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## ADDICTION, THICK MARKET EXTERNALITIES, AND THE PERSISTENCE OF THE OPIOID EPIDEMIC

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### ABSTRACT

U.S. opioid overdose death rates rose nearly continuously from 1990 to 2022, claiming over 750,000 lives. The persistence of the epidemic is surprising, as policy and behavioral responses to the epidemic would be expected to reduce harm. We examine four explanations for why death rates instead rose so greatly and for so long: exogenous and continuing increases in demand or supply of opioids, dynamic spillovers stemming from prescription opioid addiction, and spatial spillovers due to thick market externalities. We find that spillovers across time and space are the main explanation. Without them, there would have been 88 percent fewer deaths.

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# I. Introduction

The vast increase in opioid overdose death rates over the past three plus decades is one of the worst public health crises in U.S. history. Using data from the National Vital Statistics System, **Figure 1** shows trends in overdose death rates from any drug, opioids, and different types of opioids from 1990 to 2022. Opioid and total drug overdose death rates rose in all years but one over this time. In total, more than 1.2 million people died of a drug overdose, over 60 percent of which involved opioids.<sup>1</sup>

An epidemic of this magnitude and duration is surprising in relation to past epidemics, such as the crack cocaine epidemic of the 1980s. Theoretically, it is also unexpected. As people who become addicted to a new substance are seen to suffer, this should lead other people to stop initiating the substance. Policy might also respond through interventions that disrupt the drug's supply and expand access to treatment to people who are addicted.<sup>2</sup> Both these factors would be expected to make epidemics self-limiting. So far, the opioid experience belies this expectation.

In this paper, we examine why U.S. opioid death rates increased so greatly and for so long. We start by developing a theoretical model of opioid use and mortality rates, which we use to frame four theories about the large and prolonged increase in deaths: exogenous and continuing increases in demand or supply of opioids, dynamic spillovers due to prescription opioid addiction, and spillovers in demand for opioids across people, which we call thick market externalities.

With respect to demand-side changes, people may demand more opioids because they experience more physical or psychological pain and desire relief from it. One influential body of work attributes increased pain and demand for opioids to long-term declines in economic and social prospects for working class individuals in the U.S., commonly referred to as the "deaths of despair" hypothesis (Case and Deaton 2017, 2020, 2022). Marketing by pharmaceutical manufacturers may also increase demand if it causes opioids to be perceived as safer and more effective than in the past (Alpert et al. 2021; Cutler and Glaeser 2021). On the supply side, hypothesized changes include exogenous expansions of supply and the diffusion of cheaper and

<sup>&</sup>lt;sup>1</sup> This is likely an undercount, as 20-25 percent of overdose deaths are not tested for the specific cause (Ruhm 2017). Ruhm (2017) estimates that opioids were involved in 77 percent of drug deaths since 1990.

<sup>&</sup>lt;sup>2</sup> Such policies have occurred in the case of opioids. Examples include reformulating prescriptions to be abusedeterrent (Alpert, Powell, and Pacula 2018; Evans, Lieber, and Power 2019), enforcement interventions (Donahoe 2024; Soliman 2024), prescription drug monitoring programs (Buchmueller and Carey 2018; Kim 2021), changing prescribing guidelines (Zhu et al. 2019), insurer restrictions, and increasing the use of the most effective treatments for opioid use disorders (Krawczyk et al. 2022).

more potent illegal opioids (primarily fentanyl) starting in the early 2010s (Ciccarone 2017).

Demand and supply shocks may be magnified in two ways, expressed in our third and fourth theories. The third theory is that addiction prolonged the impact of temporary increases in demand or supply of prescription opioids. In the classic setting of Becker and Murphy (1988), addiction amplifies the impact of shocks across time and may cause more use and deaths for a long period of time after the initial demand or supply shock dissipates.

The fourth theory is about spatial spillovers due to thick market externalities. We define thick market externalities as a situation where one person's opioid use depends on other peoples' use. Thick market effects may result from readier access to illegal goods when more people use them, or from greater information about substances to try or how to use them. Ethnographic work shows many examples of thick market effects. Many people obtain opioids and other substances from friends or family members who have extra supply or have obtained the drug illegally rather than from the black market directly (Ondocsin et al. 2023). Friends and family members are also important in providing information about how to transition from one form of use to another, such as from taking prescription opioids to using heroin (Mars et al. 2014, 2024; Perdue et al. 2024). In the presence of such thick market effects, any exogenous shock that increases opioid use will also be amplified across space.

We use a variety of data to empirically assess each theory. Our primary source of data on opioid use is restricted-use vital records, which we use to construct opioid overdose death rates for all U.S. counties annually from 1990 to 2022. We also use data from 1997 to 2022 on demandside factors from the American Community Survey, heroin and illegally produced fentanyl prices from law-enforcement reported drug seizures, and prescription opioid shipment rates from the Automation of Reports and Consolidated Orders System (ARCOS). We measure market thickness with data on Facebook friendships (Bailey et al. 2018) and physical distance between counties. We consider county A to have a thicker market for opioids if there are more opioid deaths in counties where people in county A have more friends or are geographically closer to.

We begin our empirical analysis with descriptive evidence of dynamic and spatial spillovers. We show that changes in opioid death rates since the early 1990s are highly spatially correlated, with opioid death rates increasing in initially affected areas as well as spreading out from initial hotspots as time progressed. We explore this further in two case studies. The first shows that opioid shipments and death rates increased more in counties that had more friends in

two "pill mill" hotspots in the 1990s—Southeastern Ohio and Northern Kentucky (Quinones 2015). The second shows that shipments of *Subsys* (a prescription fentanyl spray that was first marketed in 2012) increased more in areas that had more friends where *Subsys*'s manufacturer (*Insys*) paid physicians to promote and write high volumes of *Subsys* prescriptions.

We then turn to national analyses of the determinants of opioid death rates. We relate opioid deaths to demand shifters, illicit opioid supply, the depreciated stock of prescription opioid consumption (to capture spillovers across time), and outcomes in friend and geographically nearby areas (to capture spillovers across space). Demand is proxied as a principal component underlying county time-series variables that capture the deaths of despair hypothesis: non-drug suicide death rates, alcoholic liver disease death rates, the percent of males ages 25-64 not working, log wages of people without college degrees, the percent of adults not married, and the percent of adults employed in manufacturing (Case and Deaton 2017, 2020, 2022; Charles, Hurst, and Schwartz 2019; Pierce and Schott 2020). We do not have measures of illegal opioid supply, but we have indicators that proxy for it, including the price of heroin and illegal fentanyl over time as reported in national drug seizures data and state-level seizures of illicit fentanyl.

The main challenge in our estimates is the possibility that common and unobserved shocks across areas may lead to biased estimates of spatial spillovers. We deal with this challenge in two ways. First, we estimate models that incorporate both social and physical proximity to opioid use and deaths in other counties. Thus, the coefficient on social proximity captures social spillovers that are purged from geographically correlated supply and demand shocks. Second, we use a quasimaximum likelihood approach that identifies spatial spillovers using social and physical proximity to counties with high death rates because of high past consumption capital, demand, or supply.

We complement the mortality models using similar models for opioid shipments to an area, in this case relating shipments to demand factors, past consumption capital, and spillovers. We restrict this analysis to 2007 to 2009, when we observe exact opioid shipments at the county-level from a detailed extract of ARCOS released as part of multi-district opioid litigation and before interventions that exogenously affected opioid prescribing (e.g., increased DEA interventions after 2010; Donahoe 2024). These results are like those for opioid deaths. We find that a shock leading to one more morphine milligram equivalent worth of opioid use in one county leads to 0.3-0.4 more morphine milligram equivalent opioid shipments in other counties through spillovers.

These analyses point to several conclusions. First, we find evidence that the supply changes

associated with heroin and fentanyl led to increased deaths. In contrast, there is no evidence that changes in despair-related proxies led to increased deaths. Second, both spatial and temporal linkages in opioid use and deaths are important. There is a strong relationship of past prescription opioid use with current deaths, as well as a strong cross-sectional relationship between deaths in one area and deaths in other areas nearby and where there are friends. Using counterfactual simulations, we estimate that the most important of these factors in explaining the long tail of the opioid epidemic are the spillovers. In total, roughly 88 percent of increases in opioid deaths after 1998 would not have occurred without increased addiction due to prescription opioids and thick market effects. Falling illicit opioid prices due to the diffusion of fentanyl across areas explains the remaining 12 percent of deaths. Overall, our results highlight that because of spillovers over time and across space, even modest temporary shocks to addictive product consumption have very large and long-term adverse effects.

Our paper is related to several strands of literature. One clear link is the economics of the opioid epidemic, including its demand (Case and Deaton 2017, 2020, 2022; Charles et al. 2019; Pierce and Schott 2020) and supply-side (Alpert et al. 2021; Cutler and Glaeser 2021; Moore, Olney, and Hansen 2023) determinants. Our work adds to a growing literature that concludes that changes in supply-side factors have been more important determinants of changes in opioid death rates than changes in despair or other demand-side explanations.<sup>3</sup> We also provide a novel explanation for the quantitatively large and persistent effects of these supply-side changes—the presence of addiction interacted with thick market externalities. More generally, our research shows how any shock that stimulates markets for addictive and illegal products can create a vast epidemic. This has important implications for the optimal regulation of addictive products.

Our paper also contributes to literature on social spillovers in drug use. The closest study to ours is Mäckle and Ruenzi (2022). Mäckle and Ruenzi show that counties with more friends in areas that experienced policy shocks that increased illicit opioid death rates also experienced increases in illicit opioid death rates. Another recent study using survey data finds that individuals are more likely to initiate non-medical opioid use after having a best friend experience an injury and be prescribed opioids (Adamopoulou et al. 2024). Going beyond these studies, we show that such spillovers are a main explanation for the vast and persistent opioid epidemic.

Lastly, our paper contributes to the literature on economic models of addictive product use.

<sup>&</sup>lt;sup>3</sup> See Cutler and Glaeser (2021) and Currie and Schwandt (2021) for reviews.

The Becker and Murphy (1988) rational addiction model has been widely studied in the literature (Gruber and Köszegi 2001; Cawley and Ruhm 2011). We extend this literature to consider deaths as an outcome and incorporate thick market externalities, with the latter addition being similar to Reif (2019). These extensions are vital to understanding the ongoing opioid epidemic.

The remainder of the paper is structured as follows. Section II describes a theoretical model to frame explanations for the long epidemic. Section III describes our data. Section IV presents descriptive evidence that previews our main findings and conclusions. Section V presents our empirical methodology, and Section VI presents our main results. Lastly, section VII concludes.

# **II.** Theories about the Extended Opioid Epidemic

In this section, we use a theoretical model of addictive drug use and deaths to frame four theories about why opioid death rates have increased so greatly and for so long: exogenous increases in demand or supply, the long-term effects of addiction, and thick market externalities.

