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

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Abstract

This paper examines how patient and physician behavior across legal and illegal markets have contributed to the U.S. opioid epidemic. To do so, I design and estimate a model of physician behavior in the presence of an endogenous 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 about their revenue and their impact on population health, take into account the existence of this secondary market when prescribing. Estimates demonstrate that the presence of a secondary market induces physicians to be more careful in their prescribing—thereby bringing prescriptions closer to their optimal level—but results in significant harm on net due to the reallocation of prescriptions for abuse.

1   Introduction

Every day, over 45 Americans die from a drug overdose involving a prescription opioid (CDC, 2017; Seth et al., 2018). Prescription opioids, such as OxyContin, are legal compounds that resemble opium both in their addictive properties and physiological effects. Between 2000 and 2014, their clinical use in the United States quadrupled, leading to the largest drug epidemic in American history (Dart et al., 2015; Rudd et al., 2016).[1] Despite their potential for misuse and abuse, prescription opioids are an effective treatment for acute pain.[2] Policies to address the epidemic are therefore complicated by the trade-off between maintaining access to compassionate care and reducing the supply of opioids available to non-medical users. To find the right balance, it is key to understand the forces that drive the prescribing practices of physicians and dictate the allocation of these prescriptions across the population.

   In this paper, I analyze how both patient and physician behavior across legal, primary markets and illegal, secondary markets for prescription opioids have contributed to the crisis. To do so, I develop and estimate a model of supply and demand for prescription opioids on these two inter-linked markets. I estimate my model using detailed data on the number of opioid prescriptions written by each physician from 2006–2014, unique data documenting street prices for prescription opioids across the United States, and measures of prescription opioid misuse and pain across space. Estimates demonstrate that the presence of a secondary market induces physicians to prescribe fewer opioids: prescriptions would have been 13% higher in 2014 if a secondary market did not exist. However, the reallocation of prescription opioids across patients on the secondary market results in net health losses of at least $15 billion per year. Notably, the highest health gains would be achieved by returning allocative control to physicians while simultaneously reigning in unnecessary prescribing. Even with a secondary market, estimates suggest that prescription rates are at least 20% too high. This suggests that policies to address the opioid epidemic should focus *both* on reducing the quantity, as well as controlling the allocation, of opioid prescriptions.

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[1]In 2017, deaths from drug overdoses in the United States exceeded those from car accidents and gun violence combined (CDC, 2017). This rise in drug-related mortality has been sufficient to reverse decades-long improvements in mortality (Case and Deaton, 2015) and has even contributed to recent reductions in American life expectancy (Dowell et al., 2017).

[2]While recent evidence demonstrates that their efficacy is limited for the treatment of chronic, non-cancer pain (Chou et al., 2015; Dowell et al., 2016), opioids continue to be prescribed to manage both acute and chronic pain (Boudreau et al., 2009; Chou et al., 2009).

Unlike other medical services that physicians provide, opioid prescriptions are tradeable on a secondary market. If a patient receives a prescription they do not wish to consume, or if a patient would like a prescription but cannot get one from a physician, these patients can turn to the secondary market for opioids as sellers and buyers, respectively. This market is illegal: under state and federal law, selling controlled substances (including prescription opioids) to another person or possessing a controlled substance without a prescription is a felony. Despite these legal deterrents, the secondary market remains a relevant source of prescription opioids for many users. According to results from the The National Survey on Drug Use and Health (NSDUH), nearly 30% of respondents who misused a prescription opioid in the past year turned to the secondary market to access their most recent supply (Table A.3).[3,4] 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.[5]

To examine how the secondary market influences both the prescribing practices of physicians and the equilibrium allocation of prescriptions, I 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 doctors and a centralized secondary market to access prescription opioids.[6] While it is cheaper to obtain opioids through a physician's prescription than through 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 her health impact relative to her revenue.

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[3]The NSDUH defines prescription opioid misuse as taking a prescription opioid that was "not prescribed for you or only for the experience or feeling it caused."

[4]This is likely an underestimate of users who turn to the secondary market for two reasons. First, the NSDUH only asks respondents how they obtained the *last* prescription opioid they misused. Over one-third of frequent misusers report having gotten their last prescription for free, although they arguably need to also rely on either the primary or secondary markets for a more reliable supply. Second, as the secondary market is illegal, respondents may prefer to say that they received the medication from a friend or relative for free rather than disclosing their engagement with an illegal market.

[5]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).

[6]See Peirce et al. (2012), Jena et al. (2014), and Yang et al. (2015) for a discussion of doctor shopping and its relevance for the opioid epidemic.

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.

This model delivers a number of theoretical insights. First, the model highlights that while physicians tend to overprescribe opioids, differences in preferences and incentives lead to significant heterogeneity in prescribing behaviors across physicians. As the potential for diversion will have a greater influence on the behavior of more altruistic physicians, a secondary market tends to exacerbate this heterogeneity by increasing prescribing differences between more and less lenient physicians. Despite this polarization in physician behavior, the presence of a secondary market can actually cause total prescriptions in a market to fall if enough physicians become sufficiently more strict in their prescribing because of the potential for diversion. Finally, even if the secondary market reduces total prescriptions, it can still lead to significant health losses on net due to the reallocation of prescriptions from those with a legitimate medical need to abusers.

I estimate my model in two stages using administrative and survey data. In the first stage, I group physicians into three categories based on their level of altruism, which is measured using their take-up of a new, safer formulation of a popular prescription opioid that was introduced partway through my sample. Notably, 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. Using these parameters, I then examine the roles played by the primary market, the secondary market, and the interaction between the two in the current epidemic.

Counterfactuals reveal that the potential harm caused by medications diverted to the secondary market induces physicians to be more careful in their prescribing. While policies that crack down on the secondary market will therefore cause prescription levels on the primary market to *rise*, the overall health effects of prescription opioids would be greatly improved by preventing patients from reallocating prescriptions. However, the greatest health benefits from prescription opioids at the population level would be achieved by simultaneously closing the secondary market and reducing prescribing rates on the primary market: while a secondary market results in an equilibrium allocation of prescriptions that harms the health of consumers on net, a secondary market brings

prescriptions closer to their optimal level by making physicians more hesitant to prescribe. Estimates suggest that policies targeting both the quantity and the allocation of prescription opioids have potential health gains of at least \$33 billion annually across the United States.

Contributions to the literature   Given the prominence of the opioid crisis, it is not surprising that a large body of literature analyzing the epidemic has emerged. The first wave of papers in this literature focused primarily on patient characteristics that predict opioid abuse, such as mental health problems and histories of substance abuse (Ives et al., 2006; Sullivan et al., 2010; Fischer et al., 2012). A more recent strand in the literature has turned to examining the role played by physicians. In addition to documenting that prescribing practices correlate with opioid abuse and overdose deaths across space and over time (Paulozzi and Ryan, 2006; Bohnert et al., 2011; Dart et al., 2015), new research documents both the prevalence and importance of heterogeneity in prescribing practices within a given location (Barnett et al., 2017; Schnell and Currie, 2017). Importantly, however, the opioid epidemic is an equilibrium outcome driven by the behavior of both patients and physicians. This paper is the first to develop a structural model that formalizes the incentives influencing the behavior of patients, physicians, and the interactions between the two across primary and secondary markets.

This paper further contributes to a large theoretical literature on physician behavior (see McGuire, 2000 and Chandra et al., 2011 for overviews). To accommodate defining features of the opioid epidemic, I develop a model that departs from two key assumptions previously made in this literature. First, while most medical services are non-retradeable, a secondary market for opioids exists. My model shows how the presence of a secondary market directly influences the prescribing practices of physicians, highlighting that the retradeability of opioids is important for understanding physician behavior. Second, while asymmetric information is inherent in the physician-patient relationship, it is usually presumed that physicians are the agents with superior information. In the context of opioids, physicians may have superior information regarding the benefits of different medical treatments for pain, but patients have superior knowledge regarding their intentions (i.e., consuming or reselling the prescription). My model incorporates the incentives for patients to seek opioids for non-medical consumption or resale, highlighting how private information on the side of patients can influence the behavior of physicians. Note that these extensions are important for

understanding the forces that govern prescribing practices more generally, a growing category of medical services provided by physicians in the United States.[7]

Finally, this paper contributes to a large body of literature devoted to the economics of drug abuse and other risky behaviors. This literature can broadly be divided into two categories: (1) papers studying the consumption of legal products such as alcohol and cigarettes (Manning et al., 1989; Chaloupka, 1991; Carpenter and Dobkin, 2009), and (2) papers studying consumption of illegal products such as cocaine and marijuana (Becker et al., 1991; Grossman and Chaloupka, 1998; Gruber and Koszegi, 2001; Jacobson, 2004).[8] Departing from this literature, the analysis of prescription opioids requires an analysis of both legal and illegal markets. To the best of my knowledge, Powell et al. (2015) and Meinhofer (2016) are the only papers to explicitly consider the interaction between these two markets.[9] Exploiting the rollout of Medicare Part D, Powell et al. (2015) show that drug deaths among the Medicare-ineligible population rose significantly when access to opioids (via insurance coverage) was expanded for the Medicare population. Leveraging the shutdown of nearly 600 pain clinics in Florida, Meinhofer (2016) demonstrates that prices for prescription opioids on the secondary market increased when supply was reduced on the primary market. These important findings highlight the relevance of the secondary market in the opioid epidemic and suggest that policies to address the legal supply would reduce illegal consumption. However, as Powell et al. (2015) point out, a full welfare analysis requires one to measure the trade-off between the potential health benefits and harms to patients from both the legal and illegal supply.[10] By measuring the health impacts of opioids across both markets, my model captures the effects of prescription opioids more generally and highlights how to target optimal policy in the presence of these two interlinked markets.

This paper proceeds as follows. Section 2 introduces the data sets that I use. In Section 3, I exploit the reformulation of OxyContin to estimate physician preferences and document hetero-

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[7]The CDC estimates that over two-thirds of medical visits end with the provider writing at least one prescription (CDC, 2017).

[8]This distinction is important when considering how to reduce overconsumption, as common policy levers depend critically on the legality of the product being controlled (taxation versus mandatory sentencing, for example).

[9]Alpert et al. (2016) and Evans et al. (2017) consider the interaction of the markets for prescription opioids (broadly defined) and the illegal market for heroin. Both studies find that the reformulation of OxyContin caused users to substitute to heroin.

[10]Kilby (2015) highlights the importance of considering both the positive and negative effects of prescription opioids when designing policy. She demonstrates that reducing the legal supply of opioids can result in increased pain, greater absenteeism in the labor force, and substitution towards more expensive medical care.

geneity in altruism across physicians. In Section 4, I present a model of the primary and secondary markets for opioids and formalize the forces influencing optimal patient and physician behavior. Section 5 discusses estimation. Results and counterfactuals are presented in Section 6. Section 7 provides a discussion and concludes.

2   Data

I use six main data sets that together describe the primary and secondary markets for prescription opioids across the United States. The features of each data set that are most relevant for my analysis are described below. Additional details are provided in Appendix B.

2.1   Physician-level data

Opioid prescriptions   Information on opioid prescriptions comes from an extract of the QuintilesIMS XPonent database. This data is a physician-product-level panel covering opioid prescriptions filled at 86% of U.S. retail pharmacies from January 2006 to December 2014.[11] The QuintilesIMS data has three features that are important for my analysis. First, the data include the practice address of each physician.[12] This allows me to calculate market-level equilibrium quantities for prescription opioids across the United States and to link physicians to their relevant market fundamentals, such a patient pain levels. Second, the data contain the types of insurance each physician's patients use to pay for their opioid prescriptions. As described below, I combine this information with location-specialty-insurance type specific reimbursement rates to create physician-specific reimbursements for office visits. Finally, the data contain information on the number of prescriptions written by each physician for specific opioid products over time. As outlined in Section 3, time-series variation in the mix of opioid products prescribed by individual physicians allows me to exploit the entry of the first abuse-deterrent prescription opioid to measure

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[11]The raw data contains 1,071,822 unique opioid prescribers. I exclude the 38% of prescribers who report a specialty that requires neither a degree of Doctor of Medicine (MD) or Doctor of Osteopathic Medicine (DO); providers with an MD or DO together prescribe 78% of total opioids. I further exclude physicians with no reported practice address (3.9% of physicians).

[12]I define geographic markets as commuting zones when estimating the model. After geocoding reported practice addresses to extract the county of each physician, I use a unique county-to-commuting zone crosswalk (see Dorn, 2009 and Autor and Dorn, 2013) to identify the relevant commuting zone for each physician.

physician preferences.

While comprehensive, the QuintilesIMS data are not without limitations. Notably, the data set contains no information on the number of pills or the strength of medication included with each script. As a result of this data limitation, I only consider the extensive margin of physician prescribing practices—that is, whether to write a prescription—rather than intensive margin decisions regarding the number of pills and strength of medication. As shown in Schnell and Currie (2017), the number of opioid scripts reported in the QuintilesIMS data correlates strongly with county-level mortality: a 10% increase in opioid prescriptions is associated with 1.5% more drug-related deaths. This suggests that prescription decisions along the extensive margin are relevant for understanding the current epidemic.

