Physician Behavior in the Presence of a Secondary Market: The Case of Prescription Opioids*

Molly Schnell†
Northwestern University and NBER

June 10, 2022

Abstract

This paper examines how drug diversion influences the prescribing practices of physicians and the equilibrium health impacts of prescription medications. Focusing on the case of prescription opioids, a commonly prescribed and frequently diverted medication at the heart of the worst drug crisis in U.S. history, I design and estimate a model of physician behavior in the presence of a secondary market with patient search. To access prescription opioids for medical purposes or misuse, patients search over physicians on the legal primary market or turn to an illegal secondary market. Physicians, who care both about their impact on population health and their revenue from office visits, take into account the possibility that patients might resell their prescriptions on the secondary market when prescribing. The model demonstrates that the potential for diversion will tend to make strict physicians more hesitant in their prescribing while leading lenient prescribers to loosen their prescription thresholds, thereby exacerbating prescribing differences between more and less lenient physicians. Estimates reveal that the presence of a secondary market induces most physicians to be more careful in their prescribing, which brings prescriptions closer to their optimal level, but results in significant net harm due to the reallocation of prescriptions for abuse.

Keywords: physician behavior, secondary markets, prescription opioids

---

*I thank Giulia Brancaccio, Nick Buchholz, Janet Currie, Angus Deaton, David Eil, Liran Einav, Gautam Gowrisankaran, Jonathan Guryan, Jessie Handbury, Bo Honoré, Jakub Kastl, Ilyana Kuziemko, Bentley MacLeod, Eduardo Morales, Casey Mulligan, Nicholas Papageorge, Clara Santamaría, Hannes Schwandt, Otto Toivanen, Bob Town, and Atheendar Venkataramani for helpful comments. I also thank seminar participants at Bates White, Berkeley, Bocconi, Booth, Brown, CERGE-EI, Columbia, Dartmouth, DOJ, FTC, Fuqua, Harvard, HBS, HKS, Hebrew University, Kellogg, LSE, MIT, Microsoft Research, NYU, Northwestern, Olin, Princeton, Queen Mary, Santa Barbara, Stanford, Stanford GSB, Stern, Tel Aviv, Texas A&M, UCL, UChicago, University of Copenhagen, University of Maryland, University of Minnesota, UPenn, University of Wisconsin-Madison, University of Zurich, Wharton, Yale, Yale SOM, the 2016 Conference of the American Society of Health Economists, the 2016 European Health Economics Association Conference, the 2016 Population Health Science Workshop at Boston University, the 2016 and 2017 Becker Friedman Institute Emerging Scholars Roundtables, the 2017 CEPR Applied IO Summer School, the 2017 Barcelona GSE Summer Forum (Applied IO), the 2017 European Association of Labour Economists Conference, the 2018 Tulane Conference on Health Economics, the 2018 NBER Summer Institute (Health Care), the 2018 SIEPR Postdoctoral Fellows Conference, the 2019 Society of Labor Economists Annual Meeting, and the 2019 Montreal IO Conference. Jimmy Kim provided outstanding research assistance. Generous financial support from the Center for Health and Wellbeing at Princeton University and the Becker Friedman Institute at the University of Chicago is gratefully acknowledged. The statements, findings, conclusions, views, and opinions contained and expressed herein are not necessarily those of IQVIA or any of its affiliated or subsidiary entities.

†schnell@northwestern.edu; 2211 Campus Drive, Evanston, IL 60208

I Introduction

Physicians form the core of health care markets and are entrusted with making decisions concerning which patients receive which types of care. While many of these decisions involve the provision of services that are inherently non-retradable—like diagnoses or surgeries—doctors do not always have the ability to control who will be the end users of the services they provide. Notably, once a patient fills a prescription written by a physician, the medication can be retraded among patients without the prescribing doctor's knowledge or consent. Despite legal penalties aimed at deterring such diversion, many prescriptions—such as opioids, amphetamines, and benzodiazapenes—are actively traded on secondary markets.[1] While recent literature documents that a number of factors—including physician skill (Currie and MacLeod, 2020), price incentives (Dickstein, 2021), pharmaceutical promotion (Grennan et al., 2018), and behavioral biases (Kolstad and Town, 2022)—play important roles in driving physician prescribing,[2] how the potential for diversion influences the prescribing practices of physicians remains unknown.

In this paper, I develop a model of supply and demand for prescriptions across legal primary markets and illegal secondary markets to examine how the presence of a secondary market for prescriptions influences the prescribing practices of physicians and the equilibrium health impacts of these medications. I focus on the case of prescription opioids, a medication at the root of a drug crisis that has has claimed the lives of over 500,000 Americans since the start of the twenty-first century (Hedegaard et al., 2020). The model demonstrates that strict prescribers respond to the possibility of diversion by their patients by becoming more hesitant in their prescribing, whereas lenient prescribers respond by loosening their prescription thresholds. I estimate the model using detailed data on the number of opioid prescriptions written by physicians from 2006 through 2014, unique data documenting street prices for prescription opioids, and measures of prescription opioid misuse and pain. Estimates demonstrate that the presence of a secondary market induces most physicians to reduce unnecessary prescribing: despite being near their record high, opioid prescriptions would have been 24 percent higher in 2014 if a secondary market did not exist. While the potential for diversion therefore helps bring prescriptions closer to their optimal level, the reallocation of prescriptions across patients on the secondary market nevertheless results in substantial health losses.

[1] Under state and federal law, selling controlled substances to another person or possessing a controlled substance without a prescription can be felony offenses. Nevertheless, results from the National Survey on Drug Use and Health indicate that nearly 30 percent of misused prescription opioids are purchased on the secondary market (see Figure 2 and Table A3).

[2] A closely related literature examines factors that influence physician decision making more generally, including skill (Gowrisankaran et al., 2017; Currie and MacLeod, 2017; Chan et al., 2022), beliefs (Cutler et al., 2019), and financial incentives (Clemens and Gottlieb, 2014; Alexander and Schnell, 2019).

This highlights that the effectiveness of policies targeting either the primary or secondary market in isolation will be undermined by feedback between these two interlinked markets.

I begin by documenting three novel facts that characterize the primary and secondary markets for prescription opioids. First, I show that opioid prescribing and fatal drug overdoses are highly correlated both across and within counties, highlighting the important role that physician prescribing has played in the current crisis. Second, I show that misused prescription opioids are commonly obtained on both the primary and secondary markets, underscoring the importance of considering both legal and illegal markets when studying prescription opioid abuse. Finally, I document that the secondary market for prescription opioids is closely linked to the primary market, with prescription opioid seizures by law enforcement and resale prices on the secondary market being strikingly correlated with prescribing on the primary market. This inability of providers to control who ultimately consumes the medications they prescribe complicates the prescription decision and is the focus of this paper.[3]

To examine how the secondary market influences both the prescribing practices of physicians and the equilibrium health impacts of these medications, I then design a model that incorporates supply and demand for prescription opioids across the primary and secondary markets. In the model, patients—who differ both in their severity of pain and their taste for opioids—can search over heterogenous physicians and a centralized secondary market to access prescription opioids. While it is cheaper to obtain opioids through a physician's prescription than on the secondary market, not all patients can obtain a prescription from every physician. All physicians are more likely to write a prescription for patients who exhibit higher levels of observable pain, although physicians differ in the minimum level of pain they must observe to write a prescription. These differences in physician behavior are driven by heterogeneity in office visit reimbursement rates and physician altruism, defined as the utility a physician derives from the impact she has on patient health relative to her revenue. If a patient receives a prescription from a physician, she can either consume the medication—and receive utility from this consumption that is increasing in her level of pain and taste for opioids—or resell the prescription on the secondary market.

The model delivers a number of theoretical insights. First, it highlights that while physicians tend to overprescribe opioids, differences in preferences and incentives can lead to significant het-

[3]Discussions with physicians highlight that those in clinical practice are aware of the potential for diversion and consider the possibility of misuse, either by the patient or another user, when prescribing. Moreover, the potential for diversion is commonly highlighted in clinical articles on opioid prescribing and is even discussed in the CDC's opioid prescribing guidelines (Dowell et al., 2016). This awareness is not new: for example, an editorial published in the *Canadian Medical Association Journal* in 1998 argues that "[h]ealth care providers must practice with an awareness" of the fact that "licit pharmaceuticals, prescribed in good faith by physicians and dispensed by pharmacists, can end up as commodities on the black market" (Goldman, 1998).

erogeneity in prescribing behaviors across providers. Moreover, as the potential for diversion should lead lenient providers to loosen their prescription thresholds while causing strict providers to instead become more careful in their prescribing, a secondary market will tend to exacerbate this heterogeneity by increasing prescribing differences between more and less lenient physicians. Because of these changes in physician behavior, the presence of a secondary market can cause total prescriptions to fall if enough physicians become sufficiently more strict in their prescribing. Finally, even if the secondary market reduces total prescriptions, it can still lead to significant net health losses due to the reallocation of prescriptions from those with legitimate medical needs to those who misuse the medications.

I estimate the model in two stages using administrative and survey data. In the first stage, I group physicians according to their level of altruism by measuring their take-up of a new, safer formulation of a popular prescription opioid that was introduced partway through my sample. Locations differ significantly in their composition of physician altruism, and these differences have important implications for drug-related mortality. In the second stage of estimation, I use a generalized method of moments estimator to recover structural parameters that govern the optimal behavior of patients and physicians. To highlight the economic intuition and provide a general sense of magnitudes, this second stage of estimation focuses on Baltimore County, Maryland.[4] Using these parameters, I then examine the impacts of counterfactual policies targeting the primary and secondary markets.

Counterfactuals reveal that the potential harm caused by medications diverted to the secondary market induces most physicians to be more careful in their prescribing. While policies that crack down on the secondary market can therefore cause prescription levels on the primary market to rise, thereby exacerbating rates of overprescribing, the overall health effects of prescription opioids would be improved by preventing patients from reallocating prescriptions. Notably, the greatest health benefits from prescription opioids at the population level would be achieved by simultaneously closing the secondary market and reducing unnecessary prescribing on the primary market. Estimates suggest that policies targeting both the quantity and the allocation of prescription opioids had potential health gains of nearly $13 billion across the United States in 2014.

This paper adds to the large theoretical literature on physician behavior (see McGuire, 2000 for an overview). To accommodate defining features of prescription decisions, I develop a model that departs from two key assumptions made in previous work. First, while prior work has assumed that the services provided by physicians are non-retradable, active secondary markets for many prescription drugs exist. I therefore relax the assumption of non-retradability and examine how optimal

[4] An earlier version of this paper estimated the model on the ten largest commuting zones in the United States; the take aways of the estimation and counterfactuals were very similar in this earlier formulation.

physician behavior changes when providers lose allocative control over the medical services they provide. Moreover, while asymmetric information is inherent in the physician–patient relationship, it is usually presumed that physicians are the agents with superior information. My model incorporates the incentives for patients to seek legitimate prescriptions for non-medical consumption or resale, highlighting how private information on the side of patients can influence the behavior of physicians. These extensions are important for understanding the forces that govern not only opioid prescribing in particular but also prescribing practices more generally, a growing category of medical services provided by physicians in the United States.[5]

This paper further contributes to the literature in industrial organization studying the interactions between primary and secondary markets (see, for example, Leslie and Sorensen, 2014). While previous papers typically take quantity on the primary market as given, this paper builds on existing work by endogenizing supply on the primary market. In the context of prescription drugs, this extension demonstrates how endogenous supply responses by physicians can offset health losses from reallocation among patients on the secondary market. Moreover, while resale markets are typically thought to be welfare enhancing if goods are inefficiently allocated on the primary market (Mankiw, 2007), this paper highlights that secondary markets for medical products can lead to substantial health losses when patient utility is not derived solely from health impacts. There is therefore a tension between maximizing patient welfare and the objectives of policymakers, who installed physicians as gatekeepers on the primary market to control the quantity and allocation of the product for which a secondary market has now emerged.

Finally, this paper contributes to a growing body of work analyzing the forces underlying the U.S. opioid epidemic. While recent work has highlighted the role that the supply side played in initiating the crisis (see Currie and Schwandt, 2021 for an overview), surprisingly little is known about why physicians continued to prescribe these medications in such large quantities years into the crisis.[6] Moreover, while the presence of a secondary market has helped fuel non-medical use of prescription opioids, little attention has been devoted to understanding how diversion influences

[5]Over two-thirds of medical visits end with the provider writing at least one prescription (NCHS, 2018).

[6]Recent work demonstrates that patients randomly assigned to high-prescribing physicians are more likely to be addicted to opioids both over the short and medium terms (Barnett et al., 2017; Eichmeyer and Zhang, Forthcoming). In addition to documenting the important role played by physicians in driving opioid abuse at the individual level, these papers further highlight pronounced heterogeneity in opioid prescribing across providers. This paper adds to work showing that this heterogeneity in prescribing is driven in part by differences in training (Schnell and Currie, 2018) by further uncovering the important role played by differences in altruism. An understanding of what drives heterogeneity in prescribing within locations complements work showing that a number of factors led to aggregate increases in prescribing across locations, helping to initiate the crisis in the 1990s (see Cutler and Glaeser, 2021 for a recent discussion).

the prescribing practices of physicians and the aggregate health impacts of these medications.[7] By designing and estimating an equilibrium model of supply and demand for prescription opioids across primary and secondary markets, this paper is the first to examine how the behavior of patients and physicians across legal and illegal markets have contributed to the crisis.

This paper proceeds as follows. Section II introduces the primary data sources and documents three novel sets of facts characterizing the primary and secondary markets for prescription opioids. An equilibrium model of prescription opioids that formalizes the forces influencing optimal patient and physician behavior is presented in Section III. Section IV discusses estimation, and Section V presents results and outlines counterfactuals. Section VI provides a discussion and concludes.

II Motivating facts

In this section, I present stylized facts that characterize the primary and secondary markets for prescription opioids. These stylized facts demonstrate the importance of each market, provide novel insights into their interactions, and help motivate the modeling assumptions made in Section III. The key data sets used to characterize these markets are introduced below; additional details and data sources used for estimation of the model are presented in Section IV.B.

II.A The primary market and the origins of a crisis

I begin by describing the primary market for prescription opioids and show that opioid prescribing and drug mortality are closely linked. To measure opioid prescriptions on the primary market, I use comprehensive, provider-level data from 2006 through 2014 from the IQVIA XPonent database. IQVIA collects this information directly from over 90 percent of retail pharmacies and imputes prescriptions from unsampled pharmacies to match industry totals. Importantly, these data include all prescriptions regardless of the patient's insurance status or type, thereby allowing for an unprecedented look at how prescription opioid abuse varies with the near universe of opioid prescriptions across space and over time.

Over 2.1 billion opioid prescriptions were dispensed through U.S. retail pharmacies in 2006–2014 (Table A1). Around 80 percent of these prescriptions were written by physicians, with physicians in general practice accounting for more than 40 percent. Half of the prescriptions were written for individuals aged 40–64, with women receiving a disproportionate share. Mirroring the distribution

[7] Influential work by Case and Deaton (2015, 2017) demonstrates that suicides, alcohol-related liver mortality, and self-reports of chronic pain have been increasing alongside overdose deaths, suggesting that any complete narrative of the crisis must also incorporate the demand side.

of insurance types across the general population, nearly two-thirds of opioid prescriptions were paid for with private insurance.

Figure 1a shows how opioid prescriptions in the IQVIA data and drug overdose mortality from the National Vital Statistics System (NVSS) trended nationally in 2006–2014.[8] Fatal overdoses involving prescription opioids rose steadily with the clinical use of prescription opioids since at least 2006, with both peaking around 2011. This positive correlation between prescribing and fatal overdoses can further be observed both across counties and within counties over time. Figure 1b presents binned scatterplots showing how fatal prescription opioid overdoses per 10,000 covary with opioid prescriptions per capita at the county-year level.[9] The light, thin line shows that counties with more opioid prescriptions per capita lose a larger share of their population to overdoses involving prescription opioids. Strikingly, the association between opioid prescribing and fatal prescription opioid overdoses is almost identical if within-county changes in both outcomes are instead considered (dark, thick line), indicating that fixed differences across locations are not driving the relationship. This association between prescribing and mortality is large: a one standard deviation increase in opioids per capita (0.51) is associated with 0.14 more fatal overdoses involving prescription opioids per 10,000 (30.4 percent relative to the mean; see column (2) of Table A2).[10]

Starting in 2013, fatal drug overdoses involving other drugs, including heroin and illicit fentanyl, surpassed deaths involving commonly prescribed opioids (Figure 1a). While much attention has thus shifted to these illicit substitutes, prescription opioids remain part of the problem (Schnell, 2018). Not only have deaths involving prescription opioids remained at historically high levels, but prescription opioid misuse remains the second most common type of federally illicit drug use, second only to marijuana, and is 13 times more common than heroin use (SAMHSA, 2020). Moreover, individuals who misuse prescription opioids are at far greater risk of turning to illicit opioids: heroin use is 19 times more likely among individuals who previously misused prescription opioids, with an

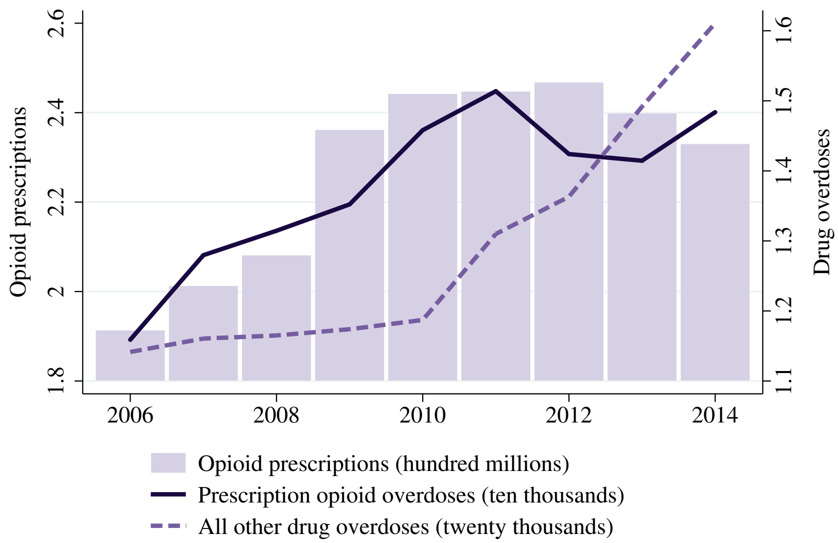
[8]The NVSS data consist of individual-level records outlining the date, location, and cause for all deaths in the United States. Following previous work, I define fatal drug overdoses as deaths with ICD-10 underlying cause of death codes X40-44, X60-X64, X85, and Y10-Y14. I further use multiple cause of death codes to isolate fatal drug overdoses involving any opioid (T40.0-T40.4 and T40.6) and prescription opioids (T40.2 and T40.3). Mortality at the county-year level is combined with population estimates from the U.S. Census Bureau to measure fatal drug overdoses per capita.

[9]Total prescriptions at the county-year level are combined with intercensal population estimates to measure opioid prescriptions per capita. As shown in Figure A1a, there is substantial variation in opioid prescriptions per capita across locations: in 2014, there was an average of over one prescription per person in eight states (Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Oklahoma, Tennessee, West Virginia) and less than a half a prescription per person in two (Hawaii and New York). Despite this pronounced geographic heterogeneity, nearly 95 percent of the total variance in opioid prescribing across providers in 2014 was due to within-county dispersion (see Figures A1b–c).

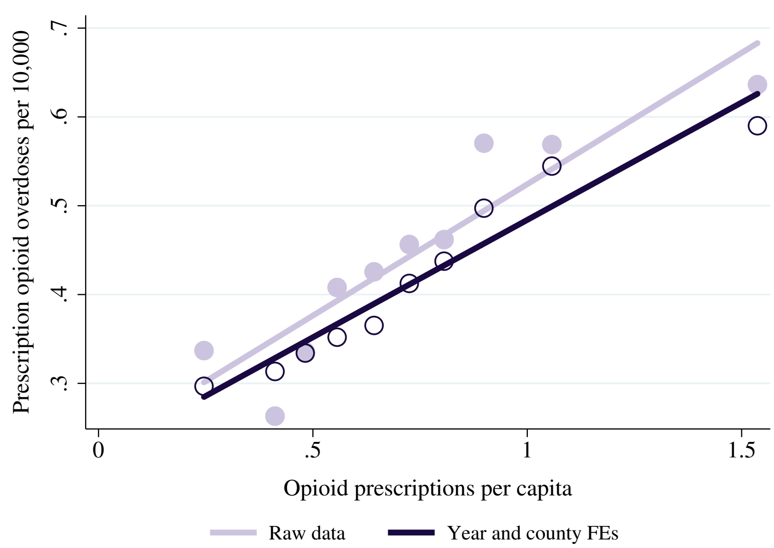
[10]Since the specific drugs involved in a fatal overdose are often not reported on the death certificate, overdose deaths involving prescription opioids are likely underreported. Table A2, column (6) shows that a one standard deviation increase in opioids per capita (0.51) is associated with 0.22 more fatal drug overdoses (from any drug) per 10,000.

Figure 1: Prescription opioid use and overdoses in the United States: 2006–2014

(a) Prescribing and mortality nationally



(b) County-level overdoses versus prescriptions



Notes: The above figures show the relationship between fatal drug overdoses from the NVSS and opioid prescriptions from IQVIA from 2006–2014. Subfigure (a) plots the annual number of opioid prescriptions (bars), fatal drug overdoses involving prescription opioids (solid line), and fatal drug overdoses involving all drugs other than prescription opioids (dashed line) nationally over time. Subfigure (b) shows how fatal drug overdoses involving prescription opioids per 10,000 and opioid prescriptions per capita covary at the county-year level. Both the raw relationship (solid circles, light line) and the relationship conditional on county and year fixed effects (hollow circles, dark line) are shown. County-year observations are grouped into deciles accounting for approximately equal shares of the population based on opioid prescriptions per capita.

estimated 80 percent of heroin users reporting prior prescription opioid misuse (SAMHSA, 2013). Finally, while important steps have been taken to reduce unnecessary prescribing, opioid prescribing remains high in parts of the country. As of 2019, at least one opioid prescription per person was dispensed in five percent of counties, nearly 25 percent higher than the national average at its peak in 2012 (CDC, 2020).

II.B Sources of misused prescription opioids and the secondary market

The strong geographic correlation between opioid prescribing and mortality suggests that not all legally prescribed opioids are used as intended. I show in this subsection that this misuse of legally prescribed opioids is confirmed by survey evidence, which reveals that opioid prescriptions are misused both by those who were—and by those who were not—prescribed the medication.

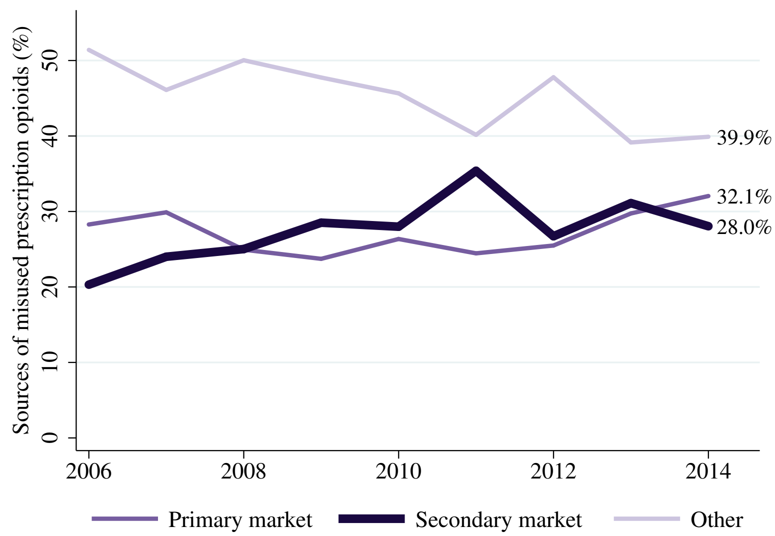
Figure 2 presents sources of misused prescription opioids as reported in the National Survey on Drug Use and Health (NSDUH), the largest survey tracking drug use among individuals aged 12 and older in the United States. Reports of individuals taking a prescription pain reliever that was not prescribed to them and only for the experience or feeling it caused ("misuse") is common: in 2014, over 10 million Americans aged 12 or older (3.9 percent) reported having misused a prescription pain reliever in the past year. I group sources of misused prescription opioids into three categories: (1) primary market (prescription from one or more doctors), (2) secondary market (paid someone for the medication), and (3) other (e.g., stole or was given the medication for free).

As shown in Figure 2a, one-third of misused prescription opioids in 2014 were obtained directly from the primary market. Among individuals misusing their own medication, most prescriptions were obtained from a single doctor (88.4 percent) rather than multiple doctors (11.6 percent; Figure 2b). Importantly, however, prescription opioids are not only misused by their intended recipients: nearly 30 percent of misused prescription opioids in 2014 were purchased on the secondary market, an increase of almost 50 percent since 2006. On the secondary market, misused prescription opioids are slightly more likely to be purchased from a friend or relative (58.6 percent) rather than a dealer or stranger (41.4 percent). Among misused prescription opioids that are neither obtained from a doctor (primary market) nor purchased (secondary market), the vast majority (80.5 percent) come from a friend or relative for free.

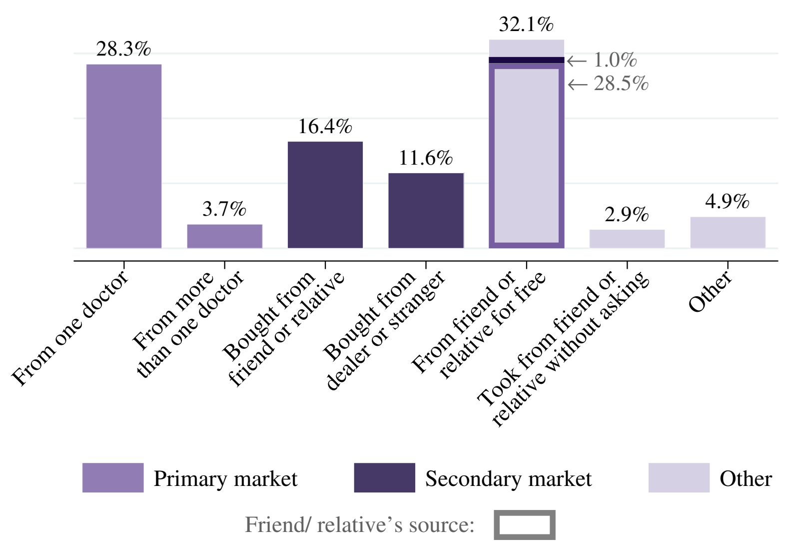
These statistics from the NSDUH highlight the importance of the primary and secondary markets in supplying misused prescription opioids. Nevertheless, they likely understate the importance of these markets for at least three reasons. First, respondents are being asked sensitive questions about their drug use; as such, they may prefer to say that they were given the medication from a friend

Figure 2: Sources of misused prescription opioids

(a) Aggregate sources: 2006–2014



(b) Detailed sources: 2014



Notes: The above figures show annual reports of sources of misused prescription opioids from the NSDUH. Both subfigures consider individuals who reported using a prescription pain reliever in the past year that was not prescribed to them or only for the experience or feeling it caused ("misuse"). Subfigure (a) plots the share of such individuals who reported receiving the last pain reliever that they misused from the primary market (one or more doctors), the secondary market (bought from a friend, relative, drug dealer, or other stranger), or other (got for free, took without asking, etc.) from 2006–2014. The shares of reported sources within these aggregate categories in 2014 are provided in subfigure (b). Respondents who reported getting the medication from a friend or relative for free are then asked where their friend or relative got the medication; the bar outlines depict the reported sources of their friend or relative's supply. Responses are weighted by the sample weights provided in the NSDUH and the reported days of misuse in the past year; Table A3 provides unweighted responses in 2014.

or relative for free rather than disclosing their misuse of the health care system or their engagement with an illegal market. Moreover, the NSDUH only asks respondents how they obtained the last prescription opioid that they misused. While one-third of those who misused prescription opioids for over one month in the past year report having gotten their most recent supply from a friend or relative for free, they arguably need to rely on the primary or secondary markets for a more consistent supply. Finally, since adverse outcomes are increasing in the frequency of opioid use (e.g., Paulozzi et al., 2014), we are particularly concerned about sources for frequent misusers. As shown in Table A3, reliance on sources other than the primary and secondary markets is decreasing in frequency of misuse; among the 8.8 percent of misusers who reported misusing prescription opioids for over six months in 2014, the secondary market was the most common source (38.4 percent) followed by the primary market (31.2 percent).

II.C Connections between the primary and secondary markets

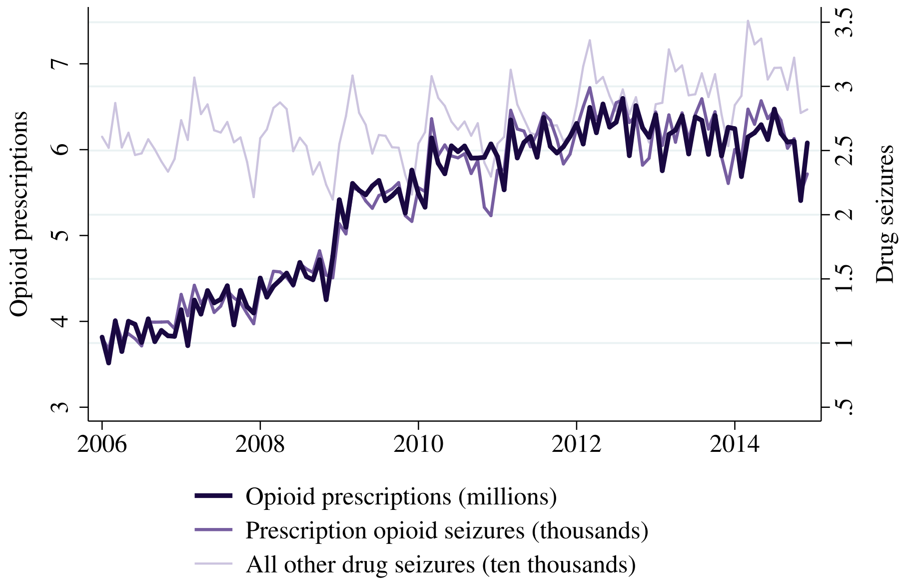
Finally, I show that the secondary market for prescription opioids is closely tied to the primary market. Although the NSDUH does not ask respondents who purchased the medication about their seller's source, the vast majority of respondents who received a prescription from a friend or relative for free reported that the prescription originated on the primary market (88.6 percent; Figure 2b). Moreover, according to the Drug Enforcement Agency (DEA), organized street gangs that have "capitalized on the controlled prescription drug abuse problem in the United States by trafficking prescription opioids" commonly source the medications by targeting "unscrupulous physicians" and pill mills (DEA, 2015).