#### A. Consumption with addiction and spillovers

We model consumer behavior allowing for addiction and spillovers, similar to Reif (2019). Consumers experience temporal utility  $V(a_{it}, s_{it}, x_{it}, c_{it}, \sum_{j=1}^{N} w_{i,j}a_{j,t})$ , where  $a_{it}$  is *i*'s total consumption of addictive goods (e.g., milligrams of morphine equivalents for opioids) in period *t*. Note that  $a_{it}$  considers consumption on the intensive margin (i.e., whether to use any addictive substances) as well as the extensive margin (i.e., movement from less potent to more potent substances, such as from prescription opioid to heroin or from heroin to illegal fentanyl).  $s_{it}$  is the consumer's consumption stock, with evolution  $s_{it+1} = (1 - d)(s_{it} + a_{it})$  and depreciation rate d.  $x_{it}$  are taste parameters that increase utility from drug use (e.g., pain, exposure to drug marketing, etc.) and  $c_{it}$  is a composite of all other goods.  $\sum_{j=1}^{N} w_{ij}a_{jt}$  denotes addictive drug consumption by a person's peers, where N is the size of the population and  $w_{ij}$  is a weighting term that represents the degree of connectedness between individuals *i* and *j* (where  $w_{it} = 0$ ). Peer use may affect utility because there is adjacent complementary in consumption (people enjoy the drug more when consuming with others), because of information spillovers across areas, or because it is safer to obtain the product from family or friends than in the black market.<sup>4</sup>

As in Reif (2019), we assume quasi-linear utility in the private and social components of consumption and linear spillovers (i.e.,  $V = U(a_{it}, s_{it}, x_{it}, c_{it}) + b_g a_{it} \sum_{j=1}^{N} w_{ij} a_{jt}$ ). Taking U as concave and quadratic and optimizing the choice of  $c_{it}^*$ , the consumer's optimization problem for use of  $a_{it}$  can be written as:

$$\max_{a_{it}} \sum_{t=1}^{\infty} \delta^{t-1} V^* \left( a_{it}, s_{it}, x_{it}, \sum_{j=1}^{N} w_{ij} a_{jt} \right), \tag{1}$$

with discount rate  $\delta$ . The consumer faces a budget constraint:

$$A_{i0} = \sum_{t=1}^{\infty} (1+r)^{-(t-1)} (c_{it}^* + p_t a_{it}), \qquad (2)$$

with interest rate r and the price of addictive drugs  $p_t$ .

For ease of illustration, consider the case where consumers are fully myopic (i.e., they ignore the effect that consuming drugs today will have on their utility in the future). Assume also that V(.) is quadratic in its elements.<sup>5</sup> Maximizing equation (1) subject to the budget constraint (2) with  $\delta = 0$  yields a demand equation of the following form,

$$a_{it}^{*} = \rho s_{it} + \lambda \sum_{j=1}^{N} w_{ij} a_{jt}^{*} + \beta p_{t} + \gamma x_{it} + k.$$
(3)

 $\rho = \frac{b_{as}}{b_{aa}} > 0$  captures addiction – how much use varies today based on use in the past.  $\lambda = \frac{b_g}{b_{aa}}$  denotes spillovers, reflecting how use among related groups affects use by any individual. Note that  $\lambda$  may be positive or negative.  $\beta = -\frac{\mu}{b_{aa}} < 0$  denotes downward sloping demand ( $\mu$  is the marginal utility of wealth).  $\gamma = \frac{b_{ax}}{b_{aa}} > 0$  reflects the impact of tastes (e.g., due to despair or pain).

<sup>&</sup>lt;sup>4</sup> The latter effect might more plausibly be modeled through lower search costs or prices. Quantitatively, this would have similar impacts.

<sup>&</sup>lt;sup>5</sup> The quadratic parameterization of  $V^*(a_{it}, S_{it}, x_{it})$  is as follows:  $b_a a_{it} + b_s S_{it} + b_x x_{it} + b_{as} a_{it} S_{it} + b_{ax} a_{it} x_{it} + b_{sx} S_{it} x_{it} - \frac{1}{2} (b_{aa} a_{it}^2 + b_{ss} S_{it}^2 + b_{xx} x_{it}^2)$ .

 $k = \frac{b_a}{b_{aa}} > 0$  is a constant term.<sup>6</sup>

In equation (3),  $a_{it}^*$  is a function of use  $a_{jt}^*$ , while  $a_{jt}^*$  is simultaneously a function of  $a_{it}^*$ . This makes analyzing the comparative statics of equation (3) challenging. To solve this, we rewrite equation (3) in matrix form:

$$A_t^* = \rho S_t + \lambda W A_t^* + \beta P_t + \gamma X_t + K , \qquad (4)$$

where  $A_t^*$ ,  $S_t$ ,  $P_t$ ,  $X_t$ , and K are  $N \times 1$  vectors of addictive drug use, mortality risk, consumption capital, prices, demand, and the constant term (respectively). W is an  $N \times N$  matrix of weighting terms for how connected two individuals are to one another (i.e., consisting of the  $w_{ij}$  terms). We eliminate the simultaneity by re-arranging equation (4) as follows (see **Appendix A**):

$$A_t^* = (I - \lambda W)^{-1} (\rho S_t + \beta P_t + \gamma X_t + K).$$
(5)

*I* in this equation is an  $N \times N$  identity matrix. Note the model given above does not necessarily have a steady state. Solving for when this will occur in the general model is complex as it depends on the structure of *W* and one must assess the dynamics through simulation.<sup>7</sup> However, for intuition, assume  $w_{ij} = \frac{1}{N-1}$  for all  $j \neq i$  and 0 otherwise. In this case, average use will only reach a steady state equilibrium if the following condition is satisfied (see **Appendix A**):

$$\frac{\rho(1-d)}{d} + \lambda < 1.$$
(6)

The equation states that the combined effects of addictiveness (i.e., how much utility from current use rises with past use), consumption capital depreciation, and spillovers may not exceed one. If these effects exceed one, use will continue increasing period after period (even with no exogenous change) as people who use in period t desire to consume more in t + 1 and cause other people to

<sup>&</sup>lt;sup>6</sup> The fully dynamic specification, where consumers have perfect foresight, is similar, with additional terms for future individual consumption, peer group consumption, prices, and tastes. See Reif (2019) for more details.

<sup>&</sup>lt;sup>7</sup> For example, an increase in opioid use in one area will have different spillover effects if that area is connected to areas with many other connections, or instead is part of a small, isolated group.

use more opioids in t + 1 due to spillover effects. The increase will also be exponential.<sup>8</sup>

Next, we turn to deaths. We model the probability of an overdose death as:

$$M_t = H(A_t^*, S_t). \tag{7}$$

We assume  $H_a > 0$  and  $H_s < 0$  and that  $M_t \in (0,1)$ .<sup>9</sup>

Our mortality equation is probabilistic rather than determinative, for several reasons. One is that even small variations in quality can cause a person to fatally overdose (Gable 2004). For example, the U.S. Drug Enforcement Administration notes that 2 mg of fentanyl, roughly what would fit on a pencil tip, is enough to kill someone. Especially in the illegal market, variation in quality of this amount is thought to be common. Second, even if a person takes the same dose that they always have, overdose can occur due to random fluctuations in a person's metabolism or interactions with other drugs or health problems (Humphreys, 2023). Finally, mortality may also vary with the presence of friends or family to revive a person, or the quality of emergency personnel. Note the time-series behavior of deaths would be expected to differ from that of use. Deaths will increase when use rises in relation to past use and fall when use stabilizes or falls.

#### B. Four Theories for the Duration of Epidemics

In light of this framework, we now consider reasons why epidemics may begin, and why they may last a long time. To understand our theories, it is helpful to depict a typical trajectory of opioid use, addiction, and overdose death. **Figure 2** shows this, drawing from the medical, ethnographic, and epidemiological literature on opioid use and addiction (Compton and Jones 2019; Mars et al. 2014, 2015; Perdue et al. 2024; Volkow, Koob, and McLellan 2016). People are often first introduced to prescription opioids through prescriptions obtained by themselves, family, or friends (Compton and Jones 2019), generally in response to pain (physical or mental). Some individuals will subsequently stop using or continue using for some time in a maintenance phase.

If the individual uses opioids for enough time, they may become addicted (Volkow et al.

<sup>&</sup>lt;sup>8</sup> Such a situation could be one possible explanation for the exponential increases in opioid and total drug overdose mortality that have been observed over time (Jalal et al. 2018).

<sup>&</sup>lt;sup>9</sup> One function that satisfies these conditions is  $M_t = 1/(1 + e^{-(a_0 + a_1A_t - a_2S_t)})$  i.e., mortality rises with each mg increment to current use relative to past consumption stock, with the relative risk of death from increasing use governed by  $a_1$  and protective effect of tolerance governed by  $a_2$ . We use this function in the simulation below.

2016). Prescription opioids will then be demanded with greater frequency or in larger doses (the abuse stage in the figure), leading to increased risk of death. If it becomes too difficult to sustain this increased use with prescription opioids (e.g., because they are expensive or it is difficult to obtain increasingly higher quantities of prescription opioids from the medical sector), individuals may then move into abusing illegal opioids. Heroin is a substitute for prescription opioids, though generally cheaper and more potent. Fentanyl is a legal drug, but is often manufactured illegally, and is even cheaper and more potent than heroin. Unlike prescription opioids which are sold in products with fixed potencies, heroin and illicit fentanyl can also differ in purity from batch to batch, raising the death rate further. In recent years, illegal opioids are the most common cause of death (see **Figure 1**), though in practice many people are simultaneously using prescription opioids and illegal opioids (along with other drugs such as methamphetamines and cocaine as well).

*Theory* #1: Exogenous increases in demand. The first theory is that opioid death rates have increased so much over time and for so long due to exogenous and continuing rises in tastes for opioids (i.e.,  $x_{it}$ ). In the literature on the U.S. opioid epidemic, one commonly attributed source of such a change is despair: longstanding declines in economic and social prospects for working class individuals in the U.S. have led to people experiencing more pain and psychological distress, increasing vulnerability to opioid use and other behaviors with negative consequences such as overeating, excessive alcohol use, and suicide (Case and Deaton 2017, 2020, 2022). Marketing could also act as a demand inducement. At least part of the increases in opioid use and deaths early on were driven by marketing of new prescription opioid formulations as being safer and more effective than past versions (Alpert et al. 2021; Cutler and Glaeser 2021; Humphreys et al. 2022).

In response to a positive demand shock for pain relief, opioid use will be driven to a new, higher level, with the magnitude of the increase being governed by the direct impact of changes in tastes on use ( $\gamma$ ) and the size of the change between time periods (i.e.,  $\bar{x}_t - \bar{x}_{t-k}$ ). The impact on mortality will follow directly (through  $M_t = H(A_t, S_t)$ ).

Such a change would lead to a permanent increase in use. As use rises, deaths would increase because current use exceeds the past stock. When drug use approaches its new steady state, however, the mortality rate would fall. This occurs because in a steady state with constant use, deaths will be lower than at a time when use is rising.<sup>10</sup> We illustrate this in **Appendix Figure** 

<sup>&</sup>lt;sup>10</sup> It could even be the case that deaths return to their pre-shock level, but this is not required in the model.

**B1**. Thus, to explain the prolonged and continuous increase in death rates, the demand change must itself continue over a long period of time.

A rational model would offer similar predictions as the myopic model, with the addition that if people expect that their tastes for opioids will be higher in the future (e.g., due to bleak economic prospects), opioid use and deaths will also increase before the actual shock.

Theory #2: Exogenous expansions of supply. The second theory that could explain the persistent opioid epidemic is technological innovations (e.g., the development and introduction of new opioids) or exogenously expanding supply (causing lower prices of opioids today than in the past). With respect to technological innovation, none of the products that are implicated in opioid deaths in recent years—i.e., heroin and fentanyl (see **Figure 1**)—are new. Heroin has been circulating in the U.S. since the early 1900s, when it was first marketed as a cough suppressant by *Bayer* (Courtwright 2009). Similarly, fentanyl was first synthesized in 1959 and has been implicated in smaller fentanyl epidemics since at least the 1970s (Henderson 1991).

What is new is the widespread incorporation of fentanyl in illicit opioid markets, beginning around 2013 (Pardo et al. 2019). As **Figure 1** shows, deaths due to fentanyl increased rapidly after this date. The reason this began around this time is generally unknown, but it is believed to have started as a supplier-imposed shift to enhance profitability from illicit opioid sales. This is supported by interviews with people who used heroin around this time which indicate that they wanted to use heroin but were supplied fentanyl or fentanyl-adulterated heroin instead, sometimes without their knowledge (Mars, Rosenblum, and Ciccarone 2019).

To the extent the diffusion of fentanyl has been driven by exogenous technological change (e.g., improvements in the ability to manufacture and distribute illicit synthetic opioids or the growth of the dark web), it is part of the explanation for increasing opioid death rates. In the model, this would be expressed as a decline in the price of illicitly produced opioids (i.e.,  $p_t$ ), standardized with respect to potency (e.g., in terms of heroin equivalent grams). The quantitative importance of this explanation is given by the magnitude of  $\beta'$  (the demand response to lower prices), the size of the change in prices ( $p_t - p_{t-k}$ ), and the effect of more illegal opioid use on death rates.<sup>11</sup>

<sup>&</sup>lt;sup>11</sup> An alternative way of viewing the impact of fentanyl is as a shock to the potency (and hence, lethality) of illicit opioid supply. However, an increase in potency conditional on price is equivalent to a decline in the potency-adjusted price of illicit opioids. Thus, shocks to potency are effectively the same as an exogenous expansion of supply.