Reimbursement rates   In Section 4, I model a physician's utility as depending on both her revenue from office visits and her impact on her patients' health. Estimation of the model therefore requires a measure of the per-patient reimbursement rate that each physician faces. I estimate the average reimbursement rate facing each physician in three steps using four data sources. First, I use publicly available Medicare claims to create average reimbursement rates at the specialty-state level. To do so, I combine 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 and the Kaiser Family Foundation, respectively, to adjust the specialty-state Medicare rates for other insurances types. Finally, I calculate the average reimbursement rate facing each physician by combining these specialty-state-insurance type reimbursement rates with information included in the QuintilesIMS data of the composition of patient insurance types seen by each physician. Variation in reimbursement rates across physicians therefore comes from variation in the state of practice, physician specialty, and composition of patient insurance types. Additional details on this process, including a list of the CPT codes considered and average billing frequencies across specialties, are provided in Appendix B.1.

Summary statistics   Summary statistics for the number of opioid prescriptions written by each physician and the office visit reimbursement rate facing each provider are provided in Table 1. For

ease of exposition, I group physicians into three categories based on their reported specialty—primary care, medical, and surgical—using specialty groupings defined by the National Center for Health Statistics. As documented in Schnell and Currie (2017), physicians in primary practice write over half of all opioid prescriptions written by physicians. This is true both because there are relatively more opioid-prescribing physicians in primary practice (column (2)) and because these physicians on average write more prescriptions per provider (column (3)). Looking at office visit reimbursement rates (columns (6)–(8)), we see that physicians in primary care on average face the lowest reimbursement rates, with physicians in medical (surgical) specialties being reimbursed an average of $67 ($19) more per office visit.

Table 1: Summary statistics: physician-level variables by specialty categories

	% opioids (1)	N phys. (2)	Monthly opioid scripts			Office visit reimbursement		
			Mean (3)	Std. Dev. (4)	Range (5)	Mean (6)	Std. Dev. (7)	Range (8)
Primary	50.8	138,890	51.1	69.7	[1,2043]	102.9	22.2	[72,277]
Medical	31.6	99,131	44.6	112.5	[1,4982]	169.8	104.7	[52,1321]
Surgical	17.6	65,567	37.5	48.6	[1,2209]	121.9	30.4	[68,320]
Total	100	303,588	46.1	83	[1,4982]	128.9	69.8	[52,1321]

Notes: The above table provides summary statistics for opioid prescriptions and office visit reimbursement by physician specialty groups in 2014. Data on opioid prescriptions come from QuintilesIMS; refer to the text for an overview of how reimbursement rates are constructed. Analogous summary statistics by individual specialties are reported in Tables A.4 and A.5.

2.2 Market-level data

Street prices To measure equilibrium prices on the secondary market, I use novel black market price data from the StreetRx program. Maintained through the Researched Abuse, Diversion, and Addiction-Related System (RADARS), StreetRx.com is a platform that gathers and presents information on user-submitted black market prices for diverted prescription drugs. Visitors to the site can either search a medication and location to view previously submitted prices or anonymously submit a price themselves. When submitting a price, users are required to provide the name (e.g. OxyContin), formulation (e.g., pill/tablet), and dose (e.g. 5 mg) of the medication and the date and location (state and/or city) of purchase. As of 2013, the website averaged 200 visitors and 20 street price submissions per day (Dasgupta et al., 2013).

Estimation of the model presented in Section 4 requires an average resell price for an opioid prescription across the United States. To create commuting zone-specific resale prices, I combine information from the StreetRx program, publicly available Medicare Part D claims, and the QuintilesIMS data. In particular, I combine (1) prices per morphine milligram equivalent (MME) at the commuting zone level from StreetRx,[13] (2) the median number of MMEs per pill resold on the secondary market as reported in the StreetRx data (10 MME per pill), (3) the average number of pills per day computed using the share of immediate release (IR) to extended release (ER) opioid products prescribed in the QuintilesIMS data (3 pills per day), and (4) the average days supplied per opioid prescription computed using Medicare Part D claims (21 days per script). Letting p_c^{MME} denote price per MME in commuting zone c, $\left(\frac{\overline{days}}{script}\right)$ denote the average number of days supplied per opioid script, $\left(\frac{\overline{pills}}{day}\right)$ the average number of pills per day supplied, and $\left(\frac{\overline{MME}}{pill}\right)$ the average number of MME per pill, the expected resell price for an opioid prescription in commuting zone c, p_c, is given by

$$p_c = \left(\frac{\overline{days}}{script}\right) \cdot \left(\frac{\overline{pills}}{day}\right) \cdot \left(\frac{\overline{MME}}{pill}\right) \cdot p_c^{MME}$$

With an average street price of \$0.88 per MME across the ten largest commuting zones in 2014, this corresponds to an average street price of over \$550 $(21 \cdot 3 \cdot 10 \cdot \$0.88)$ per opioid prescription.

Secondary market prices collected through the StreetRx program provide valid estimates of the street prices of diverted prescription drugs. Dasgupta et al. (2013) cross-validate prices from StreetRx with law enforcement office reports from RADARS and find that prices are highly correlated (Spearman rho of 0.93, p-value < 0.001). The authors further demonstrate that crowdsourced prices follow clinical equianalgesic potency. For example, 1.5 mg of hydrocodone provides an amount of analgesia equivalent to 1 mg of oxycodone, and prices per mg of hydrocodone reported online are about 25% lower than prices reported per mg of oxycodone. In fact, having validated the crowdsourced data, RADARS has discontinued providing pricing data from law enforcement and relies solely on crowdsourced prices collected through StreetRx.

Pain and taste distributions In addition to differing in street prices for prescription opioids, locations also differ in the distribution of pain severities and tastes for opioids among their popula-

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[13]To create prices per MME at the commuting zone level, I link cities of purchase to commuting zones by using city-to-county and county-to-commuting zone crosswalks. In doing so, I exclude price submissions for which the user did not submit the city of purchase (33.8% of price submissions in 2014).

tion. To calculate moments of local pain and taste distributions, I combine reports of pain from the 2014 National Health Interview Survey (NHIS) and reports of opioid misuse from the 2014 National Survey on Drug Use and Health (NSDUH) with population demographics from the five-year pooled (2010–2014) American Community Survey (ACS). In particular, I compute the average pain severity and prescription opioid misuse rate in each commuting zone by taking a weighted average across national age-gender-race-specific pain severities and prescription opioid misuse rates, respectively, where the weights reflect the demographic profile of a given commuting zone. Based on this methodology, variation in pain severities and opioid misuse rates across space comes from differences in population demographics: if two commuting zones have the same proportion of their population in each age-gender-race bin, they will have the same average pain severity and opioid misuse rate. Additional details, including the survey questions used and variation in pain and opioid misuse across age-gender-race cells, are provided in Appendix B.2.

Table 2: Summary statistics: market-level variables

Commuting zone	Rx opioids per cap (1)	Prices Rx (2)	Prices MME (3)	Avg. pain (4)	Misuse rates All (5)	Misuse rates SM (6)	Physician altruism % low (7)	Physician altruism % high (8)
Los Angeles	0.47	539.95	0.86	0.46	3.66	0.43	0.29	0.42
Chicago	0.49	703.32	1.12	0.48	3.84	0.51	0.27	0.44
Houston	0.60	436.07	0.69	0.46	3.86	0.46	0.30	0.45
Philadelphia	0.77	472.90	0.75	0.48	3.83	0.53	0.35	0.36
Washington DC	0.46	627.52	1.00	0.47	3.89	0.48	0.29	0.42
Boston	0.54	591.50	0.94	0.49	3.82	0.58	0.30	0.35
Detroit	0.95	360.93	0.57	0.49	3.84	0.54	0.30	0.40
San Francisco	0.46	499.03	0.79	0.45	3.50	0.42	0.26	0.44
Atlanta	0.67	352.31	0.56	0.47	3.96	0.48	0.30	0.42
Dallas	0.67	581.75	0.92	0.47	3.88	0.50	0.27	0.45
Average	0.64	553.84	0.88	0.48	3.78	0.52	0.30	0.41

Notes: The above table provides summary statistics for the ten largest commuting zones in 2014 (New York is excluded due to poor coverage of street prices). "All" misuse measures the fraction of respondents who reported misusing prescription opioids; "SM" misuse measures the fraction of respondents who reported turning to the secondary market to access prescription opioids for misuse. Physician altruism is defined as in Section 3.

Summary statistics Summary statistics for the ten largest commuting zones are provided in Table 2. There is significant variation across locations in terms of the number of prescriptions: while Los Angeles had 0.47 prescriptions per capita in 2014, rates were almost two times as high in Detroit (column (1)). Street prices for prescription opioids likewise differ across locations, with

patients being able to resell their prescriptions for over $350 more in Chicago than Atlanta (column (2)).[14] Pain severities and misuse rates also vary across commuting zones, with nearly 4% of the population misusing prescription opioids on average (columns (4)-(6)).

3   Physician preferences

A physician whose main concern is the health benefit or harm she bestows on her patients will likely behave differently than a physician whose main concern is her own income. While this potential heterogeneity across physicians has long been considered in the theoretical literature on physician behavior (see, for example, McGuire, 2000 and Chandra et al., 2011), it has been difficult to measure this dimension of physician altruism empirically. To measure the weight that individual physicians place on patient well-being relative to their revenue, I exploit differences in physician-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.[15] 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 1, 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 over 25% to only 469,000 per month by July 2011. Total opioid prescriptions also fell over the same period, but only by 3%.[16]

Given that the reformulated version has less abuse potential, physicians who are concerned with their patients' health should be more likely to prescribe OxyContin once it has been reformulated. On the other hand, given that reformulated OxyContin produces the same effects as the original formulation if taken as intended but cannot easily be manipulated for misuse, demand should ei-

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[14] While users report knowing that there may be cheaper prices elsewhere, many have resigned themselves to paying local prices. See, for example, the discussion in Figure A.15.

[15] The reformulation was heavily advertised in the news. For example, *The New York Times* ran articles on the reformulation both when it was approved and once the new version began shipping (NYTimes (2010, 2011)).

[16] As new drugs are often more expensive than their predecessors, the pattern observed in Figure 1 could be driven by higher copayments for reformulated OxyContin relative to the original formulation. However, the average copayment for OxyContin actually decreased when OxyContin was reformulated (Figure A.11).

Figure 1: OxyContin prescriptions nationally
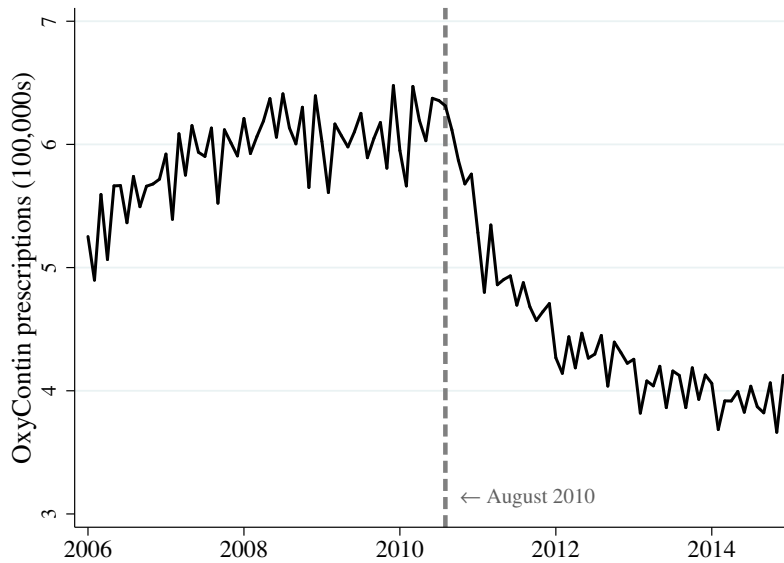
Notes: The above figure presents the number of OxyContin prescriptions filled in U.S. retail pharmacies monthly as reported by QuintilesIMS. The vertical line denotes the month in which the original formulation of OxyContin stopped shipping and the reformulated version began shipping. See Figure A.11 for average copayments for OxyContin over the same time period.

ther stay the same or decrease as a result of the reformulation. I examine how each physician's prescribing practices changed when OxyContin was reformulated to measure physician "altruism": high-altruism physicians increase their use of OxyContin following the reformulation while low-altruism doctors respond to changing demand by switching their OxyContin patients to other opioids without abuse-deterrent properties.[17]

As shown in Figure 2, physician-level responses to the reformulation of OxyContin were not identical. The left figure in each subplot shows an individual physician's quarterly percent of opioid prescriptions for OxyContin, and the right figure shows the same physician's prescriptions for all opioids other than OxyContin. Subplot (a) provides an example of a low-altruism doctor: while her non-OxyContin scripts rose continuously after OxyContin was reformulated, her use of OxyContin dropped from 30% to nearly zero after reformulated OxyContin began shipping. In

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[17]Physicians who switched their patients away from OxyContin following the reformulation switched their patients to a variety of opioid products without abuse-deterrent properties (Figure A.14). Furthermore, while the average copayment of patients seen by low-altruism physicians decreased as their physician switched them away from Oxy-Contin, this is the result of OxyContin's high cost relative to other opioids rather than a lack of cheaper products. Patients seeing low-altruism providers are prescribed opioid products with higher copayment on average, both before and after the OxyContin reformulation (Figure A.13).

contrast, the doctor in subplot (b) switched her patients to OxyContin once it had been reformulated and decreased her use of opioids without abuse-deterrent properties.