To further examine the interactions between the primary and secondary markets for prescription opioids, Figure 3a plots the number of opioid prescriptions as reported in the IQVIA data and the number of prescription opioid seizures from the Federal Bureau of Investigation's National Incident Based Reporting System (NIBRS) in 2006–2014.[11] These two time series are strikingly aligned, with opioid prescribing on the primary market and prescription opioid seizures on the secondary market covarying nearly perfectly over time. While all drug seizures excluding prescription opioids in the NIBRS (light, thin line) show similar seasonality, the general time trend is noticeably different, indicating that the close relationship between opioid prescribing and prescription opioid seizures is

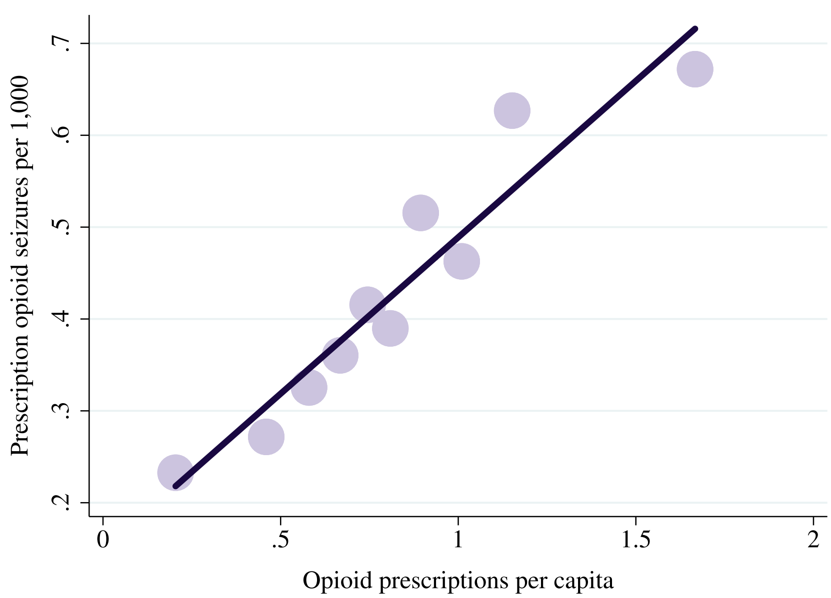
[11] With over 6,000 law enforcement agencies participating in the NIBRS as of 2014, the data cover incidents in 1,619 counties accounting for 43.3 percent of the U.S. population. Since the geographic jurisdictions of law enforcement agencies do not always align with county delineations, I assign each reporting agency to the county with the largest number of people covered by the agency and adjust the number of seizures to account for the fraction of the agency's covered population in that county. When comparing county-level seizures with county-level opioid prescriptions, county-level opioid prescriptions are adjusted to account for the fraction of a county's population covered by the seizure data.

Figure 3: Primary market opioid prescriptions and secondary market seizures

(a) Nationally: 2006–2014



(b) By county: 2014



Notes: The above figures show the relationship between drug seizures from the NIBRS and opioid prescriptions from IQVIA. Subfigure (a) plots the monthly number of opioid prescriptions (dark, thick line), prescription opioid seizures (medium line in color and thickness), and seizures of all drugs other than prescription opioids (light, thin line) nationally from 2006–2014. Subfigure (b) shows how prescription opioid seizures per 1,000 and opioid prescriptions per capita covary at the county-year level in 2014. Counties are grouped into deciles accounting for approximately equal shares of the population based on opioid prescriptions per capita.

not driven by third factors that influence overall trends in drug use. Figure 3b shows that opioid prescribing and prescription opioid seizures are also highly correlated geographically across the United States, with counties that saw more opioid prescribing by clinicians on the primary market in 2014 likewise experiencing more prescription opioid seizures by law enforcement on the secondary market.[12]

The relationship between the primary and secondary markets for prescription opioids can further be seen using crowd-sourced, secondary market price data from StreetRx.com.[13] Figure A3b examines how state-level prices for diverted prescription opioids covary with opioid prescriptions per capita in 2014. There is a noticeable correlation between supply on the primary market and prices on the secondary market, with secondary market prices declining in the number of (legal) opioid prescriptions per capita. If the key factor differentiating geographic markets across the United States were differences in demand for prescription opioids, then we would expect secondary market prices and primary market supply to instead be positively correlated (i.e., higher demand for prescription opioids leads to higher prices on the secondary market and higher prescribing on the primary market). Instead, the negative correlation between secondary market prices and opioid prescriptions per capita suggests that different markets across the United States are on different supply curves (i.e., higher supply on the primary market leads to lower demand and higher supply on the secondary market, thereby reducing secondary market prices). This highlights the importance of physician prescribing on the primary market and motivates an analysis of physician behavior as it relates to the secondary market.

[12]It is possible that the connection between the primary and secondary markets for prescription opioids is less pronounced in more recent years due to an increase in the prevalence of counterfeit prescription pills. Counterfeit prescription pills were first mentioned in the DEA's 2016 National Drug Assessment Summary, which notes that "there was a marked surge in the availability of illicit fentanyl pressed into counterfeit prescription opioids" in 2015 (DEA, 2016). However, even in 2019, nearly all prescriptions that were given away by friends or relatives were reportedly legitimate prescriptions that came from one or more doctors (SAMHSA, 2020).

[13]Maintained through the RADARS System in collaboration with Denver Health and the Rocky Mountain Poison and Drug Safety Center, StreetRx.com is a platform that gathers and presents information on user-submitted black market prices for diverted prescription drugs. The geographic distribution of the more than 15,000 price quotes and average state-level prices per morphine milligram equivalent (MME) in 2014 are shown in Figure A3a. There is pronounced geographic heterogeneity, with average price per MME ranging from less than seventy-five cents in ten states (Alabama, Arkansas, California, Delaware, Indiana, Michigan, Missouri, Nevada, Oregon, Rhode Island) to more than one dollar in four (Maine, Montana, North Dakota, and Wyoming). Previous work documents that secondary market prices collected through StreetRx provide valid estimates of the street prices of diverted prescription drugs (see, for example, Dasgupta et al., 2013).

III Equilibrium model of prescription opioids

In this section, I introduce a model of physician behavior in the presence of a secondary market with patient search. The main questions to be answered by the model are how the presence of an illegal resale market for prescriptions influences the prescribing practices of physicians and the equilibrium health impacts of these medications. The model focuses on the case of prescription opioids, although the intuition provided can be extended to other prescription drugs that are retraded on secondary markets.

III.A Set-up

Consider a geographic market with I patients indexed by i and J physicians indexed by j. Patients differ according to their level of pain ($\kappa_i \in \mathbb{R}^+$, $\kappa_i \sim F(\kappa)$) and their taste for prescription opioids ($\gamma_i \in \mathbb{R}$, $\gamma_i \sim G(\gamma)$). Physicians differ according to their revenue per office visit ($R_j \in \mathbb{R}^+$) and their level of altruism ($\beta_j \in \mathbb{R}^+$). These patient and physician characteristics are assumed to be independent and exogenously determined.

If a patient consumes a prescription opioid, she receives a monetized health impact $h(\kappa_i)$ that is a function of her level of pain. The health impact function h is assumed to be strictly increasing and concave ($h' > 0$, $h'' < 0$). This function captures both the medicinal benefits of prescription opioids, such as effective pain relief, and the harms associated with the medication, including minor side effects such as dizziness and nausea as well as the potential for addiction and abuse. As a patient will also receive or lose additional utility depending on her taste for opioids, the total value for patient i of consuming a prescription opioid is the sum of the health impact and her tastes: $h(\kappa_i) + \gamma_i$.[14]

To obtain an opioid prescription, a patient can either go to a physician or purchase the medication on the secondary market. There is a cost of going to a physician τ^d that includes both the patient's time and any direct costs of the office visit. If a patient is prescribed an opioid at her visit, she must pay an additional cost τ^o to fill the prescription. For simplicity, these costs are assumed to be constant across individuals. The model can be easily extended to allow for heterogeneity in costs

[14] Since the IQVIA XPonent data do not allow one to follow patients over time, I do not explicitly model the dynamics of addiction. Nevertheless, the addictive nature of prescription opioids affects the decisions of both physicians and patients in the model. As shown below, the prescription decision of physicians is driven in part by the health impact of the medication; since prescription opioids are highly addictive and have the potential for abuse, the health impact of a prescription opioid at any given level of pain will be lower than an otherwise identical medication that only provides pain relief, thereby making physicians more hesitant in their prescribing. On the demand side, since a patient who is dependent on opioids will have higher tastes than an otherwise identical patient, one can think of patient tastes as reduced-form, static parameters that capture the dynamics of addiction from the patient's perspective.

due to, for example, differences in insurance status.

If a patient is prescribed an opioid, she then chooses either to consume the prescription or to resell the medication on the secondary market for price p (to be determined in equilibrium). Normalizing patient utility in the absence of a prescription to zero, patient i's utility is given by

$$U_i = \begin{cases} h(\kappa_i) + \gamma_i - \tau^d - \tau^o & \text{if consumes from doctor} \\ p - \tau^d - \tau^o & \text{if resells on sec. mkt.} \\ h(\kappa_i) + \gamma_i - p & \text{if consumes from sec. mkt.} \\ 0 & \text{if does nothing} \end{cases}$$

Physicians control the legal supply of prescription opioids. I abstract from the multitude of available treatment options and assume that physicians provide no services other than opioid prescriptions; that is, the only decision facing the provider is whether to write an opioid script.[15] For simplicity, I further assume that physicians can observe each patient's severity of pain but not her taste for opioids. The results that follow hold if physicians instead observe a noisy signal of pain.

Since a patient will only go to the physician in equilibrium if she can get a prescription, physician j's utility associated with seeing patient i is given by

$$U_j^i = \begin{cases} \beta_j \cdot h(\kappa_i) + R_j & \text{if prescribes and patient consumes} \\ \beta_j \cdot \bar{h}^{SM} + R_j & \text{if prescribes and patient resells} \\ 0 & \text{if does not prescribe} \end{cases}$$

where $\bar{h}^{SM}$ is the average health impact of an opioid prescription on the secondary market (to be determined in equilibrium).

Two features of physician utility are worth noting. First, I assume that a physician's utility is tied to the prescriptions that she writes; that is, a physician cares about the health impact of a prescription she writes even if it is consumed by someone on the secondary market.[16] This extends previous

[15]The IQVIA XPonent data contain no information on the number of pills or the strength of medication included with each script. Given this limitation, I only consider prescription decisions along the extensive margin—that is, whether to write a prescription—rather than intensive margin decisions regarding the strength of the medication and the number of days supplied. The number of opioid prescriptions reported in the IQVIA data correlates strongly with fatal overdoses involving prescription opioids both across and within counties (see Figure 1), and thus prescription decisions along the extensive margin capture variation that is relevant for understanding forces underlying the crisis.

[16]Discussions with physicians suggest that they care if someone misuses a prescription they wrote, regardless of how the individual acquired the prescription. It is therefore reasonable to assume that a physician's utility is tied to her prescriptions. However, it is possible that physicians give different weights to the prescriptions consumed by patients and non-patients. While I assume for simplicity that physicians care equally about the health impacts of their prescriptions

frameworks that only consider the provision of non-retradable medical services. I further assume that a physician does not derive utility from patient tastes. While it is generally assumed that all components of patient utility enter the physician's utility function, assuming that physicians derive no utility from patient tastes more closely captures the physician's role as a professional gatekeeper in a setting in which patients often want a medication that could harm them medically.

In what follows, I restrict attention to threshold equilibria. That is, each physician chooses a threshold severity κ_j^* and only writes prescriptions for patients with levels of pain exceeding that threshold. The physician chooses this severity threshold to maximize her utility. Much of this section is devoted to understanding how the presence of a secondary market influences the level of pain at which a physician sets her optimal threshold.

Patient search To endogenize both the number of patients and the distributions of pain severities and tastes that each physician sees, I introduce patient search. Patients begin randomly assigned to a physician. If the patient pays a search cost τ^s, she is randomly assigned to a new physician. Since patients must visit a doctor to determine whether they can get a prescription, patients must also pay the office visit fee $\left(\tau^d\right)$ when sampling a new physician. However, they only have to pay the cost of filling a prescription (τ^o) if they are able to get a prescription from the provider. For tractability, I assume that patients search with replacement.

As is standard in sequential search models, a patient will continue to search as long as the expected benefit of search exceeds the expected cost. Among patients who have yet to find a physician from whom they can get a prescription, the expected benefit of search depends both on their severity of pain, their taste for opioids, and whether a secondary market for prescription opioids exists. Patients with higher pain and tastes are more likely to search since their benefit of consumption is higher; patients with higher pain are additionally more likely to search since they have a higher probability of getting a prescription from their newly assigned provider. Optimal patient search both with and without a secondary market are considered in detail in Appendix C; the impacts of this search behavior on optimal physician behavior and the equilibrium allocation of prescriptions are discussed below.

whether it is consumed by one of their patients or by someone on the secondary market, it could be the case that physician j gives weight β_j to the medication's health impact on her own patients and weight $\alpha_j \cdot \beta_j$ to the medication's health impact on her non-patients. If $\alpha < 1$, allowing for different altruism weights will weakly dampen the effects of a secondary market on physician prescribing. However, as long as higher-altruism physicians care more about both their patients and non-patients than lower-altruism physicians (as is the case when $\alpha_j = \alpha \; \forall \; j$, for example), the primary intuition behind the model remains unchanged.

III.B Without a secondary market

Suppose first that patients cannot search for physicians. Rather, each physician has an equal number of patients $\left(\frac{I}{J}\right)$ with the same distributions of pain severities and tastes for prescription opioids as the local population as a whole ($F(\kappa)$ and $G(\gamma)$, respectively).

In the absence of a secondary market, any patient for whom the benefits of consuming a prescription opioid exceed the costs will want an opioid prescription $\left(h(\kappa_i) + \gamma_i \geq \tau^d + \tau^o\right)$. However, since there is no secondary market and patients cannot search across physicians, patients can only get a prescription if their level of pain exceeds their assigned physician's threshold $\left(\kappa_i \geq \kappa^*_{j(i)}\right)$. Patients will therefore only go to the doctor in equilibrium if they both want to consume an opioid prescription and can get one from their assigned provider. This equilibrium allocation of opioid prescriptions in a market with one physician is shown in Figure 4a.

Taking into account optimal patient behavior, physician j chooses her threshold severity κ^*_j to maximize her utility:

$$\max_{\kappa_j} \; \beta_j \cdot \frac{I}{J} \cdot \int_{\kappa_j}^{\infty} \int_{\tau^d+\tau^o-h(k)}^{\infty} h(k) dG(\gamma) dF(k) + R_j \cdot \frac{I}{J} \cdot \int_{\kappa_j}^{\infty} \int_{\tau^d+\tau^o-h(k)}^{\infty} dG(\gamma) dF(k) \tag{1}$$

The first term represents the impact that the physician has on her patients' health, and the second term represents her revenue from office visits. The bounds on the integrals are derived both from the physician's strategy and from optimal patient behavior.

Taking the derivative of equation (1) with respect to κ_j and setting equal to zero yields the physician's optimal threshold:

Result 1: *In the absence of a secondary market and without patient search, the optimal threshold of physician j $\left(\kappa^*_j\right)$ satisfies*

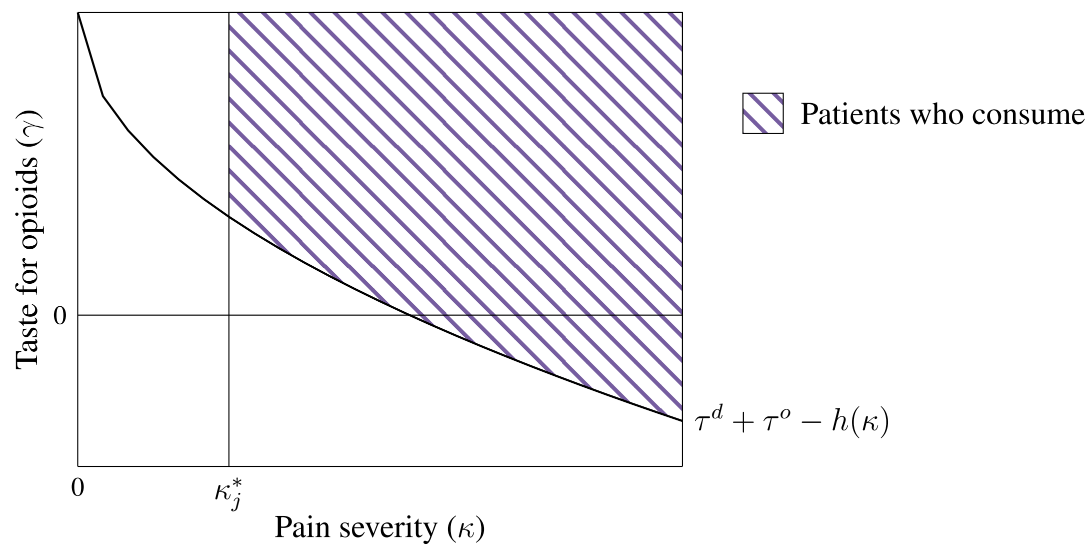
$$-\beta_j \cdot h\left(\kappa^*_j\right) = R_j \tag{2}$$

Equation (2) indicates that the physician chooses her severity threshold such that the harm that she bestows on a patient with $\kappa_i = \kappa^*_j$, weighted by her concern for the impact she has on patient health, just offsets the monetary reimbursement she receives per office visit. Given the strict monotonicity of the health impact function, this threshold is unique (Theorem 1a in Appendix D). Without a secondary market, an equilibrium in a given geographic market is characterized by a set of thresholds $\{\kappa^*_j\}$ such that physicians maximize their utility (i.e., equation (2) holds $\forall\; j \in J$).

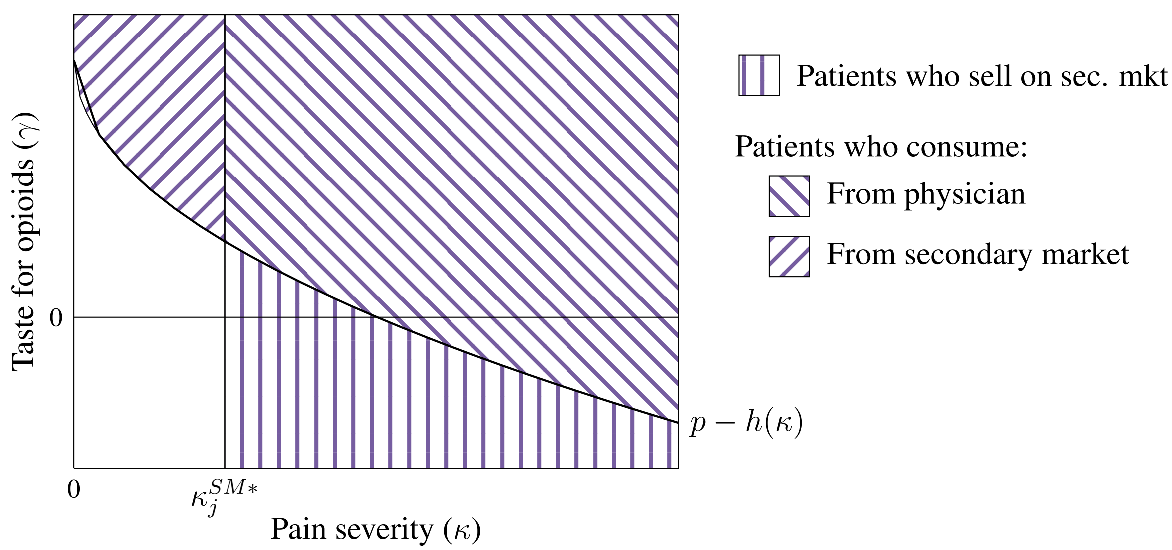
Patient search As shown in Appendix C.1, allowing for patient search changes the market shares and the types of patients seen by each physician. In particular, rather than having a random selection

Figure 4: Equilibrium allocation of opioid prescriptions: market with one physician

(a) Without a secondary market



(b) With a secondary market



Notes: The above figures depict the equilibrium allocation of opioid prescriptions without a secondary market (subfigure (a)) and with a secondary market (subfigure (b)) in a market with one physician. In the absence of a secondary market, only patients who can both get a prescription from the physician ($\kappa_i \geq \kappa_j^*$) and find it beneficial to consume ($h(\kappa_i) + \gamma_i \geq \tau^d + \tau^o$) will go to the doctor. In contrast, all patients who can a prescription from the physician ($\kappa_i \geq \kappa_j^*$) will go to the doctor and get a prescription in the presence of a secondary market. Among these patients, those with sufficiently high tastes will consume the medication ($h(\kappa_i) + \gamma_i \geq p$), whereas those for whom the price on the secondary market exceeds their own benefit of consumption ($h(\kappa_i) + \gamma_i < p$) will instead resell to patients who cannot get a prescription from the physician ($\kappa_i < \kappa_j^*$) but have a benefit of consumption that exceeds the secondary market price ($h(\kappa_i) + \gamma_i \geq p$).

of $\frac{I}{J}$ patients, physicians who are more lenient in their prescribing see more patients in equilibrium. The additional patients that lenient prescribers attract have high enough pain to make it beneficial to search (i.e., they are sufficiently likely to get a prescription) but low enough pain such that they were not able to get a prescription from their previously searched physicians. These patients also have relatively high tastes, as only patients who want to consume the medication will find it beneficial to search in the absence of a secondary market.

Despite these impacts on physician market shares, allowing for patient search does not change the physician's optimality condition (Result $1'$ in Appendix C.1). That is, physicians continue to equate the harm that they cause from prescribing to their threshold patient, weighted by their concern for this impact, to their revenue per office visit. Since physicians set the same thresholds as in the absence of patient search, but patients are able to resort across providers to find a physician who is willing to prescribe to them, the number of opioid prescriptions in equilibrium is weakly greater in the presence of patient search.

III.C With a secondary market

In the presence of a secondary market, optimal patient behavior changes, which in turn changes the prescription decision facing each physician.

Again begin under the assumption that patients cannot search across physicians. With a high price on the secondary market (or more precisely, any $p > \tau^d + \tau^o$), all patients whose pain severity allows them to get a prescription from their assigned physician will get one. The only decision facing a patient whose level of pain exceeds their physician's threshold is therefore whether to consume the medication or to resell on the secondary market: patients whose benefit of consumption exceeds the secondary market price will consume $(h(\kappa_i) + \gamma_i \geq p)$ whereas patients with a low enough combination of pain and tastes will resell $(p > h(\kappa_i) + \gamma_i)$. Moreover, patients who cannot get a prescription from their assigned physician will purchase the medication if they have a benefit of consumption that exceeds the secondary market price. This reallocation of prescriptions across patients in a market with one physician is shown in Figure 4b.

The physician's problem is therefore altered in the presence of a secondary market, as she must now consider that some of the prescriptions she writes might be consumed by people to whom she did not prescribe. Taking into account her impact on the health of patients who purchase her diverted prescriptions on the secondary market, the physician sets her threshold severity κ_j^{SM*} to solve

$$\begin{aligned} \max_{\kappa_j^{SM}} \quad & \beta_j \cdot \frac{I}{J} \cdot \int_{\kappa_j^{SM}}^{\infty} \int_{p-h(k)}^{\infty} h(k) dG(\gamma) dF(k) \\ & + \ \beta_j \cdot \frac{I}{J} \cdot \bar{h}^{SM} \cdot \int_{\kappa_j^{SM}}^{\infty} \int_{-\infty}^{p-h(k)} dG(\gamma) dF(k) \\ & + \ R_j \cdot \frac{I}{J} \cdot \int_{\kappa_j^{SM}}^{\infty} dF(k) \end{aligned} \tag{3}$$

where $\bar{h}^{SM} = \frac{\sum_{n=1}^{J} \int_0^{\kappa_n^{SM*}} \int_{p-h(k)}^{\infty} h(k) dG(\gamma) dF(k)}{\sum_{n=1}^{J} \int_0^{\kappa_n^{SM*}} \int_{p-h(k)}^{\infty} dG(\gamma) dF(k)}$ is the average health impact of a prescription purchased on the secondary market. As before, the first term represents a physician's impact on the health of her patients that consume the medications she prescribes. The second term represents the impact she has on the health of patients who purchase prescriptions she writes on the secondary market. Finally, as before, the final term represents the physician's revenue from office visits. Since all patients who can get a prescription from the physician show up in the presence of a secondary market, this term no longer includes bounds on the patient's taste for prescription opioids.

Assume that physicians internalize neither their impact on the secondary market price p nor their impact on the average health impact on the secondary market $\bar{h}^{SM}$; that is, they take both of these market-level equilibrium objects as given.[17] Taking the derivative of equation (3) with respect to κ_j^{SM} and setting equal to zero yields the physician's optimal threshold:

Result 2: *With a secondary market and without patient search, the optimal threshold of physician j $\left(\kappa_j^{SM*}\right)$ satisfies*

$$-\beta_j \cdot \left[(1 - G(p - h(\kappa_j^{SM*}))) \cdot h(\kappa_j^{SM*}) + G(p - h(\kappa_j^{SM*})) \cdot \bar{h}^{SM} \right] = R_j \tag{4}$$

Recall that in the absence of a secondary market, the physician compares the impact a prescription has on her patient's health, weighted by her concern for this impact, to the revenue she receives from an office visit when deciding whether to prescribe (equation (2)). In the presence of a secondary market, the physician instead compares the *expected* health impact that a prescription will have on whoever ends up consuming the prescription, weighted by her concern for this impact, to the revenue she receives from an office visit. This expected health impact is simply a weighted average between the health impact the prescription would have on her patient and the average health impact on the secondary market, where the weights reflect the probability that her patient will consume or

[17]This will be approximately true in markets with many physicians.

resell, respectively. The conditions under which a physician's optimal threshold in the presence of a secondary market is unique are provided in Theorem 1b in Appendix D.

With a secondary market, an equilibrium in a given geographic market is characterized by a set of thresholds $\{\kappa_j^{SM*}\}$ and a secondary market price p such that (1) physicians maximize their utility (i.e., equation (4) holds $\forall\ j \in J$), and (2) the secondary market clears (i.e., p is such that $\sum_{j=1}^{J}\int_{\kappa_j^{SM*}}^{\infty}\int_{-\infty}^{p-h(k)} dG(\gamma)dF(k) = \sum_{j=1}^{J}\int_{0}^{\kappa_j^{SM*}}\int_{p-h(k)}^{\infty} dG(\gamma)dF(k)$).

Patient search As shown in Appendix C.2, allowing for patient search again changes the market shares and the types of patients seen by each physician. As before, lenient prescribers attract additional patients due to their leniency; these additional patients have sufficiently high pain to make it beneficial to search but sufficiently low pain such that they could not get a prescription from previously searched physicians.

There are two differences relative to the case without a secondary market, however. First, since patients desiring to consume prescription opioids can now turn to the secondary market rather than searching across physicians, patients need to have a higher probability of getting a prescription on the primary market for search to be optimal. Second, while only patients with relatively high tastes found it beneficial to search without a secondary market, patients with a sufficiently high probability of getting a prescription on the primary market will now search regardless of their tastes: among patients with high enough pain, those with low tastes will search to resell whereas those with high tastes will search to consume.[18]

Turning to physician optimality, allowing for patient search again does not change the optimal threshold set by each physician (Result $2'$ in Appendix C.2). That is, in the presence of a secondary market with patient search, a physician sets her threshold to balance the expected harm from prescribing to her threshold patient, weighted by her concern for this impact, against the revenue she receives per office visit.

III.D Theoretical results

How does the presence of a secondary market for prescription opioids influence the prescribing practices of physicians? Intuition behind the key theoretical results is provided below. The interested reader may refer to Appendix D for formal statements and proofs.

I begin by considering how the presence of a secondary market affects the optimal threshold set

[18]Since the decision to search is independent of tastes in the presence of a secondary market, the additional patients that lenient providers attract no longer have disproportionately high tastes for prescription opioids.

by a given physician (Theorem 2 in Appendix D). Suppose first that a physician's optimal threshold in the absence of a secondary market is such that she would not prescribe to the average patient who consumes on the secondary market $\big($i.e., $\bar{h}^{SM} < h(\kappa_j^*)\big)$. In this case, the marginal utility of prescribing in the presence of a secondary market is negative at the physician's previous threshold patient, as there is a chance that the patient will resell to someone who will be, on average, harmed more from the medication than the patient herself. The physician will therefore increase her threshold until the expected harm she causes, weighted by her concern for this impact, just offsets her revenue. Physicians for whom $\bar{h}^{SM} < h(\kappa_j^*)$ are therefore *more strict* in the presence of a secondary market (that is, $\kappa_j^{SM*} > \kappa_j^*$). However, the opposite is the case for physicians with $\bar{h}^{SM} > h(\kappa_j^*)$: if a physician would prescribe to the average patient who buys on the secondary market, she is *more lenient* in her prescribing in the presence of a secondary market.[19]

Looking across physicians, the presence of a secondary market will generally serve to increase prescribing differences between strict and lenient prescribers (Theorem 3 in Appendix D). If some physicians become more strict and some physicians become more lenient, this is clear: since the secondary market causes relatively strict physicians (i.e., physicians with $\bar{h}^{SM} < h(\kappa_j^*)$) to become even more strict while simultaneously inducing relatively lenient prescribers (i.e., physicians with $\bar{h}^{SM} > h(\kappa_j^*)$) to become even more lenient, the secondary market polarizes physician behavior. Note, however, that even if all physicians become more strict in the presence of a secondary market, prescribing differences across relatively lenient and relatively strict prescribers can still increase.[20] In particular, as long as the probability of resale at the strictest prescriber's threshold is not too low, the secondary market will have the smallest impact on the behavior of the most lenient prescriber and the largest impact on the behavior of the most strict prescriber, thereby exacerbating differences in prescribing between the two.

How does the presence of a secondary market affect the total number of opioid prescriptions

[19]In a market with a single physician, only patients who cannot get a prescription from that provider will turn to the secondary market. It therefore follows that the sole physician would not prescribe to the average patient on the secondary market (Figure 4). In a market with more than one physician, however, a given physician's prescriptions may be resold both to patients that the physician would and would not prescribe to. Figure A4b depicts the reallocation of opioid prescriptions across patients on the secondary market in a market with two physicians. A patient of the more lenient prescriber (physician 2) who resells his prescription will sell either to a patient of the stricter provider (physician 1) with $\kappa_2^* \leq \kappa_i < \kappa_1^*$ (a patient who physician 2 would prescribe to) or to a patient of either physician with $\kappa_i < \kappa_2^*$ (a patient who physician 2 would not prescribe to).

[20]As outlined in Lemma 1, it cannot be the case that all physicians become more lenient in the presence of a secondary market. To see this, note that all physicians will become more lenient only if all physicians would be willing to prescribe to the average patient who buys on the secondary market (Theorem 2). But this is inconsistent with optimal patient behavior: since it is more expensive to get a prescription from the secondary market than from a physician (i.e., $p > \tau^d + \tau^o$), a patient who can get a prescription from all physicians will not purchase a prescription on the secondary market.

written by physicians on the primary market? First assume that demand does not change in the presence of a secondary market. If all physicians become more strict in their prescribing, supply contracts. If some physicians become more strict and some physicians become more lenient, the supply response to a secondary market will either put upward or downward pressure on the number of prescriptions depending on the share of physicians who fall into each category and the relative magnitudes of their prescribing shifts. Recall, however, that both demand and supply respond in the presence of a secondary market. Since all patients of a physician who can get a prescription show up with a secondary market, whereas only patients for whom it is beneficial to consume show up without a secondary market, the demand response to a secondary market puts upward pressure on the number of prescriptions. Whether the number of opioid prescriptions written by physicians in aggregate increases or decreases in the presence of a secondary market is therefore theoretically ambiguous (Theorem 4 in Appendix D).