Expected future price declines would also increase use and death rates in the fully rational model.

Note it is also possible that the increased availability of illegal opioids is a response to high demand. For example, with high demand for opioids, it pays to establish distribution systems with high fixed costs. In this case, greater availability of fentanyl would be an example of endogenous technological change and would properly be viewed as a consequence of demand changes.

A one-time reduction in price (perhaps spread out over time) would have an effect equivalent to that of a one-time increase in demand: use would increase and deaths would rise along the transition path. As the new equilibrium was being reached, however, deaths would fall.

Because equilibrium opioid death rates would be nearly constant in any setting without continually increasing demand or supply of opioids, it is difficult conceptually for such factors to explain a three decade increase in death rates. We thus turn to other explanations.

*Theory #3: Long-term effects of addiction to prescription opioids.* The third theory of the long epidemic is that the sustained increase in opioid deaths is due to temporary shocks that are prolonged due to addiction. Consider a demand or marketing change that increases use of opioids for some time. Even if the change in demand is reversed in the future, the increase in deaths may continue. This is because people who are addicted will continue to use opioids into the future.

For example, consider the impacts of an increase in average prescription opioid consumption capital stock due to a temporary demand shock from  $\bar{s}^{rx}_{t-k}$  to  $\bar{s}^{rx}_{t}$  (where we use rx to denote prescription opioids consumption capital stock).<sup>12</sup> The impact of this on death rates in t + 1 is  $\rho(\bar{s}^{rx}_t - \bar{s}^{rx}_{t-k})$ . Thus, it may cause death rates to be higher in t + 1 even if the shock that caused the increase up to time t has been eliminated. The persistence of the shock into the future depends on the addiction term  $\rho$  and the depreciation rate d.

It is natural to assume that  $\rho$  would be fairly high for opioids, which are among the most addictive known drugs (Courtwright 2009). One would also expect a low depreciation rate d, as addiction to opioids is a chronic disease that plays out over long periods of time (American Psychiatric Association 2022). Using data from the Treatment Episodes Dataset on Admissions (TEDS-A) in 2021, **Appendix Figure B2** plots the distribution of how long people admitted to

<sup>&</sup>lt;sup>12</sup> One could alternatively model this as an increase in tastes for prescription opioids through  $\gamma x_{it}$  (e.g., due to marketing) or a fall in the price of prescription opioids through  $\beta^{rx} p_t^{rx}$  and observe how this plays out over time, inclusive of through its effects on increasing consumption capital. However, as we are concerned with how much the result of either/both factors (i.e., increased prescribing) affected mortality, we summarize these as a change in  $s_{it}^{rx}$ .

treatment for opioid addiction in 2021 had been using opioids. The median person in treatment for opioid addiction in 2021 started using opioids roughly 10 years earlier (i.e., in 2011), and roughly 20% had been using opioids for over 20 years (i.e., since at least 2001). In such a case, addiction that results from increased opioid prescribing would be expected to last and drive death rates for a much longer period than the changes in prescribing themselves.

Theory #4: Thick market externalities. The final theory is the presence of thick market externalities. We model this as a spillover in total demand for opioid use (through  $\lambda \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} a_{jt}^*$ ). There are clear theoretical reasons that spillovers are likely to be important in markets for opioids and other illicit drugs. One reason is that in illegal markets, neither information nor products flow as freely as they do in legal markets. On the information side, opioid users and sellers cannot advertise their intent to use or sell opioids without incurring risk. Thus, informal communication through social networks becomes important. One of the earliest reports about *OxyContin* misuse in the U.S. describes the opioid epidemic spreading in this way:

"The earliest reported cases of OxyContin abuse were in rural Maine, rust-belt counties in western Pennsylvania and eastern Ohio, and the Appalachian areas of Virginia, West Virginia, and Kentucky. The problem travelled through these regions, as friends told friends and the word spread from town to town, county to county, up and down the Appalachians... Part of what makes the spread of OxyContin abuse so difficult to track, let alone to stop, is that the drug moves not physically but conceptually... a recovering OxyContin addict and former small-time dealer offered an explanation for OxyContin's sudden geographical shifts. `It's the idea that passes on,' he told me. `That's how it spreads... It's dealt by word of mouth. I call a friend in Colorado and explain it to him: Hey I've got this crazy pill, an OC 80 [OxyContin 80 mg]... You've got to go to the doctor and get it. Tell him your back hurts." (Tough 2001)

Illegal products are also easier to obtain when more people use them. Using data from the National Survey on Drug Use and Health from 2005 to 2011, **Table B1** shows nearly all (73 percent) of individuals who used prescription opioids for non-medical purposes obtained the opioids that they used from friends or a relative, rather than directly from a physician or drug dealer. Moreover, most obtained them from friends for free (54 percent).

Support for the importance of spillovers like these is also abundant in ethnographic literature (Mars et al. 2014, 2015, 2024; Perdue et al. 2024). There are two main ways spillovers have been documented, as shown in **Figure 2**: through initiation of any non-prescribed opioid use;

and through progression into increasingly risky behaviors (e.g., crushing high doses of pills to get a deeper high or using illegal opioids). This is important because it implies possibly different timeframes for spillover effects to work. Introducing a friend to heroin or fentanyl may cause death in the short term. Initiating low dose opioid use is unlikely to lead to death in the near term but could lead to a pattern where death occurs a decade or two later. **Table 1** presents four quotes that are representative of the kinds of spillover effects that have been identified in this literature. As an example, a 28-year-old Philadelphia man who used heroin explained why they started using *OxyContin* and later progressed to using heroin use as follows:

"My buddy [...], the one that introduced me to Oxies was actually doing dope [heroin] at the time. And I came over his house and I was sick [in withdrawal] and I asked him if he could get me an Oxy for ten bucks, which I needed an 80 [mg], which they were [\$]20 and I only had [\$]10. So he basically convinced me and started talking about how Oxies and dope [heroin] there is no difference." (Mars et al. 2014, p. 8)

Spillovers may also be important for legal opioids due to information flows across physicians. Many opioid manufacturers paid physicians to assure colleagues that newer formulations of opioids were safer than other formulations (Keefe 2017). Such advertising was important because earlier opioid epidemics in the U.S. had led the medical profession to view opioids as very addicting and thus to be used sparingly (Musto 1999). Other work finds spillovers in advertising across physicians in the pharmaceutical industry generally (Agha and Zeltzer 2022).

As with addiction, the presence of interpersonal relationships will not by themselves increase opioid use but can cause small changes in demand or supply to have much larger impacts on death rates than one might expect. They also amplify dynamic effects of addiction across space. We illustrate this in **Appendix Figure B1** for a case where spillovers are of similar magnitude as the effects of consumption capital (like what we find below in Section VI).

# **III.** Sources of Data

We use several sources of data to estimate the contributions of each theory to the long opioid epidemic. We describe the sources in this section.

### A. County opioid death rates

We obtained counts of county drug overdose deaths from 1990 to 2022 from restrictedaccess vital statistics data from the National Centers for Health Statistics (NCHS 2022). We used these data to construct county-specific overdose death counts from any drug, opioids, and (since 1999) opioids by type (prescription opioids, heroin, and synthetic opioids other than methadone [which includes fentanyl]). Coding conventions for these deaths followed prior literature.<sup>13</sup> Deaths are reported by area of residence. Thus, a person who travels to obtain opioids and dies in another county will be attributed to the county in which they live. Data on county population sizes, which we use to construct death rates, are from the National Institutes of Health Surveillance, Epidemiology, and End Results Program (N.I.H. and Vilhuber 2021). We age- and sex-adjust all death rates to the U.S. 2010 population.

#### B. Data on demand

We obtained data on factors that have been cited as being related to exogenously greater demand for opioids in the literature due to the deaths of despair hypothesis (Case and Deaton 2017, 2020, 2022). These include county suicide and alcoholic liver disease death rates (from NCHS) and the percent of males ages 25-64 not in the labor force, log real wages for adults without bachelor's degrees, the percent of adults not married, and the percent of adults employed in manufacturing (from the American Community Survey [ACS]). We crosswalk from PUMAs to the commuting zone associated with each county from 1990-2021, as county-level measures were not available, using a crosswalk created by Dorn (2024). We also interpolate a trend between years where the ACS was not conducted (1998-1999 and 2001-2004) and extrapolate for 2022.

<sup>&</sup>lt;sup>13</sup> Drug deaths after 1999 were identified based on the International Classification of Diseases (ICD), 10th edition underlying cause-of-death codes X40–X44, X60–X64, X85, and Y10–Y14. Overdoses by category were identified by multiple-cause-of-death codes T40.1 (heroin), T40.2 (prescription opioids = natural and semisynthetic opioids), T40.3 (methadone), and T40.4 (fentanyl/tramadol = synthetic opioids other than methadone). Total opioid deaths also included code T40.6 (other/unspecified narcotics). Drug deaths before 1999 were identified based on ICD, 9th edition underlying cause-of-death codes E850-E858, E950.0-E950.5, E9620, and E980.0-E980.5. Opioid deaths before 1999 were identified from underlying cause-of-death codes E850.1-E850.2 and 305.5, as well as multiple-cause-of-death codes (1998) and Hedegaard, Miniño, and Warner (2020) for more details. To account for the change from ICD-9 codes (1990–1998) to ICD-10 codes (1999–2017), the following comparability ratios were applied to ICD-9 codes E850.E858, E950.E858, E950.E950.5, E9620, and L0417 (Miniño et al. 2006). Total opioid deaths were adjusted upward by about 20 percent (comparability ratio = 1.195) (Hoyert et al. 2001).

### C. Data on illicit opioid supply

We draw from three sources of data on illicit supply changes. Data on national purityadjusted retail heroin prices (in \$2020) from 1997-2020 come from the United Nations Office on Drugs and Crime. These data are reports of prices by the United States Office of National Drug Control Policy and are based on reports from heroin seizures. We extrapolated data for 2021-2022 based on the average annual decline in heroin prices from 1997-2020.

National price data on illegally manufactured fentanyl from 2017 to 2020 (in \$2021) come from the data reported in Kilmer and colleagues (2022), which uses prices from law-enforcement reported seizures. We use prices for fentanyl in quantities of 1 to 10 grams, approximating smaller retail quantities, and convert them to \$2020 using the Bureau of Labor Statistics' Consumer Price Index (to match heroin prices). We imputed fentanyl prices for years that these data were not available (2013-2016 and 2021-2022) using the average annual decline from 2017 to 2020. Before 2013, there was little illegal fentanyl in the country and thus prices were effectively infinite.

Lastly, we obtained data on state-level seizures of fentanyl and heroin from 2000 to 2022 from the National Forensic Laboratory Information System (NFLIS). This data is a compilation of drug identification results from toxicology testing that was done as part of drug cases at federal, state, and local forensic laboratories. We use this data to compute the share of drug cases involving illegal opioids that were fentanyl (vs. heroin). We set this value to 0 prior to 2013 (as illegally made fentanyl was extremely rare prior to this time) and subtract the average annual number of fentanyl seizures just prior to 2013 (from 2009-2011) from each state's total count of fentanyl seizures from 2013-2022 to remove legal seizures.

#### D. County prescription opioid shipment rates

Data on prescription opioid shipments come from two sources: exact opioid shipments by recipient pharmacy from a detailed extract of the Automation of Reports and Consolidated Orders System (ARCOS) data that is available from 2006-2019 (called detailed ARCOS, hereafter) and 3-digit zip code opioid shipments from publicly available ARCOS summary reports from 1997-2022. We include all shipments of codeine, oxycodone, fentanyl base, hydrocodone, hydromorphone, meperidine, and morphine. We crosswalk 3-digit zip code opioid shipments to counties using a crosswalk that we constructed using the detailed ARCOS data and is based on the

shares of opioid shipments to each 3-digit zip code that went to different counties.<sup>14</sup> We standardized opioid shipments with respect to potency by converting them to morphine equivalent grams per capita, using the same population size data noted above for the denominator.