Figure 2: Example physicians

(a) Low-altruism

(b) High-altruism
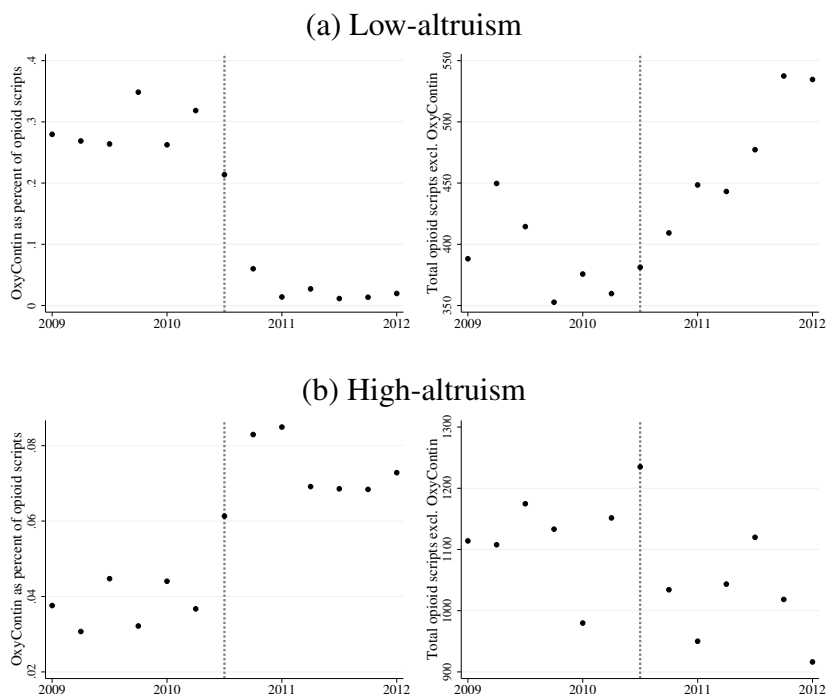
Notes: The above figures depict the percent of quarterly opioid prescriptions for OxyContin (left subplot) and the quantity of opioid prescriptions for products other than OxyContin (right subplot) for two individual physicians in the QuintilesIMS data. The vertical line denotes the quarter in which the original formulation of OxyContin stopped shipping and the reformulated version began shipping.

To group physicians according to their level of altruism, I compute the percent change around the reformulation in each physician's share of opioid scripts that were for OxyContin. To ensure that I identify true behavioral responses rather than idiosyncratic fluctuations in prescriptions, I measure how a physician's percent of opioid prescriptions for OxyContin changed in the three months following the reformulation relative to both (1) the same three months in the year prior and (2) the three months immediately before the reformulation.[18] That is, letting Q_{jm}^{All} and Q_{jm}^{O} denote the number of prescriptions written by physician j in month m for all opioids and OxyContin, respectively, and $M_1 = \{September - November,\ 2010\}$, $M_0^1 = \{September - November,\ 2009\}$, and $M_0^2 = \{May - July,\ 2010\}$ denote the post-period set of months and the two pre-period sets

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[18]Results are robust to using alternative bandwidths and to excluding a larger radius around the reformulation.

of months, respectively, I calculate

$$b_j^n = \frac{\sum_{m \in M_1} Share_{jm} - \sum_{m \in M_0^n} Share_{jm}}{\sum_{m \in M_0^n} Share_{jm}} \; for \; n \in \{1, 2\} \tag{1}$$

with $Share_{jm} = \frac{Q_{jm}^O}{Q_{jm}^{All}}$. Each of these measures captures a similar yet distinct look at physician prescribing practices: while comparing OxyContin shares in M_1 relative to M_0^1 controls for seasonality in prescribing practices, comparing prescribing behavior in M_1 relative to M_0^2 more closely measures a physician's immediate response to the reformulation.

Using output from equation (1), I group physicians into three levels of altruism:

1. Low altruism: $b_j^1 < 0$ and $b_j^2 < 0$

2. Middle altruism: $b_j^1 < 0$ and $b_j^2 > 0$ or $b_j^1 > 0$ and $b_j^2 < 0$

3. High altruism: $b_j^1 > 0$ and $b_j^2 > 0$

Low-altruism physicians are those who decreased their prescribing of OxyContin following the reformulation, middle-altruism physicians are those who experienced no systematic change in their prescribing, and high-altruism physicians are those who increased their prescribing of OxyContin following the reformulation. As shown in Table 3, this categorization creates meaningful differences across physicians in aggregate that captures this intuition: the median low-altruism provider decreased her prescribing of OxyContin by 50%, while the median high-altruism provider increased her prescribing by 100%.

This measure provides no information for opioid prescribers who did not prescribe OxyContin in the period surrounding the reformulation. However, even years later, those who did prescribe OxyContin over the relevant period prescribe a disproportionate share of opioids. In 2014, the 31.5% of physicians for whom I have a measure of altruism prescribed almost 55% of all opioids prescribed by physicians in the United States. This is reflected in the average number of opioid prescriptions written monthly by physicians of different types: while high-altruism providers write over 25% fewer opioid prescriptions monthly than low-altruism providers on average (66.59 versus 89.5), uncategorized physicians write over 50% fewer opioid prescriptions monthly than all groups of categorized physicians.

Table 3: Summary statistics: physician altruism

| | Level of physician altruism | | | | |
	Low	Medium	High	Missing	*Across all*
Median % change in OxyContin					
Sept.-Nov. 2010 vs. Sept.-Nov. 2009	-52.93	4.72	100		
Sept.-Nov. 2010 vs. May-July 2010	-46.04	-2.99	100		
N physicians	29,780	28,110	37,883	207,815	303,588
Percent of physicians	*9.81*	*9.26*	*12.48*	*68.45*	*100*
Primary: Percent of physicians	*13.57*	*12.83*	*16.24*	*57.36*	*100*
Medical: Percent of physicians	*7.83*	*7.2*	*9.88*	*75.09*	*100*
Surgical: Percent of physicians	*4.84*	*4.81*	*8.44*	*81.91*	*100*
Average opioids monthly per physician	89.5	82.74	66.59	31.15	46.07
Total opioids in 2014 (millions)	31.98	27.91	30.27	77.67	167.84
Percent of 2014 total	*19.06*	*16.63*	*18.04*	*46.28*	*100*

Notes: The above table provides summary statistics for the opioid prescribing practices of physicians across different altruism groups. See the text for how physicians are categorized by levels of altruism. "Missing" refers to opioid-prescribing physicians who prescribed OxyContin neither before or after the reformulation (and are therefore not categorized). All summary statistics are from the QuintilesIMS data for 2014.

Locations differ in their composition of physician altruism types (columns (7)–(8) of Table 2).[19] For example, while Philadelphia has a nearly equal share of high- and low-altruism physicians (36% and 35%, respectively), nearly 20 percentage point more physicians in San Francisco are high versus low altruism (44% and 26%, respectively).

As shown in Table 4, these differences in physician altruism across commuting zones translate into significant differences in mortality across locations. To simplify the interpretation of magnitudes, all variables in Table 4 are standardized. Looking first to the results for deaths involving drugs (columns (1)–(4)), we see that a one standard deviation increase in low-altruism physicians is associated with a 0.33 standard deviation increase in deaths involving drugs per capita (column (1)). While this association is reduced conditional on observable commuting zone characteristics (including race, age, education, and income profiles), a significant and large association between the share of low-altruism physicians and drug-related mortality remains. Furthermore, as shown

---

[19]Incentives to switch patients from reformulated OxyContin to a product that can still be easily misused may vary across locations. In areas where a given physician is the only provider, for example, a physician may be less likely to switch her patients since she knows that they have no outside option. To account for differences in the strength of the prescribing incentives surrounding the reformulation of OxyContin, I can residualize the relative shares of physician altruism levels across commuting zones from measures of local competition and demand. However, as less than 10% of the geographic variation in physician responses can be explained by these factors, the results using raw responses and those using responses residualized from physicians per capita, population density, percent with health insurance, percent male and the age, race, income, and education structure at the commuting zone level are nearly identical.

in columns (3) and (4), this relationship persists even conditional on the number of opioid prescriptions, suggesting that the association is driven by the allocation of prescriptions introduced by low-altruism physicians rather than simply the quantity.

Table 4: Drug-related mortality and local composition of physician altruism

	Deaths involving drugs per 10,000				Deaths involving opioids per 10,000			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% low altruism	0.33***	0.21***	0.26***	0.20***	0.34***	0.18***	0.30***	0.17***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.07)	(0.07)	(0.07)	(0.07)
Opioids per cap.			0.36***	0.37***			0.24***	0.09*
			(0.03)	(0.04)			(0.03)	(0.05)
Czone controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	704	704	704	704	704	704	704	704
R^2	0.04	0.29	0.23	0.36	0.03	0.29	0.10	0.29

Notes: The above table presents output from regressions of deaths involving drugs (columns (1)–(4)) and deaths involving opioids (columns (5)–(8)) per 10,000 residents on the share of low-altruism physicians. Observations are at the commuting zone level, all variables are standardized, and robust standard errors are used. Columns (3), (4), (7), and (8) control for the number of opioid prescriptions per capita. Columns (2), (4), (6), and (8) further control for commuting zone characteristics including population density, median household income, and the age, gender, and race profile.

Columns (5)–(8) replicate the analysis from columns (1)–(4) using deaths involving opioids in place of deaths involving any category of drug. As there are no uniform standards for reporting opioid-related deaths across locations (Goldberger et al., 2013; Hall et al., 2017), these results could be biased by differences in reporting. However, the relationship between physician altruism and mortality is robust to the mortality outcome used.

4 Model

In this section, I introduce a model of physician behavior in the presence of a secondary market with patient search. Distinct geographic markets each contain two markets for opioids: (1) a legal, primary market, and (2) an illicit, secondary market. On the primary market, patients obtain opioid prescriptions from physicians; on the secondary market, patients buy and sell prescription opioids first obtained on the primary market. Patients desiring to resell opioids search over heterogeneous physicians on the primary market, while patients desiring to consume the medication search over physicians on the primary market and a centralized secondary market. The main question to be

16

answered by the model is how the presence of an illegal resale market for prescription opioids influences both the opioid prescribing practices of physicians and the equilibrium allocation of these prescriptions.

4.1 Set-up

There are C geographic markets indexed by c. Within each geographic market c, there is a set of J_c physicians and a set of I_c patients. Across all geographic markets, there are $|J|$ physicians indexed by j and $|I|$ patients indexed by i, where $J = \cup_c J_c$ and $I = \cup_c I_c$, respectively.

Physicians differ along four dimensions: their geographic market $(c_j \in C)$, their specialty group $(g_j \in \{(P)rimary, (M)edical, (S)urgical\})$, their revenue per office visit $(R_j \in \mathbb{R}^+)$, and their level of altruism $(b_j \in \{(l)ow, (m)edium, (h)igh\})$. Let $x_j = [c_j, g_j, R_j, b_j]$ be a vector of physician characteristics for each $j \in J$.

Patients differ along three dimensions: their geographic market $(c_i \in C)$, their level of pain $(\kappa_i \in \mathbb{R}^+)$, and their taste for opioids $(\gamma_i \in \mathbb{R})$. Let $y_i = [c_i, \kappa_i, \gamma_i]$ be a vector of patient characteristics for each $i \in I$. In each geographic market, there is a distribution of pain levels, $\kappa_i \sim F_{c_i}$, and patient tastes, $\gamma_i \sim G_{c_i}$. Within a geographic market, a patient's level of pain and tastes for opioids are assumed to be independent.

If a patient consumes a prescription opioid, she receives a monetized health impact, $h(\kappa_i)$, which is a function of her level of pain. Since opioids have a greater health benefit for patients in greater pain, I assume that $h'(\kappa) > 0$. Furthermore, as the medicinal effects of prescription opioids should not vary across space, I assume that $h(\kappa)$ is constant across geographic markets. As the patient will also receive or lose additional utility depending on her taste for opioids, the total value of consuming an opioid prescription for patient i is the sum of the health impact at her level of pain and her tastes: $h(\kappa_i) + \gamma_i$.