Patient search As outlined in Sections III.B and III.C, the optimal thresholds set by physicians are not affected by patient search either when a secondary market does or does not exist. Allowing for patient search, however, does exacerbate some of the effects of a secondary market on the number of prescriptions written by each physician outlined above. In particular, since patient search allows relatively lenient physicians to attract additional patients because of their leniency, patient search exacerbates polarization in the number of prescriptions written between strict and lenient prescribers induced by a secondary market. As before, however, the effect of a secondary market on the total number of prescriptions remains theoretically ambiguous.[21]

IV Estimation

I now turn to estimating the model in order to quantify how the presence of a secondary market influences physician behavior and to consider the aggregate health impacts of different counterfactual polices. Estimation proceeds in two stage. As outlined in Section IV.A below, I first group physicians according to their level of altruism by measuring their take-up of a new, safer formulation of a popular prescription opioid that was introduced in 2010. To examine how physician altruism correlates both with prescribing practices at the individual level and opioid abuse at the geographic

[21] As outlined above, the demand response to a secondary market necessarily puts upward pressure on the number of prescriptions written by each physician in the absence of patient search. In contrast, when patients are allowed to search across physicians, a physician might see fewer patients with a secondary market even if her optimal threshold does not change. This is because some patients who previously searched across physicians to consume will now turn to the secondary market, so the demand response is not necessarily positive.

level, I consider all physicians across the United States in this exercise.

As outlined in Section IV.C, I then use a generalized method of moments estimator to recover structural parameters that govern the optimal behavior of patients and general practitioners in a single mid-sized market in 2014: Baltimore County, Maryland. While the estimation procedure can be extended to accommodate additional markets, estimates for a single market are sufficient to highlight the economic intuition and provide a sense of magnitudes.[22] Additional details about the data used for the second stage of estimation are provided in Section IV.B.

IV.A Physician preferences

To group providers according to their level of altruism, I exploit provider-level responses to the reformulation of OxyContin. In the wake of criticism surrounding the abuse and diversion of OxyContin, the FDA approved an abuse-deterrent formulation of the drug in April 2010. Compared to the original version of the pill, the reformulated version is more difficult to crush or dissolve and forms a viscous hydrogel that cannot be easily prepared for injection. The reformulated version began shipping in August 2010, replacing the original formulation. As shown in Figure 5a, the reformulation was associated with a significant drop in the number of prescriptions for OxyContin across the United States. While there were over 635,000 OxyContin prescriptions in July 2010, OxyContin prescriptions fell by nearly 25 percent, to less than 488,000 per month by August 2011; in contrast, total opioid prescriptions increased by almost 4 percent over the same period.[23]

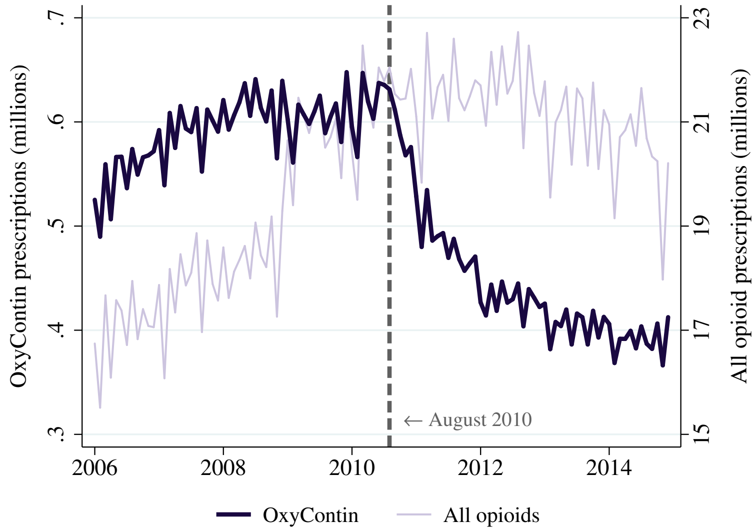
While total OxyContin prescriptions fell nationally, there was pronounced heterogeneity in responses to the reformulation across providers. Figure 5b shows the empirical cumulative distribution function of percent changes in provider-level shares of opioid prescriptions that were written for OxyContin in the six months after the reformulation (September 2010–February 2011) versus either (1) the six months prior (February 2010–July 2010; dark line), or (2) the same six months the year before (September 2009–February 2010; light line). Changes relative to the first baseline period control for prescribing immediately preceding the reformulation, whereas changes relative to the second baseline period control for seasonality in prescribing. The sample is limited to the 180,437 providers who prescribed opioids in each of these three periods and prescribed OxyContin

[22] As noted in footnote 4, an earlier version of this paper estimated the model on the ten largest commuting zones in the United States. The take aways of the estimation and counterfactuals were very similar in this earlier formulation.

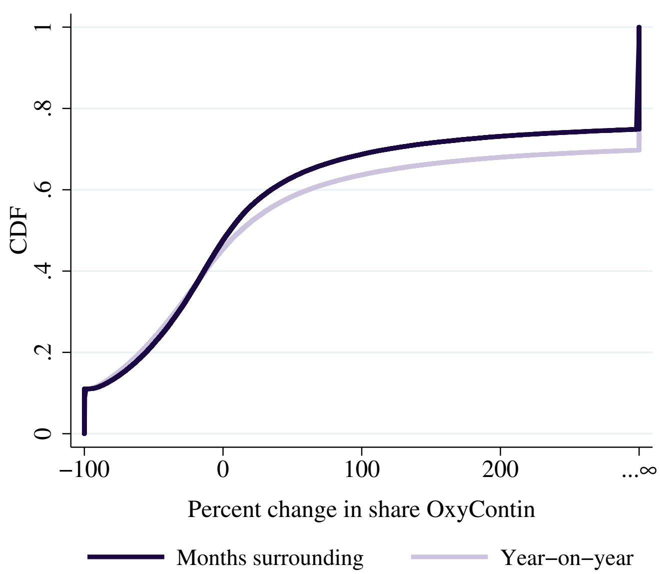
[23] As new drugs are often more expensive than their predecessors, the pattern observed in Figure 5a could be driven by higher copayments for reformulated OxyContin relative to the original formulation. However, the average copayment for OxyContin decreased surrounding the reformulation (Figure A5a). This price reduction is observed despite a shift from generic to branded OxyContin (Figure A5b).

Figure 5: Changes in OxyContin prescribing following the reformulation

(a) OxyContin and total opioid prescriptions nationally: 2006–2014



(b) Provider-level changes in share of opioids for OxyContin



Notes: The above figures show changes in OxyContin prescribing in the IQVIA data following the reformulation of OxyContin in August 2010. Subfigure (a) shows the monthly number of OxyContin prescriptions (left axis; dark, thick line) and the monthly number of opioid prescriptions across all products (right axis; light, thin line) from 2006–2014. The dashed vertical line denotes the month when the reformulated version of OxyContin began shipping. Subfigure (b) shows the empirical cumulative distribution function of provider-level percent changes in the share of opioid prescriptions written for OxyContin in the six months after the reformulation (September 2010–February 2011) versus either the six months before (February 2010–July 2010; dark line) or the same six months the year prior (September 2009–February 2010; light line).

in any of the three periods;[24] these providers account for 12.2 percent of all opioid prescribers and 52.9 percent of all opioid prescriptions written over the period 2006–2014 (see Table 1). As shown in Figure 5b, over 10 percent of OxyContin prescribers stopped prescribing the medication entirely following the reformulation, whereas nearly 30 percent only began prescribing the medication after it was reformulated. The median provider increased their OxyContin share by 4.9 percent relative to the six months immediately preceding the reformulation.

The reformulation of OxyContin provides a unique opportunity to measure physician preferences. Given that the reformulated version has less abuse potential, physicians who are concerned with population health should be more likely to prescribe OxyContin once it had been reformulated. On the other hand, since demand for OxyContin was reduced among patients wanting to misuse or resell their prescriptions, physicians who care more about maintaining their revenue should be willing to switch their OxyContin patients to other opioids without abuse-deterrent properties. I therefore use provider-level responses to the reformulation to group physicians according to their level of altruism: high-altruism providers increased their OxyContin shares in the six months following the reformulation relative to both baseline periods outlined above, whereas low-altruism providers decreased their OxyContin shares relative to both baseline periods. Medium-altruism providers saw no consistent change in their prescribing and have opposite-signed changes in their OxyContin shares depending on which baseline period is used.[25,26] By combining information from two complementary measures, this method for categorizing providers reduces type II errors in the categorization of low- and high-altruism providers.

Table 1 shows the distribution of providers across these altruism categories. Among all categorized providers, 34.8 percent are categorized as low altruism and 41.6 percent are categorized as high altruism. Low-altruism providers decreased their OxyContin shares by an average of 4.2 percentage points in the six months after the reformulation versus the six months prior, with the median low-altruism provider reducing her OxyContin share by nearly 57 percent. In contrast, high-altruism providers increased their use of OxyContin by 4.9 percentage points on average over the same period, with the median high-altruism provider increasing her OxyContin share by over 400

[24] As these measures are based on prescribing shares, they are only defined for providers with non-zero opioid prescriptions in each period. Moreover, as the experiment reveals little about the behavior of providers who never prescribe OxyContin, I exclude providers with zero OxyContin shares in all three periods.

[25] This categorization is shown visually in Figure A6.

[26] One concern with this design is that it could reflect differences in demand across providers instead of differences in preferences. That is, providers that are categorized as high-altruism might not see any patients who want to misuse or resell their opioid prescriptions. However, as shown in Figure A7, the distribution of patient characteristics across altruism categorizations at baseline is very similar. If anything, high-altruism providers see slightly more patients aged 20–39, the age group with the highest misuse of prescription opioids (Table A5).

Table 1: Distribution of physicians and prescribing patterns across altruism groups

	All	By altruism group			
		Low	Medium	High	Missing
	(1)	(2)	(3)	(4)	(5)
a. Number of providers: 2006–2014					
Total	1,479,689	62,810	42,508	75,119	1,299,252
Percent of total	100.00	4.24	2.87	5.08	87.81
Percent of categorized		34.81	23.56	41.63	
b. Changes in OxyContin shares					
Average percentage point change					
Sept. 2010–Feb. 2011 vs. Feb. 2010–July 2010		-4.18	-0.66	4.85	
Sept. 2010–Feb. 2011 vs. Sept. 2009–Feb. 2010		-5.04	0.02	5.37	
Median percent change					
Sept. 2010–Feb. 2011 vs. Feb. 2010–July 2010		-56.74	-3.85	414.82	
Sept. 2010–Feb. 2011 vs. Sept. 2009–Feb. 2010		-61.66	5.89	$+\infty$	
c. Opioid prescribing: 2006–2014					
Total (billions)	2.10	0.47	0.27	0.37	0.99
Percent of total	100.00	22.59	12.73	17.63	47.06
Percent of categorized		42.66	24.04	33.30	
Average per provider-year	246.11	874.61	729.93	576.79	141.52

Notes: The above table presents the number of unique providers (top panel), changes in OxyContin prescribing (middle panel), and total opioid prescriptions (bottom panel) across altruism groups. In the middle panel, provider-level changes in the share of opioid prescriptions written for OxyContin in the six months after the reformulation (September 2010–February 2011) versus either the six months immediately prior (February 2010-July 2010) or the same six months the year before (September 2009–February 2010) are considered. As outlined in Section IV.A, providers that decreased their OxyContin shares relative to both baseline periods are considered low altruism, providers that increased their OxyContin shares relative to both baseline periods are considered high altruism, and providers that saw no consistent change in their prescribing and have opposite-signed changes in their OxyContin shares depending on which baseline period is used are considered medium altruism. Only providers that wrote at least one opioid prescription in each of these three periods and at least one OxyContin prescription in any of these three periods are categorized; these 180,437 providers account for 12.2 percent of all opioid prescribers and 52.9 percent of all opioid prescriptions written over the period 2006–2014. Data come from IQVIA.

percent.[27] Consistent with the model presented in Section III, opioid prescriptions are decreasing in provider altruism: low-altruism physicians wrote an average of 874.6 opioid prescriptions per year compared to 729.9 among medium-altruism providers and 576.8 among high-altruism providers. Opioid-prescribing physicians who did not prescribe OxyContin over the relevant time period and therefore cannot be categorized wrote an average of only 141.5 opioid prescriptions per year.

[27] Figure A8 displays changes in provider-level prescribing shares across different opioid product categories following the reformulation. The figure highlights that providers who reduced their use of OxyContin switched their patients to a variety of other opioid products. The large drop in propoxyphene that is observed among both low-altruism and high-altruism providers is due to the drug's withdrawal from the market in November 2010; Figure A9 confirms that changes in OxyContin prescribing are robust to using a post-period that ends before propoxyphene's removal.

Differences in the composition of provider altruism across locations translate into significant differences in mortality. Table 2 presents output from county-level regressions of drug overdose mortality in 2014 on the shares of categorized providers across different altruism groups. The first four columns consider deaths involving prescription opioids; given the likely underreporting of prescription opioid deaths, the last four columns consider fatal overdoses from any source. Increasing the share of low-altruism providers by one standard deviation (0.22) is associated with 0.12 more prescription opioid deaths and 0.39 more fatal drug overdoses from any source per 10,000, increases of nearly 25 percent relative to the respective means (columns (1) and (5)). Moreover, as shown in columns (2) and (6), the share of medium-altruism providers falls between the share of low- and high-altruism providers in its association with fatal drug mortality. While these associations are reduced slightly when controlling for county-level demographics, significant and large associations between the shares of providers across different altruism categories and drug-related mortality remain (columns (3) and (7)). Furthermore, as shown in columns (4) and (8), this relationship persists even conditional on the number of opioid prescriptions per capita, suggesting that the association is driven by the allocation of prescriptions introduced by physicians of differing altruism rather than simply the quantity. Moreover, comparing Tables 2 and Table A4, we see that the main altruism measure—which is defined relative to both baseline periods—is more predictive of mortality differences across locations than altruism measures that are constructed relative to a single baseline period.

In addition to providing a grouping that can be used for estimation of the model in Section IV.C below, these altruism measures can also be used to examine whether there is empirical support for the model's predictions. While secondary markets for prescription opioids exist in all locations across the United States, there is geographic variation in their prevalence. Using information on the number of prescription opioid seizures per 1,000 by law enforcement from the NIBRS as a proxy for activity on the secondary market, Figure 6 plots average opioid prescriptions by high- and low-altruism providers against county-level prescription opioid seizures in 2014.[28] As predicted by the model, the difference between the prescribing practices of high- and low-altruism physicians increases as the secondary market becomes more widespread, highlighting that the presence of a secondary market will tend to exacerbate prescribing differences between strict and lenient providers.

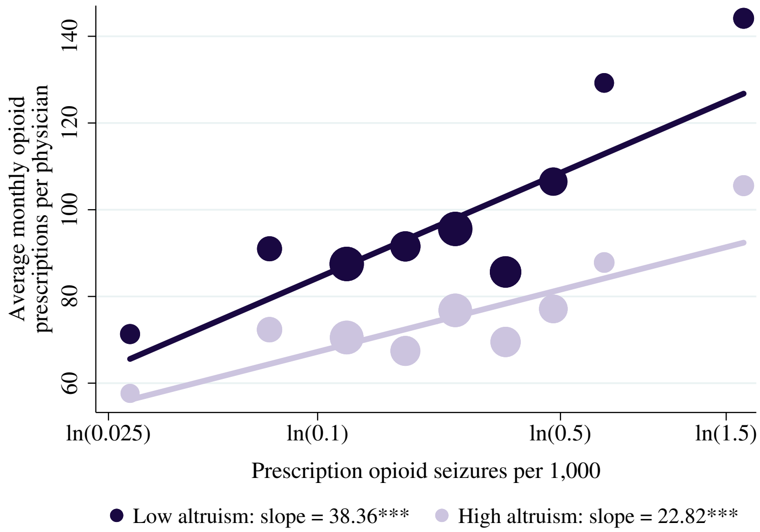
[28] As shown in Figure A2, prescription opioid seizures from the NIBRS are highly correlated with reports of secondary market activity from the NSDUH. The pattern observed in Figure 6 is therefore very similar if alternative proxies for secondary market activity are instead used.

Table 2: Association between county-level altruism shares and drug overdoses: 2014

Fatal overdoses per 10,000:	Prescription opioids				All drugs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share low altruism	0.568***	0.585***	0.479***	0.468***	1.784***	2.031***	1.769***	1.750***
	(0.146)	(0.159)	(0.154)	(0.151)	(0.309)	(0.335)	(0.306)	(0.305)
Share medium altruism		0.055	-0.069	0.002		0.775**	0.621**	0.740**
		(0.170)	(0.164)	(0.159)		(0.309)	(0.290)	(0.288)
Opioid prescriptions per capita				0.256***				0.432***
				(0.043)				(0.077)
Demographic controls			X	X			X	X
Observations	2,775	2,775	2,775	2,775	2,775	2,775	2,775	2,775
R^2	0.008	0.008	0.043	0.091	0.021	0.023	0.111	0.147
SD share low altruism	0.218	0.218	0.218	0.218	0.218	0.218	0.218	0.218
SD share medium altruism	0.201	0.201	0.201	0.201	0.201	0.201	0.201	0.201
SD opioids per capita	0.498	0.498	0.498	0.498	0.498	0.498	0.498	0.498
Mean dependent variable	0.500	0.500	0.500	0.500	1.592	1.592	1.592	1.592

Notes: The above table presents output from county-level regressions of drug overdose mortality per 10,000 in 2014 on the share of providers categorized as low and medium altruism. The share of categorized providers that are high altruism is the omitted category. Fatal overdoses involving prescription opioids are considered in columns (1)–(4), and all drug overdose deaths are considered in columns (5)–(8). Columns (3), (4), (7), and (8) control for county-level demographics including total population, population density, and the age, gender, and race profile; columns (4) and (8) additionally control for the number of opioid prescriptions per capita in 2014. The shares of low- and medium-altruism providers are defined relative to the total number of categorized providers in a given county, and observations are weighted by the number of categorized providers. Standard errors are robust. Mortality data come from the NVSS, opioid prescriptions come from IQVIA, intercensal population estimates come from the U.S. Census Bureau, and demographic controls come from the 2010–2014 five-year pooled ACS.

Figure 6: Polarization of the secondary market



Notes: The above figure shows the relationship between the average monthly number of opioid prescriptions written by physicians in the IQVIA data and the log number of prescription opioid seizures per 1,000 at the county-year level from the NIBRS in 2014. This relationship is shown separately for low-altruism physicians (dark circles and line) and high-altruism physicians (light circles and lines). Counties are grouped into deciles based on prescription opioid seizures per capita. The size of the marker denotes the number of physicians in each bin. Only active physicians who write at least one opioid prescription in every month and have non-missing information on specialty and office practice location are considered.

IV.B Additional data

Before proceeding to the method of moments estimation, I first introduce a number of additional data sources. In addition to information on the number of opioid prescriptions written by each provider, the second stage of estimation uses information on physician-level office visit reimbursement rates and local measures of patient costs, the prevalence of physical pain and prescription opioid misuse, and the price for an opioid prescription on the secondary market.

I combine data from four sources to construct physician-level reimbursements for office visits. First, I use publicly available Medicare claims data to create Medicare reimbursement rates at the specialty-state level by combining average state-level reimbursement rates for office visit CPT codes under Medicare with specialty-specific CPT shares. I then use Medicare-to-private insurance and Medicare-to-Medicaid payment ratios provided by the Government Accountability Office (GAO) and the Kaiser Family Foundation (KFF), respectively, to adjust the specialty-state Medicare rates for other insurances types.[29] Finally, I calculate the average reimbursement rate facing each physi-

[29]These payment ratios are provided in a GAO report (GAO, 2014) and can be found on the KFF website here.

cian by combining these specialty-state-insurance type reimbursement rates with the provider-level composition of patient insurance types used to pay for opioid prescriptions in the IQVIA data. According to this method, the average office visit reimbursement rate in 2014 for general practitioners in Baltimore County was $113, compared to an average of $82 across all counties.

As outlined in Section III, there are three costs associated with obtaining an opioid prescription on the primary market: (1) the cost of visiting a doctor, (2) the cost of filling a prescription, and, if a patient searches across providers, (3) the search cost. I take these measures from three sources. First, according to the Medical Expenditure Panel Survey, the average copayment for an office visit in Maryland in 2014 was $22.44 ($24.77 across the entire United States). Second, the IQVIA XPonent data contain information on patient copayments for their prescriptions; in 2014, the average copayment for an opioid prescription in Baltimore County was $8.50 ($8.38 across the United States). Finally, searching for a new physician frequently requires using the internet to find and research different providers. I therefore take the average cost of using a health care website to gain information about different providers of $48 from Brown (2019).

As outlined in Section II.B, the NSDUH contains information on sources of misused prescription opioids across the United States. However, the single-year, public-use files contain no geographic identifiers. To construct county-level measures of prescription opioid misuse from the secondary market, I combine socio-demographic correlates of misuse with local socio-demographic profiles. In particular, I first project reports of prescription opioid misuse in 2014 on a range of individual-level socio-demographics available in the NSDUH.[30] Misuse of prescription opioids is highest among young, white males, with misuse rates generally decreasing over the lifecycle (see Table A5). I then predict county-level prescription opioid misuse rates by combining these estimates with information on the socio-demographic composition of counties across the United States as reported in the five-year pooled (2010–2014) American Community Survey (ACS). This procedure works well: as shown in Figure A10c, state-level prescription opioid misuse rates constructed using an analogous methodology are highly correlated with state-level estimates of misuse provided in the two-year pooled (2013–2014) NSDUH. According to this method, 0.47 percent of Baltimore residents turned to the secondary market to buy prescription opioids in 2014, versus 0.68 percent nationally.

[30]The prediction specifications are designed to exhaust the cross-tabs available in the five-year pooled ACS. In particular, the regressions include all pairwise interactions between {sex, age} and {race/ ethnicity, income}; all three-way interactions between {sex, age, race/ ethnicity}, {sex, age, educational attainment}, {sex, age, employment status}, {sex, age, martial status}, and {sex, age, health insurance status}; and all four-way interactions between {sex, age, race/ ethnicity, poverty status}. Age and income are included in the smallest bins common to the ACS and the NSDUH. Sample regression output from estimation of a specification that includes only main effects that are common to both the NSDUH and NHIS is provided in Table A5. The exact regressors used for the prediction are outlined in Table A6. The adjusted R-squared from the full prediction model is 0.067.

To measure pain, I use information from the National Health Interview Survey (NHIS). The NHIS is the largest in-person survey tracking health conditions across the United States. Using responses to questions concerning pain in the neck, lower back, and face, I construct county-level measures of pain prevalence following the same procedure outlined above for misuse in the NSDUH. In particular, I project reports of pain from the 2014 NHIS on individual-level socio-demographics and combine these associations with socio-demographic compositions of counties across the United States from the ACS.[31] Reports of physical pain increase over the lifecycle, with older, white women reporting the most pain (see Table A5). As such, older, less diverse counties are considered to have higher pain on average (see Figure A11). Baltimore County is projected to have average pain of 0.327 on a three-point scale, compared to 0.375 across all U.S. counties.

Finally, to compute local resale prices per prescription, I combine average prices per morphine milligram equivalent (MME) from the StreetRx data with statistics from the IQVIA LRx data on the size of opioid prescriptions. According to the LRx data, the median opioid prescription in 2014 contained 337.5 MMEs.[32] In Baltimore, the price per MME was nearly \$1.31 in 2014, leading to a resale price per prescription of \$442 (compared to an average of \$0.81 per MME, and \$273 per prescription, across counties).

IV.C Method of moments estimation

Having grouped physicians according to their level of altruism and established the empirical relevance of such groupings, I turn to quantifying the structural parameters of the model for Baltimore County, Maryland. Taking physician reimbursement and patient costs as given, three additional sets of primitives that govern the optimal behavior of patients and physicians need to be recovered: (1) the distribution of patient pain and tastes, (2) the parameters of the health impact function, and (3) the set of physician altruism weights.

To take the model to the data, I assume that patient tastes for prescription opioids are normally distributed ($G(\kappa) \sim \mathcal{N}(\mu, \sigma^2)$) and that pain follows an exponential distribution ($F(\kappa) \sim Exp(\lambda)$). I further parametrize the health impact function to be of the form $a \cdot ln(b \cdot \kappa + \epsilon)$; the parameters a and b flexibly govern the scale and curvature of the health impact function, while $\epsilon = 1^{-4}$ is included to ensure that the health impact function is defined at zero. Let $\boldsymbol{\theta} = \{a, b, \epsilon\}$ denote the parameters of the

[31] The adjusted *R*-squared from the projection of pain on individual-level socio-demographics is 0.396; see Table A7 for the full list of included regressors. As shown in Figure A11c, region-level pain prevalence constructed using the region identifiers provided in the NHIS is correlated with region-level pain prevalence predicted based on socio-demographics.

[32] The mean (median) opioid prescription contained 65.79 (60) pills. The distribution of MMEs per pill is right-skewed, however, leading the mean (median) opioid prescription to have 846.0 (337.5) MMEs.

health impact function. Finally, following the categorizations introduced in Section IV.A, I assume that there are three levels of physician altruism: low, medium, and high. I further include an altruism grouping for providers who cannot be categorized. Let $g_j \in \{low, medium, high, missing\}$ denote the altruism group for each physician j, and let $\boldsymbol{\beta} = \{\beta_{low}, \beta_{medium}, \beta_{high}, \beta_{missing}\}$ denote the set of altruism weights.

The nine parameters to be recovered are listed in Table 3. Combining data from the NHIS and the ACS (see Section IV.B), the scale parameter of the pain distribution is calibrated to match the average level of pain in Baltimore County $\left(\text{i.e., } \frac{1}{\lambda} = 0.327\right)$. Moreover, in line with the intuition introduced in Section IV.A, I set the altruism weight for medium-altruism physicians to one $(\text{i.e., } \beta_{medium} = 1)$. The remaining seven parameters are estimated using a generalized method of moments estimator.

Recalling the optimality condition first displayed in equation (4) and adding explicit notation for the parameters on which each component depends, the optimality condition of physician j becomes

$$\left[\left(1 - G(p - h(\kappa_j^* : \boldsymbol{\theta})\right) \cdot h(\kappa_j^* : \boldsymbol{\theta}) + G(p - h(\kappa_j^* : \boldsymbol{\theta})) \cdot \bar{h}^{SM}\right] = -\frac{R_j}{\beta_{g_j}} \tag{5}$$

$$where \;\; G(\gamma) \sim \mathcal{N}(\mu, \sigma^2)$$

Since p and $\{R_j, g_j\}_{\forall j}$ are data, if we knew the average health impact of a prescription purchased on the secondary market $\left(\bar{h}^{SM}\right)$, then for a given set of parameters $\{\mu, \sigma^2, \boldsymbol{\theta}, \boldsymbol{\beta}\}$ we could simply solve each physician's optimality condition to obtain the health impact at their threshold $\left(h(\kappa_j^*)\right)$. Since the average harm on the secondary market is not known, but rather is determined in equilibrium, add $\bar{h}^{SM}$ as a nuisance parameter to be estimated.

Estimation then proceeds as follows. For a given set of parameter values $\left\{\mu, \sigma^2, \boldsymbol{\theta}, \boldsymbol{\beta}, \bar{h}^{SM}\right\}$, I first solve equation (5) for each physician to obtain the health impact at their optimal threshold. Inverting these health impacts yields the optimal threshold for each physician. This distribution of thresholds gives the empirical distribution of prescription probabilities as a function of pain, which combined with patient costs and the secondary market price yields optimal patient search behavior. Assigning patients to physicians based on physicians' thresholds and optimal patient search (see equation (A8)), I then compute: (1) the number of prescriptions written by each physician, (2) the number of patients that buy and sell on the secondary market, and (3) the total health impact of prescription opioid consumption on the secondary market.

The ten moments used for estimation are listed in Table 4. As outlined in the top panel, two sets of moments match model predictions for the number of opioid prescriptions written by differ-

Table 3: Key model parameters

Parameter	Value	95% CI	Source
Altruism weights			
β_{low}	0.854	[0.804, 0.904]	Estimation
β_{medium}	1.000		Normalization
β_{high}	1.142	[1.112, 1.171]	Estimation
$\beta_{missing}$	10.84	[6.86, 14.81]	Estimation
Health impact function ($h(\kappa) = a \cdot ln(b \cdot \kappa + \epsilon)$)			
a	450.3	[440.6, 459.9]	Estimation
b	0.688	[0.688, 0.688]	Estimation
ϵ	0.0001		Normalization
Pain distribution ($F(\kappa) \sim Exp(\lambda)$)			
$1/\lambda$	0.327		NHIS, ACS
Taste distribution ($G(\gamma) \sim \mathcal{N}(\mu, \sigma^2)$)			
μ	504.2	[479.2, 529.3]	Estimation
σ	86.69	[65.35, 108.0]	Estimation
Patient costs			
Office visit copay (τ_d)	22.44		MEPS
Search cost (τ_s)	48		Brown (2019)
Prescription copay (τ_o)	8.50		IQVIA

Notes: The above table outlines the key model parameters and their sources. As outlined in the text, estimation proceeds in two stages. First, physicians are grouped according to their level of altruism based on their change in prescribing following the reformulation of OxyContin in 2010 (see Section IV.A). A generalized method of moments estimator is then used to recover structural parameters that govern the optimal behavior of patients and general practitioners in Baltimore County, Maryland in 2014 (see Section IV.C).

ent groups of physicians to those observed in the data: (1) the monthly average number of opioid prescriptions across altruism groups (four moments), and (2) the monthly average number of opioid prescriptions across terciles of office visit reimbursements (three moments). The remaining three moments compare model predictions for activity on the secondary market to the observed equilibrium outcomes (bottom panel). In particular, comparing the model predictions for supply and demand on the secondary market provides information on market clearing. Another moment measures demand on the secondary market and compares it to the misuse rate from the secondary market predicted by combining information from the NSDUH with the local socio-demographic profile (see Section IV.B). Finally, the average health impact among patients that buy on the secondary market is directly used to match the nuisance parameter $\bar{h}^{SM}$.

Table 4: Moments and model fit

Moment	Data	Model
a. Average opioid prescriptions		
By altruism group		
Low	54.67	54.32
Medium	43.55	43.43
High	32.40	32.23
Missing	7.311	8.272
By revenue tercile		
Bottom	12.12	18.55
Middle	30.02	26.72
Top	20.44	18.87
b. Secondary market activity		
Share of population buying	0.005	0.007
Market clearing		
Supply	–	5842
Demand	–	5520
Average health impact		
Estimated parameter	–	-138.1
Model prediction	–	-144.1

Notes: The above table outlines the moments used for estimation and the model fit. As outlined in Section IV.C, these moments are used to recover the structural parameters (listed in Table 3) that govern the optimal behavior of patients and general practitioners in Baltimore County, Maryland in 2014. Average opioid prescriptions across altruism groups and revenue terciles reflect monthly averages in 2014. See Section IV.B for details on the data used for estimation.

Identification While all of the moments listed in Table 4 are used to jointly identify the parameters listed in Table 3, we can consider what variation in the data allows for the identification of each parameter. Suppose first that the health impact function and the distribution of patient tastes were known. Conditional on the medical impact of prescription opioids, optimal patient behavior, and each provider's revenue per office visit, the utility weights for each altruism group are identified by the average level of prescriptions within that group. If low-altruism physicians write many prescriptions, for example, then low-altruism physicians must place relatively little weight on the impact they have on patient health to rationalize this amount of prescribing. This can be seen in equation (5) and is shown in Figure A16b: taking $h(\kappa)$ and $G(\gamma)$ as given, a smaller altruism weight leads to a lower solution of κ^*—a threshold that is consistent with more prescriptions.