### E. Measures of social interactions across areas

We obtained two measures of interactions between people living in different counties. The first is the geographic distance (in miles) between county centroids (denote  $d_{i,j}$  for counties *i* and *j*).<sup>15</sup> This measures how physically close two counties are to one another and picks up, among other things, how easily one can travel from one county to another to obtain opioids that are supplied there. The second is based on the amount of Facebook friendships between people in different counties, from Bailey and colleagues (2018). Specifically, it is the normalized total number of Facebook friendship links between two counties *i* and *j* as of April 2016.<sup>16</sup> We refer to this measure as the Social Connectedness Index (denote  $SCI_{i,j}$  for counties *i* and *j*). We translate this to a measure of relative probability by dividing the SCI for counties *i* and *j* by the sum of the SCI for county *i* and all other counties  $j \neq i$ , as in Kuchler, Russel, and Stroebel (2021). This measure is likely to be particularly valuable in picking up information flows about opioids and their availability across counties.

As described in Bailey and colleagues (2018), social connectedness is inversely correlated with distance. Averaging across counties, the elasticity of social connectedness with respect to distance is -1.2 (Bailey et al. 2018). Still, the relationship is non-monotonic and may differ across areas, as we discuss below.

# **F. Descriptive Evidence**

In this section, we motivate our main empirical results on the importance of thick market externalities. We first show there is high spatial correlation in the spread of county opioid death rates over time. We then analyze a case study of two counties in central Appalachia that were among the first areas where prescription opioid addiction and overdose deaths greatly increased

<sup>&</sup>lt;sup>14</sup> Specifically, for each 3-digit zip-code-by-state pair, we created an attribution factor that is equal to the share of each pair's opioid shipments that were shipped to each county that was part of the zip-code-by-state pair each year from 2006 to 2019. We used the attribution factors from 2006 for 1997-2005 and 2019 for 2020-2022.

<sup>&</sup>lt;sup>15</sup> Data are from the Census Gazetteer files.

<sup>&</sup>lt;sup>16</sup> Note that this stock measure reflects current friendships in April 2016 as well as friendships in a person's past.

and the counties that were most connected with them. We conclude by analyzing a case study of the introduction of *Subsys*. Both case studies suggest significant spillovers in opioid use.

#### A. Mapping the opioid epidemic's spread

**Figure 3** shows a county-level map of average annual opioid deaths rates per 100,000 people for four intervals of time: 1995-2000, 2001-2006, 2011-2016, and 2017-2022. Per our data use agreement, we do not present rates in the figure when fewer than 10 deaths occurred. Visually, there is a high amount spatial correlation. Counties with high death rates tend to be near other counties with high death rates (and vice versa). Further, over time, death rates continue to increase in the areas with the highest death rates early in the epidemic as well as spread out into nearby areas—for example, from early hotspots of the prescription opioid epidemic in Appalachia into surrounding areas.

#### B. Case study of initial pill mill counties

To understand how such hotspots can spread, we consider a case study of exposure to two neighboring counties that were among earliest opioid hotspots in **Figure 3**—Greenup County, Kentucky, and Portsmouth County, Ohio. David Procter, considered the founder of the first pill mill in the U.S. (and who was ultimately arrested and sentenced to jail in 2003), practiced in these two counties and prescribed large amounts of opioids to patients who did not have legitimate medical need for them in exchange for cash payments, in the 1990s (Quinones 2015). Soon after, these counties became hotbeds for pill mills and were home to a number of notorious prescribers who were later indicted or sentenced for prescription opioid trafficking charges (Caniglia 2019).

**Supplementary Appendix Figure B3** maps where people had more friends in Greenup and Scioto County based on Facebook data from 2016. Distance is clearly an important predictor of social connectedness. The elasticity of social connectedness to Greenup and Scioto counties with respect to distance between them is -0.81. However, social connectedness does not decline as rapidly as distance increases. There is significant interaction between Greenup and Scioto counties and other areas of the U.S. that are not immediately nearby, as shown in the map. **Figure 4** shows trends in opioid shipments and death rates<sup>17</sup> from 1997 to 2022 for four cohorts of counties: Greenup and Scioto counties (where the initial pill mills were established); counties with very high (above the 90<sup>th</sup> percentile) social connectedness to Greenup and Scioto counties; counties with medium (between the 11<sup>th</sup> to 89<sup>th</sup> percentiles) social connectedness to them; and counties with low (less than 10<sup>th</sup> percentile) connectedness. We censor the rates when fewer than ten total opioid deaths occur, per stipulations from the National Center for Health Statistics.

As early as the first period for which we have data (1997-1998), prescription opioid shipments were higher and increasing at a faster rate than the rest of the U.S. in Greenup and Scioto County. This continued through 2010, after which an Ohio opioid distributor lost its license to distribute controlled substances and a particularly large pain clinic was raided by the Drug Enforcement Administration (in June 2010 and May 2011, respectively) (Caniglia 2019; Donahoe 2024). Just a few years after our time series began (in 2000), opioid shipments also began increasing more to areas which had the most friends in Greenup and Scioto County. All told, opioid shipments rose roughly 16,000 percent from 1997 until they peaked in Greenup and Scioto County and 13,000 percent in the counties in the top decile of social connectedness to them. The increase in counties with the least social connectedness to them was much smaller, roughly 391 percent.

For death rates, in the late 1990s, the counties with the highest rates of opioid deaths were those with the lowest degree of social connectedness to Greenup and Scioto County. Many of these areas are urban, such as New York and San Francisco, where there was a longstanding rate of heroin use. However, as time progressed, the relationship reversed. By 2002, opioid death rates in Greenup and Scioto counties were roughly twice as high as in the counties with the lowest social connectedness to them and sharply increasing up until flattening out in 2005.<sup>18</sup> Consistent with other work, there was a reduction in opioid death rates after the pill mills were shut down, from 2012 to 2014 (Donahoe 2024). Death rates then surged starting around 2015, with deaths from fentanyl being the biggest component (see **Appendix Figure B4**). Fentanyl became more prominent in areas where prescription opioids were more prevalent, as shown by the Greenup and Scioto County examples. By 2022, the opioid death rate was 391 percent higher in Greenup and

<sup>&</sup>lt;sup>17</sup> We present death rates as a two-year moving average, as our data use agreement only allow us to report results when at least ten total deaths occurred. This allows us to show more years of data for Greenup and Scioto County, both of which are rural and thus sometimes have below 10 total deaths in a given year.

<sup>&</sup>lt;sup>18</sup> After 2005, shipments to Greenup and Scioto counties kept increasing, even as deaths flattened out. It is possible that some of the growth in shipments after 2005 were dispensed to people who did not live in those counties.

Scioto counties than in the counties with the least connectedness to them (and which had the highest opioid death rates prior to the pill mills).

Consistent with spillovers, opioid death rates in counties with the most friends in Greenup and Scioto counties closely followed the trajectory in Greenup and Scioto County. By 2011, death rates in the initial pill mill counties and the counties with the most friends in them converged. Opioid death rates continued increasing in these areas and remained far higher than in other areas throughout the remainder of the epidemic.

Not only are the long-term trends similar in the pill mill and related counties, but the timing of changes is temporally quite correlated as well. Opioid shipments to Greenup and Scioto counties jumped in 2000 and increased more rapidly after that year. So did shipments to top decile connected counties as well. This is not true for the least connected counties.

### C. Case study of the introduction of Subsys

We use our detailed ARCOS data to perform a similar case study analysis around the introduction of *Subsys*, one of the later prescription opioids to be introduced (launched by *Insys* in February 2012). *Subsys* is a highly addicting and potent sublingual fentanyl spray that was approved for treating cancer patients experiencing breakthrough pain. *Insys* executives were ultimately convicted of a racketeering conspiracy in May 2019 for bribing prescribers to heavily prescribe and promote its products, the first successful criminal prosecution of pharmaceutical executives for crimes related to prescription opioids. Because of *Subsys*'s later introduction (after detailed ARCOS data are available) and its recordkeeping, we observe Subsys shipments and the physicians who *Insys* made payments to during the first year that it was marketed (in 2012).<sup>19</sup> We examine whether prescribing of *Subsys* increased more in areas where *Insys* paid physicians to prescribe it, as well as in counties that had more friends in these areas.

**Figure B5** shows a map of the locations of practitioners whom *Insys* made payments to as well as the distribution of social connectedness to them. The paid physicians were spread across the country, though somewhat more concentrated in urban areas. **Figure 5** shows trends in Subsys shipment rates to counties where *Insys* paid physicians and groups of other counties according to their degree of social connectedness to where *Insys* incentivized increased prescribing. Not surprisingly, *Susbys* prescribing increased to a much greater degree in the areas where *Insys* paid

<sup>&</sup>lt;sup>19</sup> Data on payments came from UCSF's opioid industry documents library.

physicians to prescribe and promote it to others. As in the case study of pill mills, there is a strong relationship between increased social connectedness to the areas where *Subsys* was marketed by physician promoters and increased prescribing in one's own county. Areas in the highest decile of links to high *Subsys* prescribers were more likely to prescribe *Subsys* than areas further away. Indeed, *Subsys* barely sold at all in counties with the lowest association with paid prescribers.

The spillovers across areas happen relatively quickly. Even in 2012, *Subsys* shipments in counties with high connectedness to counties where *Insys* made payments are roughly double *Subsys* shipments in counties with moderate connectedness (p<.01), even though *Subsys* was not even FDA approved until January of that year.

# V. Empirical Framework and Formation of Independent Variables

In this section, we present the empirical model that we use to estimate the determinants of the extended opioid epidemic. Our primary model focuses on county opioid death rates. We also estimate similar models with opioid shipment rates as the dependent variable.

### A. Modeling determinants of opioid death rates

To model mortality, we estimate the empirical analogue of equation (3) of Section II:

$$y_{c,s,t} = \rho s_{c,t}^{rx} + \lambda \sum_{j=1}^{N} w_{j,c} y_{j,t} + \gamma x_{c,t} + \beta p_{s,t}^{ill} + \alpha_c + \epsilon_{c,t}.$$
(8)

 $y_{c,s,t}$  denotes county *c* in state *s*'s opioid death rate at time *t*. This is regressed on a measure of the county's prescription opioid consumption capital stock  $(s_{c,t}^{rx})$ , weighted averages of outcomes in other counties at time t  $(\sum_{j\neq c}^{l} w_{j,c} y_{j,t})$ , which capture thick market externalities, variables that capture demand for opioids  $(x_{c,t})$ , and illicit opioid prices  $(p_{s,t}^{ill})$ . Relative to equation (3), we also add county fixed effects  $\alpha_c$  to control for unobserved differences across counties and an error term.

We use two alternative forms of weighting of death rates in other counties to capture spillovers between counties j and c (i.e.,  $w_{jc}$ ) (note:  $w_{cc} = 0$ ). The first is based on the relative probability of a Facebook friendship between county j and c (see section III). The second is the inverse geographic distance (in miles) between county j and c (i.e.,  $d_{j,c}^{-1}$ ). Counties closer together are higher by this metric. We normalize the  $N \times N$  matrix of weighting terms for each pair of counties (denoted *W*) by the largest eigenvalue of the matrix (Drukker et al. 2013).

Several points are worth noting about the area-level equation (8) versus the individual level equation (3) presented in Section II. The first is about spillovers. In equation (3),  $\lambda$  incorporates spillovers across any two people, including those who live in the same geographic area. In contrast, equation (8) includes only spillovers across areas. Spillovers within areas are not captured in equation (8). Because within-area spillovers are likely, this implies that our area-level estimation is likely to understate the role of spillovers in the opioid epidemic. Equation (8) also models spillovers in death rates rather than spillovers in use. While we present some models for use as well below, our data here is more limited.