To obtain an opioid prescription, a patient can either go to a physician or purchase the pills on the secondary market. There is a cost of going to a physician, τ_c^d, which includes both the patient's time and any direct costs of the office visit. If a patient is prescribed an opioid at her office visit, she must pay an additional cost τ_c^o to fill the prescription. Once given an opioid prescription, the patient then chooses either to consume the medication or to resell the medication to another patient

on the secondary market for p_{c_i}. Letting $-\tilde{\kappa}$ be the disutility associated with pain level κ, the utility of patient i is given by

$$
U_i = \begin{cases}
h(\kappa_i) + \gamma_i - \tau^d_{c_i} - \tau^o_{c_i} - \tilde{\kappa}_i & \text{if consumes from doctor} \\
p_{c_i} - \tau^d_{c_i} - \tau^o_{c_i} - \tilde{\kappa}_i & \text{if sells on sec. mkt.} \\
h(\kappa_i) + \gamma_i - p_{c_i} - \tilde{\kappa}_i & \text{if consumes from sec. mkt.} \\
-\tilde{\kappa}_i & \text{if does nothing}
\end{cases}
$$

Since a patient has disutility from her underlying pain regardless of her action, this disutility will not affect her behavior. Rather, her behavior will be driven (in part) by the pain relief that is captured in the health impact function.

Physicians control the legal supply of prescription opioids. For simplicity, I abstract from the multitude of available treatment options and assume that doctors provide no services other than opioid prescriptions; that is, the only decision facing the provider is whether to write an opioid script. I further assume that physicians can observe each patient's severity of pain but not her taste for opioids. Since a patient only goes to the physician if she can get a prescription, physician j's utility associated with seeing a patient with severity of pain κ_i is given by

$$
U_j(\kappa_i) = \begin{cases}
\beta_{b_j} \cdot h(\kappa_i) + R_j & \text{if prescribes and patient consumes} \\
\beta_{b_j} \cdot \bar{h}^{SM}_{c_j} + R_j & \text{if prescribes and patient sells} \\
0 & \text{if does not prescribe}
\end{cases}
$$

where $\bar{h}^{SM}_c$ is the average health impact of an opioid prescription on the secondary market in geographic market c. Note that a physician's utility is tied to the prescription not the patient; 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. Furthermore, I assume that a physician cares equally about the health impact of her medication whether it is consumed by one of her patients or by someone on the secondary market and that she does not derive utility from patient tastes.

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 this 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 threshold.

Patient search   To endogenize both the number of patients and the distribution of pain severities and tastes that each physician sees, I introduce patient search using a variation of the Carlson and McAfee (1983) search model.[20] While the Carlson and McAfee (1983) model allows search costs to vary across individuals but holds the expected benefit of search constant, I assume the reverse: in each market geographic market c there is a constant search cost, τ_c^s, although the expected benefit of search varies across patients. Patients with high pain and tastes have the highest expected benefit of search, as both their probability of getting a prescription and the benefit of consuming the medication if given a prescription is higher.

Patients begin randomly assigned to a physician. If the patient pays the search cost, τ_c^s, they will be 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 $\left(\tau_c^d\right)$ when sampling a new physician. However, they only have to pay the cost of filling a prescription $\left(\tau_c^o\right)$ if they are able to get a prescription from the physician. For tractability, I assume that patients search with replacement and can revisit previously searched physicians.

As is standard in sequential search models, a patient will continue to search as long as the expected marginal benefit of search exceeds the expected marginal cost of search. If a patient has found a doctor from whom they 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. For a patient who has not found a doctor from whom she can get a prescription, the expected marginal benefit of search depends both on her severity of pain, her taste for opioids, and whether or not a secondary market for opioids exists. Optimal patient search with and without a secondary market are considered below.

---

[20]The search model of Carlson and McAfee (1983) has been used in a variety of contexts. For example, Hortacsu and Syverson (2004) apply the model to rationalize price dispersion in index funds, while Maestas et al. (2009) use the model to examine differential pricing of MediGap policies.

4.2 Without a secondary market

4.2.1 Without patient search

Suppose first that patients cannot search for physicians. That is, each patient is randomly assigned to a physician in each specialty group, and each physician in a given geographic market and specialty group has an equal number of patients $\left(\frac{\left|I_{c_j}\right|}{\left|J_{c_j,g_j}\right|}\right)$ with the same distribution of pain severities and tastes for opioids as the local population as a whole (F_{c_j} and G_{c_j}, respectively). For ease of exposition, suppose there is only one specialty grouping, so that each physician in a given geographic market has $\frac{\left|I_{c_j}\right|}{\left|J_{c_j}\right|}$ patients.

In the absence of a secondary market, any patient for whom $h(\kappa_i) + \gamma_i \geq \tau_{c_i}^d + \tau_{c_i}^o$ will want to consume the medication. Note that patients who need the medication for legitimate medical purposes ($h(\kappa_i) > 0$) will not want to consume the medication if they have low enough tastes; likewise, patients who do not have a legitimate need for the medication may want to consume the medication if they have high enough tastes. Since there is a cost of going to a physician, only patients who want a prescription $\left(h(\kappa_i) + \gamma_i \geq \tau_{c_i}^d + \tau_{c_i}^o\right)$ and can get a prescription from their assigned physician $\left(\kappa_i \geq \kappa_{j_i}^*\right)$ will go to the doctor. I assume each patient knows his physician's decision rule in equilibrium.

Taking into account this optimal patient behavior, physician j chooses her threshold severity, κ_j^*, to solve the following problem:

$$
\begin{aligned}
\max_{\kappa_j} \ & \beta_{b_j} \cdot \frac{\left|I_{c_j}\right|}{\left|J_{c_j}\right|} \cdot \int_{\kappa_j}^{\infty} \int_{\tau_{c_j}^d + \tau_{c_j}^o - h(k)}^{\infty} h(k) f_{c_j}(k) g_{c_j}(\gamma) d\gamma dk \\
& + R_j \cdot \frac{\left|I_{c_j}\right|}{\left|J_{c_j}\right|} \cdot \int_{\kappa_j}^{\infty} \int_{\tau_{c_j}^d + \tau_{c_j}^o - h(k)}^{\infty} f_{c_j}(k) g_{c_j}(\gamma) d\gamma dk
\end{aligned}
\tag{2}
$$

where f_c and g_c are the density functions of pain and tastes in geographic market c, respectively. 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 (only prescribe to those with $\kappa_i \geq \kappa_j^*$) and from optimal patient behavior.

Taking the derivative of equation (2) with respect to κ_j and setting equal to zero yields the physician's optimal threshold:

Result 1a: *In the absence of a secondary market and without patient search, the physician's optimal threshold κ_j^* satisfies*

$$- \beta_{b_j} \cdot h\left(\kappa_j^*\right) = R_j \tag{3}$$

Equation (3) 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 her patients' health, just offsets the monetary reimbursement she receives from each office visit. Given the strict monotonicity of the health impact function, this threshold is unique.

4.2.2 With patient search

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

$$\underbrace{\frac{1}{|J_{c_i}|} \sum_{j \in J_{c_i}} \mathbb{1}\{\kappa_j^* \leq \kappa_i\} \cdot [h(\kappa_i) + \gamma_i]}_{\equiv P_{c_i}(\kappa_i)} \tag{4}$$

where $P_{c_i}(\kappa_i)$ 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 is willing to prescribe to her, the expected marginal cost of search is given by

$$\tau_{c_i}^s + \tau_{c_i}^d + P_{c_i}(\kappa_i) \cdot \tau_{c_i}^o \tag{5}$$

A patient will therefore continue searching if (1) her current physician will not prescribe to her and (2) the expected marginal benefit of search exceeds the expected marginal cost of search. That is, letting

$$T_{c_i}(\kappa_i) = \frac{\tau_{c_i}^s + \tau_{c_i}^d}{P_{c_i}(\kappa_i)} + \tau_{c_i}^o - h(\kappa_i) \tag{6}$$

patients with $\gamma_i \geq T_{c_i}(\kappa_i)$ will search until they find a physician who will prescribe to them while patients with $\gamma_i < T_{c_i}(\kappa_i)$ will keep their initial physician assignment (whether they can get an opioid prescription from the physician or not).

We can use this 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. $\kappa_{1,c}^* > \kappa_{2,c}^* > \ldots > \kappa_{|J_c|,c}^*$. The market share of physician 1 is then the patients who are randomly assigned to physician 1 initially and either (1) can get a prescription from physician 1, or (2) cannot get a prescription from physician 1 but do not find it optimal to search. The equilibrium market share of physician 1 in geographic market c is therefore given by

$$q_{1,c}^* = \frac{1}{|J_c|} \cdot \left[\int_{\kappa_{1,c}^*}^{\infty} f_c(k)dk + \int_0^{\kappa_{1,c}^*} \int_{-\infty}^{T_c(k)} f_c(k)g_c(\gamma)d\gamma dk \right]$$

Now consider the market share of the physician with the second-highest threshold in geographic market c, 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 also gets 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.[21] Therefore, the market share of physician 2 is given by

$$q_{2,c}^* = \frac{1}{|J_c|} \cdot \left[\int_{\kappa_{2,c}^*}^{\infty} f_c(k)dk + \int_0^{\kappa_{2,c}^*} \int_{-\infty}^{T_c(k)} f_c(k)g_c(\gamma)d\gamma dk \right]$$
$$+ \frac{1}{|J_c|\,(|J_c| - 1)} \cdot \int_{\kappa_{2,c}^*}^{\kappa_{1,c}^*} \int_{T_c(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk$$

Continuing in this way, it can be shown that the market share of patients for physician j in geographic market c is given by[22]

$$q_{j,c}^* = \frac{1}{|J_c|} \cdot \left[\int_{\kappa_{j,c}^*}^{\infty} f_c(k)dk + \int_0^{\kappa_{j,c}^*} \int_{-\infty}^{T_c(k)} f_c(k)g_c(\gamma)d\gamma dk \right]$$
$$+ \sum_{n=1}^{j-1} \left[\frac{1}{(|J_c| - n + 1)\,(|J_c| - n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} \int_{T_c(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right] \qquad (7)$$

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

---

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

[22] These market shares are shown pictorially in Figure A.4 for a market with two physicians.

With patient search and without a secondary market, physician j in geographic market c then chooses her threshold severity to solve the following problem:

$$
\begin{aligned}
\max_{\kappa_{j,c}} \quad & \beta_{b_j,c} \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{\tau_c^d + \tau_c^o - h(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right] \\
& + \beta_{b_j,c} \cdot \sum_{n=1}^{j-1} \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa_{j,c}}^{\kappa_{n,c}^*} \int_{T_c(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right] \\
& + R_{j,c} \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{\tau_c^d + \tau_c^o - h(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk \right] \\
& + R_{j,c} \cdot \sum_{n=1}^{j-1} \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa_{j,c}}^{\kappa_{n,c}^*} \int_{T_c(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk \right]
\end{aligned}
\tag{8}
$$

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

Taking the derivative of equation (8) with respect to κ_j and setting equal to zero yields the physician's optimal threshold:

Result 1b: *In the absence of a secondary market, the optimal threshold of physician j in geographic market c $\left(\kappa_{j,c}^* \right)$ satisfies*

$$
- \beta_{b_j,c} \cdot h(\kappa_{j,c}^*) = R_{j,c}
\tag{9}
$$

As in Result 1a, the uniqueness of this threshold is guaranteed by the strict monotonicity of the health impact function. Comparing equations (9) and (3), we see that the optimal threshold set by the physician is the same regardless of whether patients are allowed to search across physicians. The equilibrium quantity of prescriptions, however, is 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.[23]

4.3 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. Since the existence of a secondary market requires

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[23]The equilibrium allocation of opioid prescriptions with search and without a secondary market is shown pictorially in Figure A.3 for a market with two physicians.

that the resale price (p_c) outweighs the cost of accessing an opioid prescription $\left(\tau_c^d + \tau_c^o\right)$, any patient whose pain severity allows them to get a prescription will get one in the presence of a secondary market. The only decision facing a patient who can get a prescription from his doctor is therefore whether to consume the medication or to resell the medication on the secondary market. Furthermore, in the presence of a secondary market, patients who do not receive a prescription from a physician have the option of purchasing the medication from patients who find it optimal to resell.

Before analyzing how the presence of a secondary market influences physician behavior, let us first consider how a secondary market influences the equilibrium allocation of prescriptions. Again begin under the assumption that patients cannot search for physicians.

