, particularly when they are in health information exchange networks and the same integrated delivery systems. Another stream of studies focuses on the spillover effects of electronic health records (EHR). Studies reported that EHR improves care quality and reduces costs by minimizing medical errors and duplicate testing. For instance, Lammers et al. (2014) discovered that sharing patient information across hospitals could significantly reduce repeated tests. Similarly, Ayabakan et al. (2017) demonstrated how health information sharing reduced the rate of duplicate testing within the hospital network.

In this regard, our study extends the healthcare literature by focusing specifically on the negative spillover effects of EPCS, with particular attention on the behavior of drug users. Our study adds to the limited empirical literature on the information externality of health IT, and highlights the importance of understanding spillover effects in healthcare.

Impact of EPCS on Opioid Epidemic

Prior to EPCS, another policy addressing the opioid epidemic was the Prescription Drug Monitoring Program (PDMP). State-administered PDMPs require pharmacies to transmit data on controlled substance prescriptions to a centralized repository shared with prescribers. Despite PDMPs' intention to reduce opioid overdoses by allowing doctors access to patients' comprehensive medication histories, research on their impact has produced inconclusive findings. Some studies indicate their efficacy in curbing opioid overdoses (Bao et al. 2016), while others suggest minimal or no effect (Ali et al. 2017, Meara et al. 2016). Voluntary PDMP usage is a primary issue, with limited mandated implementation by pharmacists and prescribers across various states, compounded by differing PDMP mandate standards (Matthay & Glymour, 2022). Moreover, PDMPs' non-real-time updates contribute to data inaccuracies, and manual patient data reporting disrupts pharmacists' workflows (Holmgren & Apathy, 2020).

The EPCS has been introduced to overcome the limitation of PDMP. The EPCS system requires prescribers to electronically transmit opioid prescriptions to pharmacies through an e-prescribing system (Gawande, 2017). The primary provider of the EPCS system is Surescripts, which held 95% of the market share in 2019. Once the prescription is electronically signed, it is sent to the pharmacy, which then obtains the digital prescription containing all the necessary medication details. The pharmacist can confirm the prescription with the prescriber and provide the medication to the patient, allowing for a comprehensive and precise medication history. Enforcing the use of EPCS is expected to help decrease opioid overprescribing and misuse by integrating it into daily practice (Gabriel et al. 2013).

EPCS has attracted substantial attention in various studies, showcasing its impact on opioid prescribing rates, medication error reduction, and overall prescribing practices. Figge et al. (2009) stressed the significance of e-prescribing for controlled substances and discussed regulatory measures proposed by the

DEA to ensure secure implementation, underscoring the importance of pharmacist involvement and compliance. Thomas et al. (2012) recognized EPCS's benefits in minimizing medication errors, though prescriber challenges and security measures could influence its adoption. Danovich et al. (2019) employed a pre-/post-test design, noting a 53% reduction in opioid prescriptions after New York State's EPCS mandate.

However, the impact of EPCS mandates on opioid overdose has been controversial, with an extensive body of work reporting mixed results. Holmgren and Apathy (2020) conducted a cross-sectional study and found that EPCS adoption in hospitals did not lead to lower opioid prescribing in the county where the hospital was located. Similarly, Everson et al. (2020) analyzed state-level EPCS mandate data and reported that EPCS mandates were not linked to decreased opioid prescribing and were associated with a small increase in opioid prescribing. Conversely, some studies suggest that EPCS mandates may help lower opioid overdose rates. Danovich et al. (2019) found that opioid prescribing by emergency physicians decreased after the implementation of EPCS mandates. Overall, the impact of EPCS mandates on reducing opioid overdose rates requires further investigation.

Our study aims to address the gap in research by investigating the spillover effects of EPCS mandates, which have not been extensively studied. Specifically, we seek to quantify the impact of EPCS on opioid overdose by analyzing a county-level panel dataset spanning ten years and examining any spillover effects on neighboring counties. Through our research, we aim to contribute to the existing literature and resolve the conflicting findings surrounding the impact of EPCS on opioid overdose.