There are also issues to note with the consumption capital stock,  $s_{c,t}^{rx}$ . Empirically, we form the consumption stock is the sum of the depreciated past shipments of opioids to the area from 1997 through the end of the prior year:  $s_{c,t}^{rx} = \sum_{u=1997}^{t-1} (1-d)^{t-u} s_{c,u}$ , where  $s_{c,u}$  denotes per capita MMEs of opioids shipped to county *c* at time *u* and *d* denotes the depreciation rate. At the county level, not all opioids that are shipped to a given county are consumed there.<sup>20</sup> Thus, the consumption capital stock is measured with error.

The consumption capital stock variable in equation (8) is also at the area rather than the individual-level and reflects a combination of many different types of prescription opioid use—e.g., initial use for pain treatment, casual misuse, and heavy abuse. The appropriate area-level depreciation rate to use in this measure likely differs for different types of use. For example, one might expect a longer time lag (and hence lower depreciation rate) for initial pain treatment to cause death compared to how long it would take heavy opioid abuse to result in death. In practice, our county prescription opioid shipments data do not allow us to distinguish between different types of use and we must choose an overall depreciation rate that approximates the average depreciation rate in the population. Our baseline model uses a low depreciation rate of 5% (i.e., d = 0.05) consistent with section II. However, we also show robustness to a wide range of other rates to ensure that our conclusions are not sensitive to this choice.<sup>21</sup> As we show below, low depreciation rates (even lower than 5%) improve model fit; initiation into prescription opioid use

<sup>&</sup>lt;sup>20</sup> For example, Florida was for many years a destination location for people looking for easy access to opioids. the "Oxy Express" brought people from across the eastern U.S. to Florida (Allen 2011).

<sup>&</sup>lt;sup>21</sup> In principle, we could estimate d alongside the other parameters. In practice, our data are not rich enough to permit this. Thus, we fix d and explore the impact of changing the level of d.

taking a long time to cause high-dose or illegal opioid use and death is a possible reason why.

A key concern with estimating equation (8) with Ordinary Least Squares (OLS) is differentiating spillovers from unobserved, spatially correlated demand or supply shocks. We deal with these issues two ways. First, we estimate equation (8) with distance *and* friend-based weighting terms. Unobserved demand shocks would be expected to be more correlated with distance than social networks. Thus, we can interpret the distance-based weighting term as controlling for such shocks and use the friends-based term to assess spillovers (Kuchler et al. 2021). Of course, it is still possible for there to be unobserved shocks through social networks.

Second, we use an instrumental variables approach to identify spillovers. Expressing equation (8) in matrix form and consolidating the terms in  $Y_t$  yields an estimation equation:

$$Y_t = (I - \lambda W)^{-1} \left( \rho S_t^{rx} + \gamma X_t + \beta P_t^{ill} + A_c + U_t \right), \tag{9}$$

where the matrices are defined as above.<sup>22</sup>

Equation (9) effectively instruments for deaths in other counties using exogenous variables that predict greater opioid use in those counties (i.e., consumption capital, demand, and illicit opioid prices). This will causally identify spillovers under the assumption that changes in consumption capital, demand, and illicit opioid prices are exogenous.<sup>23</sup> We estimate the model using the quasi-maximum likelihood (QMLE) approach that is developed in Lee and Yu (2010), which yields consistent estimation in the presence of fixed effects.

One final question about estimating spillover effects is whether opioid death rates should be related to contemporaneous or lagged death rates in other areas (i.e., whether the weighting term should involve  $\sum_{j\neq c}^{I} w_{j,c} y_{j,t}$  or  $\sum_{j\neq c}^{I} w_{j,c} y_{j,t-1}$ ). Using  $\sum_{j\neq c}^{I} w_{j,c} y_{j,t}$  is appropriate if the period is sufficiently long for information and access to spread within the time interval. Given that we analyze annual deaths and observe quick spillovers in our case studies, we use  $\sum_{j\neq c}^{I} w_{j,c} y_{j,t}$ .

#### B. Modeling determinants of opioid shipments

We use a similar approach to estimate determinants of opioid shipments. The years here

<sup>&</sup>lt;sup>22</sup> Note this uses the same idea as was used to solve the simultaneity problem in Section II.

<sup>&</sup>lt;sup>23</sup> Case and Katz (1991) use this approach to examine risk behavior spillovers among youth living in low-income Boston neighborhoods.

are somewhat different. Because we want to know exact shipments to each county, we start with the detailed ARCOS data on shipments in 2006 (see section III). We end our analysis in 2009, after which there were several policy interventions designed to reduce prescription opioid use – increased enforcement against pill mills and high prescribing doctors, the reformulation of *OxyContin* to be abuse-deterrent, and prescription drug monitoring programs.<sup>24</sup> As a result of these factors, the relationship between past and current shipments, and shipments in one area and linked areas, may be substantially different after these interventions.

Because we focus on the 2006-2009 period, we do not include illegal drug market prices. Further, because we include past opioid shipments to the area via the consumption capital stock measure, we do not include county fixed effects.<sup>25</sup> Thus, our estimating equation is:

$$y_{c,t} = \rho s_{c,t}^{rx} + \lambda \sum_{j \neq c}^{l} w_{j,c} y_{j,t} + \gamma x_{c,t} + \xi_{c,t},$$
(10)

As before, we also estimate the model via maximum likelihood to purge common shocks from leading to bias in estimation of  $\lambda$ :

$$Y_t = (I - \lambda W)^{-1} (\rho S_t^{rx} + \gamma X_t + N_t).$$
(11)

Because this model does not incorporate fixed effects, we use standard maximum likelihood estimation (MLE) instead of the QMLE approach that we use for opioid death rates.

#### C. Measuring opioid demand

We now discuss the exogenous determinants of opioid death rates: demand for opioids  $(x_{c,t})$  and illicit opioid supply  $(p_t^h \text{ and } v_t^f)$ . We assume that exogenously driven demand for opioids in each county and year is a latent factor underlying several county time-series variables:

<sup>&</sup>lt;sup>24</sup> See Alpert et al. (2018), Donahoe (2024), Evans et al. 2019, Kim (2021), and Soliman (2024) for studies of these interventions, which largely took place mid-2010 and later, and their effects on opioid prescribing and mortality. <sup>25</sup> Including lagged dependent variables and fixed effects in the same model leads to inconsistent estimation in finite samples (Angrist and Pischke 2009).

$$x_{c,t} = \Omega' F_{c,t} + \nu_{c,t},\tag{12}$$

for an  $r \times 1$  vector of factors  $F_{c,t}$  and associated factor loadings  $\Omega'$ . We estimate equation (12) using principal component analysis and several variables that the literature suggests are indicative of despair or pain (and thus demand for opioids): county suicide and alcoholic liver disease death rates, the percent of males ages 25-64 who are not working, log real wages for adults without college degrees, the percent of adults not married, and the percent of adults employed in manufacturing.<sup>26</sup> Results from the factor analysis are presented in **Supplementary Appendix C**. We extract the first principal component from this analysis (which has a large eigenvalue of 1.9).

### D. Measuring illicit opioid supply

In modeling the supply of illicit opioids, our goal is to measure the price per unit potency of illegal opioids given their availability in different areas at different times. There are two drugs to consider: heroin and illegally produced fentanyl. For each, we form a time series: 1997-2022 for heroin  $(p_t^h)$ , and 2013-2022 for fentanyl  $(p_t^f/\Omega)$ , where  $\Omega$  is a conversion factor that translates fentanyl into heroin equivalent grams – roughly 20). Both data series are national as local data were not available. However, as we show changes in heroin prices were limited over this time, the diffusion of fentanyl across areas will dominate price changes. To capture this, we weight the two prices for each county using the share of total heroin and fentanyl seizures in each state and year that are fentanyl  $(\delta_{s,t})$ :

$$p_{s,t}^{ill} = \left(1 - \delta_{s,t}\right) p_t^h + \delta_{s,t} \frac{p_t^f}{\Omega}.$$
(13)

In practice, fentanyl was adopted in the farthest eastern states around 2013 and spread westward over time. It did not reach the west coast in large quantities until around 2019-2020 (Zoorob et al. 2024). The data for each component is presented in **Supplementary Appendix C**. We also use log prices in estimation to facilitate interpretation using percentage terms.

<sup>&</sup>lt;sup>26</sup> See Case and Deaton (2017, 2020, and 2022); Charles and colleagues (2019); and Pierce and Schott (2020).

# **VI.** Results

We start by presenting trends in consumption capital and the exogenous determinants of opioid death rates (demand and illicit opioid prices). We then examine how each of these factors and spillovers affect opioid death rates and opioid shipments.

#### A. Trends in consumption capital and exogenous determinants of opioid death rates

**Figure 6** presents trends in demand, prescription opioid consumption capital, and the illicit price series. To facilitate interpretation of this figure, we standardize each variable to have mean 0 and standard deviation 1. The demand factor rose steadily by roughly 1 standard deviation total from 1998 to 2022. As we show in **Appendix C**, this is picking up the correlated trends of stagnant real wages for adults without college degrees, rising suicide and alcoholic liver disease death rates, increases in the share of adults not married, declining labor force participation rates among males, and declining employment rates in manufacturing all unfolding over roughly the same period. This is consistent with prior literature that has documented these trends are intertwined with the timing of the opioid epidemic (Case and Deaton 2017).

In standard deviation units, changes prescription opioid use and illicit opioid supply expansions were much larger (see also Currie and Schwandt 2021; Cutler and Glaeser 2021). Prescription opioid consumption capital increased by 2.6 standard deviations between 1997 and 2022. Even though opioid shipments peaked in 2011 (see **Supplementary Appendix B Figure B6** panel A), consumption capital increased for many years beyond, given the relatively low (5%) depreciation rate. **Figure 6** shows the peak occurred in 2019. **Figure B6** panel B shows the prescription opioid consumption stock with alternative depreciation rates. The peak had yet to occur even in 2022 with d = 0.01 and occurred in 2017 with d = 0.10.

On the illicit opioid supply side, prices fell by 1.37 standard deviations in total during the period when illicit opioid supply mostly entailed heroin (i.e., from 1998 to 2012). However, prices also spiked once over this period, from 2007-2010. The biggest changes to prices were after fentanyl began to replace heroin starting in 2013. As we show in **Supplementary Appendix C**, this did not have much effect on prices from 2013-2016 as heroin prices were rising and fentanyl was still relatively rare and not available in most of the U.S. After 2017, however, the share of illicitly produced opioids that were fentanyl increased dramatically. Coupled with falling fentanyl prices, this caused illicit opioid prices to fall 2.7 standard deviations between 2017 to 2022.

### B. Determinants of the opioid death rates

**Table 2** presents estimates of equations (8) and (9). Model (1)-(3) shows OLS results – i.e., without accounting for the potential for common and unobserved demand or supply shocks. In each case, higher prescription opioid consumption capital is strongly related to increased death rates. Each one morphine equivalent gram per capita increase in consumption capital (roughly one-sixth of the change from 1997 through 2019) is related to 0.35 more opioid deaths per 100,000, an increase of 25 percent over the average baseline death rate in 1998. There are also large and positive spillovers in death rates across areas. In column (1), for example, a shock that increases deaths by 1 death per 100,000 in an index county leads to 0.92 deaths per 100,000 in other areas that are social connected to the index county (a 64 percent increase over the baseline death rate).<sup>27</sup>

In terms of the exogenous shock variables, opioid death rates are positively but not significantly related to the despair measure. Illicit opioid prices, on the other hand, are strongly related to deaths. A 10 percent decrease in illegal opioid prices leads to 0.13 more deaths per 100,000 (an increase of 9 percent over baseline). Overall, the key drivers of death rates in this specification are the dynamic and spatial spillovers, and lower illicit opioid prices.

Model (2) uses an alternative weighting term for spillovers based on the inverse physical distance between counties. The results are largely similar, including similarly sized coefficients on spillovers. Model (3) includes the two weighting metrics together. One way to interpret these results is that the distance weighted term controls for geographically correlated supply and demand shocks and the friend metric is then a measure of spillovers purged of correlated area shocks. The results are very similar to model (1), with spillovers loading more heavily on social networks than distance. However, we interpret this model with caution as the friend and neighbor deaths terms are highly correlated with one another (Pearson's correlation coefficient = 0.85; see Figure B7).