Of course, the health impact function and the distribution of patient tastes are not known. Instead, identification of the health impact function comes predominately from the average levels of prescriptions across revenue terciles. In particular, conditional on provider altruism and optimal patient behavior, differences in the average number of prescriptions and the average revenue per office visit across these groups provides information on differences in the health impact between their respective prescribing thresholds. Intuitively, if providers j and j' have the same level of altruism, but provider j gets paid more per office visit, this difference in revenue informs the difference in the monetized health impact between their threshold patients. With three revenue bins considered, this is sufficient to trace out the health impact function, thereby identifying the shape parameter b. Moreover, the scale parameter of the health impact function (a) is predominately identified by the levels of prescriptions across revenue and altruism bins.[33] The simplest way to see this is to consider equation (5) for medium-altruism providers, whose level of altruism was set to one following the intuition outlined in Section IV.A.[34] Conditional on patient behavior, the curvature of the health impact function, and each provider's revenue per office visit, the scale of the health impact function adjusts such that the optimal threshold of these providers is consistent with the number of prescriptions that they are observed to write in the data.

Finally, patient tastes are identified by the behavior of patients on the secondary market and its subsequent influence on the primary market. As average tastes (μ) increase, fewer patients who get a prescription on the primary market want to sell and more patients who cannot get a prescription on the primary market want to buy. Average tastes therefore adjust such that the secondary market clears given the level of demand on the secondary market observed in the data. Moreover, as the variance of tastes (σ^2) decreases, fewer patients who have very negative health impacts from consuming a prescription opioid buy on the secondary market. This moderates the effect of the secondary market on the behavior of physicians on the primary market; the variance of tastes therefore adjusts such that the health impact of prescriptions on the secondary market predicted by the model is consistent with the level necessary to rationalize physician behavior.

[33] While increases in the shape parameter (b) make prescription opioids better at all levels of pain, increases in the scale parameter (a) serve to make opioids better for those in severe pain and worse for those in little pain. This serves to dampen secondary market activity by reducing demand to buy among those who cannot get a prescription (and who are thus in little pain) and reducing the probability of resale among those who can get a prescription (and are thus in greater pain). Identification of the health impact function—in contrast to the altruism weights, which only directly affect primary market behavior—is therefore further helped by moments governing secondary market activity.

[34] Since physician altruism weights only affect the number of prescriptions written on the primary market, whereas the health impact function influences both the number of prescriptions written by physicians and the optimal behavior of patients on the secondary market, the scale of the health impact function and the physician altruism weights can in principle be separately identified. However, in practice there is insufficient variation in the data to recover these levels separately, and thus I set the altruism weight for medium-altruism providers to one following the intuition outlined in Section IV.A.

V Results and counterfactuals

Before proceeding to the estimation results (Section V.A) and counterfactuals (Section V.B), I first consider the model fit. As shown in Table 4, the estimated model matches the targeted moments well. In particular, the predicted number of opioid prescriptions across different altruism groups closely matches the average levels of opioid prescriptions observed in the data, and the general pattern of prescribing across revenue terciles follows the true prescribing pattern.[35] Moreover, the share of the population turning to the secondary market to buy a prescription opioid accords with that predicted based on the NSDUH; with a similar share of the population turning to the secondary market to sell, the secondary market clears. Finally, the average health impact of a prescription on the secondary market is close to the estimated nuisance parameter, indicating that the average health impact used to compute optimal physician behavior is consistent with the observed equilibrium outcome.

V.A Model estimates

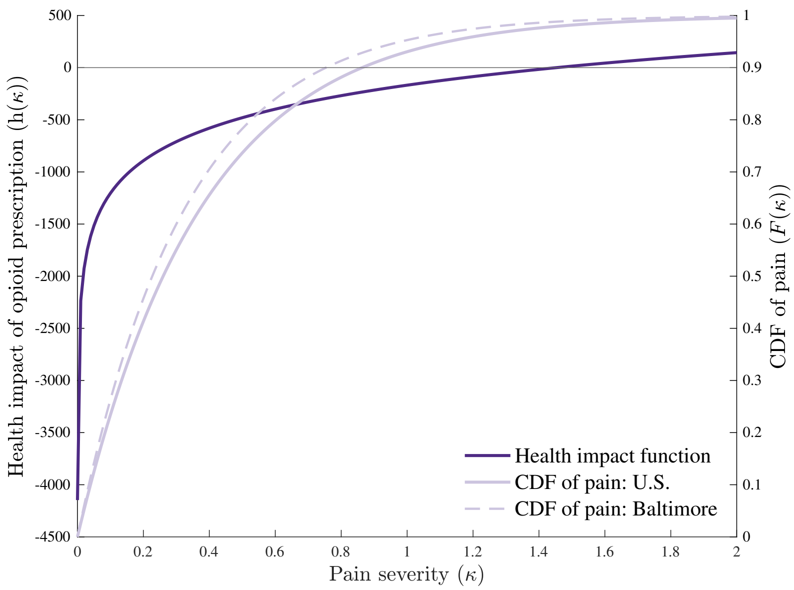
Estimation results are provided in Table 3. Looking first to the results for physician utility weights, we see that the ordering of altruism groups by the average weight physicians place on the impact they have on patient health accords with the intuition previously introduced. In particular, among providers that can be categorized, low-altruism physicians place the least weight on the impact they have on patient health whereas high-altruism providers have the greatest concern for the medical impact of their prescribing behaviors. Notably, while low-altruism physicians are revealed to have greater concern for their revenue ($\hat{\beta}_{low} = 0.85 < 1$), high-altruism physicians place more weight on how their actions influence patient health ($\hat{\beta}_{high} = 1.14 > 1$). Given the relatively low number of opioid prescriptions written by physicians whose level of altruism cannot be categorized (see Table 1), these providers must place significantly more weight on the health impacts of their actions relative to their revenue for the model to rationalize their prescribing.[36]

The estimated health impact function is depicted in Figure 7. The y-intercept is estimated to be around –\$4,150, indicating that consuming a prescription opioid leads to substantial health losses

[35]In the raw data, the number of opioid prescriptions is monotonically increasing across revenue terciles conditional on altruism. However, physicians in Baltimore County who cannot be categorized according to their level of altruism are disproportionately in the highest revenue tercile, leading the unconditional average number of opioid prescriptions in the top revenue tercile to be less than in the middle revenue tercile.

[36]The behavior of providers who place significant weight on their impact on patient health should be largely unaffected by revenue. Notably, the correlation between the physician-level number of opioid prescriptions and revenue per office visit is lower among physicians with missing altruism ($\rho = 0.074$) than among physicians with low, medium, or high altruism ($\rho = 0.31$, 0.30, and 0.14, respectively).

Figure 7: Estimated health impact function



Notes: The above figure depicts the estimated health impact function (solid, dark line) and the cumulative distribution function of pain in the United States (solid, light line) and in Baltimore County, Maryland (dashed, light line) in 2014. The health impact function is assumed to be of the form $a \cdot ln(b \cdot \kappa + 0.0001)$ with the parameters a and b recovered using a generalized methods of moments estimator. The distribution of pain is assumed to follow an exponential distribution with the scale parameter calibrated to match either the average level of pain in counties across the United States or in Baltimore County.

for individuals with no physical pain.[37] Moreover, the health impact function is still negative at the average severity of pain observed across U.S. counties (0.375), suggesting that a patient with average pain is harmed from a medical perspective if they consume a prescription opioid. This makes sense: the medical literature and prescribing guidelines indicate that patients should only take opioids in cases of severe pain that do not respond to non-opioid analgesics (Dowell et al., 2016). In fact, the health impact function depicted in Figure 7 suggests that a patient needs to have pain that is nearly three standard deviations above the mean before prescription opioids are beneficial (i.e., the health impact exceeds zero) from a medical perspective. As shown by the overlaid cumulative distribution functions of pain across the United States (solid, light line) and Baltimore County (dashed, light line), the estimated health impact function suggests that prescription opioids have positive health impacts for only 2.1 and 1.2 percent of individuals in these locations, respectively.

Finally, recall that each patient has both a severity of pain and a taste for opioids. Even though some patients will be harmed by consuming a prescription opioid from a medical perspective, they

[37]This can be benchmarked to estimates of the effects of a marginal opioid prescription. Eichmeyer and Zhang (Forthcoming) estimate that being prescribed an opioid increases the probability of opioid overdose mortality by 0.075 percentage points. Combining this estimate with ranges of the value of a statistical life of \$5 to \$9 million (Viscusi and Aldy, 2003), this suggests that a marginal opioid prescription leads to health losses of \$3,750 to \$6,750.

will still want to consume the medication if they have high enough tastes. While the health impact function depicted in Figure 7 suggests that most individuals have negative health impacts from prescription opioid consumption, patients are estimated to have high tastes for prescription opioids on average (see Table 3), thereby rationalizing much higher consumption. Notably, while a patient in Baltimore County with average pain and tastes will not want to consume a prescription opioid, a two standard deviation increase in tastes is sufficient to overcome the negative health impacts.

V.B Counterfactuals

V.B.1 Shutting down the secondary market

What is the impact of a secondary market for prescription opioids? In this section, I use the estimates presented in Section V.A to quantify the impact of a secondary market on the total number of opioid prescriptions written by physicians and on the equilibrium health impacts of these medications.

Shutting down the secondary market requires recomputing the optimal thresholds of physicians and the optimal search behavior of patients. To do so, I first solve equation (2) (physician optimality in the absence of a secondary market) for each physician to obtain the health impact at each physician's optimal threshold. Using the estimated parameters of the health impact function, I then invert the health impact at each physician's threshold to obtain their counterfactual threshold. The distribution of thresholds gives the empirical distribution of prescription probabilities as a function of pain, which combined with patient costs and the estimated distribution of tastes yields optimal patient search behavior. Assigning patients to physicians based on physicians' thresholds and optimal patient search in the absence of a secondary market (equation (A4)), it is then straightforward to compute the number of prescriptions written by each physician and the health impact that these prescriptions have on their patients. As with the estimation in Section IV.C, this exercise is done for general practitioners in Baltimore County, Maryland; to provide a sense of magnitudes for the country, these figures are then scaled to represent the entire United States according to these providers' share of total opioid prescriptions in 2014.

Table 5 shows how the total number of opioid prescriptions and the aggregate health impacts change as the secondary market is shut down. For comparison, the total number of opioid prescriptions and aggregate health impacts with a secondary market are shown in panel (a). Estimates suggest that the 240 million opioids that were prescribed in 2014 led to net health losses of over three billion dollars. This is due in large part to the reallocation across patients; as shown in the top row of panel (b), if all patients who received these prescriptions were unable to resell the medication and instead had to consume the prescriptions themselves, the aggregate health impacts would have

Table 5: Counterfactual prescriptions and health impacts

	Opioid prescriptions		Health impacts	
	Levels (hundred millions)	Relative to status quo (%)	Levels (billions)	Difference from status quo (billions)
	(1)	(2)	(3)	(4)
a. Status quo	2.40	–	-3.15	–
b. Shutting down the secondary market				
No patient reallocation	2.40	–	2.89	6.04
+ Changed demand	2.38	-0.85	3.02	6.16
+ New optimal prescribing thresholds	2.97	23.8	-2.75	0.40
c. Stopping overprescribing ($h(\kappa^*) = 0$)				
With secondary market	1.10	-54.2	5.67	8.82
Without secondary market	1.10	-54.2	9.33	12.5

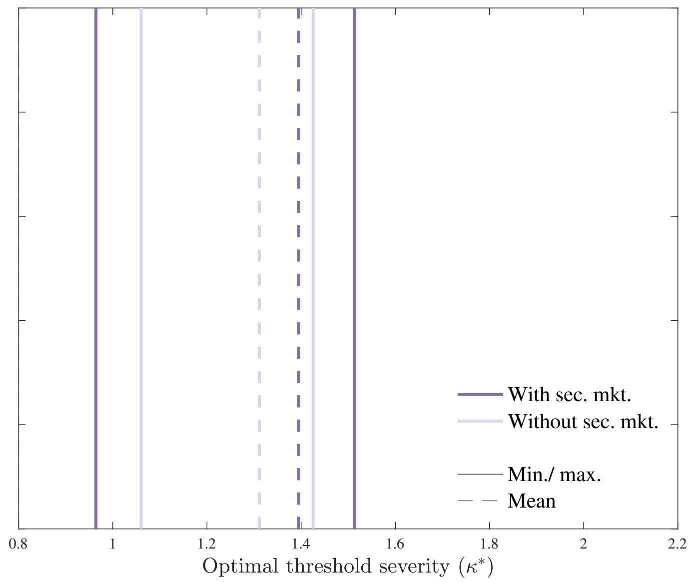
Notes: The above table shows how the number of opioid prescriptions and the aggregate health impacts compare under the status quo (top panel) and alternative counterfactual scenarios (bottom two panels). Estimates are based on Baltimore County, Maryland and are scaled to represent the entire United States according to Baltimore's share of total opioid prescriptions in 2014.

instead been substantially positive. Moreover, if the patients who did not want to consume the medication and only went to the doctor with the intention of reselling were likewise allowed to update their behavior, the aggregate health impacts would have further increased (second row, panel (b)).

However, preventing patients from reselling does not only prevent reallocation and alter demand among patients. Importantly, the supply side also responds, with physicians on the primary market adjusting their optimal prescribing thresholds when there is no potential for resale. Figure 8 shows the range of physician thresholds in Baltimore County with and without a secondary market. The presence of a secondary market induces most physicians (over 98 percent) to be more strict in their prescribing. This indicates that the vast majority of providers would be unwilling to prescribe to the average patient on the secondary market, and thus they must see patients in greater observable pain to be willing to prescribe when a secondary market exists.

However, some physicians respond to the possibility of their patients reselling by becoming more lenient. This is because they have sufficiently low altruism and sufficiently high revenue such that the average patient on the secondary market benefits more from the medication than their threshold patient in the absence of a secondary market. As outlined in Section III.D, these differential responses to the presence of a secondary market serve to polarize physician behavior. As shown in Figure 8, the secondary market leads to a wider range of prescribing thresholds, with relatively

Figure 8: Optimal prescribing thresholds with versus without secondary market



Notes: The above figure shows the range of optimal prescribing thresholds with a secondary market (dark lines) and without a secondary market (light lines) among general practitioners in Baltimore County, Maryland in 2014. Optimal prescribing thresholds with a secondary market are obtained by inverting equation (4); counterfactual prescribing thresholds without a secondary market are instead obtained by inverting equation (2).

lenient providers becoming more lenient and relatively strict providers becoming more strict.

The final row of panel (b) in Table 5 shows the net impacts of these changes in demand and supply on the number of opioid prescriptions and aggregate health impacts. While the demand-side effects lead to a slight reduction in the number of opioid prescriptions and large improvements in population health, enough providers on the primary market become sufficiently more lenient to outweigh much of these benefits. As shown in column (1), there would have been an estimated 297 million opioid prescriptions in 2014 if a secondary market did not exist, a 24 percent increase over the status quo. Moreover, even though patients would be unable to reallocate these medications, this increase in provider leniency leads to aggregate health impacts that are still negative: while prescription opioids led to net health losses of over three billion dollars with a secondary market in 2014, the estimates suggest that net health losses would have been reduced by only $400 million if a secondary market had not existed.

V.B.2 Stopping overprescribing

The results in the previous section highlight the significant health costs of overprescribing and show that shutting down the secondary market—while leading to benefits from preventing reallocation across patients and reducing demand for resale—can serve to exacerbate such behavior among providers. The final panel of Table 5 therefore considers how the number of opioid prescriptions and aggregate health impacts would differ if physicians did not overprescribe, both with and without a secondary market. In particular, this analysis increases the prescribing thresholds of physicians with $h(\kappa^*) < 0$ to $\kappa^* = h^{-1}(0)$.

As shown in column (1), the total number of opioid prescriptions would be reduced substantially if physicians were not able to prescribe to patients with negative health impacts, both with and without a secondary market.[38] This suggests that even though the secondary market put downward pressure on the number of prescriptions, the number of opioid prescriptions in 2014 was still too high. In particular, the estimates suggest that over 50 percent of opioid prescriptions in 2014 were prescribed to individuals who would have been harmed by consuming the medication; this number is consistent with the 40 percent reduction in the number of opioid prescriptions written nationally from 2014 to 2020 as providers have aimed to limit overprescribing (CDC, 2020).

Importantly, reductions in overprescribing are accompanied by substantial health benefits. As shown in column (3), even with a secondary market, preventing overprescribing leads prescription opioids to have large, positive health impacts. Moreover, since allowing patients to reallocate the medication leads to substantial health losses for some individuals even when providers do not overprescribe, the largest health gains are accrued by shutting down the secondary market and preventing overprescribing on the primary market: as shown in the last row of panel (c), doing so would have led to aggregate health impacts of over $9 billion across the United States in 2014, an increase of nearly $13 billion over the status quo.

It is important to note that these results only capture the health impacts of prescription opioids and thus do not account for potential substitution to heroin or illicit fentanyl. Recent work demonstrates that disruptions to the legal supply of prescription opioids can lead some individuals to switch to illicit opioids (e.g., Meinhofer, 2018; Kim, 2021), suggesting that deaths from non-prescription opioids would rise if physicians were to stop overprescribing. While incorporating substitution to illicit opioids is beyond the scope of this paper, it is important to recognize that any increases in illicit opioid consumption stemming from reductions in overprescribing would likely be temporary. Eighty percent of heroin users report prior prescription opioid misuse (SAMHSA, 2020), so reducing access to prescription opioids should reduce the size of the next generation at risk of abusing opioids. Reining in unnecessary prescribing therefore has the potential to change the trajectory of

[38]This reduction in the number of prescriptions leads the secondary market to not clear. Therefore, this exercise further requires solving for a new secondary market price. This is done iteratively; if more (fewer) individuals show up on the secondary market to buy than to sell, the optimal behavior of physicians and patients is re-solved with a higher (lower) price until supply and demand on the secondary market balance. This leads to a counterfactual resale price of $531, a 20.5 percent increase over the status quo.

drug crises that are borne from legal prescribing by making it less likely that addiction begins in the first place. Identifying policies that can limit addiction among the next generation while mitigating harm for current users is a fruitful area for future research.

VI Discussion and conclusion

Physicians are entrusted with making most decisions regarding patient care. As these decisions have first-order implications for patient outcomes and costs, a large literature in economics has emerged to examine the determinants of physician decision making. Yet, while the prescriptions that physicians write are often retraded on secondary markets, baseline models of physician behavior assume that physicians control the allocation of the services that they provide (McGuire, 2000). This paper sheds light on how the retradability of a physician service influences both the behavior of providers and the equilibrium health impacts of their service provision.

While the primary focus of this paper is on the case of prescription opioids, the framework provides general take aways that can be applied to any prescription medication or other retradable service that physicians provide. In particular, the model highlights that the potential for diversion should lead physicians who would not provide the divertable service to the average patient on the secondary market (i.e., relatively strict providers) to become even stricter in their decision making while simultaneously inducing providers who would provide the service to the average patient on the secondary market (i.e., relatively lenient providers) to become even more lenient. This tends to exacerbate heterogeneity in physician behavior, thereby highlighting how the potential for diversion can interact with incentives and preferences to help rationalize pronounced differences in behavior across providers.

In addition to providing general take aways for our understanding of physician decision making, this paper provides specific lessons for the opioid crisis. In particular, the framework highlights that policies to address the opioid epidemic are complicated by a trade-off between reducing the supply of prescription opioids available for misuse while maintaining the supply for those in severe pain. This policy trade-off makes the opioid epidemic unique relative to previous drug crises like the heroin epidemic in the early 1970s and the crack epidemic in the late 1980s: while reducing the supply of drugs with no legitimate medical use is an uncontroversial policy objective, there is no agreement among the medical community, policymakers, or the public about the optimal level of opioid prescribing. This paper introduces an equilibrium model that can be used to quantify the health impacts of prescription opioids under alternative prescribing regimes. Estimates demonstrate that about half of the opioid prescriptions in 2014 were written for patients who were harmed by the medications, suggesting that despite sweeping efforts from state governments (Meara et al., 2016), the level of opioid prescribing remained too high even years into the crisis.

Moreover, while the trade-off between legitimate and illegitimate use of prescription opioids has been widely recognized, this paper uncovers another trade-off that further complicates the design of policies to address drug crises borne from prescription medications. In particular, while reducing activity on the secondary market will reduce the medical harm caused by the reallocation of legally prescribed medications to those abusing the medication, policies that target the secondary market can have the unintended consequence of increasing unnecessary prescribing by physicians, thereby undoing many of the health benefits that would otherwise accrue from a more closely controlled allocation. Furthermore, while policies that target the primary market can reduce the total number of prescriptions written, the reallocation across patients on the secondary market will still result in medications being consumed by patients without a legitimate medical need. It follows that policies to address crises like the opioid epidemic should simultaneously target both the primary and secondary markets.[39] Estimates demonstrate that such policies would have led prescription opioids to have large, positive health impacts in 2014, a stark contrast to the horrific damages from a prescription drug crisis that has consumed the United States for decades.

References

Alexander, D. and M. Schnell, "The Impacts of Physician Payments on Patient Access, Use, and Health," NBER Working Paper No. 26095, 2019.

Barnett, M., A. Olenski, and A. Jena, "Opioid-Prescribing Patterns of Emergency Physicians and Risk of Long-Term Use," *New England Journal of Medicine*, 2017, *376*, 663–673.

Brown, Z., "An Empirical Model of Price Transparency and Markups in Health Care," Working Paper 2019.

Case, A. and A. Deaton, "Rising Morbidity and Mortality in Midlife Among White Non-Hispanic Americans in the 21st Century," *Proceedings of the National Academy of Sciences*, 2015, *112* (49), 15078–15083.

[39]One way to simultaneously target both markets while maintaining access to appropriate pain management for acute illnesses is to restrict prescription opioid use outside of inpatient settings. Such a model reduces prescribing on the primary market by limiting the conditions and settings for which prescription opioids are commonly used and reduces medications available for resale on the secondary market by limiting the number of prescriptions sent home with patients. Notably, this model is more common in other countries that have not suffered from an opioid crisis. For example, while prescription opioid use is common in inpatient settings in Germany, less than five percent of patients received prescription opioids in outpatient settings in 2010 (Schubert et al., 2013; Rosner et al., 2019). For comparison, the IQVIA LRx database indicates that over 50 million people, or more than 16 percent of the U.S. population, filled an opioid prescription at a U.S. retail pharmacy in 2010.

— **and** — , “Mortality and Morbidity in the 21st Century,” *Brookings Papers on Economic Activity*, Spring 2017, pp. 397–476.

Centers for Disease Control and Prevention, “U.S. Opioid Dispensing Rate Maps,” 2020.

Chan, D., M. Gentzkow, and C. Yu, “Selection with Variation in Diagnostic Skill: Evidence from Radiologists,” *Quarterly Journal of Economics*, 2022, *137* (2), 729–783.

Clemens, J. and J. Gottlieb, “Do Physicians’ Financial Incentives Affect Medical Treatment and Patient Health?,” *American Economic Review*, 2014, *104* (4), 1320–1349.

Currie, J. and H. Schwandt, “The Opioid Epidemic Was Not Caused by Economic Distress But by Factors that Could be More Rapidly Addressed,” *Annals of the American Academy of Political and Social Science*, 2021, *695* (1), 276–291.

— **and W.B. MacLeod**, “Diagnosing Expertise: Human Capital, Decision Making, and Performance among Physicians,” *Journal of Labor Economics*, 2017, *35* (1), 1–43.

— **and** — , “Understanding Doctor Decision Making: The Case of Depression Treatment,” *Econometrica*, 2020, *88* (3), 847–878.

Cutler, D. and E. Glaeser, “When Innovation Goes Wrong: Technological Regress and the Opioid Epidemic,” *Journal of Economic Perspectives*, 2021, *35* (4), 171–196.

— **, J. Skinner, A.D. Stern, and D. Wennberg**, “Physician Beliefs and Patient Preferences: A New Look at Regional Variation in Health Care Spending,” *American Economic Journal: Economic Policy*, 2019, *11* (1), 192–221.

Dasgupta, N. et al., “Crowdsourcing Black Market Prices for Prescription Opioids,” *Journal of Medical Internet Research*, 2013, *15.*

Dickstein, M., “Efficient Provision of Experience Goods: Evidence from Antidepressant Choice,” Working Paper 2021.

Dowell, D., T.M. Haegerich, and R. Chou, “CDC Guidelines for Prescribing Opioids for Chronic Pain—United States, 2016,” *MMWR Recommendations and Reports*, 2016, *65* (1), 1–49.

Drug Enforcement Agency, “2015 National Drug Threat Assessment Summary,” DEA-DCT-DIR-008-16.

— , “2016 National Drug Threat Assessment Summary,” DEA-DCT-DIR-001-17.

Eichmeyer, S. and J. Zhang, “Pathways into Opioid Addiction: Evidence from Practice Variation in Emergency Departments,” *American Economic Journal: Applied Economics*, Forthcoming.

Goldman, B., “The News on the Street: Prescription Drugs on the Black Market,” *Canadian Medical Association Journal*, 1998, *159* (2).

Government Accountability Office, “Medicaid Payment: Comparisons of Selected Services under Fee-for-Service, Managed Care, and Private Insurance,” GAO-14-533 2014.

Gowrisankaran, G., K. Joiner, and P.-T. Leger, “Physician Practice Style and Healthcare Costs: Evidence from Emergency Departments,” NBER Working Paper No. 24155, 2017.

Grennan, M., K. Myers, A. Swanson, and A. Chatterji, "No Free Lunch? Welfare Analysis of Firms Selling Through Expert Intermediaries," NBER Working Paper No. 24864, 2018.

Hedegaard, H., A. Miniño, and M. Warner, "Drug Overdose Deaths in the United States, 1999–2019," NCHS Data Brief No. 394., National Center for Health Statistics 2020.

Kim, B., "Must-Access Prescription Drug Monitoring Programs and The Opioid Overdose Epidemic: The Unintended Consequences," *Journal of Health Economics*, 2021, *75*, 102408.

Kolstad, J. and R. Town, "Behavioral Health Economics and Competition Policy," Working Paper 2022.

Leslie, P. and A. Sorensen, "Resale and Rent-Seeking: An Application to Ticket Markets," *Review of Economic Studies*, 2014, *81*, 266–300.

Mankiw, N.G., *Principles of Microeconomics*, Thomson Southwestern, 2007.

McGuire, T., "Physician Agency," in A. J. Culyer and J. P. Newhouse, eds., *Handbook of Health Economics*, 1 ed., Vol. 1, Elsevier, 2000, chapter 09, pp. 461–536.

Meara, E. et al., "State Legal Restrictions and Prescription-Opioid Use among Disabled Adults," *New England Journal of Medicine*, 2016, *375*, 44–53.

Meinhofer, A., "Prescription Drug Monitoring Programs: The Role of Asymmetric Information on Drug Availability and Abuse," *American Journal of Health Economics*, 2018, *4* (4), 504–526.

National Center for Health Statistics, "NAMCS: 2018 National Summary Tables," 2018.

Paulozzi, L., K. Zhang, C. Jones, and K. Mack, "Risk of Adverse Health Outcomes with Increasing Duration and Regularity of Opioid Therapy," *Journal of the ABFM*, 2014, *27* (3), 329–338.

Rosner, B., J. Neicun, J.C. Yang, and A. Roman-Urrestarazu, "Opioid Prescription Patterns in Germany and the Global Opioid Epidemic: Systematic Review of Available Evidence," *PLoS ONE*, 2019, *14* (8), e0221153.

Schnell, M., "The Opioid Crisis: Tragedy, Treatments and Trade-offs," *SIEPR Policy Brief*, 2018.

_ **and J. Currie**, "Addressing the Opioid Epidemic: Is There a Role for Physician Education?," *American Journal of Health Economics*, 2018, *4*, 383–410.

Schubert, I., P. Ihle, and R. Sabatowski, "Increase in Opiate Prescription in Germany Between 2000 and 2010," *Deutsches Ärtzeblatt International*, 2013, *110* (4), 45–51.

Substance Abuse and Mental Health Services Administration, "Association of Nonmedical Pain Reliever Use and Initiation of Heroin Use in the United States," *CBHSQ Data Review*, 2013.

_ , "Key Substance Use and Mental Health Indicators in the United States: Results from the 2019 National Survey on Drug Use and Health," HHS Publication No. PEP20-07-01-001, NSDUH Series H-55 2020.

Viscusi, W.K. and J. Aldy, "The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World," *Journal of Risk and Uncertainty*, 2003, *27* (1), 5–76.