4.3.1 Without patient search

The reallocation of prescriptions across patients with a secondary market (and no patient search) is shown pictorially in Figure 3. Consider first a market with a single physician (subfigure (a)). With a secondary market, the physician knows that her patients that have a pain severity exceeding her threshold $\left(\kappa_i \geq \kappa_j^*\right)$ but have tastes such that reselling is optimal given the market price $(p_{c_i} > h(\kappa_i) + \gamma_i)$ will not consume the medication. Rather, those prescriptions will be reallocated to patients to whom she would not prescribe $\left(\kappa_i < \kappa_j^*\right)$ but who have tastes such that purchasing the medication is optimal given the market price $(h(\kappa_i) + \gamma_i > p_{c_i})$. In a market with two physicians (subfigure (b)), each physician again knows that her patients with pain exceeding her threshold but low enough tastes will resell their prescriptions. However, in a market with more than one physician, a single physician's prescriptions may be resold both to patients that the physician would and would not prescribe to. For example, a patient of physician 2 in subfigure (b) who resells his prescription will sell either to a patient of physician 1 with $\kappa_2^* \leq \kappa_i < \kappa_1^*$ (a patient who physician 2 would prescribe to) or to a patient of physician 1 or 2 with $\kappa_i < \kappa_2^*$ (a patient who physician 2 would not prescribe to).

Figure 3: Equilibrium allocation of opioids: with secondary market and no patient search
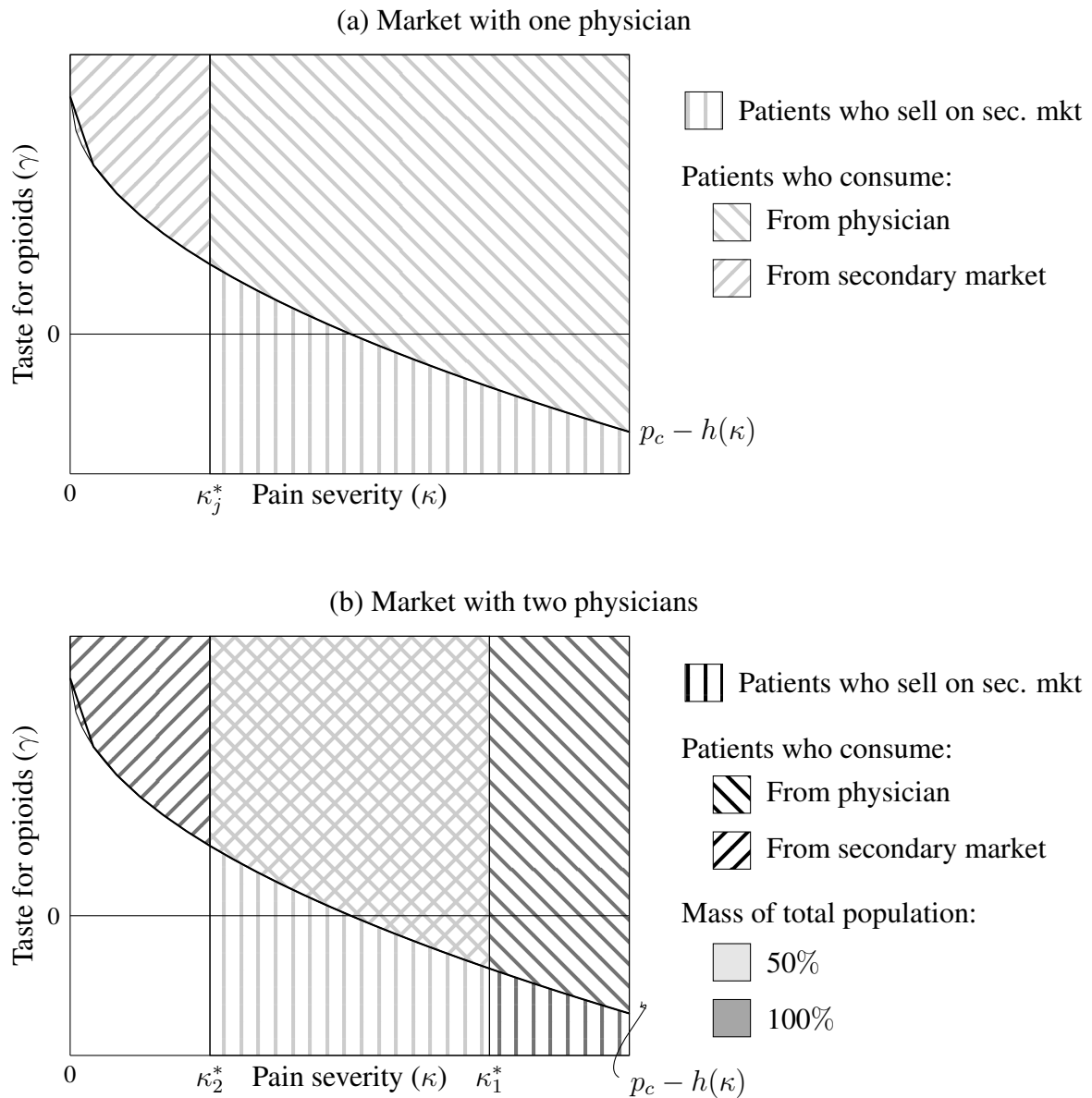
(a) Market with one physician

(b) Market with two physicians

Notes: The above figures display the equilibrium allocation of opioid prescriptions with a secondary market but without patient search, both in a market with a single physician (subfigure (a)) and in a market with two physicians (subfigure (b)).

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 will be consumed by people she did not prescribe to. 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^* to solve

$$
\begin{aligned}
\max_{\kappa_j} \quad & \beta_{b_j} \cdot \frac{|I_{c_j}|}{|J_{c_j}|} \cdot \int_{\kappa_j}^{\infty} \int_{p_{c_j} - h(k)}^{\infty} h(k) f_{c_j}(k) g_{c_j}(\gamma) d\gamma dk \\
+ \quad & \beta_{b_j} \cdot \frac{|I_{c_j}|}{|J_{c_j}|} \cdot \bar{h}_{c_j}^{SM} \cdot \int_{\kappa_j}^{\infty} \int_{-\infty}^{p_{c_j} - h(k)} f_{c_j}(k) g_{c_j}(\gamma) d\gamma dk \\
+ \quad & R_j \cdot \frac{|I_{c_j}|}{|J_{c_j}|} \cdot \int_{\kappa_j}^{\infty} f_{c_j}(k) dk
\end{aligned}
\tag{10}
$$

where $\bar{h}_c^{SM} = \dfrac{\sum_{j \in J_c} \int_0^{\kappa_j^*} \int_{pc - h(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk}{\sum_{j \in J_c} \int_0^{\kappa_j^*} \int_{pc - h(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk}$ is the average health impact of a prescription purchased on the secondary market in geographic market c. As before, the first term represents a physician's impact on the health of her patients that consume the medication she prescribes. The second term represents the impact that she has on the health of patients who buy the prescriptions she writes on the secondary market: this is simply the number of her prescriptions that are resold times the average health impact of a prescription 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 an incentive compatibility condition on the patient's taste for opioids. Note that I assume that physicians internalize neither their impact on the secondary market price nor on $\bar{h}_c^{SM}$; that is, they take both of these market-level equilibrium objects as given.[24]

Taking the derivative of equation (10) with respect to κ_j and setting equal to zero yields the physician's optimal threshold:

Result 2: *With a secondary market, the physician's optimal threshold κ_j^* satisfies*

$$
-\beta_{b_j} \cdot \left[(1 - G_{c_j}(p_{c_j} - h(\kappa_j^*))) \cdot h(\kappa_j^*) + G_{c_j}(p_{c_j} - h(\kappa_j^*)) \cdot \bar{h}_{c_j}^{SM} \right] = R_j
\tag{11}
$$

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 that she receives from an office visit when deciding whether to prescribe (equation (3)). In the presence of

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[24]The fact that physicians are not infinitesimal with respect to quantity on the secondary market is at odds with the average health impact and price-taking assumptions. I am therefore making the behavioral assumption that physicians recognize that their prescriptions may have a non-negligible impact on supply on the secondary market but do not go through the math to internalize their impact on price and average health impact.

a secondary market, the physician instead compares the *expected* 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 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 resell, respectively.

Equilibrium With a secondary market, an equilibrium in geographic market c is therefore characterized by a set of thresholds $\{\kappa_j^* : c_j = c\}$ and a secondary market price p_c such that

1. Physicians maximize utility (i.e., equation (11) holds $\forall\ j \in J_c$)

2. The secondary market clears. That is, p_c adjusts such that

$$\sum_{j \in J_c} \int_{\kappa_j^*}^{\infty} \int_{-\infty}^{p_c - h(k)} f_c(k) g_c(\gamma) d\gamma dk = \sum_{j \in J_c} \int_0^{\kappa_j^*} \int_{p_c - h(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk \tag{12}$$

Theoretical predictions How does the presence of a secondary market influence the quantity and origin of prescriptions? Intuition behind the key theoretical takeaways is provided below. The interested reader may refer to Appendix A for formal statements and proofs.

First, consider how an individual physician responds to the presence of a secondary market (Lemma 1 in Appendix A). Let κ_j^{SM*} (κ_j^*) denote physician j's threshold with (without) a secondary market. Note that the average health impact of an opioid prescription consumed on the secondary market will either be less than or greater than the health impact at her optimal threshold in the absence of a secondary market. In the first case—i.e., if $\bar{h}_{c_j}^{SM} < h(\kappa_j^*)$—the physician would not prescribe to the average person who consumes on the secondary market. Therefore, the marginal utility of prescribing is now 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 altruism, just offsets her revenue. Physicians for whom $\bar{h}_{c_j}^{SM} < h(\kappa_j^*)$ 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 $\bar{h}_{c_j}^{SM} > h(\kappa_j^*)$: if a physician would prescribe to the average person who buys on the secondary market, she is *more lenient* in

her prescribing in the presence of a secondary market. This is because the marginal utility of prescribing is now positive 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 less from the medication than the patient herself.

While a physician can either become more or less lenient in the presence of a secondary market, in aggregate only two things are possible: (1) either all physicians in a given geographic market become more strict, or (2) some physicians become more strict and some physicians become more lenient (Lemma 2 in Appendix A). Not all physicians can become more lenient, as this contradicts optimal patient behavior. To see this, note that all physicians are more lenient in the presence of a secondary market only if all physicians would be willing to prescribe to the average patient who buys on the secondary market. This is inconsistent with optimal patient behavior: since it is more expensive to get a prescription from the secondary market than from a physician, a patient who can get a prescription from all physicians will not purchase a prescription on the secondary market.

How does the presence of a secondary market for prescription opioids affect the total number of prescriptions written by physicians on the primary market? If all physicians become more strict, 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 necessarily puts upward pressure on the number of prescriptions. Therefore, whether the number of opioid prescriptions written by physicians in aggregate increases or decreases in the presence of a secondary market is theoretically ambiguous (Theorem 1 in Appendix A).

While the impact of a secondary market on the number of prescriptions is ambiguous, under moderate conditions a secondary market will increase prescribing differences between strict and lenient prescribers (Theorem 2 in Appendix A). If some physicians become more strict and some physicians become more lenient this is clear: since the secondary market causes relatively strict physicians (physicians with $\bar{h}_{c_j}^{SM} < h(\kappa_j^*)$) to become even more strict while simultaneously in-

ducing relatively lenient prescribers to become even more lenient (physicians with $\bar{h}_{c_j}^{SM} > h(\kappa_j^*)$), the secondary market polarizes physician behavior. Note, however, that even if all physicians become more strict, prescribing differences across relatively lenient and relatively strict prescribers will also likely increase. While both the most lenient and the most strict physician become stricter, the secondary market has 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.

Figure 4: Opioid prescriptions and secondary market prevalence
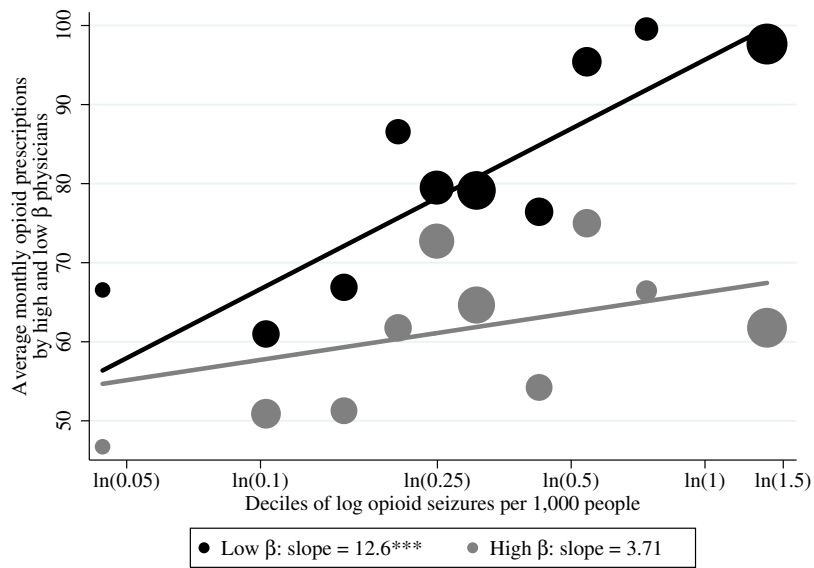
Notes: The above figure plots county-level averages for the number of opioid prescriptions written monthly by high- and low-altruism physicians against log prescription opioid seizures per capita in 2014. The size of the marker indicates the number of physicians in a given bin. The data on prescription opioid seizures come from the FBI's NIBRS.