Model (4), our preferred model, instruments for the friend-based spillovers term using the QMLE approach described in section V. This purges bias from common shocks as the spillovers term is identified off social and physical proximity to counties with exogenous factors that lead to higher opioid use (higher consumption capital, higher demand, and/or lower illicit opioid prices), conditional on these same factors in one's own county. Consistent with OLS picking up some common shocks, there is moderate attenuation of the spatial spillover terms. Still, the spillovers

<sup>&</sup>lt;sup>27</sup> We obtain the approximate spillover from one death by interacting the estimates of  $\lambda$  with  $\frac{1}{N}\sum_{i}\sum_{j} w_{i,j}$ . This quantity is equal to 0.99 for the friends-based measure and 0.91 for the distance-based measure.

are large and significant. An additional one death per 100,000 in an area is associated with 0.72 additional deaths in other areas based on the specification with friend-based weighting.

The effects of past consumption on opioid death rates are even larger in this specification, 66% above those in column (1). Demand continues to be unrelated to death rates. However, the effect of lower opioid prices is even larger. In this specification, a 10 percent decline in prices leads to 0.35 more opioid deaths per 100,000 (a 24 percent increase over baseline). Model (5) uses distance-based weighting and results are largely similar, with a larger role for spillovers through distance than social networks. That said, spillovers with each type of weighting are large. We return to what the magnitude of these effects implies below.

### C. Results with different depreciation rates

One question about the results of **Table 2** is how sensitive they are to choice of d. Our baseline model uses d = 0.05—however, as this is an assumption, it is important to examine how results vary at alternative rates. One exercise that we performed is to examine what depreciation rate leads to the model achieving the best fit, based on the Wald Chi-squared statistic for model fit. Results are presented in **Appendix Figure B8** for the specification in column (4), varying the depreciation rate in one percentage point intervals over the range of d = 0 to d = 0.99.

The model with the best fit is the model with the lowest depreciation rate (d = 0). The reason for this is shown in **Figures 3-4**. Areas with high prescription opioid supply and death rates early on in the epidemic had high death rates throughout the next two decades, even though the mix of substances leading to death changed over time. Thus, our descriptive evidence and the results from **Appendix Figure B8** both suggest a very low depreciation rate for prescription opioid use and a long horizon between initial prescription opioid use and overdose deaths.

To examine how our results vary with different depreciation rates, **Appendix Table B2** presents results for overall opioid death rates (based on our preferred specification presented in **Table 2 model 4**) with alternative depreciation rates of 0%, 1%, 5%, 10%, 25%, and 50%. We obtain generally similar results across specifications. The coefficients on the exogenous shock parameters do not vary much across specifications, though the demand factor becomes more important with higher depreciation rates. One interpretation of this is that demand conditions are related to long-term prescription opioid consumption, and thus are subsumed there. The coefficient on the consumption capital stock grows with higher depreciation rates, though the magnitude of

the change over time in consumption capital is smaller with a higher discount rate. Lastly, the spillovers term is essentially the same across specifications, varying no more than 5 percent. In general, our results are not very sensitive to our choice of d. Very low discount rates, however, imply some implausible predictions. For example, with a discount rate of 1%, an increase in shipments in one year has 60% as much effect 5 decades later, when almost everyone affected will be dead. We use a d of 5% for our primary results to avoid such scenarios.

### D. Counterfactual analysis of the opioid epidemic

Using the estimates from our preferred specification (**Table 2** model (4)), **Figure 7** shows how each factor affected opioid death rates over time. The figure shows the direct effects of each variable, as well as indirect effects through spillovers. To construct these estimates, we predicted counterfactuals that restricted each of the exogenous variables independently to remain at 1998 levels and took the difference between these predictions and counterfactual predictions based on observed changes in each variable over time, with and without allowing for spatial spillovers.

Three variables stand out as driving the epidemic: dynamic spillovers due to increased prescription opioid consumption capital, falling prices for illicit opioids, and spatial spillovers. Starting with the exogenous variables, the diffusion of fentanyl and corresponding declines in illegal opioid prices have led to larges increases opioid death rates over time, particularly after 2016-2017. By 2022, our model implies that lower illicit opioid prices increased death rates 415 percent over baseline levels (see **Figure 7** Panel C). Rising demand due to despair was not a significant contributor to the epidemic at any point (see **Figure 7** Panel B). Exogenously rising demand due to despair, on the other hand, was not a significant contributor.

While fentanyl and falling illicit opioid prices are clearly important in driving death rates in recent years, dynamic and spatial spillovers in opioid use were even larger contributors. **Figure** 7 Panel A shows that increased prescription opioid consumption capital caused opioid death rates to rise by 240 percent over their baseline levels from 1998 to 2022. Spatial spillovers amplified this effect even further, leading increased consumption capital to indirectly increase opioid death rates by another 530 percent. Spatial spillovers magnified the direct effect of falling fentanyl prices too—causing them to increase death rates another 1,011 percent by 2022.

**Table 3** presents additional analyses illustrating the contribution of each of these factors to the cumulative total increase in opioid death rates from 1998 to 2022. First, the direct effects of

falling illicit opioid prices explain roughly 12 percent of total increases in opioid death rates. Dynamic spillovers due to prescription opioid addiction explain 18 percent of the increase. Thick market externalities were the biggest contributor, explaining 70 percent of increased opioid deaths.

### E. Analysis of opioid shipments

**Table 4** presents results from estimating equations (10) and (11) with opioid shipment rates as the dependent variable. As noted in section V, we restrict the sample to 2007 to 2009, which is the period we have exact county opioid shipments and before major policy initiatives were implemented to reduce opioid prescribing and use.

Columns (1)-(3) show OLS estimates. The results are similar to the models for opioid death rates. Like for deaths, higher prescription opioid consumption capital is related to increased prescription opioid shipments in the future. Each 1 higher MEG per capita increase in consumption capital is related to 0.37 more opioid shipments – an increase of 78 percent over the baseline unadjusted mean in 2007. Further, there are large spatial spillovers in opioid shipment rates. For every 1 MEG per capita shipped to one region, there is an additional 0.3 MEG per capita shipped to other socially related areas due to spillovers. One difference from the models for mortality is that exogenous demand factors are positively related to opioid shipments growth. However, the magnitude of the relationship is small. The QMLE models that instrument for spillovers using friend and distance proximity to demand and consumption capital, reported in columns (4) and (5), also show evidence of strong addiction effects and spillover effects.

Appendix Table B3 shows results that vary the depreciation rate. Results are generally similar across specifications. However, estimates of  $\rho$  increase at higher depreciation rates and spillovers attenuate somewhat at depreciation rates from 10-50%.

Using the estimates of the model, we also simulate out the dynamics of temporary shocks to opioid use that are not followed by intervention in **Figure B9**. First, we estimate equation (6) and approximate if use dynamics are unstable: i.e., if  $\hat{\rho}(1-d) + \hat{\lambda} > 1$ .<sup>28</sup> Estimates of this equation are presented below the coefficients in **Table 4** and show there is no steady state equilibrium in any of these specifications due to the strength of addiction and spillovers.

Using our preferred specification (Table 4 model 4), we simulate the dynamics of a one-

<sup>&</sup>lt;sup>28</sup> It is an approximation because this equation assumes  $w_{i,j} = \frac{1}{N-1}$  for all  $j \neq i$ . To assess the actual dynamics, we simulate out the dynamics using the actual  $w_{i,j}$  for each county based on our cross-county friendship measure.

period increase in opioid use of 0.1 MEG per capita in all U.S. counties. From this shock, we compute the implied dynamic spillovers (based on  $\hat{\rho}$  and d) and spatial spillovers (based on  $\hat{\lambda}$  and cross-county Facebook friend linkages for all counties) over ten periods. The figure shows that addiction and spillovers act to significantly amplify the shock across time and space, with spatial spillovers generating the largest degree of amplification. The result of these dynamics is an exponential rise in opioid use over time, with opioid use increasing 776 percent without any exogenous changes. This illustrates how the presence of addiction and spatial spillovers combine with one another and provide an economic explanation for epidemics.

# **VII.** Conclusions

Historically, some drug epidemics have lasted a long time, and others have been short term, over within a decade. This paper studies why the current opioid epidemic has lasted for over three decades and been so destructive. This long epidemic is puzzling since policy has tried to address the opioid epidemic for at least the past 15 years. Still, it continues to worsen.

Our main finding is that we can explain the long epidemic with reference to the dynamic and spatial spillovers that stem from opioid use. As people used more prescription opioids throughout the 2000s, they became more likely to demand opioids in the future. The direct effect of this is more addiction to opioids, dangerous illegal opioid use, and overdose mortality. However, even more quantitatively important is that this made opioid markets thicker, and information flows and ease of obtaining the substances led to more opioid use by others as well. This continued even as the epidemic transitioned to new substances. Substantially lower illicit opioid prices due to the diffusion of illicit fentanyl in the U.S. have been a secondary driver of increased overdose deaths, particularly since 2016-2017. However, our estimates imply that even most of the effect that this had is more related to spillovers from falling prices than the demand response to prices itself.

Our data do not allow us to test specific mechanisms for thick market effects—e.g., whether they are due to information flows, access to products, or peer effects. However, evidence in our research and other studies that we cite suggest that several mechanisms may be important to some degree. Our finding that *Subsys* shipments increased more in areas with more friends in places where physicians were paid to prescribe *Subsys* suggests information flows matter. Further, survey data showing that most people obtained prescription opioids from peers and qualitative reports that most people initiated opioid use or transitioned to illegal opioid use with the help of a peer are suggestive of spillovers through access and peer effects channels. Examining the quantitative importance of these mechanisms is a key issue following from this research, as different mechanisms suggest different ways policies could respond to the epidemic more effectively.

Understanding how the opioid epidemic differs from other epidemics, like the crack cocaine epidemic (which had a shorter duration), is another important topic for future research. If the difference between the duration of the opioid and crack cocaine epidemic is due to differences in ease of accessing products and their distribution (for example, due to less violence in the illegal opioid market than the market for crack cocaine or lack of a legal formulation of crack cocaine like is available for opioids), it could imply that the dynamics of drug epidemics depend as much on the economics of the market as on the properties of the drug.

Overall, this paper's findings have important implications for policy. They show that in markets for addictive products, even temporary mistakes or misconduct on the part of regulators or suppliers that stimulate demand for addictive products can lead to long-term harms, even well after the initial mistake or misconduct that first stimulated demand has ended. It is critical that policy takes this potential into account when regulating addictive product markets.

# **FIGURES**



Figure 1: Trends in drug and opioid overdose deaths per 100,000, 1990 to 2022.

*Notes.* Data on overdose deaths are from the National Center for Health Statistics, age and sex adjusted to the U.S. population in 2010. Cause of death codes that were used to identify overdose deaths (overall and by cause) are described in section III.A of the text.



Figure 2: Path of opioid initiation, abuse, and overdose death

{---- } Areas with potential thick market effects



# Figure 3: Map of Average Annual Opioid Deaths Per 100,000, 1999 to 2022.

*Notes.* Data are from the National Vital Statistics System. Death rates in counties with fewer than ten total opioid overdose deaths over the period are censored from the figure, per NCHS requirements.

Figure 4: Trends in opioid shipments and death rates in Greenup County, Kentucky, and Scioto County, Ohio, and socially connected counties, 1997 to 2022.



*Notes.* Data are from ARCOS and NVSS. The figure presents trends in opioid shipments and deaths (2-year moving average) for Greenup County, Kentucky, and Scioto County, Ohio, one of the first areas to have significant pill mills (the last major one, a clinic run by Margaret Temponeras, which was raided in 2011). It also presents trends for counties in the top, middle (i.e., 2<sup>nd</sup> to 8<sup>th</sup>), and bottom deciles of social connectedness to the counties Greenup and Scioto Counties. \*Deaths in Greenup/Scioto counties are not shown when less than 10 deaths occurred (1997-2001).