Online Appendix

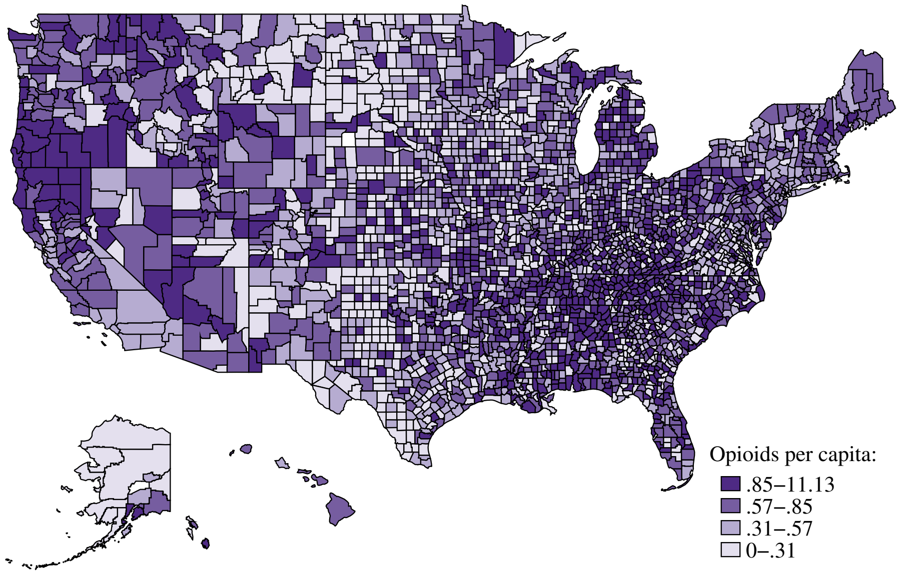
Physician Behavior in the Presence of a Secondary Market: The Case of Prescription Opioids

Schnell (2022)

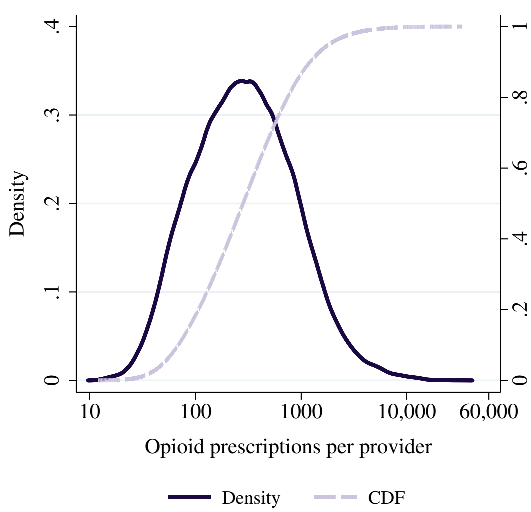
A Supplementary figures

Figure A1: Opioid prescribing: 2014

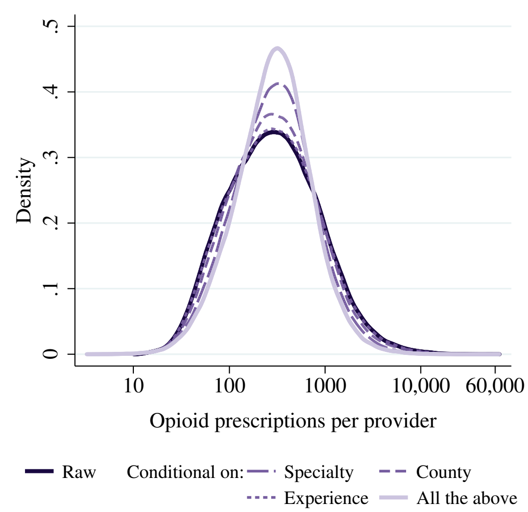
(a) County-level prescription opioids per capita



(b) Raw distribution of physician-level prescribing



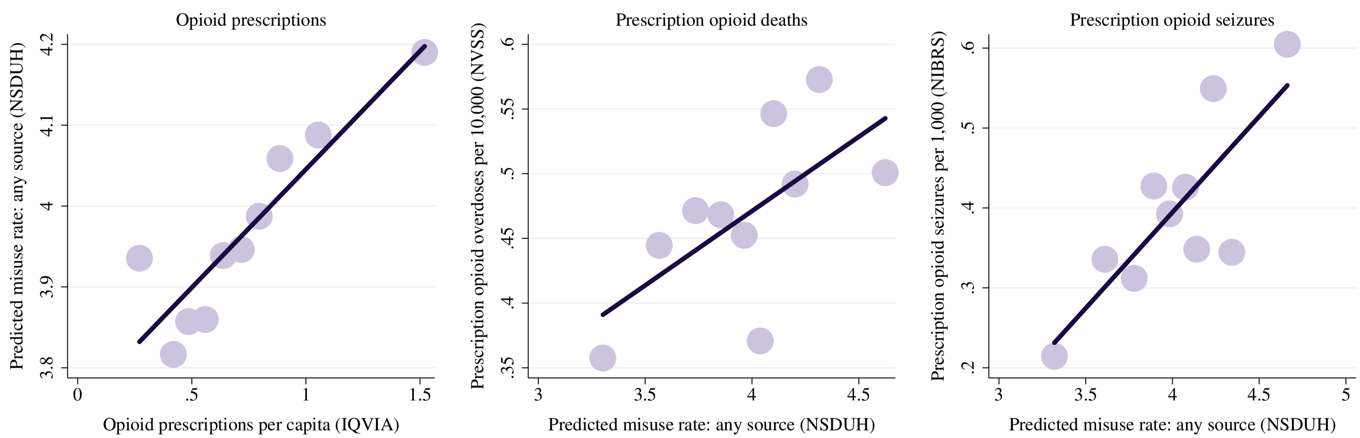
(c) Conditional dist. of physician-level prescribing



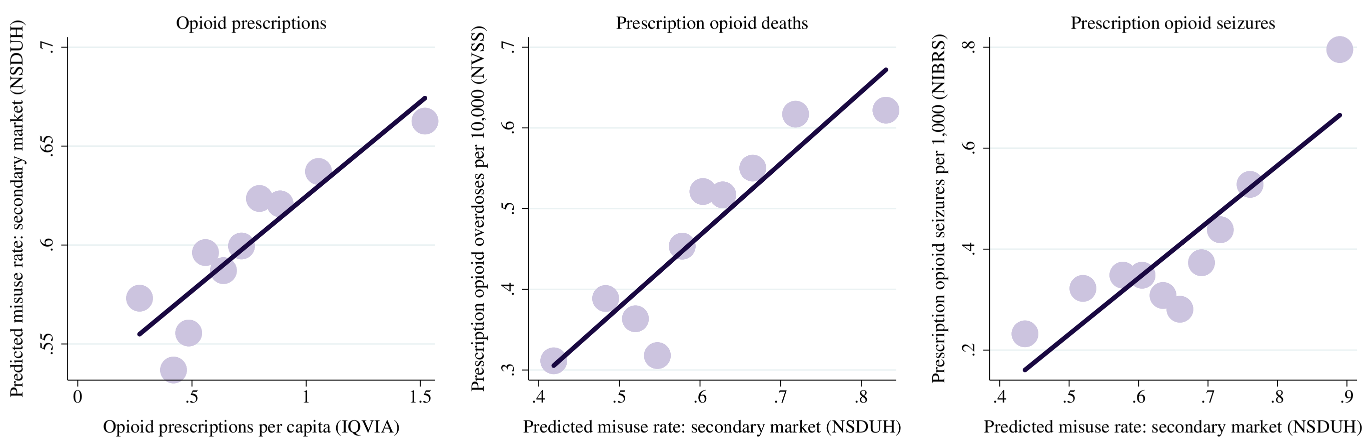
Notes: The above figures show the distribution of opioid prescriptions across counties and providers in 2014. Subfigure (a) displays county-level opioid prescriptions per capita across the United States. Subfigure (b) shows the raw distribution of prescriptions across physicians; subfigure (c) shows this distribution conditional on specialty, county, and experience fixed effects. Subfigures (b) and (c) only consider active physicians with non-missing information on specialty and office practice location that prescribed at least one opioid in each month in 2014 (308,889 providers accounting for 91.9 percent of opioid prescriptions written by physicians, and 71.6 percent of all opioid prescriptions, in 2014). Opioid prescriptions come from IQVIA, intercensal population estimates come from the U.S. Census Bureau, and physician characteristics come from the AMA Master File.

Figure A2: Correlates of county-level prescription opioid misuse: 2014

(a) Misuse from any source



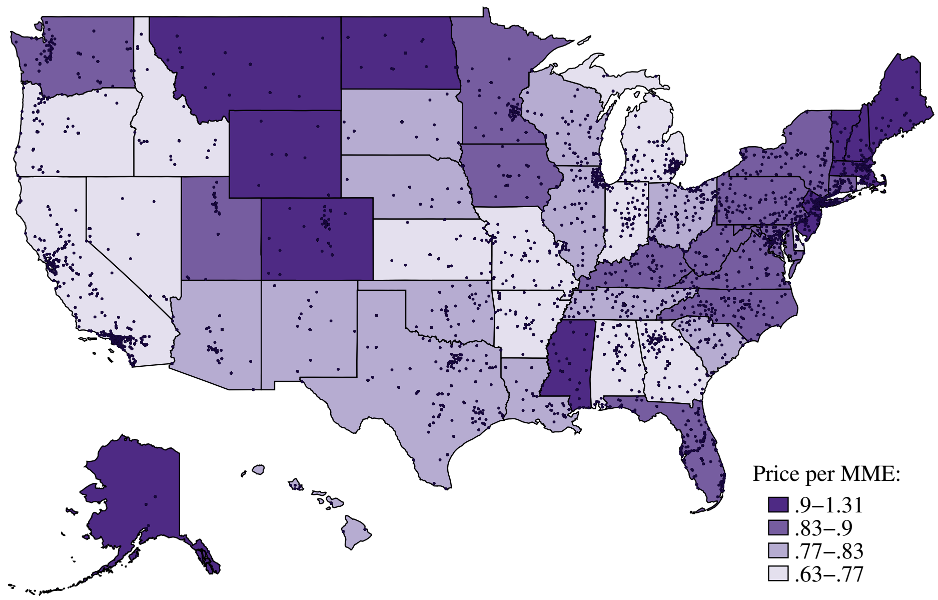
(b) Misuse from the secondary market



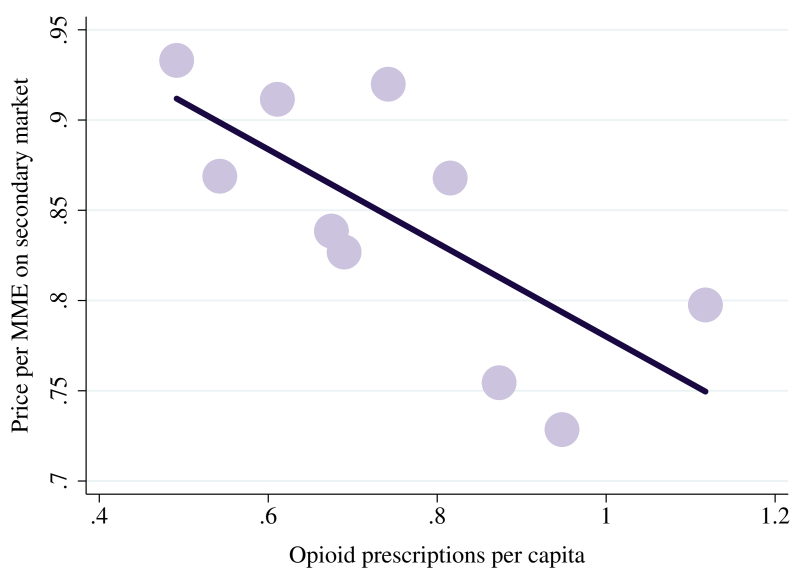
Notes: The above figures show how county-level prescription opioid misuse rates from any source (subfigure (a)) and from the secondary market (subfigure (b)) covary with opioid prescriptions per capita (left panel), fatal overdoses involving prescription opioids per 10,000 (middle panel), and opioid seizures per 1,000 (right panel) in 2014. Counties are grouped into deciles accounting for approximately equal shares of the population based on opioid prescriptions per capita (left panel) and prescription opioid misuse rates (middle and right panels). As described in Section IV.B, county-level measures of prescription opioid misuse are constructed by (1) projecting individual-level reports of prescription opioid misuse from the 2014 NSDUH on a range of socio-demographics and (2) combining these coefficient estimates with information on local socio-demographic compositions from the five-year pooled (2010–2014) ACS. Opioid prescriptions come from IQVIA, intercensal population estimates come from the U.S. Census Bureau, mortality comes from the NVSS, and seizures come from the NIBRS.

Figure A3: Secondary market prices for prescription opioids: 2014

(a) Geographic distribution of quotes and prices



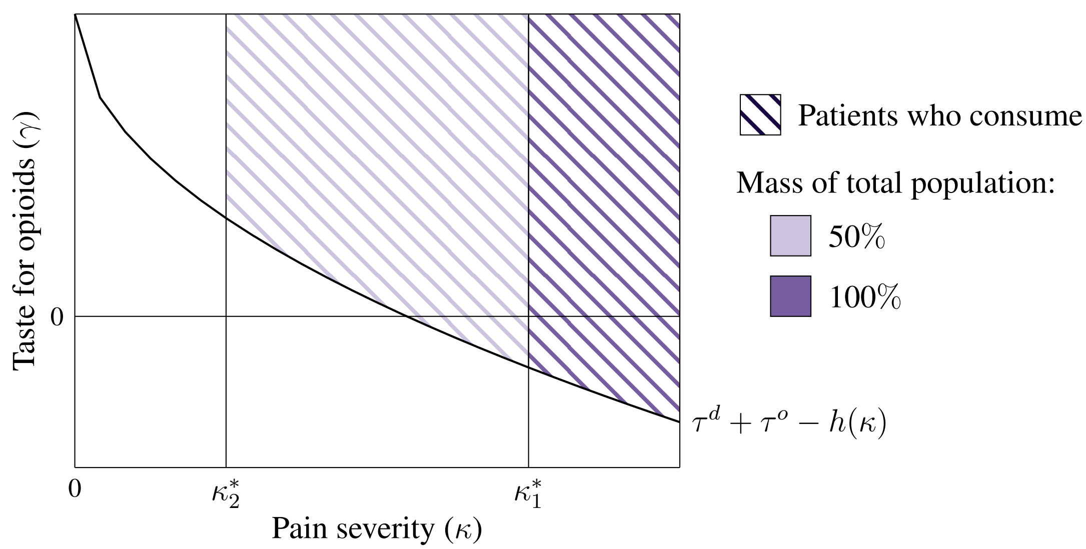
(b) Secondary market prices versus legal prescriptions



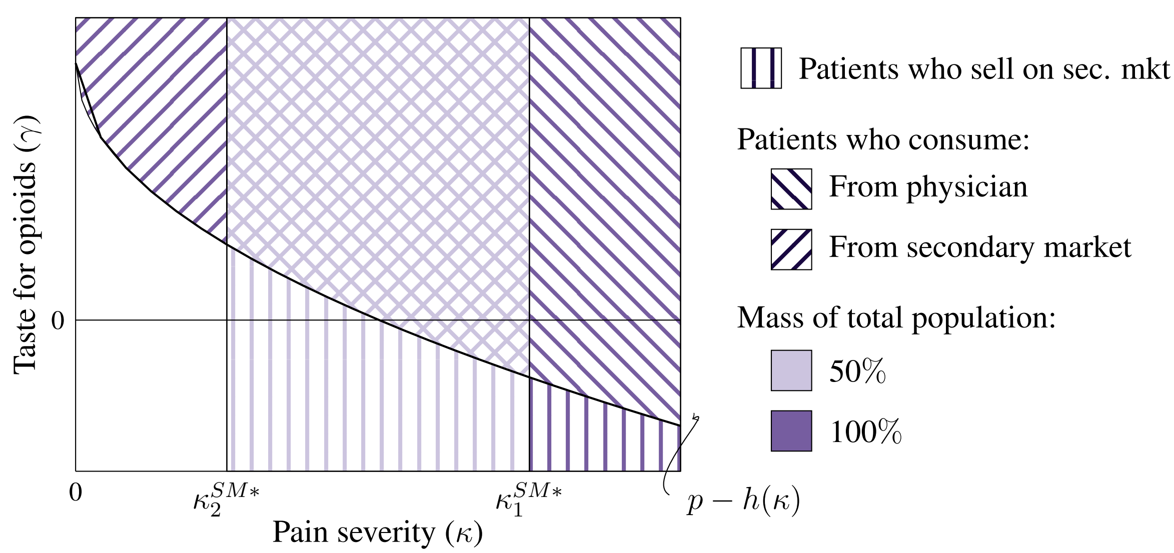
Notes: The above figures show the geographic distribution and correlates of secondary market prices for prescription opioids in 2014. The dots in subfigure (a) depict geocoded locations of individual price quotes; the shading depicts average state-level prices per morphine milligram equivalent (MME). Subfigure (b) shows how average state-level prices per MME on the secondary market covary with opioid prescriptions per capita on the primary market; states are grouped into deciles accounting for approximately equal shares of the population based on opioid prescriptions per capita. Prices of diverted prescription opioids come from StreetRx, opioid prescriptions come from IQVIA, and intercensal population estimates come from the U.S. Census Bureau. When working with the StreetRx data, I only consider price quotes for pill/tablet formulations with dosages reported in milligrams (95.93 percent of total prescription opioid quotes). I further drop quotes for opioid products not included in standard equianalgesic tables (0.12 percent) and those submitted either before or more than one year after the reported quote date (0.44 percent). To reduce noise, I further trim the top and bottom five percent of price quotes.

Figure A4: Equilibrium allocation of opioid prescriptions: market with two physicians

(a) Without a secondary market



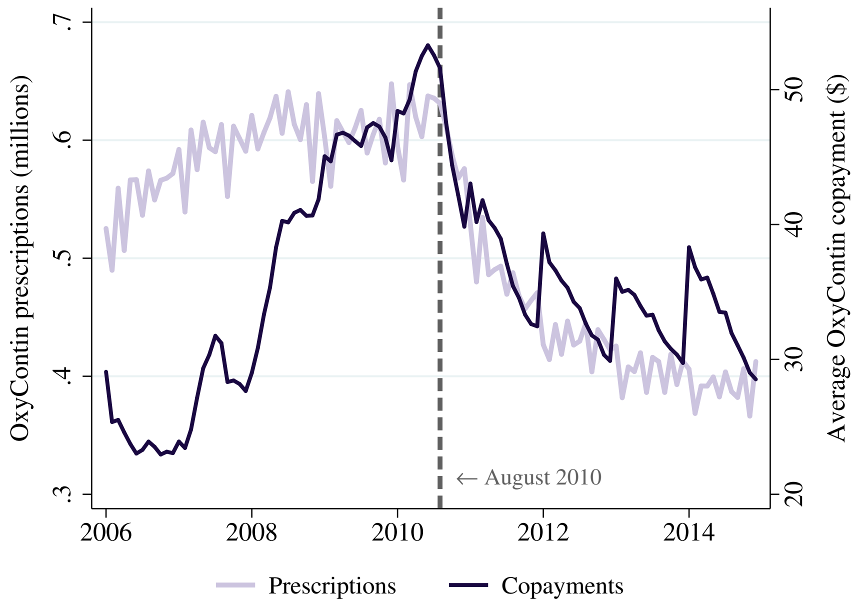
(b) With a secondary market



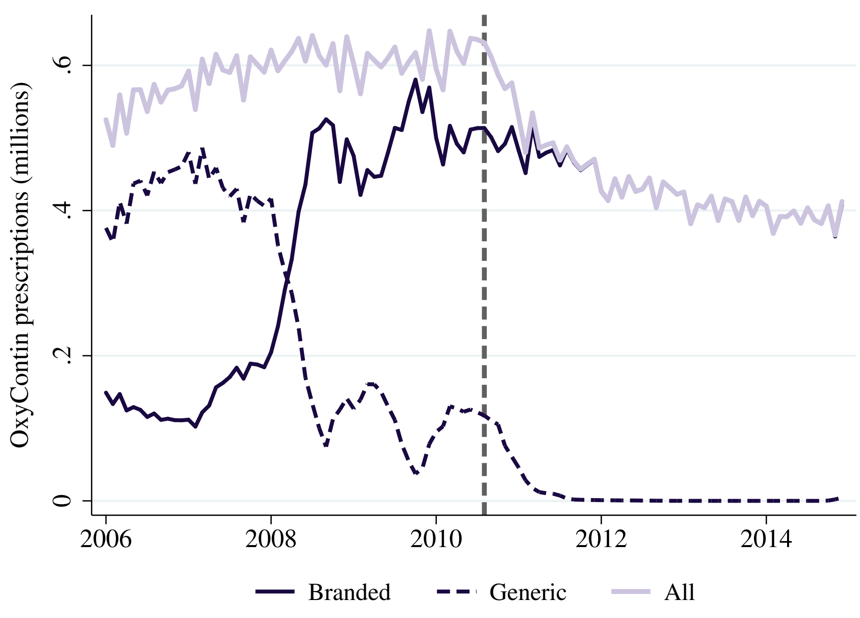
Notes: The above figures depict the equilibrium allocation of prescriptions without a secondary market (subfigure (a)) and with a secondary market (subfigure (b)) in a market with two physicians and no patient search. Patients are randomly assigned to physicians; in a market with two physicians, each physician therefore sees half of the population, with each patient base having distributions of pain and tastes that are equivalent to the market as a whole. In the absence of a secondary market, only patients who can both get a prescription from their assigned physician ($\kappa_i \geq \kappa_j^*$) and find it beneficial to consume ($h(\kappa_i)+\gamma_i \geq \tau^d+\tau^o$) will go to their doctor. In contrast, all patients who can a prescription from their physician ($\kappa_i \geq \kappa_j^*$) will go to the doctor and get a prescription in the presence of a secondary market. Among these patients, those with sufficiently high tastes will consume the medication ($h(\kappa_i) + \gamma_i \geq p$), whereas those for whom the price on the secondary market exceeds their own benefit of consumption ($h(\kappa_i) + \gamma_i < p$) will instead resell to patients who cannot get a prescription from their physician ($\kappa_i < \kappa_j^*$) but have a benefit of consumption that exceeds the secondary market price ($h(\kappa_i) + \gamma_i \geq p$).

Figure A5: Features of OxyContin prescriptions: 2006–2014

(a) OxyContin prescriptions and average copayments

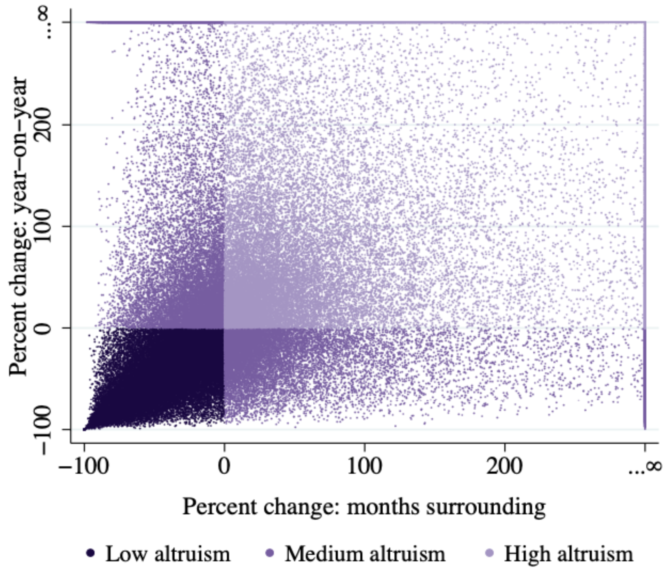


(b) OxyContin prescriptions by type (branded versus generic)



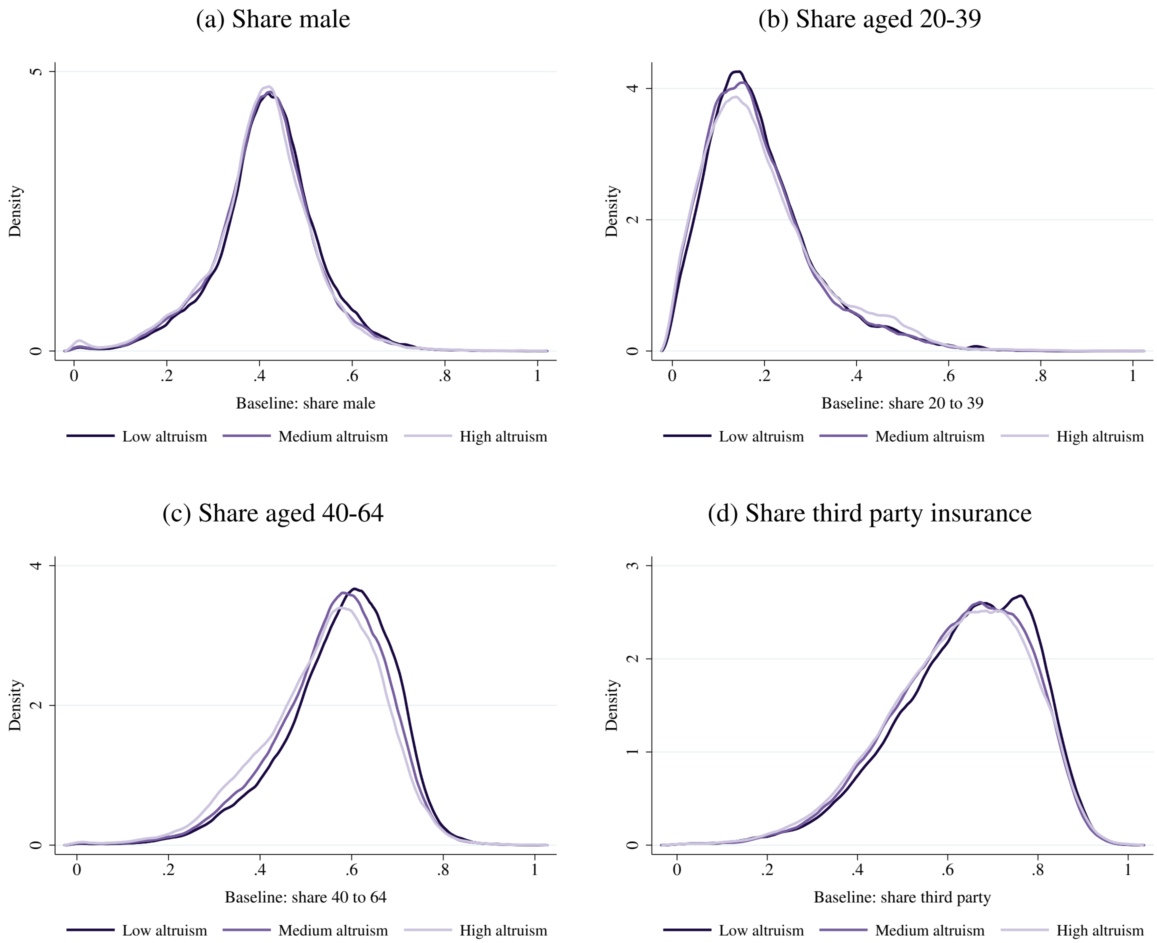
Notes: The above figures show average monthly characteristics of OxyContin prescriptions in the IQVIA data from 2006–2014. Subfigure (a) plots the monthly number of OxyContin prescriptions (light line) and the average copayment for these prescriptions (dark line). Subfigure (b) plots the monthly number of prescriptions for branded OxyContin (solid, dark line), generic OxyContin (dashed, dark line), and OxyContin of either form (solid, light line). The dashed vertical line denotes the month when the reformulated version of OxyContin began shipping (August 2010).

Figure A6: Provider-level changes in OxyContin shares across altruism groups



Notes: The above figure shows the relationship between the two measures of provider-level changes in the share of opioid prescriptions written for OxyContin that are used to categorize providers by their level of altruism in the IQVIA data. These measures reflect percent changes in OxyContin shares in the six months after the reformulation (September 2010–February 2011) versus either the six months before (February 2010–July 2010; x-axis) or the same six months the year prior (September 2009–February 2010; y-axis). Providers with negative percent changes relative to both baseline periods are considered low altruism (dark circles; 34.8 percent), providers with positive percent changes relative to both baseline periods are considered high altruism (light circles; 41.6 percent), and providers with percent changes of differing signs depending on the baseline period being used are considered medium altruism (medium circles; 23.6 percent).

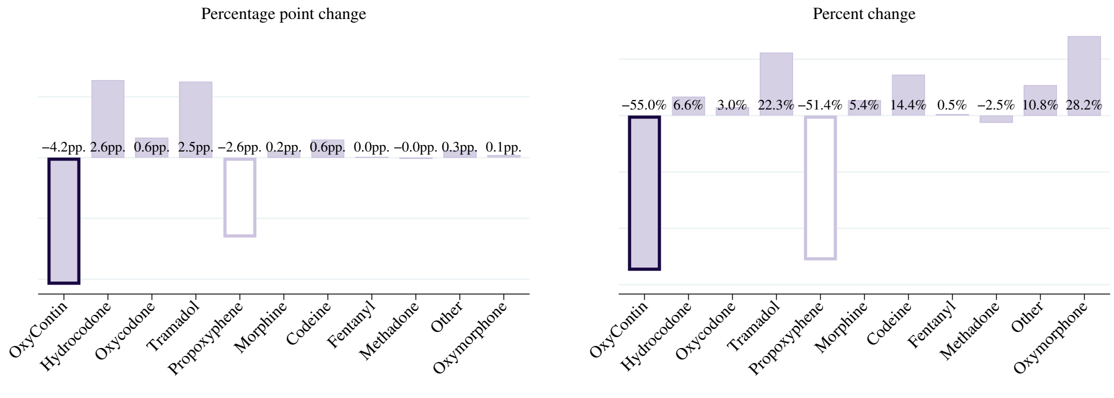
Figure A7: Baseline patient characteristics across altruism groups



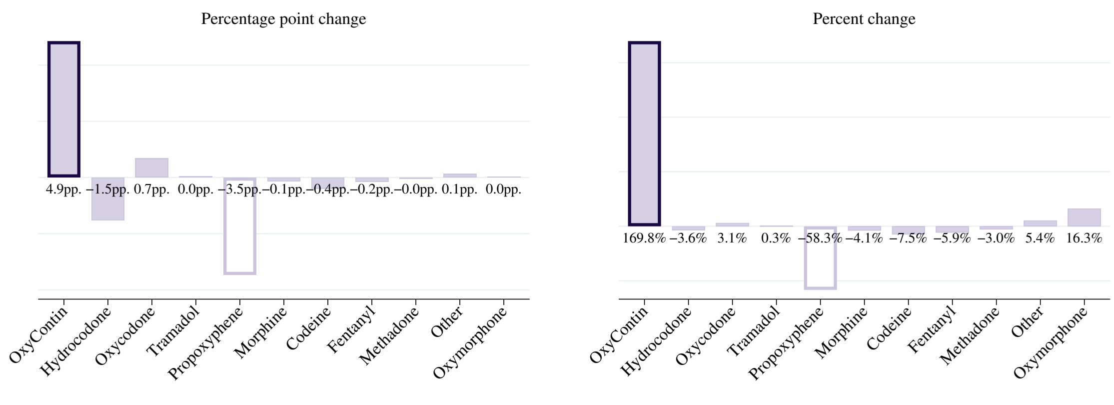
Notes: The above figures show distributions of average patient characteristics of opioid prescriptions across physicians in the IQVIA data in the year preceding the reformulation of OxyContin (July 2009–July 2010). These distributions are shown separately for low-altruism physicians (dark line), medium-altruism physicians (medium line), and high-altruism physicians (light line). Subfigure (a) shows the share male; subfigure (b) shows the share aged 20–39; subfigure (c) shows the share aged 40–59; and subfigure (d) shows the share paying for the prescription with third party insurance.

Figure A8: Prescribing changes in the six months following the OxyContin reformulation

(a) Low altruism



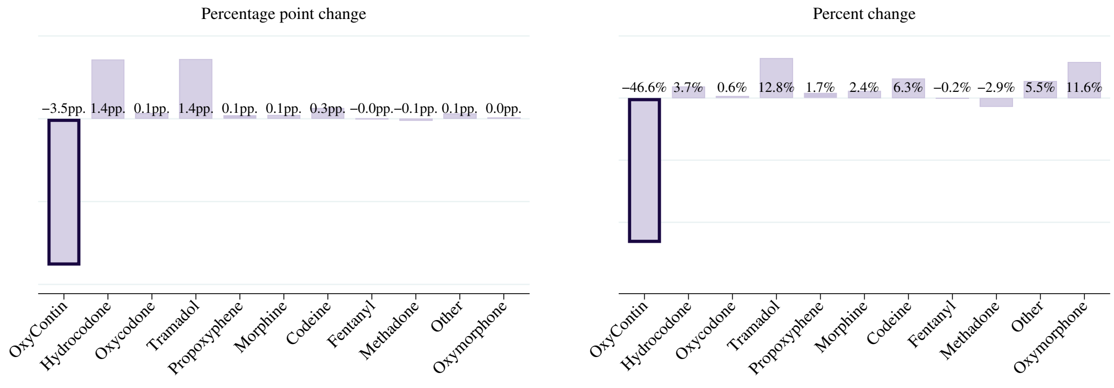
(b) High altruism



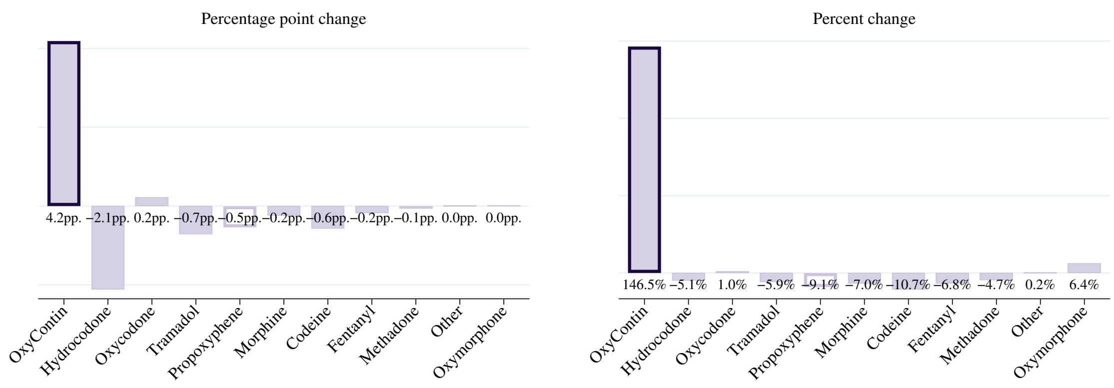
Notes: The above figures show average provider-level changes in opioid prescribing across product categories in the IQVIA data in the six months following the reformulation of OxyContin (September 2010–February 2011) versus the six months before (February 2010–July 2010). The left subplots show the average percentage point change in the share of opioids written for a given product category across low-altruism providers (subfigure (a)) and high-altruism providers (subfigure (b)). The right subplots show the corresponding percent change; since percent changes cannot be calculated for providers with zero shares in the pre-period, percent changes are taken relative to the mean product category share in the pre-period across all providers of a given type. “Oxycodone” shares exclude prescriptions for OxyContin. Product categories excluding OxyContin are ordered according to the total number of scripts written in the pre-period by providers with non-missing altruism measures. OxyContin (bar with dark outline) was reformulated in August 2010; propoxyphene (bar with light outline) was withdrawn from the market in November of the same year.