Rational Choice Theory and Doctor Shopping

According to the Rational choice theory (Clarke and Cornish 1985), individuals make rational choices when committing crimes based on a set of trade-offs and benefits rather than psychological factors or inherent criminal tendencies. Rational choice theory suggests that offenders choose specific situations based on the likelihood of being caught, the benefits of the crime, and the costs of different options. Translating this into the opioid overdose context, individuals choose whether to engage in the behavior based on the risk of being caught, the cost of alternatives (e.g., seeing multiple doctors, obtaining prescriptions illegally), and the benefits of obtaining the intended medication.

Under the Rational choice theory, if patients cannot obtain scripts for opioids in large quantities for sake of their addiction, they might instead have to "doctor-shopping" by visiting multiple providers. Filling multiple prescriptions in one location may also be difficult, so users would be forced to travel out of town to find pharmacies. Previous studies have demonstrated this potential by showing that suburban and urban buyers travel to various locations to purchase drugs (Johnson et al., 2013). Consider two neighboring states with opioid users and opioids crossing state lines. The cost of obtaining opioids from a neighboring state is dependent on the distance traveled. When a state adopts the EPCS, obtaining opioids from within the same state becomes more difficult. However, since the neighboring state has not adopted EPCS yet, the cost of obtaining opioids from a neighboring state remains the same, leading more individuals to cross state borders, as is shown in (Guth & Zhang, 2022). As the cost of obtaining opioids within the state increases, more individuals are incentivized to cross the border for pills. Consequently, we expect that when the neighboring state adopts EPCS, bordering counties of the focal state (without EPCS) will experience an increase in opioid prescribing rate and opioid-related death.

Methodology

Data

This study aims to investigate the spillover effects of EPCS across counties in the United States over a period of ten years. Although Drug Enforcement Administration (DEA) proposed a rule to allow for EPCS as early as 2008, it was not until the last two years that more states began to adopt this mandate. As indicated in Table 1, the earliest recorded mandate dated back to 2011 and the most recent instances occurred in 2020. The records are retrieved from Board of Pharmacy in each state. This decade-long period encompassed most of the spectrum of mandate patterns that we aimed to examine. As EPCS was carried out in different states (counties) in different times, this staggered rollout allows us to use a DID set up.

States	Mandated date (Month/Year)	States	Mandated date (Month/Year)
Minnesota	01/2011	Florida	01/2020
New York	03/2016	Iowa	01/2020
Maine	07/2017	Oklahoma	01/2020
Connecticut	01/2018	Rhode Island	01/2020
Pennsylvania	10/2019	Virginia	07/2020

Table 1. Listing of EPCS Mandated States Across Years

To empirically estimate the negative spillover effect, we create a unique dataset from Centers for Disease Control and Prevention (CDC) (for dependent variables) and United States Census Bureau (for controls). When combined, this dataset comprises over 25,000 observations over 3,000 counties in US. Summary statistics can be found in Table 2.

Logged Variables	Mean	Std. Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Dispensing rate	4.11	0.81	1.00							
(2) Death rate	0.23	0.47	0.09	1.00						
(3) Population	10.55	1.38	0.23	0.51	1.00					
(4) Employment	0.41	0.10	0.04	0.08	0.15	1.00				
(5) Male	0.41	0.01	-0.18	-0.16	-0.24	-0.07	1.00			
(6) Age25to34	0.11	0.02	0.05	0.18	0.46	0.22	0.26	1.00		
(7) White	0.61	0.10	0.01	-0.01	-0.18	0.04	0.11	-0.32	1.00	
(8) Insurance	0.46	0.24	-0.29	0.10	-0.11	0.01	0.04	-0.00	0.01	1.00
(9) HCV	1.79	0.30	0.14	-0.02	0.06	-0.06	0.04	0.07	-0.04	-0.11

Table 2. Summary Statistics and Correlations

To address skewness in the data, we applied a log transformation to the variable. Our primary dependent variable, *Disp_rate* is an opioid dispensing rate per person in county *c* during year *i*. *Death_rate* is the number of people who were dead with the cause related to opioids divided the population in the county by per 10,000 persons.