Figure 5: Trends in *Subsys* shipments to counties with paid clinician prescribers, and socially connected counties, 2012 to 2019.



*Notes*. Data are from ARCOS. The figure presents trends in *Subsys* shipments in counties where *Insys* paid clinicians to prescribe and promote it. It also presents trends for counties in the top, middle (i.e., 2<sup>nd</sup> to 8<sup>th</sup>), and bottom deciles of social connectedness to these counties.



Figure 6: Trends in determinants of opioid overdose death rates

Notes. See sections V-VI of the text and Appendix C for more details.



Figure 7: Determinants of changes in opioid death rates, 1999-2022.

*Notes*. Results are from model (4) in Table 2. See sections V-VI of the text for more details. The percent increase is relative to the unadjusted mean opioid overdose death rate across counties in 1998.

# **TABLES**

Table 1	. Quotes that highlight	the importance	ofpeer	spillovers	in a	person's	s initiatic	on or
		escalation of	opioid u	ise.				

Study	
Mars, Bourgois, et al., (2014), p. 8.	This account of a transition to heroin after four months using <i>OxyContin</i> is from a 28-year- old Philadelphia man who had been injecting heroin. It typifies many of the younger heroin injectors' experiences:
	A: My buddy [], the one that introduced me to Oxies was actually doing dope [heroin] at the time. And I came over his house and I was sick [in withdrawal] and I asked him if he could get me an Oxy for ten bucks, which I needed an 80 [mg], which they were [\$]20 and I only had [\$]10. So he basically convinced me and started talking about how Oxies and dope [heroin] there is no difference.
Mars, Bourgois, et al., (2014), p. 9.	Older heroin initiates typically described their first use as a social process, offered by a friend, sexual partner or family member Only one interviewee, a heroin initiate, reported seeking out the drug without knowing any other heroin users. More typically, this 56 year old female heroin initiate had been injecting heroin for several decades after transitioning from alcohol, marijuana and crack cocaine:
	Q: Okay. So how did you get started; what happened?
	A: I was always a curious person. I always hung around grown people, you know, at 14 I was hanging with my first boyfriend [] So I started going to clubs and stuff like that and the people I hung around did it so I was just curious [].
Mars, Ondocsin, et al., (2024), p. 6.	Typically, several interviewees recalled their initial reluctance to inject and how this had been overcome with the economic and dependence-related demands of opioid use and the proximity of injecting norms among close associates
	I: Who introduces you to injection?
	S: One of my friends that I knew introduced me [] and I was totally against injecting drugs, that's the craziest thing, you know, I mean, these people were crazy to ever do that. And I was driving around in my car one day and I had a 20 mg OxyContin and I remember thinking, I crush this up and snort it it's not gonna help me a bit. But my buddy's over here and I'll have him inject'em. I'm gonna go over there and have him show me.
Perdue, Carlson, et al., (2024), p. 5.	Peers were influential in communicating how to transition from prescription opioids to heroin. These peers often had extensive heroin use histories and showed participants how to purchase heroin, or even instructed them in their first use of heroin. Intra-familial use also played a role in the transition from prescription opioids to heroin, as reflected by one participant who remembered her initiation into heroin use at age 16 after misusing her prescription:
	My older cousin shot me up [with heroin]. I was fresh out of surgery and ran out of pain pills, and they told me that it would make it better.

*Notes.* Direct quotes from interviewers/interviewees are in *italics.* Non-italicized text are direct quotes from the articles cited in the table.

	OLS			QM	ILE
	(1)	(2)	(3)	(4)	(5)
Rx opioid consumption capital $(\hat{\rho})$	0.354***	$0.296^{***}$	0.281***	$0.580^{***}$	0.352***
	(0.029)	(0.031)	(0.029)	(0.020)	(0.022)
Friend spillovers $(\hat{\lambda}^f)$	0.934***		$0.884^{***}$	$0.720^{***}$	
	(0.017)		(0.022)	(0.006)	
Distance spillovers $(\hat{\lambda}^d)$	. ,	$0.984^{***}$	0.117***		0.932***
		(0.019)	(0.025)		(0.009)
Demand (despair) factor	0.003	-0.069	-0.010	0.017	-0.062**
	(0.042)	(0.043)	(0.042)	(0.026)	(0.028)
Log illicit opioid prices	-1.326***	-0.646***	-0.617***	-3.472***	-1.183***
	(0.214)	(0.249)	(0.223)	(0.132)	(0.153)
Spillovers from one death	0.92	0.90	0.98	0.71	0.85
Baseline unadjusted mean (1998)	1.43	1.43	1.43	1.43	1.43
N (counties $\times$ years)	77,875	77,875	77,875	77,875	77,875

**Table 2:** Estimates of the determinants of opioid death rates, 1997-2022.

*Notes.* Estimates of equations (8)-(9) of the text using data on opioid overdose death rates per 100,000 for all U.S. counties from 1997-2022. Models (1)-(3) uses OLS and equation (8). Models (4)-(5) use QMLE and equation (9). All models include county fixed effects to control for time invariant confounding. Standard errors are reported in parentheses. \*(\*\*)\*\*\* denotes statistical significance at level p<0.1(0.05)0.01. See section V-VI of the text for more details.

	1999-2022		
	# deaths	% of deaths	
Exogenous changes			
Falling illicit opioid prices	98,990	12.3	
Rising demand	1,031	0.1	
Total direct effects	100,021	12.4	
Spillovers			
<i>Dynamic due to prescription opioid use</i>	144,919	18.1	
Spatial due to thick market externalities	557,406	69.5	
Total spillovers	702,325	87.6	

**Table 3:** Counterfactual analysis of the opioid epidemic's main determinants.

*Notes.* Counterfactuals are based on model (4) in **Table 2** and estimate the total number and percentage of opioid deaths explained by changes in each factor relative to 1998 levels (the first year in our estimation) from 1999-2022. See sections V-VI of the text for more details.

	OLS			MI	LE
	(1)	(2)	(3)	(4)	(5)
Rx opioid consumption capital $(\hat{\rho})$	0.367***	0.398***	0.367***	$0.370^{***}$	0.398***
	(0.007)	(0.006)	(0.007)	(0.003)	(0.003)
Friend spillovers $(\hat{\lambda}^f)$	0.305***		0.367***	$0.278^{***}$	
	(0.018)		(0.021)	(0.013)	
Distance spillovers $(\hat{\lambda}^d)$		$0.048^{***}$	-0.116***		$0.048^{***}$
• • • •		(0.014)	(0.016)		(0.013)
Demand factor	$0.004^{***}$	$0.008^{***}$	0.004***	$0.004^{***}$	$0.008^{***}$
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dynamics					
$\hat{ ho}(1-d)/d + \hat{\lambda}$	7.28	7.61	7.19	7.31	7.61
Baseline unadjusted mean (2007)	0.47	0.47	0.47	0.47	0.47
N (counties $\times$ years)	9,345	9,345	9,345	9,345	9,345

Table 4: Estimates of the determinants of opioid shipment rates, 2007-2009.

*Notes.* Estimates of equations (10)-(11) of the text using data on opioid overdose death rates per 100,000 for all U.S. counties from 2007-2009. Models (1)-(3) use OLS and models (4)-(5) use QMLE. Standard errors are reported in parentheses. \*(\*\*)\*\*\* denotes statistical significance at level p<0.1(0.05)0.01. See section V-VI for more details.

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# **APPENDIX A. THEORY APPENDIX**

### **Derivation of equation (5)**

Equation (4) can be rewritten as follows:

$$A_t^* - \lambda W A_t^* = \rho S_t + \beta P_t + \gamma X_t + K.$$
(A1)

Re-arranging terms further, this leads to:

$$(I - \lambda W)A_t^* = \rho S_t + \beta P_t + \gamma X_t + K.$$
(A2)

Inverting the  $I - \lambda W$  matrix to solve for  $A_t^*$  yields equation (5) in the text.

### **Derivation of equation (6)**

An individual's steady state equilibrium satisfies  $a^* = S^*d/(1 - d)$ . Plugging this into equation (3), solving for average use, and re-arranging terms implies:

$$\frac{1}{N}\sum_{i=1}^{N}a_{i}^{*} = \frac{1}{N}\sum_{i=1}^{N}\left(\rho\frac{a_{i}^{*}(1-d)}{d} + \lambda\sum_{j=1}^{N}w_{ij}a_{j}^{*} + \beta p + \gamma x_{i} + k\right).$$
 (A3)

Substituting  $\frac{1}{N-1}$  for  $w_{ij}$  and 0 for  $w_{ii}$  yields

$$\frac{1}{N}\sum_{i=1}^{N}a_{i}^{*} = \frac{1}{N}\sum_{i=1}^{N}\left(\rho\frac{a_{i}^{*}(1-d)}{d} + \frac{\lambda}{N-1}\sum_{j=1:j\neq i}^{N}a_{j}^{*} + \beta p + \gamma x_{i} + k\right).$$
 (A4)

Note that  $\sum_{i=1}^{N} \sum_{j=1: j \neq i}^{N} a_j^* = (N-1) \sum_{i=1}^{N} a_i^*$ . Thus, we can re-write equation (A4) as:

$$\frac{1}{N}\sum_{i=1}^{N}a_{i}^{*} - \frac{\rho(1-d)}{d}\frac{1}{N}\sum_{i=1}^{N}a_{i}^{*} - \lambda\frac{1}{N}\sum_{i=1}^{N}a_{i}^{*} = \frac{1}{N}\sum_{i=1}^{N}(\beta p + \gamma x_{i} + k).$$
(A5)

Solving (A5) for average use yields:

$$\frac{1}{N}\sum_{i=1}^{N}a_{i}^{*} = \frac{\frac{1}{N}\sum_{i=1}^{N}(\beta p + \gamma x_{i} + k)}{\left(1 - \frac{\rho(1-d)}{d} - \lambda\right)}.$$
 (A6)

Hence, for stable demand, the following condition must be satisfied:

$$\frac{\rho(1-d)}{d} + \lambda < 1. \tag{A7}$$

### Simulation details

Our simulation in **Appendix Figure B1** uses a closed population of 10 individuals with homogenous tastes for opioids. Parameter values are as follows.

Parameter	Meaning	Value
PANEL A. Demand	l parameters	
d	Depreciation rate (consumption stock)	0.25
ρ	Intertemporal complementarity (i.e., addiction)	0.20
λ	Spillover effect	0.20
w <sub>ij</sub>	Degree of interaction for all individuals $j \neq i$	0.10
γ	Demand responses to taste shocks	0.50
Panel B. Demand S	Shock	
$x_{i,t}$ for $t \in [0,5)$	Initial demand	0
$x_{i,t}$ for $t \in [5,T]$	Exogenous and permanent increase in demand in period 5	1
Panel C. Hazard R	ate	
$a_0$	Constant	-9
$a_1$	Increase in hazard with drug use	1
$\bar{a_2}$	Decrease in hazard with consumption capital stock	-0.15

# **APPENDIX B. ADDITIONAL TABLES AND FIGURES**

Figure B1. A hypothetical opioid epidemic with and without addiction and spillovers



Notes. See Section II of the text and Appendix A for more details.





*Notes.* Data are from the Treatment Episodes Dataset on Admissions (TEDS-A) in 2021. We calculated the number of years since first opioid use as the difference between each individual's age in 2021 and the age that they reported first using opioids. The variable for age at first use was top coded at 30 (roughly 22 percent of individuals initiated at age 30 or later). We conservatively assumed that all individuals who initiated opioid use after age 30 initiated the same year that they were admitted to treatment (i.e., had been using opioids for 0 years). The median number of years using opioids if we instead exclude individuals with top coded ages of first opioid use is 15 years. Thus, the true median is somewhere between 10 and 15 years.



Figure B3: Distribution of social connectedness to Greenup County, Kentucky, and Scioto County, Ohio.

*Notes.* The figure plots the percentile of social connectedness between each county in the U.S. and Greenup, Kentucky/Scioto, Ohio, where many early pill mills were established.