Figure A9: Prescribing changes in the two months following the OxyContin reformulation

(a) Low altruism



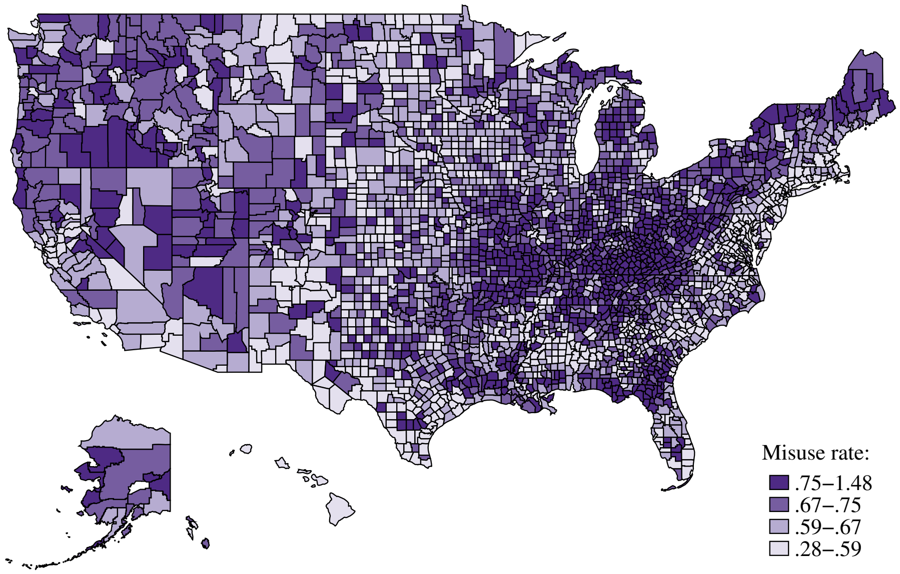
(b) High altruism



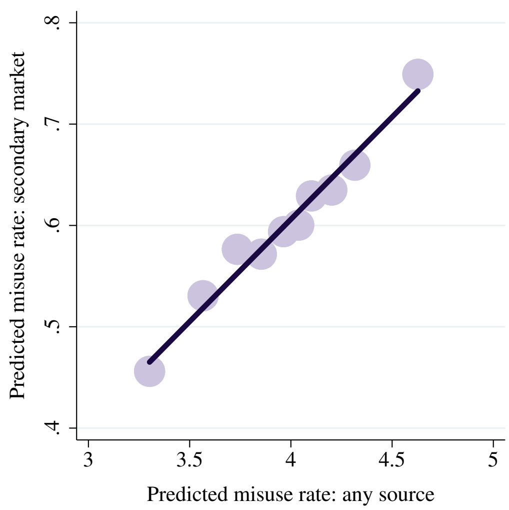
Notes: The above figures show average provider-level changes in opioid prescribing across product categories in the IQVIA data in the two months following the reformulation of OxyContin (September 2010–October 2010) versus the six months before (February 2010–July 2010). The left subplots show the average percentage point change in the share of opioids written for a given product category across low-altruism providers (subfigure (a)) and high-altruism providers (subfigure (b)). The right subplots show the corresponding percent change; since percent changes cannot be calculated for providers with zero shares in the pre-period, percent changes are taken relative to the mean product category share in the pre-period across all providers of a given type. “Oxycodone” shares exclude prescriptions for OxyContin. Product categories excluding OxyContin are ordered according to the total number of scripts written in the pre-period by providers with non-missing altruism measures. OxyContin (bar with dark outline) was reformulated in August 2010. Propoxyphene (bar with light outline) was withdrawn from the market in November 2010; data following the removal of propoxyphene are not included in these figures.

Figure A10: Prescription opioid misuse rates: 2014

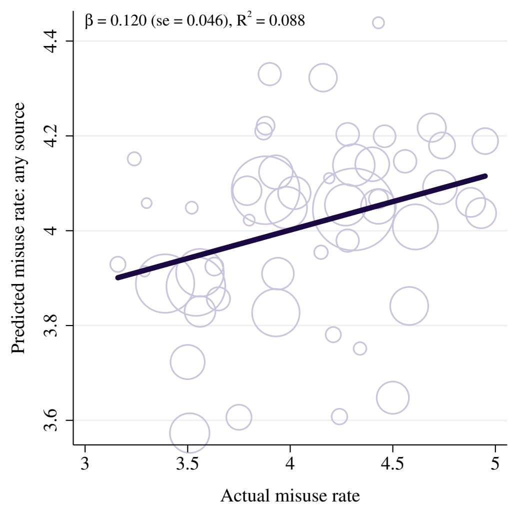
(a) County-level misuse on secondary market



(b) County-level: secondary market versus all



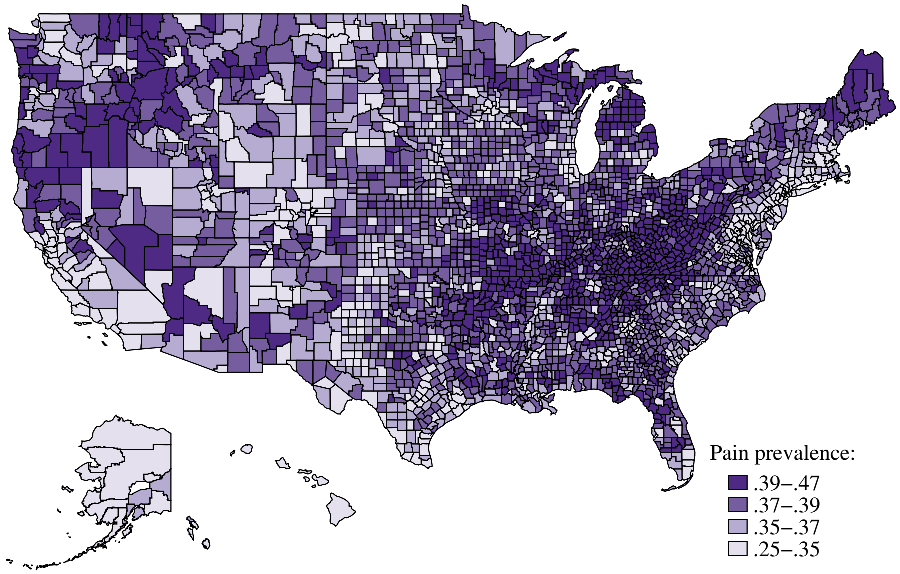
(c) State-level: predicted versus actual misuse



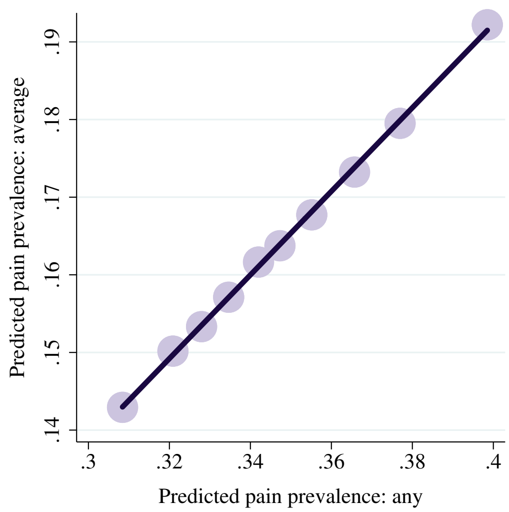
Notes: The above figures show the geographic distribution and correlates of opioid misuse rates in 2014. As described in Section IV.B, geographic measures of prescription opioid misuse are constructed by (1) projecting individual-level reports of prescription opioid misuse from the 2014 NSDUH on a range of socio-demographics and (2) combining these coefficient estimates with information on local socio-demographic compositions from the five-year pooled (2010–2014) ACS. Subfigure (a) displays predicted measures of county-level prescription opioid misuse rates on the secondary market across the United States. Subfigure (b) compares predicted county-level prescription opioid misuse rates from any source and from the secondary market; counties are grouped into deciles accounting for approximately equal shares of the population based on predicted prescription opioid misuse from any source. Subfigure (c) compares actual state-level prescription opioid misuse rates from the two-year pooled (2013–2014) NSDUH with predicted state-level prescription opioid misuse rates over the same years.

Figure A11: Pain prevalence: 2014

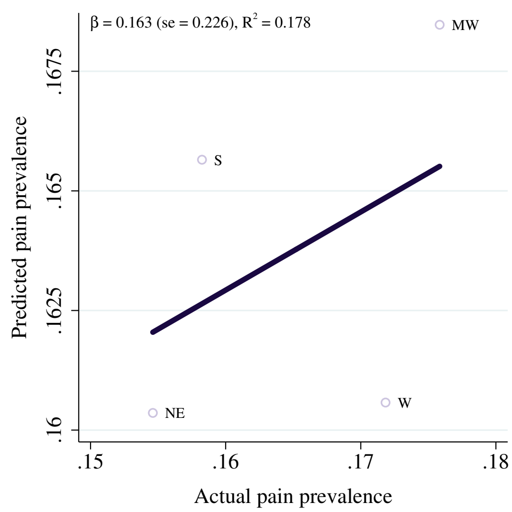
(a) County-level pain prevalence



(b) County-level: average versus any pain



(c) Region-level: predicted versus actual pain



Notes: The above figures show the geographic distribution and correlates of predicted pain prevalence in 2014. As described in Section IV.B, geographic measures of pain prevalence are constructed by (1) projecting individual-level reports of pain from the 2014 NHIS on a range of socio-demographics and (2) combining these coefficient estimates with information on local socio-demographic compositions from the five-year pooled (2010–2014) ACS. Subfigure (a) displays predicted measures of county-level pain prevalence across the United States. Subfigure (b) compares predicted county-level measures of pain prevalence when individual-level pain in the NHIS is measured using either an indicator denoting any reports of pain (pain in the neck, lower back, or face) or the share of the three surveyed body parts affected; counties are grouped into deciles accounting for approximately equal shares of the population based on pain prevalence predicted using an indicator denoting any reports of pain. Subfigure (c) compares actual region-level pain prevalence from the NHIS with predicted region-level pain prevalence.

B Supplementary tables

Table A1: Summary statistics: opioid prescriptions

	All prescribers (1)	Physicians (2)	General practice physicians (3)
a. Prescribers			
Number of providers			
Total	1,479,689	935,431	386,308
Percent of total	100.00	63.22	26.11
Opioid prescribing			
Total (billions)	2.10	1.73	0.91
Percent of total	100.00	82.45	43.48
Average per provider-year	246.11	302.72	358.64
b. Patients			
Sex (%)			
Male	39.09	38.91	38.60
Female	56.02	56.12	57.00
Age (%)			
0–19	3.34	3.02	1.04
20–39	23.10	21.70	17.15
40–64	50.51	50.80	52.02
65+	19.83	21.30	26.48
Payment type (%)			
Cash	11.50	10.98	10.50
Medicaid	7.14	6.86	6.70
Medicare	18.57	19.98	24.89
Private	62.79	62.18	57.92

Notes: The above table presents summary statistics for opioid prescriptions written by all prescribers (first column), all physicians (second column), and physicians in general practice (third column) in the IQVIA data from 2006–2014. The top panel provides information on the number of unique prescribers and their associated opioid prescriptions; the bottom panel provides information on the characteristics of patients receiving those prescriptions. Patient characteristics do not sum to one due to missing information.

Table A2: Association between county-level opioid prescribing and drug overdoses: 2006–2014

Fatal overdoses per 10,000:	Prescription opioids		All opioids		All drugs	
	(1)	(2)	(3)	(4)	(5)	(6)
Opioid prescriptions per capita	0.290***	0.266***	0.317***	0.257***	0.613***	0.433***
	(0.034)	(0.060)	(0.046)	(0.084)	(0.053)	(0.100)
Year FEs	X	X	X	X	X	X
County FEs		X		X		X
Observations	28,260	28,260	28,260	28,260	28,260	28,260
R^2	0.064	0.670	0.070	0.676	0.119	0.687
SD independent variable	0.510	0.510	0.510	0.510	0.510	0.510
Mean dependent variable	0.446	0.446	0.708	0.708	1.281	1.281

Notes: The above table presents output from regressions of county-year drug overdose mortality per 10,000 on county-year opioid prescriptions per capita from 2006–2014. All regressions include year fixed effects; columns (2), (4), and (6) additionally include county fixed effects. The set of deaths included in the dependent variable becomes more expansive as one moves right across the table: prescription opioid overdoses are considered in columns (1) and (2), overdoses from both prescription and non-prescription opioids are considered in columns (3) and (4), and all drug overdose deaths are considered in columns (5) and (6). Standard errors are clustered by county. Mortality data come from the NVSS, opioid prescriptions come from IQVIA, and intercensal population estimates come from the U.S. Census Bureau.

Table A3: Sources of misused prescription opioids in 2014

	All misusers		Frequent misusers	
	Unweighted	Frequency weighted	$\geq$ 1 months	$\geq$ 6 months
	(1)	(2)	(3)	(4)
Primary market				
From one doctor	22.95	28.34	28.36	28.51
From more than one doctor	3.58	3.71	5.30	2.71
Total	26.53	32.05	33.66	31.22
Secondary market				
Bought from friend of relative	10.12	16.45	14.30	23.65
Bought from drug dealer or other stranger	5.08	11.60	9.68	14.73
Total	15.20	28.05	23.98	38.38
Other				
Got from friend or relative for free	48.45	32.14	35.21	23.32
Took from friend of relative without asking	5.18	2.90	3.01	1.53
Stole from office, clinic, hospital, or pharmacy	0.18	0.13	0.09	0.24
Wrote fake prescription	0.12	0.14	0.11	0.18
Got some other way	4.34	4.60	3.95	5.14
Total	58.27	39.90	42.36	30.40
Share of misusers (%)	100.00	100.00	38.17	8.77

Notes: The above table lists sources of misused prescription opioids as reported in the 2014 NSDUH. Columns (1) and (2) consider responses among all individuals who reported using a prescription pain reliever in the past year that was not prescribed to them or only for the experience or feeling it caused ("misuse"). Columns (3) and (4) limit the sample to respondents who reported misusing a prescription pain reliever for more than 30 days or more than 182 days in the previous year, respectively. All responses are weighted by the sample weights provided in the NSDUH; responses in Column (2) are further weighted by the reported days of misuse in the past year.

Table A4: Association between county-level altruism shares and drug overdoses: 2014

Fatal overdoses per 10,000:	Prescription opioids			All drugs		
	(1)	(2)	(3)	(4)	(5)	(6)
a. Months surrounding only						
Share low altruism	0.072	0.151	0.132	0.772**	0.851***	0.820***
	(0.137)	(0.131)	(0.129)	(0.318)	(0.272)	(0.267)
Opioid prescriptions per capita			0.257***			0.430***
			(0.043)			(0.077)
Demographic controls		X	X		X	X
Observations	2,812	2,812	2,812	2,812	2,812	2,812
R^2	0.000	0.039	0.088	0.003	0.101	0.137
SD share low altruism	0.222	0.222	0.222	0.222	0.222	0.222
SD opioids per capita	0.498	0.498	0.498	0.498	0.498	0.498
Mean dependent variable	0.498	0.498	0.498	1.586	1.586	1.586
b. Year-on-year only						
Share low altruism	0.478***	0.495***	0.454***	1.163***	1.104***	1.035***
	(0.136)	(0.133)	(0.131)	(0.277)	(0.244)	(0.245)
Opioid prescriptions per capita			0.252***			0.422***
			(0.044)			(0.078)
Demographic controls		X	X		X	X
Observations	2,818	2,818	2,818	2,818	2,818	2,818
R^2	0.005	0.044	0.091	0.009	0.103	0.138
SD share low altruism	0.228	0.228	0.228	0.228	0.228	0.228
SD opioids per capita	0.498	0.498	0.498	0.498	0.498	0.498
Mean dependent variable	0.499	0.499	0.499	1.588	1.588	1.588

Notes: The above table presents output from county-level regressions of drug overdose mortality per 10,000 in 2014 on the share of providers categorized as low altruism. The share of categorized providers that are high altruism is the omitted category. Fatal overdoses involving prescription opioids are considered in columns (1)–(3), and all drug overdose deaths are considered in columns (4)–(6). Columns (2), (3), (5), and (6) control for county-level demographics including total population, population density, and the age, gender, and race profile; columns (3) and (6) additionally control for the number of opioid prescriptions per capita in 2014. The share of low-altruism providers is defined relative to the total number of categorized providers in a given county. The top panel only considers the sign of provider-level changes in OxyContin shares in the six months after the reformulation (September 2010–February 2011) versus the six months before (February 2010–July 2010) when categorizing providers, whereas the bottom panel only considers the sign of provider-level changes in OxyContin shares in the six months after the reformulation (September 2010–February 2011) versus the same six months the year prior (September 2009–February 2010). Results using the main categorization of providers that leverages provider-level prescribing changes relative to both baseline periods are provided in Table 2. Observations are weighted by the number of categorized providers, and standard errors are robust. Mortality data come from the NVSS, opioid prescriptions come from IQVIA, intercensal population estimates come from the U.S. Census Bureau, and demographic controls come from the 2010–2014 five-year pooled ACS.

Table A5: Projection of misuse and pain on individual socio-demographics

	Misuse		Pain	
	Overall (1)	Secondary market (2)	Any (3)	Average (4)
Sex				
Male	0.048***	0.062***	-0.077***	-0.103***
	(0.010)	(0.010)	(0.011)	(0.011)
Age				
25–34	-0.004	-0.010	0.182***	0.179***
	(0.017)	(0.019)	(0.021)	(0.021)
35–49	-0.093***	-0.060***	0.299***	0.309***
	(0.017)	(0.017)	(0.022)	(0.022)
50–64	-0.128***	-0.089***	0.322***	0.335***
	(0.018)	(0.017)	(0.022)	(0.022)
65+	-0.227***	-0.111***	0.158***	0.080***
	(0.019)	(0.018)	(0.025)	(0.024)
Race/ ethnicity				
White	0.066***	0.075***	0.174***	0.159***
	(0.017)	(0.015)	(0.019)	(0.019)
Black	-0.008	-0.042**	0.023	-0.006
	(0.021)	(0.017)	(0.024)	(0.023)
Hispanic	-0.037*	-0.029	0.018	0.025
	(0.020)	(0.018)	(0.023)	(0.023)
Education				
High school	-0.121***	-0.052**	-0.062***	-0.076***
	(0.019)	(0.020)	(0.018)	(0.019)
Some college	-0.099***	-0.058***	-0.038**	-0.032*
	(0.020)	(0.021)	(0.018)	(0.019)
College+	-0.163***	-0.116***	-0.163***	-0.158***
	(0.019)	(0.019)	(0.020)	(0.020)
Income				
50–74k	-0.017	-0.017	-0.100***	-0.114***
	(0.014)	(0.014)	(0.016)	(0.016)
75k+	-0.034***	-0.017	-0.148***	-0.172***
	(0.013)	(0.013)	(0.015)	(0.015)
Employment				
Employed	0.007	0.013	-0.211***	-0.262***
	(0.013)	(0.012)	(0.014)	(0.015)
Unemployed	0.098***	0.057*	-0.067***	-0.108***
	(0.028)	(0.030)	(0.024)	(0.024)
Marital status				
Married	-0.122***	-0.075***	0.014	0.010
	(0.014)	(0.014)	(0.015)	(0.015)
Divorced	-0.046**	-0.049***	0.067***	0.070***
	(0.018)	(0.018)	(0.017)	(0.017)
Health insurance				
Insured	-0.050***	-0.041**	0.066***	0.070***
	(0.017)	(0.019)	(0.017)	(0.017)
Observations	41,671	41,671	32,900	32,900
R^2	0.019	0.009	0.040	0.047
Full model: adjusted R^2	0.067	0.02	0.396	0.352

Notes: The above table presents output from regressions of individual-level prescription opioid misuse (columns (1) and (2)) and pain (columns (3) and (4)) on individual socio-demographics. The dependent variables are standardized for ease of comparison across columns. Data in columns (1) and (2) come from the 2014 NSDUH; data in columns (3) and (4) come from the 2014 NHIS. The dependent variable in column (1) is an indicator denoting whether a respondent reported using a prescription pain reliever in the past year that was not prescribed to them or only for the experience or feeling it caused ("misuse"); the dependent variable in column (2) is an indicator denoting whether a respondent reported purchasing the last prescription pain reliever that they misused from a friend, relative, drug dealer, or other stranger. The dependent variable in column (3) is an indicator denoting whether a respondent reported having pain lasting more than one day in the past three months in either the neck, lower back, or face; the dependent variable in column (4) is an individual-level average of indicators denoting lasting pain in the neck, lower back, and face. The final row reports the adjusted R-squared's from the full regression specifications used for prediction; these regressions include the full set of independent variables listed in Tables A6 and A7.

Table A6: Socio-demographic categories used to predict county-level prescription opioid misuse

	Sex	Age		Race	Other	
	(1)	(2)		(3)	(4)	
{sex, age}	Male Female	12–14 15–17 18–19 20–25 26–29	30–34 35–49 50–64 65+			
{race, income}				White Black Hispanic Other	0–10k 10–19k 20–29k 30–39k	40–49k 50–74k 75k+
{sex, age, race}	Male Female	12–17 18–25 26–34	35–64 65+	White Black Hispanic Other		
{sex, age, education}	Male Female	18–25 26–34 35–64 65+			Less than high school High school graduate Some college College+	
{sex, age, employment}	Male Female	16–19 20–25 26–34	35–64 65+		Employed Unemployed Not in labor force	
{sex, age, marital}	Male Female	15–17 18–25 26–34	35–49 50–64 65+		Married Never married Other	
{sex, age, health insurance}	Male Female	12–17 18–25 26–34	35–64 65+		Insured Not insured	
{sex, age, race, poverty}	Male Female	12–17 18–25 26–34	35–64 65+	White Black Hispanic Other	Below poverty line Above poverty line	

Notes: The above table outlines the socio-demographics used to predict prescription opioid misuse at the county-level in 2014. In particular, individual-level reports of prescription opioid misuse in the 2014 NSDUH are projected on all pairwise interactions between {sex, age} and {race/ ethnicity, income}; all three-way interactions between {sex, age, race/ ethnicity}, {sex, age, educational attainment}, {sex, age, employment status}, {sex, age, martial status}, and {sex, age, health insurance status}; and all four-way interactions between {sex, age, race/ ethnicity, poverty status}. The estimated coefficients from this regression are then used to predict prescription opioid use at the county-level using population shares from the 2010–2014 five-year pooled ACS. Age and income are included in the smallest bins common to the ACS and the NSDUH, and the combinations between variables were chosen to exhaust all cross-tabs available in the ACS.

Table A7: Socio-demographics used to predict county-level pain prevalence

	Sex	Age		Race	Other	
	(1)	(2)		(3)	(4)	
{sex, age}	Male Female	18–19 20 21 22–24 25–29 30–34 35–39 40–44 45–49 50–54	55–59 60–61 62–64 65–6 67–69 70–74 75–79 80–84 85+			
{race, income}				White Black Hispanic Other	0–34k 35–49k 50–74k	75–99k 100k+
{sex, age, race}	Male Female	18–19 20–24 25–29 30–34 35–44	45–54 55–64 65–74 75–84 85+	White Black Hispanic Other		
{sex, age, education}	Male Female	18–24 25–34 35–44	45–64 65+		Less than high school High school graduate Some college College+	
{sex, age, employment}	Male Female	18–19 20–21 22–24 25–29 30–34 35–44 45–54	55–59 60–61 62–64 65–69 70–74 75+		Employed Unemployed Not in labor force	
{sex, age, marital}	Male Female	18–19 20–24 25–29 30–34 35–39 40–44 45–49	50–54 55–59 60–64 65–74 75–84 85+		Married Never married Other	
{sex, age, health insurance}	Male Female	18–24 25–34 35–44 45–54	55–64 65–74 75+		Insured Not insured	
{sex, age, race, poverty}	Male Female	18–24 25–34 35–44 45–54	55–64 65–74 75+	White Black Hispanic Other	Below poverty line Above poverty line	

Notes: The above table outlines the socio-demographics used to predict pain prevalence at the county-level in 2014. In particular, individual-level reports of pain in the 2014 NHIS are projected on all pairwise interactions between {sex, age} and {race/ ethnicity, income}; all three-way interactions between {sex, age, race/ ethnicity}, {sex, age, educational attainment}, {sex, age, employment status}, {sex, age, martial status}, and {sex, age, health insurance status}; and all four-way interactions between {sex, age, race/ ethnicity, poverty status}. The estimated coefficients from this regression are then used to predict pain prevalence at the county-level using population shares from the 2010–2014 five-year pooled ACS. Age and income are included in the smallest bins common to the ACS and the NHIS, and the combinations between variables were chosen to exhaust all cross-tabs available in the ACS.

C Equilibrium model with patient search

As introduced in Section III.A, the model can be extended to allow for patient search. Incorporating patient search endogenizes both the number and the types of patients seen by each physician.

Recall that each patient begins randomly assigned to a physician. If the patient cannot get a prescription from her randomly assigned provider, she will choose to search (with replacement) for a new provider if the expected benefit of search exceeds the expected cost. The cost of sampling a new physician always includes a search cost (τ^s) and the cost of visiting the provider (τ^d), but the patient only needs to pay the cost of filling a prescription (τ^o) if she is able to get a prescription from the provider. The expected benefit of search, on the other hand, depends on whether a secondary market for prescription opioids exists. Optimal patient and physician behavior with patient search, both when a secondary market does and does not exist, are considered below.

C.1 Without a secondary market

Set-up When a secondary market for prescription opioids does not exist, the expected marginal benefit of search is given by

$$\underbrace{\frac{1}{J}\sum_{j\in J}\mathbb{1}\{\kappa_j^* \leq \kappa_i\}}_{\equiv P(\kappa_i)} \cdot [h(\kappa_i) + \gamma_i] \tag{A1}$$

where $P(\kappa_i)$ is the probability that a patient with pain severity κ_i can get a prescription from a physician in her geographic market in equilibrium. Since the patient must pay the search cost and the office visit fee in order to sample a physician, but only has to pay the cost of an opioid prescription if the physician prescribes to her, the expected marginal cost of search is given by

$$\tau^s + \tau^d + P(\kappa_i) \cdot \tau^o \tag{A2}$$

A patient will continue searching if her current physician will not prescribe to her and the expected marginal benefit of search exceeds the expected marginal cost (i.e., if (A1) $\geq$ (A2)).[40] Rearranging and letting

$$T(\kappa_i) \equiv \frac{\tau^s + \tau^d}{P(\kappa_i)} + \tau^o - h(\kappa_i) \tag{A3}$$

it follows that patients with $\gamma_i \geq T(\kappa_i)$ will search until they find a physician who will prescribe to

[40] If a patient has found a doctor from whom she can get a prescription, the marginal benefit of search is less than or equal to zero since the benefit of receiving a prescription does not vary for a given patient across doctors, and there is a chance that she will not be able to get a prescription from her newly assigned physician.

them while patients with $\gamma_i < T(\kappa_i)$ will keep their initial physician assignment (whether they can get an opioid prescription from the physician or not).

Market shares We can use optimal search behavior to determine the market share of each physician in equilibrium. For ease of notation, label physicians within a geographic market by descending thresholds, i.e. $\kappa_1^* > \kappa_2^* > \ldots > \kappa_J^*$. The market share of physician 1 is then the patients who are randomly assigned to physician 1 initially and either can get a prescription from physician 1 or cannot get a prescription from physician 1 but do not find it optimal to search. The equilibrium market share of physician 1 is therefore given by

$$q_1^* = \frac{1}{J} \cdot \left[\int_{\kappa_1^*}^{\infty} dF(k) + \int_0^{\kappa_1^*} \int_{-\infty}^{T(k)} dG(\gamma) dF(k) \right]$$

Now consider the market share of the physician with the second-highest threshold, physician 2. As with physician 1, any patient who is randomly assigned to physician 2 initially and can get a prescription from physician 2 will stay. Furthermore, any patient who is initially assigned to physician 2, cannot get a prescription, but does not find it optimal to search will also stay with physician 2. In contrast to physician 1, however, physician 2 will also get the patients who are initially assigned to physician 1, cannot get a prescription, and keep searching physician 1 until they find physician 2 and can get a prescription.[41] The market share of physician 2 is therefore given by

$$\begin{aligned} q_2^* = \frac{1}{J} \cdot \left[\int_{\kappa_2^*}^{\infty} dF(k) + \int_0^{\kappa_2^*} \int_{-\infty}^{T(k)} dG(\gamma) dF(k) \right] \\ + \frac{1}{J\,(J-1)} \cdot \int_{\kappa_2^*}^{\kappa_1^*} \int_{T(k)}^{\infty} dG(\gamma) dF(k) \end{aligned}$$

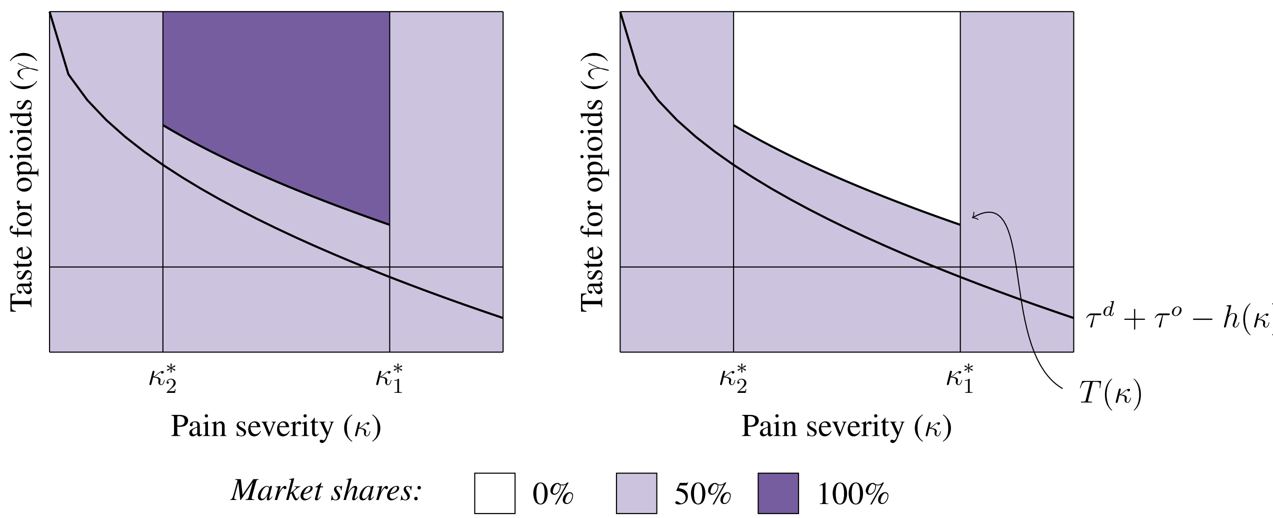
Continuing in this way, the market share of physician j is given by

$$\begin{aligned} q_j^* = \frac{1}{J} \cdot \left[\int_{\kappa_j^*}^{\infty} dF(k) + \int_0^{\kappa_j^*} \int_{-\infty}^{T(k)} dG(\gamma) dF(k) \right] \\ + \sum_{n=1}^{j-1} \left[\frac{1}{(J-n+1)\,(J-n)} \cdot \int_{\kappa_j^*}^{\kappa_n^*} \int_{T(k)}^{\infty} dG(\gamma) dF(k) \right] \end{aligned} \tag{A4}$$

These market shares are shown in Figure A12 for a market with two physicians.