We can see whether this prediction holds in the data. In particular, while a secondary market for prescription opioids exists in all locations across the United States, there is geographic variation in the prevalence of these secondary markets. To proxy for secondary market prevalence, I use information on prescription opioid seizures from the Federal Bureau of Investigation's (FBI) National Incidence-Based Reporting System (NIBRS)—a system that tracks crimes known to law enforcement. In the cross-section, I consider areas with more prescription opioid seizures per capita to have a secondary market for prescription opioids that is more widespread. Figure 4 plots average opioid prescriptions written by high- and low-altruism physicians in counties across the United

States against this proxy for secondary market prevalence. As predicted by the model, we see that the difference between the prescribing practices of high- and low-altruism physicians increases as the secondary market for prescription opioids becomes more widespread.

4.3.2 With patient search

When a secondary market for opioids exists, the marginal cost of search remains as before (equation (5)). However, since patients can search over physicians to obtain opioid prescriptions not just to consume but also to resell, the expected marginal benefit of search increases for some patients. More precisely, for patients who prefer to resell prescriptions given the market price $(p_{c_i} > h(\kappa_i) + \gamma_i)$, the marginal benefit of search is now given by $P_{c_i}(\kappa_i) \cdot p_{c_i}$, where $P_{c_i}(\kappa_i)$ is defined as in equation (4). For patients who would prefer to consume the medication rather than resell $(h(\kappa_i) + \gamma_i \geq p_{c_i})$, however, the expected marginal benefit of search is unchanged.

Optimal patient search behavior in the presence of a secondary market can therefore be summarized as follows:

- Patients with $h(\kappa_i) + \gamma_i \geq p_{c_i}$ search $\Leftrightarrow$

$$P_{c_i}(\kappa_i) \cdot [h(\kappa_i) + \gamma_i] \geq \tau_{c_i}^s + \tau_{c_i}^d + P_{c_i}(\kappa_i) \cdot \tau_{c_i}^o \qquad (13)$$

- Patients with $p_{c_i} > h(\kappa_i) + \gamma_i$ search $\Leftrightarrow$

$$P_{c_i}(\kappa_i) \cdot p_{c_i} \geq \tau_{c_i}^s + \tau_{c_i}^d + P_{c_i}(\kappa_i) \cdot \tau_{c_i}^o \qquad (14)$$

Rearranging the inequality in equation (14), we see that patients with $p_{c_i} > h(\kappa_i) + \gamma_i$ and $\kappa_i \geq P_{c_i}^{-1}\left(\frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} - \tau_{c_i}^o}\right)$ will search to resell. Furthermore, since the inequality in equation (13) always holds for patients with $h(\kappa_i) + \gamma_i \geq p_{c_i}$ and $\kappa_i \geq P_{c_i}^{-1}\left(\frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} - \tau_{c_i}^o}\right)$, it follows that *all* patients with $\kappa_i \geq P_{c_i}^{-1}\left(\frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} - \tau_{c_i}^o}\right)$ find it optimal to search.[25] As this observation will be helpful in deriving

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[25]The probability that a physician's patient resells therefore depends on whether $\kappa_i \lessgtr P_{c_i}^{-1}\left(\frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} - \tau_{c_i}^o}\right)$. This implies that it would be optimal for a physician to set two thresholds in the presence of a secondary market with patient search: one for patients with $\kappa_i \geq P_{c_i}^{-1}\left(\frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} - \tau_{c_i}^o}\right)$ and another for patients with $\kappa_i < P_{c_i}^{-1}\left(\frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} - \tau_{c_i}^o}\right)$. However, there is

physician market shares and subsequently optimal physician behavior, let

$$\tilde{P}_c \equiv P_c^{-1}\left(\frac{\tau_c^s + \tau_c^d}{p_c - \tau_c^o}\right)$$

Again label physicians within a geographic market by descending thresholds, i.e. $\kappa_{1,c}^* > \kappa_{2,c}^* > \ldots > \kappa_{|J_c|,c}^*$. As without a secondary market, the patients of physician 1 in geographic market c in equilibrium are the patients who are randomly assigned to physician 1 initially and either (1) can get a prescription from physician 1, or (2) do not find it optimal to search. Since all patients with $\kappa_i \geq \tilde{P}_{c_i}$ search in the presence of a secondary market, while patients with $\kappa_i < \tilde{P}_{c_i}$ only search if the inequality in equation (13) holds, the market share of physician 1 in geographic market c depends on whether $\kappa_{1,c}^* \geq \tilde{P}_c$ or $\kappa_{1,c}^* < \tilde{P}_c$. The market share of doctor 1 can therefore be summarized as follows:

$$q_{1,c}^* = \begin{cases} \frac{1}{|J_c|} \cdot \left[\int_{\kappa_{1,c}^*}^{\infty} f_c(k)dk + \int_0^{P_c^*} \int_{-\infty}^{T_c(k)} f_c(k)g_c(\gamma)d\gamma dk\right] & \text{if } \kappa_{1,c}^* \geq \tilde{P}_c \\ \frac{1}{|J_c|} \cdot \left[\int_{\kappa_{1,c}^*}^{\infty} f_c(k)dk + \int_0^{\kappa_{1,c}^*} \int_{-\infty}^{T_c(k)} f_c(k)g_c(\gamma)d\gamma dk\right] & \text{if } \kappa_{1,c}^* < \tilde{P}_c \end{cases}$$

where $T_c(\kappa)$ is defined as in equation (6).

Continuing in this way, we can likewise derive the equilibrium market share of physician j in geographic market c. As highlighted above for physician 1, the market share for physician j will depend on whether $\kappa_{j,c}^* \gtrless \tilde{P}_c$. Denote by $j_{p,c}$ the doctor with $\min_{\kappa_{j,c}^*}\left(\tilde{P}_c - \kappa_{j,c}^* : \tilde{P}_c - \kappa_{j,c}^* \geq 0\right)$; that is, the doctor whose threshold is closest from below to the pain level $\tilde{P}_c$.[26] The equilibrium

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no empirical support for two thresholds: evidence suggests that even if a physician suspects a patient is diverting the medication, they will still prescribe if the patient is in sufficient pain to justify a prescription (Lembke, 2012). I therefore restrict attention to threshold equilibria, although I am working on an extension in which each physician can set two thresholds.

[26]If all physicians have $\kappa^* > \tilde{P}$, then the market shares will be as in the case for doctors with $j \leq j_p$ below.

market share for doctor j in geographic market c is given by[27]

$$
q_{j,c}^* = \begin{cases}
\frac{1}{|J_c|} \cdot \left[\int_{\kappa_{j,c}^*}^{\infty} f_c(k)dk + \int_0^{P_c^*} \int_{-\infty}^{T_c(k)} f_c(k)g_c(\gamma)d\gamma dk \right] & \text{if } \kappa_{j,c}^* \geq \tilde{P}_c \\
\quad + \sum_{n=1}^{j-1} \cdot \left[\frac{1}{(|J_c|-n+1)(|J_c|-n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} f_c(k)dk \right] & \\[2mm]
\frac{1}{|J_c|} \cdot \left[\int_{\kappa_{j,c}^*}^{\infty} f_c(k)dk + \int_0^{\kappa_{j,c}^*} \int_{-\infty}^{T_c(k)} f_c(k)g_c(\gamma)d\gamma dk \right] & \\
\quad + \sum_{n=j_{p,c}}^{j-1} \cdot \left[\frac{1}{(|J_c|-n+1)(|J_c|-n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} \int_{T_c(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right] & \text{if } \kappa_{j,c}^* < \tilde{P}_c \\
\quad + \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{1}{(|J_c|-n+1)(|J_c|-n)} \cdot \left(\int_{\kappa_{j,c}^*}^{P_c^*} \int_{T_c(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk + \int_{P_c^*}^{\kappa_{n,c}^*} f_c(k)dk \right) \right] &
\end{cases}
$$

$$(15)$$

As before, each physician sets her threshold to maximize utility. Furthermore, the intuition behind the physician's optimality condition remains the same: in the presence of a secondary market, the physician sets her threshold such that the expected impact of her medication at her threshold patient, weighted by her concern for this impact, just offsets her revenue. However, since the market shares with patient search are more complicated than without, the physician's utility function is likewise more complicated. Refer to Appendix A.2 for the physician's problem with patient search and a secondary market.

With patient search, physicians with low thresholds write more prescriptions for two reasons: (1) they are more lenient for a given patient, and (2) they see more patients because of this leniency. Since patients will sort towards more lenient prescribers, allowing for patient search exacerbates the 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.

4.4 Discussion

Addiction is a fundamental characteristic of the opioid epidemic: patients who are addicted to opioids are more likely to use the medications non-medically, shop over doctors to find a physician who is willing to prescribe to them, and turn to the secondary market to access prescriptions for misuse. As I do not have information on patients over time, I do not explicitly model the dynamics

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[27]These market shares are shown pictorially in Figure A.5 for a market with two physicians.

of addiction. However, addiction enters the model in two places: (1) patient tastes for opioids, γ, and (2) the health impact function, $h(\kappa)$. Since a patient who is addicted to opioids will have higher tastes than an otherwise identical patient who has no previous exposure to the medication, one can think of γ as a reduced-form, static parameter that captures the dynamics of addiction. Furthermore, the health impact function captures both the medicinal benefits of 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 abuse.

I assume that physicians perfectly observe each patient's level of pain. In many cases, however, a physician will only observe reported pain. As long as reported pain is increasing monotonically in true pain, one can suppose that κ_i instead reflects the severity of pain reported to the physician by patient i. If misreporting one's pain is costly, however, this will not hold. While I do not have the data necessary to estimate a cost of misreporting pain, the model can easily be extended to account for this scenario. Since costly misreports of pain would drive all physicians, regardless of their level of altruism, to be more strict in their prescribing practices, the primary intuition of the model is robust to this extension.

Finally, I assume that a physician cares equally about the health impact of her medication whether it is consumed by one of her patients or by someone on the secondary market. It is reasonable to assume that a physician's utility is tied to her prescriptions: discussions with physicians demonstrate that they care if someone misuses a prescription they wrote, regardless of how the individual acquired the prescription. However, it is possible that physicians give different weights to patients and non-patients. For example, it could be the case that a physician gives weight β_{b_j} to the medication's health impact on her own patients and weight $\alpha_j \cdot \beta_{b_j}$ to the medication's health impact on her non-patients. If $\alpha < 1$, allowing for different altruism weights will dampen the effects of a secondary market on physician prescribing for all altruism groups (unless patients only resell to patients of the same physician). However, as long as $\alpha_l \cdot \beta_l < \alpha_h \cdot \beta_h$—that is, high-altruism physicians care more about both their patients and non-patients than low-altruism physicians—the primary intuition behind the model will remain unchanged.

5 Empirical strategy

There are four sets of parameters in the model: (1) the distribution of tastes in each commuting zone, (2) the search cost in each commuting zone, (3) the parameters of the health impact function, and (4) the relative utility weights for each altruism group. Under the assumption that the distribution of tastes in commuting zone c is of the form $\mathcal{N}(\mu_c, \sigma_c^2)$ and the health impact function is of the form $h(\kappa) = a \cdot ln(b \cdot \kappa + d)$,[28] there are $3 \cdot C + 6$ parameters to be estimated, where C is the number of commuting zones being considered. In practice, I estimate these parameters on the ten largest commuting zones excluding New York[29]: Los Angeles, Chicago, Houston, Philadelphia, Washington DC, Boston, Detroit, San Francisco, Atlanta, and Dallas. The parameters to be estimated are summarized in Table 5.

Table 5: Parameters to be estimated

Parameters	#	Description
$G_c(\gamma) \sim \mathcal{N}(\mu_c, \sigma_c^2)$	$2 \cdot C$	Distribution of tastes in czone c
$\tilde{\tau}_c^s$	C	Search cost in czone c*
$\boldsymbol{\theta} = \{a, b, d\}$	3	Parameters of health impact function
$\boldsymbol{\beta} = \{\beta_l, \beta_m, \beta_h\}$	3	Relative altruism weights

* Includes cost of doctor visit
$(\tilde{\tau}_c^s = \tau_c^s + \tau_c^d)$

Notes: The above table displays the $3 \cdot C + 6$ parameters of interest. I estimate the model on the ten largest commuting zones (listed in Table 2), resulting in 36 parameters. As noted in the text, the health impact function is parameterized to be of the form $h(\kappa) = a \cdot ln(b \cdot \kappa + d)$. Recall that physicians are categorized into altruism groups outside of the model using physician-level responses to the reformulation of OxyContin (see Section 3).