Figure B4: Synthetic opioid (primarily fentanyl) and total opioid death rates in Greenup County, KY, and Scioto County, OH, 1997-2022.



*Notes.* Data are from the National Vital Statistics System. Rates are not shown when fewer than 10 total opioid or synthetic opioid deaths occurred. See Section IV for more details.



Figure B5: Distribution of social connectedness to counties where *Insys* paid prescribers in 2012

*Notes.* The figure plots the percentile of social connectedness between each county in the U.S. and the counties where *Insys* paid *Subsys* prescribers and promoters in 2012, the first year the drug was marketed.



Figure B6: Trends in prescription opioid shipment rates and consumption stock, 1997-2022.

*Notes.* Data are from the Automation of Reports and Consolidated Orders System. Panel B shows trends in consumption capital under three different depreciation rates: d = 0.01, d = 0.05, and d = 0.10. See sections V-VI of the text for more details.



Figure B7: Binned scatter plot of friend- vs. neighbor-weighted opioid death rates.

*Notes.* Binned scatter plot of county exposure to opioid death rates in other counties from weighting relationships between counties based on cross-county Facebook friendships and distance. See section V-VI for more details.



Figure B8: Choice of depreciation rate (d) that maximizes model fit for total opioid death rates

*Notes.* Wald Chi-squared statistics from estimating equation (8) of the text using data on opioid overdose death rates per 100,000 for all U.S. counties from 1997-2022, varying d from 0.00 to 0.99 in one percentage point intervals. See section V-VI of the text for more details.





Notes. Simulation uses estimates from equation (11), reported in Table 4 model (4). See section V-VI of the text for more details.

Source	Percent
I got it from a friend or relative for free	54.3%
I got a prescription from just one doctor	15.2%
I bought it from a friend or relative	11.6%
I took it from friend/relative without asking	6.6%
I bought it from a drug dealer or other stranger	5.1%
I got it in some other way	5.1%
I got prescriptions from more than one doctor	1.4%
I stole it from doctors office/clinic/hospital/pharmacy	0.4%
I wrote a fake prescription	0.2%
I bought it on the Internet	0.2%

 Table B1: Where NSDUH respondents obtained the last prescription opioids that they misused, 2005-2011.

Notes. Data are from the National Survey on Drug Use and Health (NSDUH), 2005-11.

	Depreciation rate (d)					
	0.00	0.01	0.05	0.10	0.25	0.50
	(1)	(2)	(3)	(4)	(5)	(6)
Rx consumption capital ( $\hat{\rho}$ )	0.411***	$0.444^{***}$	$0.580^{***}$	$0.756^{***}$	1.292***	2.502***
	(0.013)	(0.014)	(0.020)	(0.028)	(0.063)	(0.172)
Friend spillovers $(\hat{\lambda}^f)$	$0.715^{***}$	$0.716^{***}$	$0.720^{***}$	$0.727^{***}$	$0.745^{***}$	$0.759^{***}$
• • • •	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Demand (despair) factor	0.017	0.016	0.017	0.025	0.059**	0.095***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Log illicit opioid price	-3.031***	-3.123***	-3.472***	-3.840***	-4.447***	-4.698***
	(0.135)	(0.135)	(0.132)	(0.129)	(0.126)	(0.126)
N (counties $\times$ years)	77,875	77,875	77,875	77,875	77,875	77,875

**Table B2:** Robustness of Table 2 model (4) results to alternative depreciation rates.

*Notes.* Estimates of equation (9) of the text using data on opioid overdose death rates per 100,000 for all U.S. counties from 1997-2022, varying *d* from 0.01 to 0.50. Standard errors are reported in parentheses. \*(\*\*)\*\*\* denotes statistical significance at level p<0.1(0.05)0.01. See section V-VI of the text for more details.

			Depreciati	on rate ( <i>d</i> )		
	0.00	0.01	0.05	0.10	0.25	0.50
	(1)	(2)	(3)	(4)	(5)	(6)
Rx consumption capital ( $\hat{\rho}$ )	0.3293***	0.3369***	0.3695***	0.4160***	$0.6070^{***}$	1.2574***
	(0.0029)	(0.0029)	(0.0031)	(0.0034)	(0.0043)	(0.0068)
Friend spillovers $(\hat{\lambda}^f)$	0.2941***	$0.2909^{***}$	$0.2779^{***}$	0.2612***	$0.2080^{***}$	0.1164***
	(0.0130)	(0.0129)	(0.0128)	(0.0125)	(0.0116)	(0.0096)
Demand (despair) factor	$0.0046^{***}$	$0.0046^{***}$	$0.0044^{***}$	$0.0042^{***}$	$0.0035^{***}$	$0.0022^{***}$
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0008)
N (counties × years)	77,875	77,875	77,875	77,875	77,875	77,875

Table B3: Robustness of Table 4 model (4) results to alternative depreciation rates.

*Notes.* Estimates of equation (9) of the text using data on opioid overdose death rates per 100,000 for all U.S. counties from 1997-2022, varying *d* from 0.01 to 0.50. Standard errors are reported in parentheses. \*(\*\*)\*\*\* denotes statistical significance at level p<0.1(0.05)0.01. See section V-VI of the text for more details.

### SUPPLEMENTARY APPENDIX C. ADDITIONAL EMPIRICAL DETAILS

### Principal components analysis of demand

This section presents results from the factor analysis used to measure exogenous demand shocks for opioids. As noted in Section III of the text, data are drawn from measures that have been hypothesized as picking up the deaths of despair hypothesis in the literature: suicide and alcoholic liver disease death rates (from NCHS) and the percent of males ages 25-64 not in the labor force, log real wages for adults without bachelor's degrees, the percent of adults not married, and the percent of adults employed in manufacturing (from the ACS).

Because ACS data are not available in all years, data are interpolated or extrapolated for the variables % males not working, log real wages for adults without bachelor's degrees, % not married, and % employed in manufacturing for the following years: 1997-1999; 2001-2004; and 2022. Measurement changes in the ACS lead to a non-comparability of the % of men who are not married between 2005 and 2006. We adjust for this by predicting 2006 rates based on extrapolating the change in the % of males not working from 2004-2005. We then adjust all years prior to 2006 by the ratio of actual 2006 % not working to the predicted value for that year.

**Figure C1** presents national trends in standardized units for each of these measures of from 1997-2022. Consistent with prior literature, they show rising suicide and alcoholic liver disease death rates being correlated with deteriorating conditions for working class individuals: in particular, stagnating wages for people without bachelor's degrees and increasing shares of males not working, adults not being married, and adults not being employed in manufacturing. As shown in the figure and consistent with prior literature Case and Deaton (2017, 2020, and 2022) these trends have been fairly correlated over time.

Results from the factor analysis – equation (11) in the text – are presented in **Tables C1-C2**. **Table C1** shows how much variance different factor loadings explain. The factor with the largest eigenvalue (1.92) explains 32 percent of variance in the six included variables. Adding a second factor (eigenvalue 1.66) increases the share of variance explained to 60 percent.

**Table C2** shows scores for the first two factors. The first factor is positively correlated with suicide and alcoholic liver disease death rates, the percentage of males not working, and the percentage of people and not married, and negatively correlated with wages for people with less than bachelor's degrees and the percentage of people employed in manufacturing. This is very

consistent with the idea of despair. The second factor is negatively correlated with suicide rates, the percentage of males out of the labor force, and the percentage of people employed in manufacturing, but positively correlated with alcoholic liver disease death rates, wages, and the percentage of people not married. This is less consistent with the deaths of despair hypothesis. Thus, in our analysis, we only use the first factor score.

Trends in the overall demand factor score are presented in Figure C2.



Figure C1. Trends in determinants of demand for opioids.

Notes. The figure reports national data.





Component	Eigenvalue	Cumulative variance explained				
Factor 1	1.92	0.32				
Factor 2	1.66	0.60				
Factor 3	0.88	0.74				
Factor 4	0.72	0.86				
Factor 5	0.51	0.95				
Factor 6	0.31	1.00				
Notes. Results are from estimation with county-level data, 1997-2022.						

 Table C1. Eigenvalues from the demand factor analysis.

Variable	Factor 1 score	Factor 2 score					
Suicide death rate	0.4389	-0.0781					
Alcoholic liver disease death rate	0.4403	0.1371					
% males not in the labor force	0.5605	-0.0651					
log(real wage < BA)	-0.5252	0.2570					
% not married	0.1189	0.6770					
% employed in manufacturing	-0.0970	-0.6682					
Eigenvalue	1.92	1.66					

Table C2. Demand factor analysis scores

Notes. Results are from estimation with county-level data, 1997-2022.

### **Illicit Opioid Price Time Series**

This section presents our construction of the illicitly produced opioid price series according to equation (13) of the text using national data on heroin and illegally produced fentanyl prices, and state-level data on heroin and fentanyl seizures. Data on heroin prices come from U.S. law enforcement agency estimates of retail prices reported to the United Nations Office on Drug Control Policy (UNODCP), based on seizures data. Data on fentanyl prices come from fentanyl seizures and are reported in Kilmer et al., (2022). Data on seizures come from the National Forensic Laboratory Information System (NFLIS).

The price variables are not available in all years (2021-2022 for heroin and 2013-2016 and 2021-2022 for fentanyl). Note that we do not require fentanyl prices prior to 2013 as illegally produced fentanyl was extremely rare before then. We impute based on the average annual decline for these variables (-\$13.4 per pure gram annually for heroin and -\$868.1 per pure gram annually for fentanyl). The decline that we use to impute fentanyl prices from 2013-2016 (roughly 16 percent annually) is also very similar to the decline in fentanyl prices reported from another source from 2014 to 2016, based on scrapes of the dark web (Miller 2020).

We start by presenting national trends in each of these variables in **Figure C3**. Both price variables are in constant \$2020 and represent the price of a pure gram to adjust for differences in purity across substances and years. Panel A presents trends in prices for heroin and illegally produced fentanyl, standardizing the price for fentanyl into heroin equivalent grams. Dashed lines indicate years the prices are imputed. Heroin prices declined modestly over time but were variable, exhibiting spikes from 2007-2010 and 2014-17. Declines in fentanyl prices were much sharper. Fentanyl prices were also much lower than heroin prices. Starting in the first year we observe them (2017), the price for retail quantities of fentanyl was roughly 69 percent cheaper than an equivalent amount of heroin. By 2020 (the last year we observe), fentanyl was roughly 77 percent cheaper than heroin.

Panel B presents trends in the share of illicit opioid seizures that are fentanyl nationally and for states east and west of the Mississippi River. We calculated this by dividing the number of fentanyl seizures in each state and year by the total number of fentanyl and heroin seizures. Prior to 2013, most fentanyl seizures were due to legal prescription fentanyl. Thus, we used a value of 0 for all states prior to 2013. To remove legal fentanyl from post-2013 seizures, we also quantified the average quantity of fentanyl seizures in each state from 2009 to 2011 – which were largely

legal fentanyl – and subtracted this quantity from the fentanyl count in each state in each year post-2013.

The share of illicit opioid seizures associated with fentanyl increase sharply after 2013, with diffusion occurring more rapidly in eastern than western states. This is consistent with prior literature (Zoorob 2019; Zoorob et al. 2024). Nationally, the share of seizures involving fentanyl increased from less than 1 percent in 2013 to 80 percent in 2022.

**Figure C4** presents the price measure from equation (13) of the text, nationally and for eastern and western states. The spike in heroin prices from 2014-2017, combined with a limited presence of fentanyl in supply by that point, leads to no overall decline in prices from 2013 to 2017. However, after that, increasing diffusion of cheaper fentanyl lowered prices considerably. Overall, prices fell 72 percent in eastern states from 2013 to 2022 and 63 percent in western states.

Figure C3. Trends in heroin and fentanyl prices, and the share of illicit opioid seizures that are fentanyl, 1997-2022.



Notes. Dashed lines indicate years that heroin and fentanyl prices were imputed.



Figure C4. Trends in illicitly produced opioid prices, 1997-2022.