[41] The probability that a search sequence only yields physician 1 until physician 2 is given by $\frac{1}{J^2} + \frac{1}{J^3} + \frac{1}{J^4} + \ldots = \sum_{n=2}^{\infty} \frac{1}{J^n} = \frac{1}{J(J-1)}$.

Figure A12: Equilibrium market shares: without secondary market and with patient search



Notes: The above figure depicts the patient market shares in a market with two physicians, patient search, and the absence of a secondary market. Without patient search, each physician would see half of all patients throughout the pain and taste distributions. With patient search, the physician who is more lenient in her prescribing instead sees more patients in equilibrium. While the physician with the higher threshold (physician 1) sees half of all patients who can either get a prescription from her ($\kappa_i \geq \kappa_1^*$) or do not find it beneficial to search ($\gamma_i < T(\kappa_i)$), physician 1 sees no patients who can get a prescription from physician 2 but not from her ($\kappa_2^* \leq \kappa_i < \kappa_1^*$) and find it beneficial to search ($\gamma_i \geq T(\kappa_i)$). Rather, these patients keep searching until they find physician 2, so physician 2 sees all of these patients in equilibrium. As defined in equation (A3), $T(\kappa) \equiv \frac{\tau^s+\tau^d}{P(\kappa)} + \tau^o - h(\kappa)$.

Physician optimality With patient search and without a secondary market, physician j chooses her threshold severity to solve the following problem:

$$\begin{aligned}\max_{\kappa_j}\ & \beta_j \cdot \frac{I}{J} \cdot \left[\int_{\kappa_j}^{\infty} \int_{\tau^d+\tau^o-h(k)}^{\infty} h(k) dG(\gamma) dF(k)\right] \\ & + \beta_j \cdot \sum_{n=1}^{j-1} \left[\frac{I}{(J-n+1)(J-n)} \cdot \int_{\kappa_j}^{\kappa_n^*} \int_{T(k)}^{\infty} h(k) dG(\gamma) dF(k)\right] \\ & + R_j \cdot \frac{I}{J} \cdot \left[\int_{\kappa_j}^{\infty} \int_{\tau^d+\tau^o-h(k)}^{\infty} dG(\gamma) dF(k)\right] \\ & + R_j \cdot \sum_{n=1}^{j-1} \left[\frac{I}{(J-n+1)(J-n)} \cdot \int_{\kappa_j}^{\kappa_n^*} \int_{T(k)}^{\infty} dG(\gamma) dF(k)\right]\end{aligned} \tag{A5}$$

where the first two terms represent the health impact that the physician has on her patients and the last two terms represent her revenue from office visits.

Assume that physicians take the optimal thresholds of other physicians in their market as given.

Further assume that physicians do not internalize their effect on the probability that a given patient can get a prescription in her geographic market; this will be approximately true in markets with many physicians, as each provider will have a negligible impact on the patient's probability of getting a prescription from a randomly chosen provider. Taking the derivative of equation (A5) with respect to κ_j and setting equal to zero yields the physician's optimal threshold:

Result 1': *In the absence of a secondary market but with patient search, the optimal threshold of physician j $\left(\kappa_j^*\right)$ satisfies*

$$-\beta_j \cdot h(\kappa_j^*) = R_j \tag{A6}$$

As in Result 1, the uniqueness of this threshold is guaranteed by the strict monotonicity of the health impact function. Without a secondary market but with patient search, an equilibrium in a given geographic market is characterized by a set of thresholds $\{\kappa_j^*\}$ such that physicians maximize their utility (i.e., equation (A6) holds $\forall\ j \in J$).

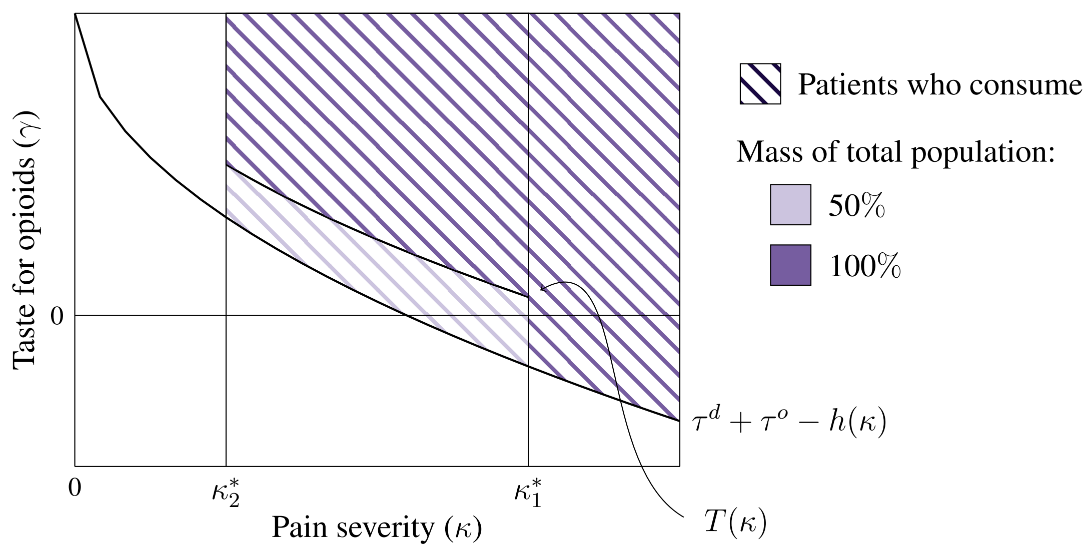
Comparing equations (2) and (A6), we see that the optimal threshold set by the physician is the same regardless of whether patients are allowed to search across providers. The equilibrium quantity of prescriptions, however, is weakly higher because patient search allows patients who want to consume prescription opioids to sort towards more lenient prescribers and in turn access prescriptions on the primary market. The equilibrium allocation of opioid prescriptions with search and without a secondary market is shown in Figure A13 for a market with two physicians.

C.2 With a secondary market

Set-up When a secondary market for prescription opioids exists, the expected marginal cost of search remains as before (equation (A2)). However, since patients can search over physicians to obtain opioid prescriptions not just to consume but also to resell, the expected benefit of search increases for some patients. More precisely, for patients who prefer to resell prescriptions given the secondary market price $(p > h(\kappa_i) + \gamma_i)$, the expected benefit of search is now given by $P(\kappa_i) \cdot p$, where $P(\kappa_i)$ is defined as in equation (A1). A patient with $h(\kappa_i) + \gamma_i < p$ will therefore search if her current physician will not prescribe to her and $P(\kappa_i) \cdot p \geq \tau^s + \tau^s + P(\kappa_i) \cdot \tau^o \;\Rightarrow\; \kappa_i \geq P^{-1}\left(\frac{\tau^s + \tau^d}{p - \tau^o}\right)$.

For patients who would prefer to consume the medication rather than to resell $(h(\kappa_i) + \gamma_i \geq p)$, the expected benefit of search remains as in the case without a secondary market (equation (A1)). However, since these patients can now access the medication by turning to the secondary market rather than searching over physicians, a patient who prefers to consume the medication will only search if her utility from searching to consume $\left(h(\kappa_i) + \gamma_i - \left[\tau_o + \frac{\tau^s + \tau^d}{P(\kappa_i)}\right]\right)$ exceeds her utility

Figure A13: Equilibrium allocation: without secondary market and with patient search



Notes: The above figure displays the equilibrium allocation of opioid prescriptions in a market with two physicians, patient search, and the absence of a secondary market. All patients with pain above the most stringent physician's threshold who find it beneficial to consume prescription opioids will do so since they can get a prescription from whichever physician they are originally assigned. Moreover, patients who are initially assigned to a physician from whom they cannot get a prescription but find it beneficial to search will access and consume prescription opioids in equilibrium. In a market with two physicians, all of the patients who cannot get a prescription from physician 1 ($\kappa_i < \kappa_1^*$) but who find it beneficial to search ($\gamma_i \geq T(\kappa_i)$) will access prescription opioids on the primary market from physician 2 in equilibrium. As defined in equation (A3), $T(\kappa) \equiv \frac{\tau^s+\tau^d}{P(\kappa)} + \tau^o - h(\kappa)$.

from turning to the secondary market to buy the medication $(h(\kappa_i) + \gamma_i - p)$. That is, a patient with $h(\kappa_i) + \gamma_i \geq p$ will search if her current physician will not prescribe to her and $h(\kappa_i) + \gamma_i - \left[\tau_o + \frac{\tau^s+\tau^d}{P(\kappa_i)}\right] \geq h(\kappa_i) + \gamma_i - p \;\Rightarrow\; \kappa_i \geq P^{-1}\left(\frac{\tau^s+\tau^d}{p-\tau^o}\right)$.

Since both patients with $h(\kappa_i) + \gamma_i < p$ (patients preferring to resell) and $h(\kappa_i) + \gamma_i \geq p$ (patients preferring to consume) search if $\kappa_i \geq P^{-1}\left(\frac{\tau^s+\tau^d}{p-\tau^o}\right)$, it follows that all patients with $\kappa_i \geq P^{-1}\left(\frac{\tau^s+\tau^d}{p-\tau^o}\right)$ search in the presence of a secondary market. For ease of notation, let

$$\tilde{P} \equiv P^{-1}\left(\frac{\tau^s + \tau^d}{p - \tau^o}\right) \tag{A7}$$

Market shares Again label physicians within a geographic market by descending thresholds, i.e. $\kappa_1^{SM*} > \kappa_2^{SM*} > \ldots > \kappa_J^{SM*}$. As is the case without a secondary market, the patients of physician 1 in equilibrium are the patients who are randomly assigned to physician 1 initially and either can get a prescription from physician 1 or do not find it optimal to search. Since all patients with $\kappa_i \geq \tilde{P}$ search in the presence of a secondary market, the market share of physician 1 depends on whether

$\kappa_1^{SM*} < \tilde{P}$ or $\kappa_1^{SM*} \geq \tilde{P}$. The market share of physician 1 can therefore be summarized as follows:

$$q_1^* = \begin{cases} \frac{1}{J} & \text{if } \kappa_1^{SM*} < \tilde{P} \\ \frac{1}{J} \cdot \left[\int_{\kappa_1^{SM*}}^{\infty} dF(k) + \int_0^{\tilde{P}} dF(k) \right] & \text{if } \kappa_1^{SM*} \geq \tilde{P} \end{cases}$$

Continuing in this way, we can likewise derive the equilibrium market share of physician j. As highlighted above for physician 1, the market share for physician j depends on whether $\kappa_j^{SM*} \gtreqless \tilde{P}$. Denote by j_p the doctor with $\min_{\kappa_j^{SM*}} \left(\kappa_j^{SM*} - \tilde{P} \ : \ \kappa_j^{SM*} - \tilde{P} \geq 0 \right)$; that is, the doctor whose threshold is closest from above to the pain level $\tilde{P}$. The equilibrium market share for physician j is given by

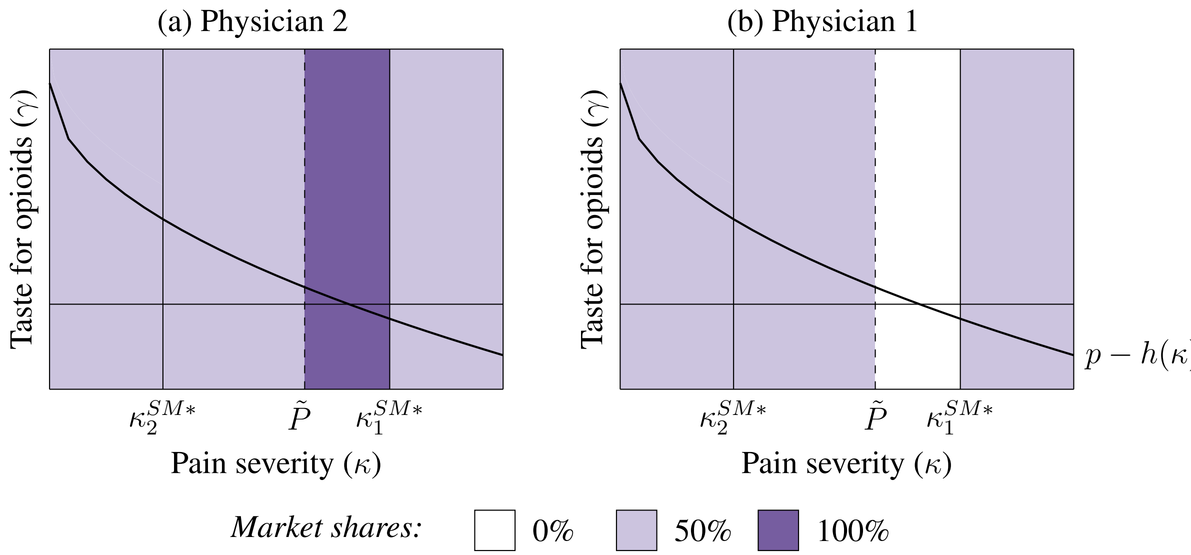
$$q_j^* = \begin{cases} \frac{1}{J} + \sum_{n=1}^{j_p} \cdot \left[\frac{1}{(J-n+1)(J-n)} \cdot \int_{\tilde{P}}^{\kappa_n^{SM*}} dF(k) \right] & \text{if } \kappa_j^{SM*} < \tilde{P} \\ \frac{1}{J} \cdot \left[\int_{\kappa_j^{SM*}}^{\infty} dF(k) + \int_0^{\tilde{P}} dF(k) \right] + \sum_{n=1}^{j-1} \cdot \left[\frac{1}{(J-n+1)(J-n)} \cdot \int_{\kappa_j^{SM*}}^{\kappa_n^{SM*}} dF(k) \right] & \text{if } \kappa_j^{SM*} \geq \tilde{P} \end{cases} \tag{A8}$$

These market shares are shown in Figure A14 for a market with two physicians.

Physician optimality In the presence of a secondary market and with patient search, physician j chooses her threshold severity to solve the following problem:

$$\max_{\kappa_j^{SM}} \begin{cases} \beta_j \cdot \frac{I}{J} \cdot \left[\int_{\kappa_j^{SM}}^{\infty} \int_{p-h(k)}^{\infty} h(k) dG(\gamma) dF(k) \right] \\ +\beta_j \cdot \sum_{n=1}^{j_p} \cdot \left[\frac{I}{(J-n+1)(J-n)} \cdot \int_{\tilde{P}}^{\kappa_n^{SM*}} \int_{p-h(k)}^{\infty} h(k) dG(\gamma) dF(k) \right] \\ +\beta_j \cdot \left(\bar{h}^{SM} \right) \cdot \frac{I}{J} \cdot \left[\int_{\kappa_j^{SM}}^{\infty} \int_{-\infty}^{p-h(k)} dG(\gamma) dF(k) \right] & \text{if } \kappa_j^{SM*} < \tilde{P} \\ +\beta_j \cdot \left(\bar{h}^{SM} \right) \cdot \sum_{n=1}^{j_p} \cdot \left[\frac{I}{(J-n+1)(J-n)} \cdot \int_{\tilde{P}}^{\kappa_n^{SM*}} \int_{-\infty}^{p-h(k)} dG(\gamma) dF(k) \right] \\ +R_j \cdot \left(\frac{I}{J} \cdot \int_{\kappa_j^{SM}}^{\infty} dF(k) + \sum_{n=1}^{j_p} \cdot \left[\frac{I}{(J-n+1)(J-n)} \cdot \int_{\tilde{P}}^{\kappa_n^{SM*}} dF(k) \right] \right) \\ \\ \beta_j \cdot \frac{I}{J} \cdot \left[\int_{\kappa_j^{SM}}^{\infty} \int_{p-h(k)}^{\infty} h(k) dG(\gamma) dF(k) \right] \\ +\beta_j \cdot \sum_{n=1}^{j-1} \cdot \left[\frac{I}{(J-n+1)(J-n)} \cdot \int_{\kappa_j^{SM}}^{\kappa_n^{SM*}} \int_{p-h(k)}^{\infty} h(k) dG(\gamma) dF(k) \right] \\ +\beta_j \cdot \left(\bar{h}^{SM} \right) \cdot \frac{I}{J} \cdot \left[\int_{\kappa_j^{SM}}^{\infty} \int_{-\infty}^{p-h(k)} dG(\gamma) dF(k) \right] & \text{if } \kappa_j^{SM*} \geq \tilde{P} \\ +\beta_j \cdot \left(\bar{h}^{SM} \right) \cdot \sum_{n=1}^{j-1} \left[\frac{I}{(J-n+1)(J-n)} \cdot \int_{\kappa_j^{SM}}^{\kappa_n^{SM*}} \int_{-\infty}^{p-h(k)} dG(\gamma) dF(k) \right] \\ +R_j \cdot \left(\frac{I}{J} \cdot \int_{\kappa_j^{SM}}^{\infty} dF(k) + \sum_{n=1}^{j-1} \left[\frac{I}{(J-n+1)(J-n)} \cdot \int_{\kappa_j^{SM}}^{\kappa_n^{SM*}} dF(k) \right] \right) \end{cases} \tag{A9}$$

Figure A14: Equilibrium market shares: with secondary market and patient search



Notes: The above figure depicts the patient market shares in a market with two physicians, patient search, and a secondary market. Without patient search, each physician would see half of all patients throughout the pain and taste distributions. With patient search, the physician that is more lenient in her prescribing instead sees more patients in equilibrium. While the physician with the higher threshold (physician 1) sees half of all patients who can either get a prescription from her $\left(\kappa_i \geq \kappa_1^{SM*}\right)$ or do not find it beneficial to search $\left(\kappa_i < \tilde{P}\right)$, physician 1 sees no patients who can get a prescription from physician 2 but not from her $\left(\kappa_2^{SM*} \leq \kappa_i < \kappa_1^{SM*}\right)$ and find it beneficial to search $\left(\kappa_i \geq \tilde{P}\right)$. Rather, these patients keep searching until they find physician 2, so physician 2 sees all of these patients in equilibrium. As defined in equation (A7), $\tilde{P} \equiv P^{-1}\left(\frac{\tau^s+\tau^d}{p-\tau^o}\right)$.

where $\bar{h}^{SM} = \frac{\sum_{n=1}^{jp}\int_0^{\tilde{P}}\int_{p-h(k)}^{\infty} h(k)dG(\gamma)dF(k)+\sum_{n=jp+1}^{J}\int_0^{\kappa_n^{SM*}}\int_{p-h(k)}^{\infty} h(k)dG(\gamma)dF(k)}{\sum_{n=1}^{jp}\int_0^{\tilde{P}}\int_{p-h(k)}^{\infty} dG(\gamma)dF(k)+\sum_{n=jp+1}^{J}\int_0^{\kappa_n^{SM*}}\int_{p-h(k)}^{\infty} dG(\gamma)dF(k)}$ is the average health impact of an opioid prescription purchased on the secondary market.

Again assume that the market is sufficiently large such that each physician has a negligible impact on the secondary market price, the average health impact on the secondary market, and the probability that a given patient can get a prescription. Taking the derivative of equation (A9) with respect to κ_j^{SM} and setting equal to zero yields the physician's optimal threshold:

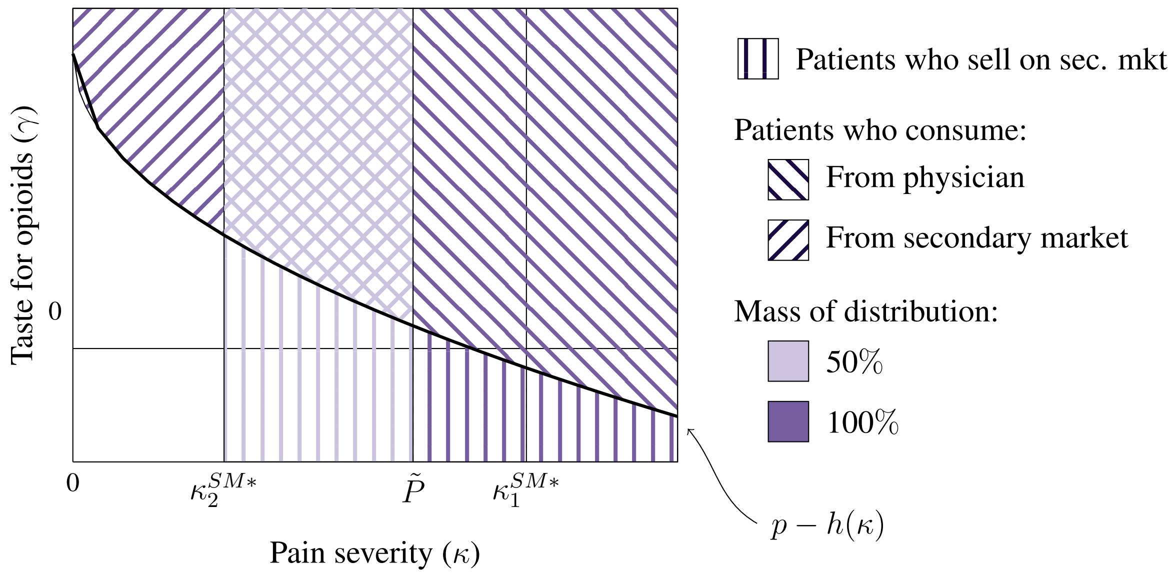
Result 2': *In the presence of a secondary market and with patient search, the optimal threshold of physician j $\left(\kappa_j^{SM*}\right)$ satisfies*

$$-\beta_j\left[\left[1-G(p-h(\kappa_j^{SM*}))\right]\cdot h(\kappa_j^{SM*})+G(p-h(\kappa_j^{SM*}))\cdot\bar{h}^{SM}\right]=R_j \qquad \text{(A10)}$$

With a secondary market and with patient search, an equilibrium in a given geographic market is characterized by a set of thresholds $\{\kappa_j^*\}$ and a secondary market price p such that (1) physicians maximize their utility (i.e., equation (A10) holds $\forall\ j\ \in\ J$), and (2) the secondary market clears (i.e., p is such that $\frac{I}{J}\sum_{j=1}^{j_p}\int_0^{\tilde{P}}\int_{p-h(k)}^{\infty} dG(\gamma)dF(k) + \frac{I}{J}\sum_{j=j_p+1}^{J}\int_0^{\kappa_j^{SM*}}\int_{p-h(k)}^{\infty} dG(\gamma)dF(k) = \frac{I}{J} \cdot \sum_{j=1}^{J}\int_{\kappa_j^{SM*}}^{\infty}\int_{-\infty}^{p-h(\kappa)} dG(\gamma)dF(k) + \sum_{j=1}^{j_p}\sum_{n=1}^{j-1}\frac{I}{(J-n+1)(J-n)}\int_{\kappa_j^{SM*}}^{\kappa_n^{SM*}}\int_{-\infty}^{p-h(k)} dG(\gamma)dF(k) + \sum_{j=j_p+1}^{J}\sum_{n=1}^{j_p}\frac{I}{(J-n+1)(J-n)}\int_{\tilde{P}}^{\kappa_n^{SM*}}\int_{-\infty}^{p-h(k)} dG(\gamma)dF(k)$)

Comparing equations (4) and (A10), we see that the optimal threshold set by the physician is again the same regardless of whether patients are allowed to search across providers. However, there are two key differences in the types of patients participating in the secondary market relative to the case without patient search (Figure 4b). First, when patients can search across providers, patients buying opioid prescriptions on the secondary market will have lower pain on average. This is because it is cheaper to get the medication from a physician (i.e., $p > \tau^d + \tau^o$), so patients who want to consume and have a high enough probability of getting a prescription from a physician (i.e., high enough pain) will search on the primary market rather than turning to the secondary market. Second, when patients can search across physicians, some patients who otherwise would not have gone to the doctor or participated in the secondary market will now search to access a prescription to resell. In particular, patients with a sufficiently high probability of accessing a prescription (i.e., high enough pain) but low enough tastes (i.e., $p > h(\kappa_i) + \gamma_i$) will search on the primary market in order to resell on the secondary market. The equilibrium allocation of opioid prescriptions with a secondary market and patient search is shown in Figure A15 for a market with two physicians.

Figure A15: Equilibrium allocation: with secondary market and patient search



Notes: The above figure displays the equilibrium allocation of opioid prescriptions in a market with two physicians, patient search, and a secondary market. Patients originally assigned to a doctor from whom they can get a prescription (patients with $\kappa_i \geq \kappa_1^{SM*}$ for physician 1 and patients with $\kappa_i \geq \kappa_2^{SM*}$ for physician 2) will get a prescription and will either consume the medication $(h(\kappa_i) + \gamma_i \geq p)$ or resell it on the secondary market $(h(\kappa_i) + \gamma_i < p)$. Moreover, patients that cannot get a prescription from their original doctor but have high enough pain $\left(\kappa_i \geq \tilde{P}\right)$ will search across physicians on the primary market either to consume or to resell. Patients that cannot get a prescription from their original doctor, do not find it beneficial to search, but find it beneficial to consume will purchase the medication on the secondary market. Taken together, all patients with positive utility from consuming prescription opioids given the secondary market price $(h(\kappa_i) + \gamma_i \geq p)$ will access and consume prescription opioids in the presence of a secondary market. As defined in equation (A7), $\tilde{P} \equiv P^{-1}\left(\frac{\tau^s + \tau^d}{p - \tau^o}\right)$.

D Theoretical results: formal statements and proofs

Recalling the notation introduced in Section III, let κ_j^{SM*} (κ_j^*) denote physician j's optimal threshold with (without) a secondary market, and let $\bar{h}^{SM}$ denote the average health impact of an opioid prescription purchased on the secondary market. Furthermore, recall that the physician sets her optimal threshold such that

$$R_j = \begin{cases} -\beta_j \cdot h(\kappa_j^*) & \text{without a sec. market (Result 1)} \\ -\beta_j \cdot \left[\left(1 - G(p - h(\kappa_j^{SM*}))\right) \cdot h(\kappa_j^{SM*}) + G\left(p - h(\kappa_j^{SM*})\right) \cdot \bar{h}^{SM}\right] & \text{with a sec. market (Result 2)} \end{cases}$$

Combining Results 1 and 2, we have that

$$h\left(\kappa_j^*\right) = \left(1 - G\left(p - h\left(\kappa_j^{SM*}\right)\right)\right) \cdot h\left(\kappa_j^{SM*}\right) + G\left(p - h\left(\kappa_j^{SM*}\right)\right) \cdot \bar{h}^{SM} \equiv \tilde{h}(\kappa_j^{SM*})$$

Two observations about this expression are worth noting. First, the expression indicates that the physician sets her threshold in the presence of a secondary market such that the expected health impact of a prescription given to her threshold patient $\left(\tilde{h}(\kappa_j^{SM*})\right)$ equals the health impact of a prescription at her threshold patient in the absence of a secondary market $\left(h(\kappa_j^*)\right)$. Moreover, since $G\left(p - h\left(\kappa_j^{SM*}\right)\right) \in [0,1]$, $h\left(\kappa_j^*\right)$ is a weighted average between $h\left(\kappa_j^{SM*}\right)$ and $\bar{h}^{SM}$.

Theorem 1a: *Without a secondary market, a single threshold strategy is optimal, and each physician's optimal threshold is unique.*

Proof: From Result 1, we have that physician j sets her optimal threshold in the absence of a secondary market such that $h(\kappa^*) = -\frac{R}{\beta}$. Since $h' > 0$ by assumption, this threshold is necessarily unique. Moreover, prescribing only to patients with $\kappa \geq \kappa^*$ is optimal, as the physician's marginal utility of prescribing is weakly positive for all patients with $\kappa \geq \kappa^*$ and strictly negative for all patients with $\kappa < \kappa^*$. The determination of a physician's optimal threshold in the absence of a secondary market is shown in Figure A16a. ■

Theorem 1b: *With a secondary market, each physician's threshold in unique when restricting to single threshold strategies unless $\tilde{h}' = 0$ for $\kappa^{SM} \in [0, \epsilon)$ for some $\epsilon > 0$. Moreover, a single threshold strategy is optimal for all physicians when $\bar{h}^{SM} = h(0)$. When $\bar{h}^{SM} > h(0)$, a single threshold strategy is optimal for physicians with either $-\frac{R}{\beta} > \tilde{h}(0)$ or $-\frac{R}{\beta} < \underline{\tilde{h}}$, where $\tilde{h}(0)$ is the y-intercept and $\underline{\tilde{h}}$ is the minimum of the expected health impact function.*

Proof: Before considering the physician's optimal strategy and the uniqueness of a provider's optimal threshold, it is useful to consider the shape of the expected health impact function $\left(\tilde{h}(\kappa^{SM})\right)$. The y-intercept of the expected health impact function is given by $\tilde{h}(0) = (1 - G(p - h(0)))\cdot h(0) + G(p - h(0)) \cdot \bar{h}^{SM}$. As κ^{SM} increases and moves away from zero, two things happen: (1) $h(\kappa^{SM})$ increases (since $h' > 0$) and (2) the provider places less weight on $\bar{h}^{SM}$ and more weight on $h(\kappa^{SM})$ (since $G(p - h(\kappa^{SM}))$ is decreasing in κ^{SM}).

Suppose that $\bar{h}^{SM} = h(0)$. Since $h' > 0$, it follows that $h(\kappa^{SM}) > \bar{h}^{SM}\ \forall\ \kappa^{SM} \neq 0$. Moreover, when $h(\kappa^{SM}) > \bar{h}^{SM}$, placing more weight on $h(\kappa^{SM})$ for a given $h(\kappa^{SM})$ leads to an increase of the expected health impact function, as the expected health impact function is a weighted average between $h(\kappa^{SM})$ and $\bar{h}^{SM}$. Since both the increase in $h(\kappa^{SM})$ and the change in weighting therefore leads the expected health impact function to increase as κ^{SM} increases, we have that $\tilde{h}' > 0$. By analogous logic as in the case without a secondary market, it follows that a single threshold strategy is optimal and that each physician's optimal threshold is unique.

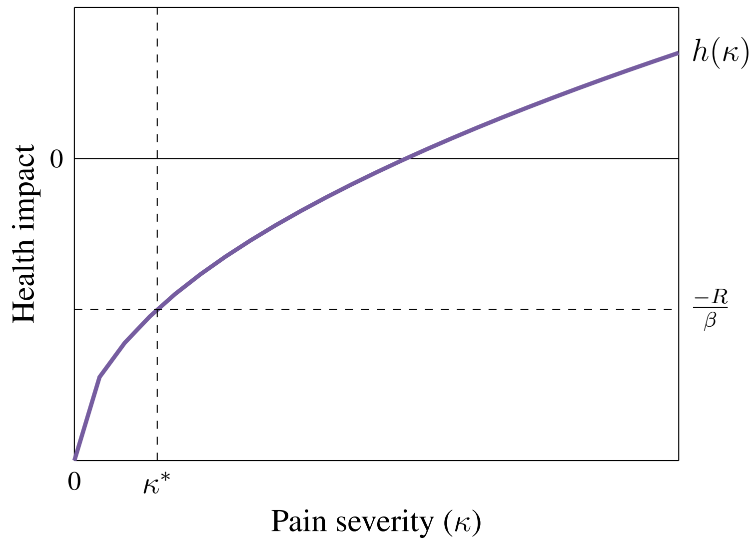
Now suppose that $\bar{h}^{SM} > h(0)$. As above, $\tilde{h}' > 0\ \forall\ \kappa^{SM}$ such that $h(\kappa^{SM}) > \bar{h}^{SM}$. However, when $h(0) \leq h(\kappa^{SM}) < \bar{h}^{SM}$, placing more weight on $h(\kappa^{SM})$ for a given $h(\kappa^{SM})$ leads to a lowering of the expected health impact function. Therefore, as κ^{SM} increases away from zero in the region $\left[0, h^{-1}(\bar{h}^{SM})\right)$, one of three things happens: (1) the increase in $h(\kappa^{SM})$ dominates the change in weighting, leading the expected health impact function to increase; (2) the change in weighting initially just offsets the increase in $h(\kappa^{SM})$, leading the expected health impact function to be flat (equivalently, all weight could be placed on $\bar{h}^{SM}$ and the weight does not change); or (3) the change in weighting initially dominates the increase in $h(\kappa^{SM})$, leading the expected health impact function to decrease.[42] In case (3), despite initially decreasing, the expected health impact function eventually increases as κ^{SM} approaches $h^{-1}(\bar{h}^{SM})$. To see this, suppose not: i.e., suppose that $\tilde{h}' < 0\ \forall\ \kappa^{SM} \in \left[0, h^{-1}(\bar{h}^{SM})\right)$. Since the expected health impact function is increasing $\forall\ \kappa^{SM} > h^{-1}(\bar{h}^{SM})$, it follows that $\min \tilde{h} = \bar{h}^{SM}$. This is a contradiction: since $\tilde{h}(0) \leq \bar{h}^{SM}$ (because $\bar{h}^{SM} > h(0)$ by supposition) and $\tilde{h}' < 0$ near zero (by definition of case (3)), $\exists\ \epsilon > 0$ such that $\tilde{h}(\epsilon) < \bar{h}^{SM}$.