Recall the optimality condition for each physician first displayed in equation (11). Adding explicit notation for the parameters on which each component depends, the optimality condition for physician j becomes

$$-\beta_{b_j} \cdot \left[(1 - G_{c_j}(p_{c_j} - h(\kappa_j^* : \boldsymbol{\theta}))) \cdot h(\kappa_j^* : \boldsymbol{\theta}) + G_{c_j}(p_{c_j} - h(\kappa_j^* : \boldsymbol{\theta})) \cdot \bar{h}_{c_j}^{SM} \right] = R_j \qquad (16)$$

$$where \ \ G_{c_j}(\gamma) \sim \mathcal{N}(\mu_{c_j}, \sigma_{c_j}^2)$$

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[28]Consistent with the medical literature, this functional form implies that the health impact of prescription opioids is increasing in pain at a decreasing rate (i.e., monotonically increasing and concave). Furthermore, estimates demonstrate that parameterizing the health impact function in this way provides a better model fit than a variety of other specifications (e.g., linear or quadratic). Results for alternative specifications are available upon request.

[29]New York is excluded due to data limitations. While the StreetRx data has good coverage of Manhattan, coverage of the other boroughs is extremely limited.

Since $\{p_c\}_{\forall c}$ and $\{R_j, b_j\}_{\forall j}$ are data, if we knew the average harm on the secondary market in each commuting zone c $\left(\{\bar{h}_c^{SM}\}_{\forall c}\right)$, then for a given set of parameters $\{\{\mu_c, \sigma_c^2\}_{\forall c}, \boldsymbol{\theta}, \boldsymbol{\beta}\}$ we could simply solve each physician's optimality condition to obtain the health impact at their threshold, $h(\kappa_j^*)$. Since the average harm on the secondary market is not known, but rather is determined in equilibrium, add $\{\bar{h}_c^{SM}\}_{\forall c}$ as nuisance parameters to be estimated.[30] There are therefore $4 \cdot C + 6$ parameters to be estimated.

5.1 Estimation

The $4 \cdot C + 6$ parameters are estimated using a generalized method of moments (GMM) estimator based on the $4 \cdot C + 6$ moments listed in Table 6. As outlined in Appendix A.3, for a given set of parameter values $\left\{\{\tilde{\tau}_c^s, \mu_c, \sigma_c^2, \bar{h}_c^{SM}\}_{\forall c}, \boldsymbol{\theta}, \boldsymbol{\beta}\right\}$, I first solve equation (16) 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 us the empirical distribution of prescription probabilities as a function of pain in each commuting zone, which combined with search costs and the distributions of tastes yields optimal patient search behavior. Assigning patients to physicians based on physicians' thresholds and optimal patient search (equation (15)), I can then compute (1) the number of prescriptions written by each physician, (2) the share of each physician's patients that buy and sell on the secondary market, and (3) the total health impact of opioid consumption on the secondary market.

Three sets of moments match model predictions for the number of opioid prescriptions to equilibrium outcomes observed in different cross-sections of the data: (1) the total number of opioid prescriptions in each commuting zone (C moments), (2) the total number of opioid prescriptions across altruism groups (3 moments), and (3) the total number of prescriptions across specialty groups (3 moments). The remaining three sets of moments compare model predictions for activity on the secondary market to the observed equilibrium outcomes. In particular, comparing the model predictions for supply and demand on the secondary market in each commuting zone provides information on market clearing (C moments). Another set of moments measures the difference

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[30]The average health impact of a prescription opioid on the secondary market in each commuting zone is determined by all other parameters in equilibrium and thus is not a free parameter. However, the estimation algorithm described below requires a guess for $\bar{h}_c^{SM}$ in each commuting zone to arrive at the model predictions used to construct moments. I therefore treat $\{\bar{h}_c^{SM}\}_{\forall c}$ as free parameters that are simply matched to functions of the other parameters in estimation.

between demand on the secondary market and the misuse rate observed in each commuting zone (C moments). Finally, the average health impact among patients that buy on the secondary market in each commuting zone is used directly to match nuisance parameters $\left\{\bar{h}_c^{SM}\right\}_{\forall c}$ (C moments).

Table 6: Moments used for estimation

Moments	#	Description
$m_{1,c} = \sum_{j\in J_c} N_j^{\text{sell}} - \sum_{j\in J_c} N_j^{\text{buy}}$	C	Market clearing in czone c
$m_{2,c} = \bar{h}_c^{SM} - \frac{\sum_{j\in J_c} H_j^{\text{buy}}}{\sum_{j\in J_c} N_j^{\text{buy}}}$	C	Avg. harm on secondary market in czone c
$m_{3,c} = \sum_{j\in J_c} Q_j - \sum_{j\in J_c} \left(N_j^{\text{consume}} + N_j^{\text{sell}}\right)$	C	Total Rx in czone c
$m_{4,c} = \eta_c - \frac{1}{|I_c|}\sum_{j\in J_c} N_j^{\text{buy}}$	C	Misuse rate from secondary mkt. in czone c
$m_{5,b} = \frac{1}{|J_b|}\cdot\sum_{j\in J_b} Q_j - \frac{1}{|J_b|}\cdot\sum_{j\in J_b}\left(N_j^{\text{consume}} + N_j^{\text{sell}}\right)$	3	Avg. Rx per physician in altruism group b
$m_{6,g} = \frac{1}{|J_g|}\cdot\sum_{j\in J_g} Q_j - \frac{1}{|J_g|}\cdot\sum_{j\in J_g}\left(N_j^{\text{consume}} + N_j^{\text{sell}}\right)$	3	Avg. Rx per physician in specialty group g

Notes: The above table displays the $4\cdot C + 6$ moments used to estimate the $3\cdot C + 6$ parameters listed in Table 5 and the C nuisance parameters $\left\{\bar{h}_c^{SM}\right\} \forall c$. Q_j denotes the average quantity of opioid prescriptions written monthly by physician j in 2014 in the QuintilesIMS data. $N_j^{consume}$, N_j^{sell}, and N_j^{buy} denote the model predictions for the number of physician j's patients that consume the prescription they get from the physician, sell the prescription they get from the physician, or do not get a prescription and turn to the secondary market to buy, respectively. H_j^{buy} denotes the model prediction for the total health impact among physician j's patients who buy on the secondary market. Equations for the model predictions $\left(N_j^{consume}, N_j^{sell}, N_j^{buy}, H_j^{buy}\right)$ are provided in Appendix A.3. I estimate the model on the ten largest commuting zones (listed in Table 2), resulting in 46 moments and 46 parameters.

Identification   While all of the moments listed in Table 6 are used to jointly identify the parameters listed in Table 5, we can consider what variation in the data allows for the identification of each parameter. Intuitively, local tastes are identified by the misuse rate on the secondary market and the total number of prescriptions written within a given commuting zone. Since these moments provide estimates of the empirical cumulative distribution function of tastes over different supports of the distribution, matching these two moments is sufficient to identify both the mean and standard deviation of the underlying distribution.

Furthermore, market clearing helps to identify the search cost in each commuting zone. If the search cost is too high, too many patients will turn to the secondary market instead of searching across physicians to access prescription opioids, and thus demand will exceed supply. If the search cost is instead too low, too many patients will search to consume and resell, resulting in excess supply on the secondary market. The search cost is therefore the cost of searching over physicians that results in a balance between the number of patients turning to the secondary market to buy and sell opioid prescriptions.

Conceptually, identification of the relative utility weights for each altruism group is driven by differences in the level of prescriptions across these groups. If low-altruism physicians write more prescriptions on average conditional on their revenue than middle-altruism physicians, for example, then low-altruism physicians must put relatively less weight on the impact that they have on their patients' health to rationalize this difference.

Finally, identification of the health impact function comes from the relationship between reimbursement per patient and prescription rates. Consider two physicians of equal altruism in the same commuting zone, one who makes more money per office visit and writes more opioid prescriptions than the other. Precisely how many more prescriptions the physician writes relative to how much more the physician gets paid informs the difference in the health impact at each of their thresholds, as this tells us how much a physician must be compensated to cause a certain amount of additional harm.

5.2 Robustness

The GMM procedure introduced above can be adapted to examine the sensitivity of the estimates and to make the framework more flexible. As suggested by Table 1, there are outliers in the distribution of prescriptions. To ensure that my results are not being driven by a few physicians, I re-estimate my model matching median opioid prescriptions instead of average opioid prescriptions. The estimates are quite similar using these alternative moments.

Next, while the interpretations of physicians in the low-altruism and high-altruism groupings are straightforward (that is, they either decrease or increase their use of OxyContin following the reformulation), it is less clear that the middle-altruism physicians are properly categorized.[31] Given that I observe no consistent change in their prescribing of OxyContin following its reformulation, the natural experiment reveals less about their preferences than the preferences of physicians who

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[31] As noted in Section 3, it is likely that physicians have different incentives to respond to the reformulation of OxyContin depending on local market fundamentals. For example, a physician who is the only provider in her area may be less likely to switch her patients since she knows that they have no outside option. While across-location disparities in the share of low-altruism providers persist conditional on measures of local competition and demand, I am in the process of re-estimating my model to allow for location-specific altruism weights. That is, instead of restricting $\beta_{b,c} = \beta_b \ \forall c$, I estimate $\{\beta_{b,c}\}_{\forall c}$. With this formulation, there are $6 \cdot C + 3$ parameters and C nuisance parameters. I can easily create $3 \cdot C$ additional moments by using the average number of prescriptions per physician within each altruism group b within each commuting zone c in place of the average within an altruism group across commuting zones (that is, $m_{5,b,c}$ rather than $m_{5,b}$). Preliminary results suggest that while there is variation across commuting zones in the point estimates of altruism weights, the ordering and relative magnitudes remain consistent.

respond by significantly changing their behavior. To ensure that the inclusion of these physicians does not bias my estimates, I re-estimate my model excluding physicians in the middle-altruism category. Note that this removes one parameter (β_m) and one moment $(m_{5,m})$, so the estimation proceeds as before. Despite having implications for market clearing, estimates are stable to excluding middle-altruism physicians. In particular, the estimated altruism weights for low- and high-altruism physicians are relatively unaffected by the exclusion of the middle group.

As discussed above, the health impact function is identified in part by differences in reimbursement and prescription rates across specialty groups. As this may be biased by differences in the distributions of pain severities across specialties, I can instead use the variance of prescriptions within each altruism group to train the parameters of the health impact function. Reassuringly, results are robust to a variety of selected moments.

6 Results

6.1 Model estimates

Estimation results are provided in Table 7. Looking first to the results for relative utility weights, we see that the ordering of altruism groups by the average weight physicians place on their health impact accords with the intuition previously introduced. In particular, low-altruism physicians place the least weight on the impact they have on their patients' health whereas high-altruism providers have the greatest concern for the medical impact of their actions. In fact, while low-altruism physicians are revealed to have greater concern for their revenue ($\hat{\beta}_l = 0.91 < 1$), high-altruism physicians place more weight on how their actions impact their patients' health relative to their revenue ($\hat{\beta}_h = 1.10 > 1$). The estimates further reveal that middle-altruism physicians place nearly equal weights on both terms in their utility function ($\hat{\beta}_m = 0.96$).

Table 7: Parameter estimates

Parameters	Estimates	
	Average across czones	*Range*
μ_c	44.65	[-94.20,156.21]
σ_c^2	619.93	[486.34, 718.89]
$\tilde{\tau}_c^s$	112.86	[89.12,179.41]
	Point estimate	
$\{a, b, c\}$	$\{684.72, 0.66, 0.012\}$	
$\{\beta_l, \beta_m, \beta_h\}$	$\{0.91, 0.96, 1.10\}$	

Notes: The above table summarizes estimates of the 36 parameters listed in Table 5. These estimates reflect the parameters in ten commuting zones: Los Angeles, Chicago, Houston, Philadelphia, Washington DC, Boston, Detroit, San Francisco, Atlanta, and Dallas.