Regarding control variables, we initially consider population due to its potential impact on opioid availability. Larger populations might increase opioid demand and attract drug-related activities. We incorporate employment and health insurance rates. Employment can grant access to healthcare, addiction treatment, and social support, while unemployment and lack of insurance could raise substance abuse risks. Age and ethnicity proportions could influence drug use likelihood and opioid overdose deaths (Han et al., 2022). Proportions within the 25-34 age group and white Americans also influence opioid misuse risks. An additional control variable is the yearly Hepatitis C Virus (HCV) death rate, informed by (Schalkoff et al., 2020) findings connecting the prescription opioid epidemic to various diseases, including HCV. Accounting for these covariates enhances the isolation of EPCS spillover effects on opioid outcomes for precise results.

Empirical Estimation

As mentioned above, we use a difference-in-difference (DID) estimation to establish the effect of EPCS on opioid dispensing rate and deaths. This model enables us to simulate an experimental design using observational data, given that the treatment is implemented at different times and locations, as shown in Table 1. Since our data includes information on both treated and untreated locations, as well as pre-and post-treatment periods, we can measure the net impact of the treatment as the difference in the change in the dependent variable across these locations.

To address the assumption of a homogeneous pretreatment trend between treated and control observations (Angrist & Pischke, 2008), we employed coarsened exact matching (CEM) (Iacus et al., 2012) during data processing, following the prior literature by Burtch et al. (2018). We focused on counties within the treatment group, identifying their dispensing rates from two years prior, and then matched them with control group counties exhibiting similar dispensing rates in the same year. Upon examination of T-statistics, the P-values exceeded 0.1 after CEM, indicating the absence of significant differences between the treated and matched control groups. We also conducted propensity score matching for robustness testing, though due to space constraints, these results are not shown here but remain consistent. Ultimately, our dataset encompassed over 21,000 observations.

We estimate the effect using the following equation:

$$y_{ct} = \beta_0 + \beta_1 NB\_Mandate_c + \beta_2 Post_t + \beta_3\ (NB\_Mandate_c \times Post_t) + \lambda_c + \gamma_t + \varepsilon_{ct} \qquad (1)$$

Where y_{ct} represents the log of death rate, or opioid dispensing rate, λ is the vector of county fixed effects, and γ is the vector of year fixed effects. To reduce heteroscedasticity concerns, we leverage robust standard errors clustered at the county level.

Our primary independent variable of interest is the treatment indicator *NB_Mandate*, which indicates whether EPCS is mandated in the neighboring county on the condition that the focal county *c* has not mandated EPCS. Time indicator *Post* is 1 if the neighboring county mandated EPCS in year *i*. To complete the DID estimation, we include year and county fixed effects (i.e., a single dummy for each year and county). The coefficient of interest is the interaction term β_3, which captures the spillover effect on the focal county when the neighbor county has mandated EPCS.

Results and Robustness Checks

We first run the regression for the main model and then replicate the estimation of equation (1) with additional control included. The results are demonstrated in Table 3.

Dependent Variables	(1) ln(Dispensing Rate)	(2) ln(Dispensing Rate)	(3) ln(Death Rate)	(4) ln(Death Rate)
NB_Mandate*Post	0.0863**	0.0866**	0.154***	0.154***
	(0.0376)	(0.0376)	(0.0357)	(0.0357)
Original Controls	Yes	Yes	Yes	Yes
ln(HCV rate)	Not included	0.137	Not included	0.0193
		(0.646)		(0.503)
Constant	8.618***	8.584***	-3.850***	-3.855***
	(1.730)	(1.721)	(1.246)	(1.261)
Observations	21,225	21,225	21,225	21,225
R-squared	0.800	0.800	0.705	0.705

Table 3. County-level analysis of EPCS Spillover Effect

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
We log-transform the variable to adjust the skewness of data.