We can now consider the optimal strategy and the uniqueness of each provider's threshold. Let $\underline{\tilde{h}}$ denote the minimum of the expected health impact function. In case (1), since $\tilde{h}' > 0\ \forall\ \kappa^{SM}$, we again have that a single threshold strategy is optimal and that the threshold is unique. Now consider case (2). Recall that in case (2), $\tilde{h}' = 0\ \forall\ \kappa^{SM} \in \left[0, h^{-1}(\bar{h}^{SM})\right]$ and $\tilde{h}' > 0\ \forall\ \kappa^{SM} > h^{-1}(\bar{h}^{SM})$. A

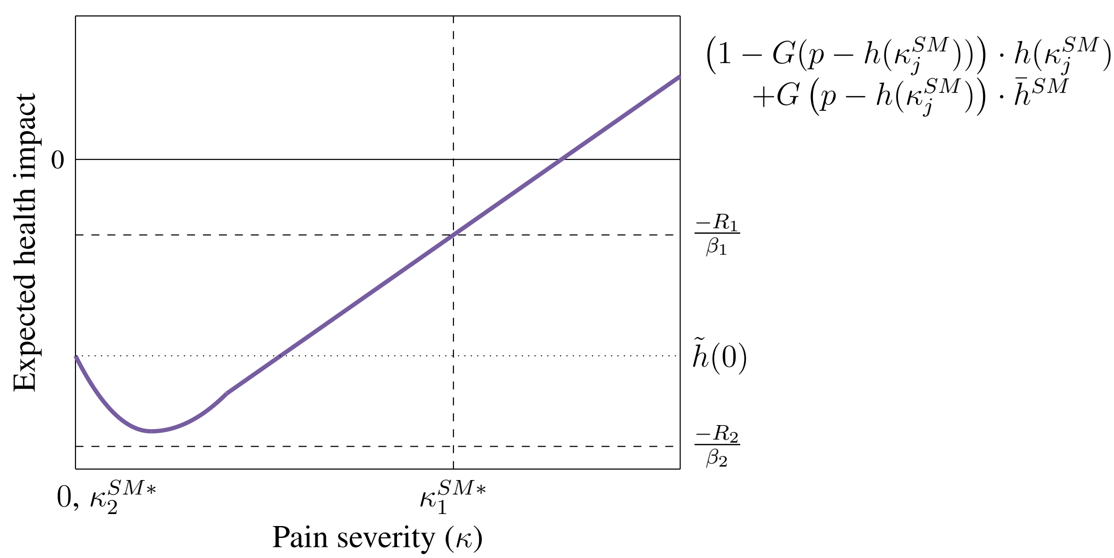
[42]There are also mixed cases between (1) and (2) (i.e., the health impact function is initially flat and then increases) and (2) and (3) (i.e., the health impact function is initially flat and then decreases). The optimal strategy and the uniqueness of each provider's threshold is each of these cases is a simple extension of the logic from the component pure cases.

Figure A16: Determination and uniqueness of optimal thresholds

(a) Without a secondary market



(b) With a secondary market



Notes: The above figures display the determination of a provider's optimal threshold. In the absence of a secondary market (subfigure (a)), a physician sets her threshold such that the health impact of a prescription at her threshold patient $(h(\kappa^*))$, weighted by her concern for her impact on patient health (β), just offsets her monetary reimbursement per office visit (R). Since the health impact function is assumed to be strictly increasing, this threshold is unique. In the presence of a secondary market (subfigure (b)), the physician instead sets her threshold such that the expected health impact of a prescription at her threshold patient $\left(\tilde{h}(\kappa^{SM*}) = (1 - G(p - h(\kappa^{SM})) \cdot h(\kappa^{SM*}) + G(p - h(\kappa^{SM})) \cdot \bar{h}^{SM}\right)$, weighted by her concern for her impact on patient health (β), just offsets her monetary reimbursement per office visit (R). This threshold is unique for providers with $-\frac{R}{\beta} > \tilde{h}(0)$ or $-\frac{R}{\beta} < \underline{\tilde{h}}$, where $\tilde{h}(0)$ is the y-intercept and $\underline{\tilde{h}}$ is the minimum of the expected health impact function.

single threshold strategy is therefore optimal and the threshold is unique for providers with $-\frac{R}{\beta} > \bar{h}^{SM} = \tilde{h}(0)$. Moreover, for providers with $-\frac{R}{\beta} < \underline{\tilde{h}}=\bar{h}^{SM}=\tilde{h}(0)$, the marginal utility of prescribing to any patient is strictly positive, so a single threshold strategy with a threshold of $\kappa^{SM*} = 0$ is optimal. Finally, for providers with $-\frac{R}{\beta} = \underline{\tilde{h}}=\bar{h}^{SM}=\tilde{h}(0)$, the marginal utility of prescribing to a patient with $\kappa^{SM} \in \left[0, h^{-1}(\bar{h}^{SM})\right]$ is zero, so the single threshold is not unique.

Lastly, consider case (3). Recall that in case (3), $\tilde{h}' \leq 0 \; \forall \; \kappa^{SM} \leq \underline{\tilde{h}}$ and $\tilde{h}' > 0 \; \forall \; \kappa^{SM} > \underline{\tilde{h}}$. The determination of a physician's optimal threshold in this case is shown in Figure A16b. Similarly to case (2), the marginal utility of prescribing to any patient for providers with $-\frac{R}{\beta} < \underline{\tilde{h}}$ is strictly positive, so a single threshold strategy with a threshold of $\kappa^{SM*} = 0$ is optimal. Moreover, since $\tilde{h}' > 0 \; \forall \; \kappa^{SM} > \tilde{h}(0) > \underline{\tilde{h}}$ and $\tilde{h}$ is one-to-one over this region, a single threshold strategy is optimal and the threshold is unique. Finally, for providers with $-\frac{R}{\beta} \in \left[\underline{\tilde{h}}, \tilde{h}(0)\right]$, there are two values of κ^{SM*} such that $\tilde{h}(\kappa^{SM*}) = 0$. Let $\underline{\kappa^{SM*}}$ denote the lower solution and $\overline{\kappa^{SM*}}$ the higher solution. Since the marginal utility of prescribing is strictly positive for patients with either $\kappa < \underline{\kappa^{SM*}}$ or $\kappa > \overline{\kappa^{SM*}}$, the provider would prefer to set two thresholds and prescribe for those above (below) the higher (lower) threshold. However, when restricting attention to single threshold strategies (prescribe for those with $\kappa > \kappa^{SM*}$), the threshold $\kappa^{SM*} = \overline{\kappa^{SM*}}$ is optimal and unique. ■

Theorem 2: *Physicians with*

1. $h(\kappa_j^*) < \bar{h}^{SM}$ *are more lenient in the presence of a secondary market (i.e.,* $\kappa_j^{SM*} < \kappa_j^*$*)*
2. $h(\kappa_j^*) = \bar{h}^{SM}$ *do not change their optimal prescribing behavior in the presence of a secondary market (i.e.,* $\kappa_j^{SM*} = \kappa_j^*$*)*
3. $h(\kappa_j^*) > \bar{h}^{SM}$ *are less lenient in the presence of a secondary market (i.e.,* $\kappa_j^{SM*} > \kappa_j^*$*)*

Proof: Combining Results 1 and 2, we have that $h\left(\kappa_j^*\right) = \left(1 - G\left(p - h\left(\kappa_j^{SM*}\right)\right)\right) \cdot h\left(\kappa_j^{SM*}\right) + G\left(p - h\left(\kappa_j^{SM*}\right)\right) \cdot \bar{h}^{SM}$. Since $G\left(p - h\left(\kappa_j^{SM*}\right)\right) \in [0,1]$, it follows that $h\left(\kappa_j^*\right)$ is a weighted average between $h\left(\kappa_j^{SM*}\right)$ and $\bar{h}^{SM}$. Therefore, if $h\left(\kappa_j^*\right) < \bar{h}^{SM}$, it must be the case that $h\left(\kappa_j^{SM*}\right) < h\left(\kappa_j^*\right)$. Since $h' > 0$ (by assumption), it follows that $\kappa_j^{SM*} < \kappa_j^*$. By analogous logic, $h\left(\kappa_j^*\right) > \bar{h}^{SM} \;\Rightarrow\; h\left(\kappa_j^{SM*}\right) > h\left(\kappa_j^*\right) \;\Rightarrow \kappa_j^{SM*} > \kappa_j^*$ and $h\left(\kappa_j^*\right) = \bar{h}^{SM} \;\Rightarrow\; h\left(\kappa_j^{SM*}\right) = h\left(\kappa_j^*\right) \;\Rightarrow\; \kappa_j^{SM*} = \kappa_j^*$. ■

Lemma 1: *In the presence of a secondary market, either*

1. *All physicians become more strict (i.e.,* $\kappa_j^{SM*} \geq \kappa_j^* \; \forall \; j \in J$*) or*

2. *Some physicians become more strict and some physicians become more lenient (i.e., $\exists\ j,\ j' \in J\ :\ \kappa_j^{SM*} < \kappa_j^*\ \&\ \kappa_{j'}^{SM*} > \kappa_{j'}^*$)*

Proof: Suppose not. That is, suppose that $\kappa_j^{SM^*} < \kappa_j^*\ \forall\ j \in J$. By Theorem 1, $\kappa_j^{SM^*} < \kappa_j^*\ \forall\ j \in J\ \Rightarrow\ h\left(\kappa_j^*\right) < \bar{h}^{SM}\ \forall\ j \in J$. Since $h' > 0$ (by assumption), it follows that $\kappa_j^{SM*} < \kappa_j^* < h^{-1}\left(\bar{h}^{SM}\right)\ \forall\ j \in J$. This implies that $\exists$ at least one patient i with $\kappa_i > \kappa_j^{SM*}\ \forall\ j \in J$ who buys on the secondary market. However, this violates optimal patient behavior: it is cheaper to obtain an opioid prescription from a physician than from the secondary market (i.e., $p > \tau^d + \tau^o$), so a patient who can get a prescription from whichever physician he was originally assigned will not buy on the secondary market. Therefore, $\exists$ at least one physician j such that $\kappa_j^{SM*} > \kappa_j^*$. ■

Lemma 2: *The average health impact of opioid prescriptions consumed on the secondary market is necessarily negative. That is, $\bar{h}^{SM} < 0$.*

Proof: From Result 2, we have that $\left(1 - G(p - h(\kappa_j^{SM*}))\right) \cdot h(\kappa_j^{SM*}) + G\left(p - h(\kappa_j^{SM*})\right) \cdot \bar{h}^{SM} = -\frac{R_j}{\beta_j}\ \forall\ j \in J$. Since $R_j > 0$ and $\beta_j > 0$ (both by assumption), the right-hand side of this expression is strictly negative for all physicians. Moreover, since $G\left(p - h\left(\kappa_j^{SM*}\right)\right) \in [0,1]$, the left-hand side of the expression is a weighted average between $h\left(\kappa_j^{SM*}\right)$ and $\bar{h}^{SM}$. Suppose that $\bar{h}^{SM} \geq 0$. For the weighted average to be strictly negative $\forall\ j \in J$, it must then be the case that $h\left(\kappa_j^{SM*}\right) < 0 \leq \bar{h}^{SM}\ \forall\ j \in J$. Since $h' > 0$ (by assumption), it follows that $\kappa_j^{SM*} < h^{-1}\left(\bar{h}^{SM}\right)\ \forall\ j \in J$. This implies that $\exists$ at least one patient i with $\kappa_i > \kappa_j^{SM*}\ \forall\ j \in J$ who buys on the secondary market. However, this violates optimal patient behavior: it is cheaper to obtain an opioid prescription from a physician than from the secondary market (i.e., $p > \tau^d + \tau^o$), so a patient who can get a prescription from whichever physician he was originally assigned will not buy on the secondary market. It therefore must be the case that $\bar{h}^{SM} < 0$. ■

Lemma 3: *The ordering of physicians by prescribing leniency is preserved with a secondary market. That is, $\kappa_j^* \geq \kappa_{j'}^* \Rightarrow \kappa_j^{SM*} \geq \kappa_{j'}^{SM*}$.*

Proof: Suppose that $\kappa_j^* \geq \kappa_{j'}^*$ and let $\underline{\tilde{h}}$ denote the minimum of the expected health impact function. There are three possible cases to consider: (1) $\tilde{h}^{-1}(\underline{\tilde{h}}) > \kappa_j^* \geq \kappa_{j'}^*$, (2) $\kappa_j^* \geq \tilde{h}^{-1}(\underline{\tilde{h}}) \geq \kappa_{j'}^*$, and (3) $\kappa_j^* \geq \kappa_{j'}^* > \tilde{h}^{-1}(\underline{\tilde{h}})$. In case (1), $\kappa_j^{SM*} = \kappa_{j'}^{SM*} = 0$ as outlined in Theorem 1b, so order is preserved. By the same logic, $\kappa_{j'}^{SM*} = 0$ in case (2). Since $\kappa_j^{SM*} \geq 0$ by definition, it follows that order is again preserved. Finally, in case (3), recall that each physician sets her threshold in the presence of a secondary market such that the expected health impact of a prescription given to her threshold patient $\left(\tilde{h}(\kappa^{SM*})\right)$ equals the health impact of a prescription at her threshold patient in the absence of a secondary market $(h(\kappa^*))$. Therefore, since $\kappa_j^* \geq \kappa_{j'}^*\ \Rightarrow\ h(\kappa_j^*) \geq h(\kappa_{j'}^*)$

($h' > 0 \ \forall \ \kappa$ by assumption), we have that $\tilde{h}(\kappa_j^{SM*}) \geq \tilde{h}(\kappa_{j'}^{SM*})$. Moreover, as established in Theorem 1b, $\tilde{h}' > 0 \ \forall \ \kappa^{SM} > \tilde{h}^{-1}(\underline{\tilde{h}})$, so $\tilde{h}(\kappa_j^{SM*}) \geq \tilde{h}(\kappa_{j'}^{SM*})$ for $\kappa_j^* \geq \kappa_{j'}^* > \tilde{h}^{-1}(\underline{\tilde{h}})$ implies that $\kappa_j^{SM*} \geq \kappa_{j'}^{SM*}$. ■

Theorem 3: *Each of the following two conditions is sufficient, but not necessary, for the presence of a secondary market to increase differences in prescribing thresholds between strict and lenient prescribers within a given geographic market. In particular, letting $\underline{\kappa}^*$ ($\bar{\kappa}^*$) denote the optimal threshold of the most lenient (most strict) prescriber, we have $\bar{\kappa}^{SM*} - \underline{\kappa}^{SM*} > \bar{\kappa}^* - \underline{\kappa}^*$ whenever one of the following holds:*

1. $\underline{\kappa}^* < h^{-1}(\bar{h}^{SM})$ *(i.e., at least one provider becomes more strict in the presence of a secondary market)*

2. $h(\bar{\kappa}^{SM*}) - h(\underline{\kappa}^{SM*}) > h(\bar{\kappa}^*) - h(\underline{\kappa}^*)$ *(i.e., health impacts diverge)*

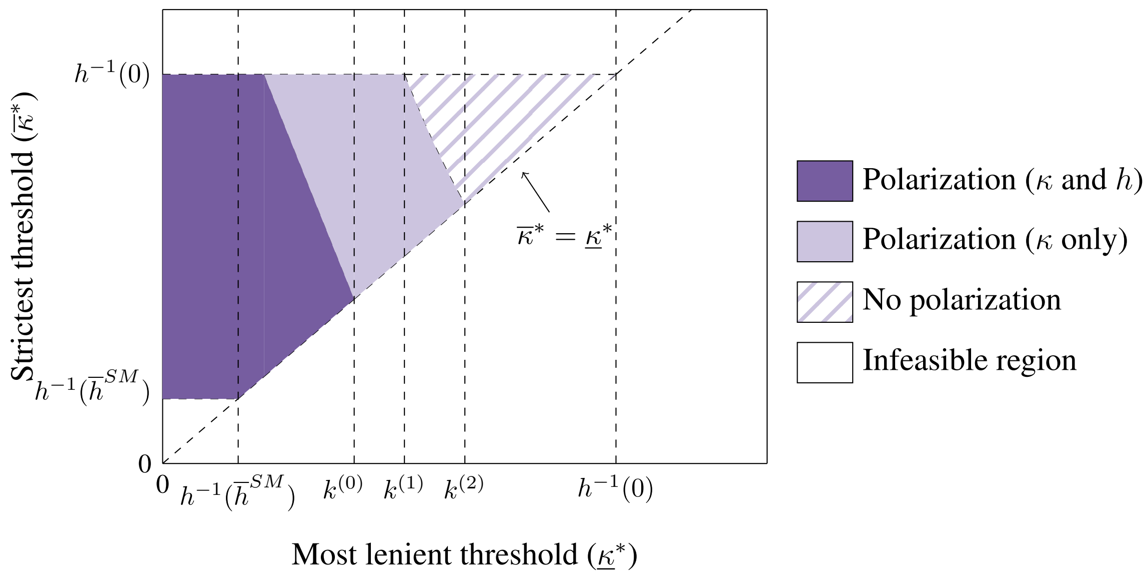
Proof: We aim to determine under which conditions $\bar{\kappa}^{SM*} - \underline{\kappa}^{SM*} > \bar{\kappa}^* - \underline{\kappa}^*$. Throughout, it will be helpful to refer to Figure A17a, which displays all combinations of $\underline{\kappa}^*$ and $\bar{\kappa}^*$ such that the presence of a secondary market leads to polarization. By definition, the set of feasible combinations of $\underline{\kappa}^*$ and $\bar{\kappa}^*$ is bounded below by the line $\underline{\kappa}^* = \bar{\kappa}^*$. Moreover, it must be the case that $\bar{\kappa}^* > h^{-1}(\bar{h}^{SM})$ (by Lemma 1), so the feasible region is further bounded below by $h^{-1}(\bar{h}^{SM})$ when $\underline{\kappa}^* < h^{-1}(\bar{h}^{SM})$. Finally, since all physicians' thresholds are negative in the absence of a secondary market, the feasible region is bounded above and on the left by $h^{-1}(0)$.

We can now consider when the presence of a secondary market leads to polarization. From Lemma 1, we know that only two things can happen when a secondary market is introduced: either (1) all physicians become more strict, or (2) some physicians become more strict and some physicians become more lenient. In the event of case (2), differences in optimal prescribing thresholds between strict and lenient prescribers necessarily increase in the presence of a secondary market. To see this, first note that if at least one physician becomes more lenient, the most lenient physician will become more lenient.[43] Moreover, since the presence of a secondary market preserves the ordering of physicians by prescribing leniency (Lemma 3), the identity of the most lenient provider stays the same. It therefore follows that $\underline{\kappa}^{SM*} < \underline{\kappa}^*$. By analogous logic, if at least one physician becomes more strict, it follows that $\bar{\kappa}^* < \bar{\kappa}^{SM*}$. Combining these expressions, we have that $\underline{\kappa}^{SM*} < \underline{\kappa}^* < \bar{\kappa}^* < \bar{\kappa}^{SM*} \ \Rightarrow \ \bar{\kappa}^{SM*} - \underline{\kappa}^{SM*} > \bar{\kappa}^* - \underline{\kappa}^*$. As depicted in Figure A17a, all feasible combinations of $\underline{\kappa}^*$ and $\bar{\kappa}^*$ therefore lead to polarization when $\underline{\kappa}^* < h^{-1}(\bar{h}^{SM})$.

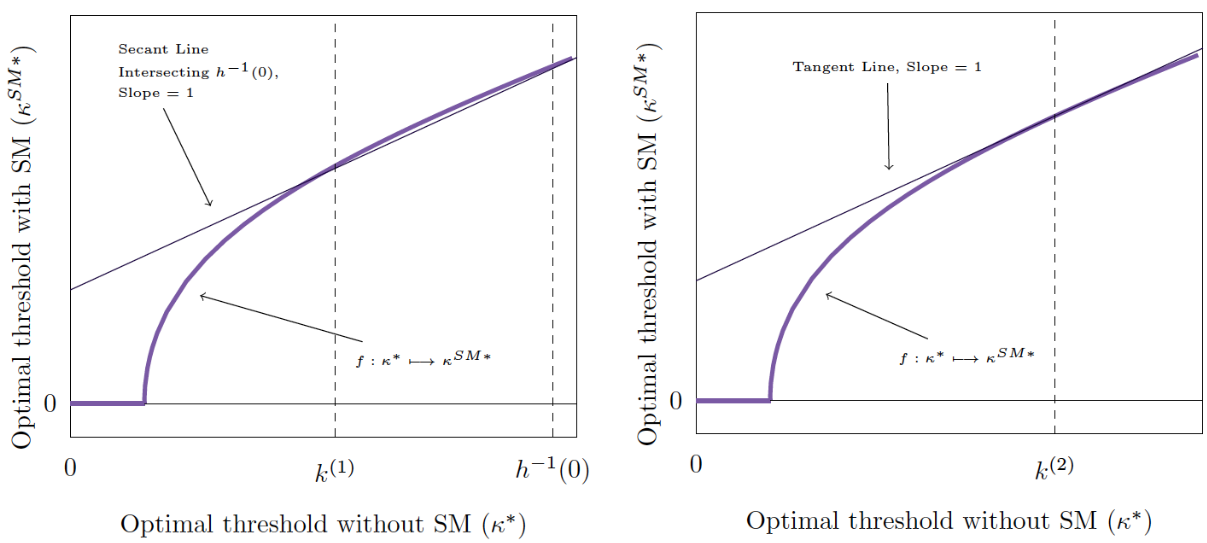
[43] If at least one physician becomes more lenient, it follows from Theorem 2 that $\exists$ at least one physician j' such that $h(\kappa_{j'}^*) < \bar{h}^{SM}$. But since $\underline{\kappa}^* \leq \kappa_{j'}^*$ (by definition), we have that $h' > 0 \ \Rightarrow \ h(\underline{\kappa}^*) \leq h(\kappa_j^*) < \bar{h}^{SM}$. It therefore follows that the most lenient physician will become more lenient.

Figure A17: Polarization of thresholds in the presence of a secondary market

(a) Polarization regions



(b) Determinants of polarization boundaries



Notes: Subfigure (a) shows all combinations of prescribing thresholds in the absence of a secondary market for the most lenient physician ($\underline{\kappa}^*$) and the most strict physician ($\bar{\kappa}^*$) such that the presence of a secondary market leads to polarization. The feasible region is bounded below by the line $\underline{\kappa}^* = \bar{\kappa}^*$ by definition. Moreover, it must be the case that $\bar{\kappa}^* > h^{-1}(\bar{h}^{SM})$ (by Lemma 1), so the feasible region is further bounded below by $h^{-1}(\bar{h}^{SM})$ when $\underline{\kappa}^* < h^{-1}(\bar{h}^{SM})$. Finally, the feasible region is bounded above and on the left by $h^{-1}(0)$, as all physicians' thresholds are negative in the absence of a secondary market. As outlined in the text, $\kappa^{(0)}$ is the highest $\underline{\kappa}^*$ for which $\exists\, \bar{\kappa}^*$ such that $h(\bar{\kappa}^*) - h(\underline{\kappa}^*) < h\big(\bar{\kappa}^{SM*}\big) - h\big(\underline{\kappa}^{SM*}\big)$; polarization occurs for all feasible combinations of $\underline{\kappa}^*$ and $\bar{\kappa}^*$ when health impacts diverge. When $\underline{\kappa}^* > \kappa^{(0)}$, health impacts converge, but polarization still occurs if $\underline{\kappa}^*$ and $\bar{\kappa}^*$ are outside of the region defined by $\kappa^{(1)}$ and $\kappa^{(2)}$. Derivations of $\kappa^{(1)}$ and $\kappa^{(2)}$ are shown in the left and right subplots of subfigure (b), respectively, and are described in the text.

Now consider case (1) and suppose that $h(\bar{\kappa}^*) - h(\underline{\kappa}^*) < h\big(\bar{\kappa}^{SM*}\big) - h\big(\underline{\kappa}^{SM*}\big)$. Since h is strictly concave (by assumption), $\bar{\kappa} - \underline{\kappa}^* > 0$ (by definition), and $\underline{\kappa}^{SM*} > \underline{\kappa}^*$ (by supposition), we have that $h(\underline{\kappa}^* + [\bar{\kappa}^* - \underline{\kappa}^*]) - h(\underline{\kappa}^*) > h\big(\underline{\kappa}^{SM*} + [\bar{\kappa}^* - \underline{\kappa}^*]\big) - h\big(\underline{\kappa}^{SM*}\big)$. Since $h' > 0$, it follows that if $\bar{\kappa}^* - \underline{\kappa}^* > \bar{\kappa}^{SM*} - \underline{\kappa}^{SM*}$, then $h(\bar{\kappa}^*) - h(\underline{\kappa}^*) > h\big(\underline{\kappa}^{SM*} + [\bar{\kappa}^{SM*} - \underline{\kappa}^{SM*}]\big) - h\big(\underline{\kappa}^{SM*}\big) = h\big(\bar{\kappa}^{SM*}\big) - h\big(\underline{\kappa}^{SM*}\big)$. By contraposition, we therefore have that $h\big(\bar{\kappa}^{SM*}\big) - h\big(\underline{\kappa}^{SM*}\big) > h(\bar{\kappa}^*) - h(\underline{\kappa}^*) \Rightarrow \bar{\kappa}^{SM*} - \underline{\kappa}^{SM*} > \bar{\kappa}^* - \underline{\kappa}^*$. Letting $\kappa^{(0)}$ denote the highest $\underline{\kappa}^*$ for which $\exists\, \bar{\kappa}^*$ such that $h(\bar{\kappa}^*) - h(\underline{\kappa}^*) < h\big(\bar{\kappa}^{SM*}\big) - h\big(\underline{\kappa}^{SM*}\big)$, Figure A17a shows that all feasible combinations of $\underline{\kappa}^*$ and $\bar{\kappa}^*$ lead to polarization when $h^{-1}(\bar{h}^{SM}) < \underline{\kappa}^* \le \kappa^{(0)}$.

Finally, again consider case (1) and suppose that $h(\bar{\kappa}^*) - h(\underline{\kappa}^*) \ge h\big(\bar{\kappa}^{SM*}\big) - h\big(\underline{\kappa}^{SM*}\big)$. While polarization need not occur in this region, polarization will still occur when $\underline{\kappa}^* > \kappa^{(0)}$ if $\underline{\kappa}^*$ and $\bar{\kappa}^*$ are outside of the region defined by $\kappa^{(1)}$ and $\kappa^{(2)}$ in Figure A17a. Derivations of $\kappa^{(1)}$ and $\kappa^{(2)}$ are shown in the left and right subplots of Figure A17b, respectively. Looking to the left subplot, we see that $\kappa^{(1)}$ is the other point of intersection of a secant line with slope $= 1$ that goes through the point corresponding to $\kappa^* = h^{-1}(0)$ on the curve mapping optimal thresholds without a secondary market (κ^*) to optimal thresholds with a secondary market (κ^{SM*}). Polarization necessarily occurs when $\underline{\kappa}^* < \kappa^{(1)}$, as the optimal threshold with a secondary market of any possible strictest physician lies above the secant line with slope $= 1$ that goes through the most lenient physician's threshold when $\underline{\kappa}^* < \kappa^{(1)}$ (and thus $\bar{\kappa}^{SM*} - \underline{\kappa}^{SM*} > 1 * (\bar{\kappa}^* - \underline{\kappa}^*)$). Turning to the right subplot, we see that $\kappa^{(2)}$ is instead the point of tangency with a line of slope $= 1$ and the same curve. Polarization never occurs when $\underline{\kappa}^* > \kappa^{(2)}$, as the optimal threshold with a secondary market of any possible strictest physician lies below the secant line with slope $= 1$ that goes through the most lenient physician's threshold when $\underline{\kappa}^* > \kappa^{(2)}$ (and thus $\bar{\kappa}^{SM*} - \underline{\kappa}^{SM*} < 1 * (\bar{\kappa}^* - \underline{\kappa}^*)$). ■

Theorem 4: *If $\sum_{j=1}^{J} \int_{\kappa_j^*}^{\kappa_j^{SM*}} dF(k) > \sum_{j=1}^{J} \int_{\kappa_j^*}^{\infty} \int_{-\infty}^{\tau^d+\tau^o-h(k)} dF(\gamma)dG(k)$, the presence of a secondary market will cause the total number of opioid prescriptions written by physicians on the primary market to decrease.*

Proof: As noted in Section III.D, both a demand effect and a supply effect influence how the number of opioid prescriptions written by a given physician change when a secondary market is introduced. Since all patients of the physician who can get a prescription show up with a secondary market (whereas only patients for whom it is beneficial to consume show up without a secondary market), the physician writes $\frac{I}{J} \cdot \int_{\kappa_j^*}^{\infty} \int_{-\infty}^{\tau^d+\tau^o-h(k)} dF(\gamma)dG(k)$ more opioid prescriptions in the presence of a secondary market. However, since the physician alters her optimal threshold, her prescriptions further change by $\frac{I}{J} \cdot \int_{\kappa_j^{SM*}}^{\kappa_j^*} dF(k)$. If the physician becomes more lenient, i.e., $\kappa_j^{SM*} < \kappa_j^*$, this term is positive; if the physician becomes more strict, i.e., $\kappa_j^* < \kappa_j^{SM*}$, this term is negative. The impact of a secondary market on the total number of prescriptions written by physicians is therefore the sum of these two terms across all physicians:

$$\underbrace{\frac{I}{J} \cdot \sum_{j=1}^{J} \int_{\kappa_j^*}^{\infty} \int_{-\infty}^{\tau^d + \tau^o - h(k)} dF(\gamma) dG(k)}_{\text{Demand effect}} - \underbrace{\frac{I}{J} \cdot \sum_{j=1}^{J} \int_{\kappa_j^*}^{\kappa_j^{SM*}} dF(k)}_{\text{Supply effect}}$$

It follows that prescriptions in a given geographic market will decrease if $\sum_{j=1}^{J} \int_{\kappa_j^*}^{\kappa_j^{SM*}} dF(k) > \sum_{j=1}^{J} \int_{\kappa_j^*}^{\infty} \int_{-\infty}^{\tau^d + \tau^o - h(k)} dF(\gamma) dG(k)$. ■