With respect to our independent variable of interest, introducing EPCS mandates has a significant positive spillover effect on the number of opioid-related mortalities and opioid dispensing rate in both models. Econometrically, our analysis found a statistically significant positive effect of EPCS mandate on the dispensing rate of opioids in Columns (1) and (2) (0.0863 and 0.0866, respectively, p<0.05). Specifically, EPCS mandate in the neighboring county increases opioid dispensing rate by 8.63%. We also found a statistically significant positive effect of EPCS mandate on death rate in Columns (3) and (4) (0.154, p<0.05). Specifically, EPCS mandate in neighboring county increases the death rate by 15.4%. These results are consistent with our conjuncture.

In addition, we conducted an alternative estimation using the Relative Time Model (Greenwood & Agarwal, 2016). By leveraging the longitudinal nature of our panel dataset, we were able to assess pretreatment trends before the implementation of the EPCS mandate. This approach allowed us to explicitly test the validity of the untreated locations we employed as the control group. As shown in Figure 1, first, none of the models exhibit a statistically significant pretreatment trend. Then, we see that the negative spillover effect of EPCS mandate on the focal county's dispensing rate becomes significant roughly two years after implementation, consistent with the previous main estimate.

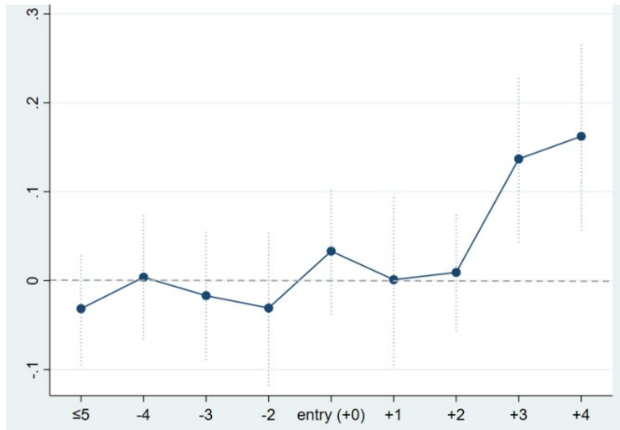

Figure 1. Effect of EPCS Mandates on the Dispensing Rate of Focal County

Additional analysis

Health Insurance Coverage

In order to explore how insurance coverage influences the relationship between EPCS mandates and opioid overdose, we split our sample counties by the median value of health insurance coverage. As presented in Table 4, our analysis reveals that in counties characterized by low health insurance coverage (Column 1), the coefficient associated with EPCS mandates exhibits a statistically significant positive effect (0.155, $p<0.05$). However, in counties marked by high health insurance coverage (Column 2), this coefficient loses its statistical significance. This outcome lends credence to the proposition that insurance coverage yields a constructive impact due to enhanced tracking and identification mechanisms, consequently mitigating the potential for doctor shopping.

Dependent Variable	ln(Dispensing Rate)	
Health Insurance Rate	(1) Low	(2) High
NB_Mandate*Post	0.155**	0.0210
	(0.0624)	(0.0543)
County Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Control Variables	Yes	Yes
Constant	4.119***	4.153***
	(0.00633)	(0.00535)
Observations	10,595	10,421
R-squared	0.828	0.831

Table 4. Moderating Effect of Health Insurance Coverage

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Discussion

Our work has several limitations that provide insight for future studies. Firstly, our analysis focuses on the impact of EPCS on opioid dispensing rate and overdose mortality. We call studies to focus on potential scenarios where patients might switch to other substances like fentanyl due to reduced access to prescription opioids. Secondly, we acknowledge the complexity of attributing the observed increase in death cases and opioid dispensing rates in treated counties solely to the EPCS mandates of the focal county and its potential influence on patients' doctor-shopping behavior. In the absence of direct measurements of such behaviors, we resort to utilizing proxies such as death rates and dispensing rates to serve as indicators of plausible impacts. Despite these limitations, we maintain that our study imparts valuable insights into the potential spillover effects of EPCS mandates, illuminating a complex and multifaceted matter.

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