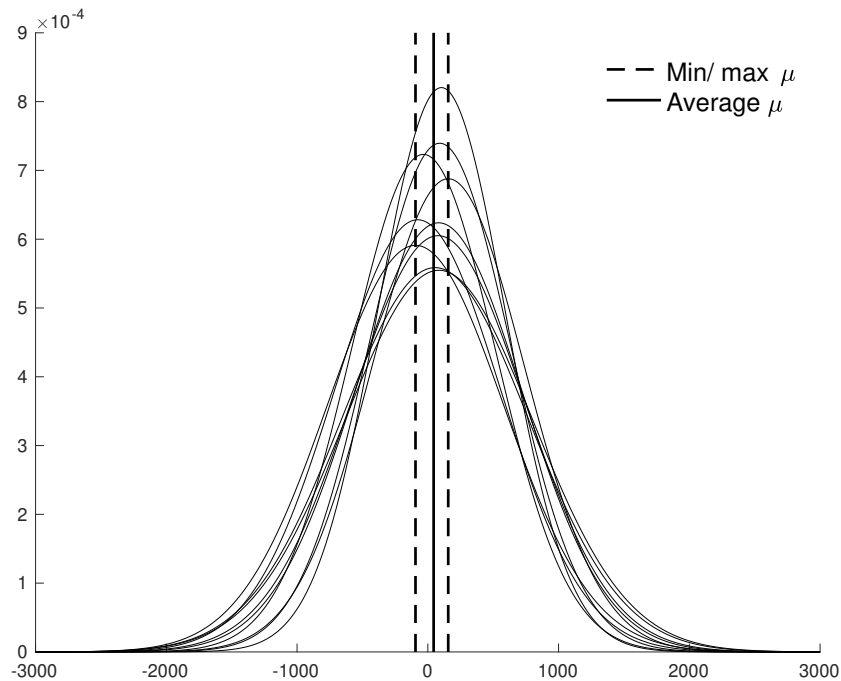Figure 5: Estimated health impact function
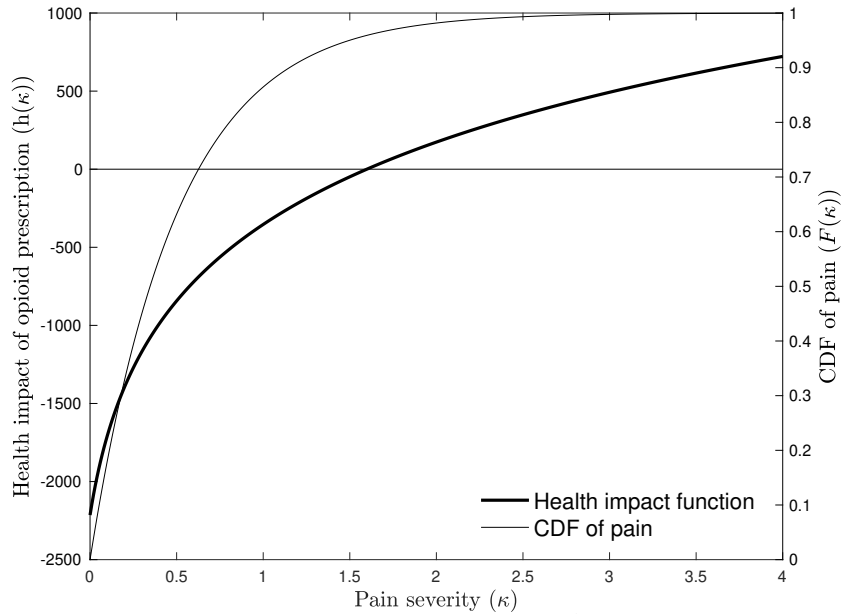
Notes: The above figure depicts the estimated health impact function $\left(\hat{h}(\kappa) = 684.72 \cdot ln(0.66 \cdot \kappa + 0.012)\right)$. To examine how the health impact of prescription opioids varies across the distribution of pain severities observed in the population, this impact function is overlaid with the CDF of pain.

The estimated health impact function is depicted in Figure 5. Recall that the health impact function maps the severity of a patient's pain to a monetized health impact and does not vary across commuting zones. The average pain across commuting zones—measured using responses to questions regarding pain on the NHIS (see Section 2)—is approximately 0.5, which indicates 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 suggest that patients

should only take opioids in cases of severe pain that does not respond to non-opioid analgesics (Dowell et al., 2016). In fact, the health impact function depicted in Figure 5 suggests that a patient needs to have pain that is nearly four standard deviations above the mean level of pain before opioids are beneficial (i.e., the health impact exceeds zero) from a medical perspective. As shown by the overlaid CDF of the distribution of pain, the estimated health impact function suggests that opioids only have a positive health impact for approximately 5% of the population.

Figure 6: Estimated distributions of tastes

Notes: The above figure depicts the estimated distributions of tastes for prescription opioids in the ten commuting zones used for estimation (listed in Table 2).

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 will still desire to consume if they have high enough tastes. Therefore, while the health impact function depicted in Figure 5 suggests that opioid consumption would be quite low if pain were to be considered in isolation, the combination of patient pain and tastes for opioids rationalize much higher consumption. As shown in Figure 6, while there is variation in the estimated distribution of tastes for prescription opioids across locations, the average taste is positive in most commuting zones. Furthermore, the substantial variance ensures that there are large tails; in particular, there are patients with very high tastes for opioids who will consume despite negative health impacts. While

a patient with the average pain (0.5) and average tastes will not consume an opioid in equilibrium, a one standard deviation increase in tastes is sufficient for the average pain patient to optimally consume.

Turning to the estimates for search costs, we see that the cost of searching for a physician varies between \$90–\$180 across commuting zones. By benchmarking these estimates to resale prices on the secondary market, we see that estimated search costs vary between 12%–28% of secondary market prices. While these costs may seem high given the prevalence of doctor shopping documented in the literature (Peirce et al., 2012; Jena et al., 2014; Yang et al., 2015), recall that estimated search costs include the cost of visiting a physician. That is, since patients must visit a physician in addition to paying the search cost to sample a new physician, estimated search costs necessarily represent a composite measure of both the costs of search and any copayment and time costs associated with visiting a physician. If, for example, a patient has a \$30 copayment for a doctor's visit, search costs and time costs would translate to less than 20% of the secondary market price across all markets.

6.2   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 6.1 to quantify the impact of a secondary market on (1) the total number of opioid prescriptions written by physicians on the primary market, (2) the share of opioid prescriptions that come from low-altruism relative to high-altruism providers, and (3) the allocation of opioid prescriptions in equilibrium. Comparing the aggregate health impacts of prescriptions opioids with and without a secondary market, I further measure how the presence of a secondary market for prescription opioids affects population health.

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 (9) (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, $\hat{\theta}$, I then invert the health impact at each physician's threshold to obtain their optimal threshold. This distribution of thresholds gives us the empirical distribution of prescription probabilities as a

function of pain levels in each commuting zone, which combined with the estimated search costs $\left\{ \hat{\tau}_c^s \right\}_{\forall c}$ and the estimated distributions of tastes $\{\hat{\mu}_c, \hat{\sigma}_c^2\}_{\forall c}$ 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 (7)), 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.

Figure 7: Optimal physician thresholds: with and without a secondary market
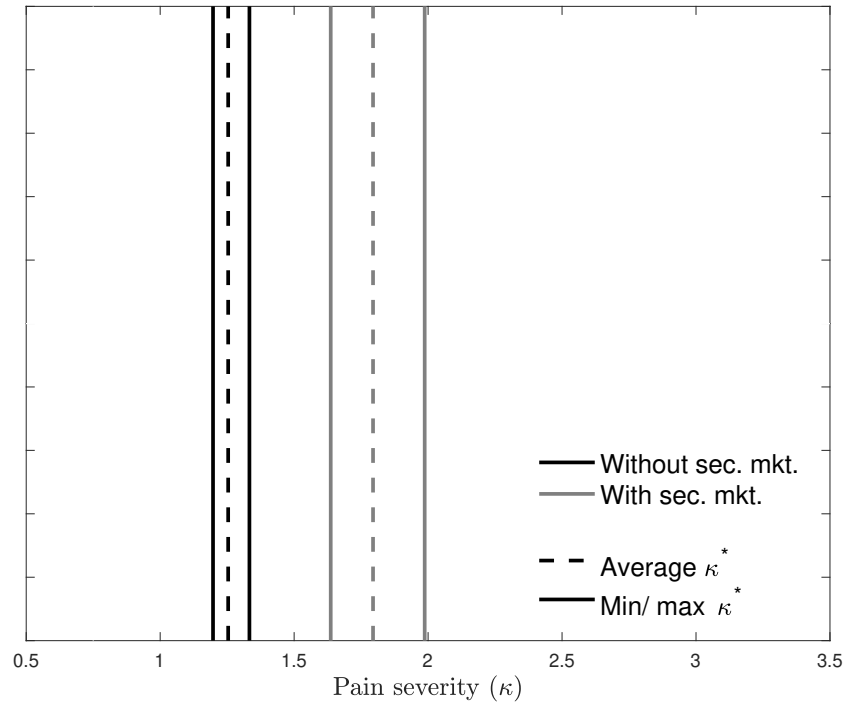
Notes: The above figure depicts the range of optimal physician thresholds with and without a secondary market. These thresholds are for Detroit; they are qualitatively representative of the thresholds in the other nine commuting zones used for estimation (listed in Table 2).

Figure 7 shows the range of physician thresholds for an example commuting zone (Detroit) with and without a secondary market. We see that the presence of a secondary market induces all physicians to be more strict, indicating that the potential harm caused by medications diverted to the secondary market induces all physicians to be more careful in their prescribing. However, the presence of a secondary market has a greater impact on the optimal thresholds of physicians who are more strict in the absence of a secondary market. Therefore, the presence of a secondary market increases prescribing differences among strict and lenient prescribers: in fact, the range of optimal thresholds is on average 2.87 times higher with versus without a secondary market. This

increasing variance has important implications for the origin of prescriptions. While nearly 42% of opioid prescriptions are currently written by low-altruism providers, this share would drop to only 31% if the secondary market were shut down.

Recall from Section 4 that both demand and supply respond to the presence of a secondary market. While all physicians are more careful in their prescribing because of a secondary market, more patients show up to physicians due to the resale option when a secondary market exists. Therefore, whether prescriptions are higher or lower with versus without a secondary market depends on which of these forces dominates. Counterfactuals demonstrate that the decrease in physician leniency outweighs the increase in patient volume: In 2014, opioid prescriptions would have been 13% higher if a secondary market for prescription opioids did not exist. Therefore, if reducing the number of prescriptions is the policy target, policies that crack down on the secondary market will actually move us away from this goal.

Despite the impact on the number of prescriptions, the total health impact of prescription opioids is reduced by patient reallocation on the secondary market. That is, while prescription opioids result in annual net harm of over $3.29 billion in the ten commuting zones considered, this figure would change to a *positive* net health impact of $3.34 billion if the secondary market were entirely shut down. This highlights the policy trade-off implicit in the regulation of prescription opioids: banning prescription opioids entirely would improve the health of misusers but harm patients with a legitimate medical need.

6.3 Maximal health benefits

What are the maximal health benefits that can be gained from prescription opioid use across the United States? Recall from Section 4 that physicians with any concern for their income will harm their threshold patient. Therefore, even though the net health impact of opioids would be higher if we were to shut down the secondary market, these gains would be even higher if we were to simultaneously limit unnecessary prescribing.

In particular, consider first the case with a secondary market. If prescribing were limited only to those with positive health impacts—that is, if physicians were to only prescribe to patients for whom $h(\kappa_i) \geq 0$—prescriptions would fall by 20%. While this demonstrates that prescriptions are

currently too high, recall that prescriptions would be *even higher* without a secondary market: as we saw in Section 6.2, prescriptions are 13% higher when the secondary market is removed. Comparing the counterfactual number of prescriptions in a world without a secondary market to the counterfactual number of prescriptions in a world where physicians only prescribe to patients with positive health impacts, we see that the rate of overprescribing would jump to 46% if the secondary market did not exist.

By definition, these additional prescriptions harm the health of consumers. Therefore, maximal health impacts would be achieved by shutting down the secondary market and preventing unnecessary prescribing. Estimates demonstrate that policies that target both the quantity of prescriptions and their allocation have potential health impacts of nearly $18 billion per year, an increase of nearly $33 billion over the status quo.

6.4 Policy discussion

What does this imply for the potential effectiveness of policies to address the epidemic? My results shed light on two policies that have received a great deal of recent attention: (1) expanding the use of prescription drug monitoring programs (PDMPs) among providers and (2) expanding access to treatment programs among addicts. PDMPs—prescription databases that allow physicians to check for signs of opioid abuse and diversion before prescribing—could help physicians avoid prescribing to patients who are diverting to the secondary market, thereby simultaneously reducing prescriptions on the primary market and supply on the secondary market. However, since physicians are more lenient in their prescribing for a given patient when the possibility of diversion is reduced, decreases in prescriptions for patients suspected of diverting to the secondary market will be met with increases in prescriptions for personal consumption among patients without a legitimate medical need. This is consistent with recent evidence demonstrating that PDMPs have little effect on average (Paulozzi et al., 2011; Reifler et al., 2012; Haegerich et al., 2014; Meara et al., 2016). My results therefore suggest that PDMPs would be more effective if they were not only used as a tool for physicians to identify diversion but also as a tool for law enforcement to identify physicians who are overprescribing.

A similar logic governs the limited potential for expanded treatment access alone to quell the

opioid epidemic. Funneling users into treatment programs will reduce demand on the secondary market, thereby lowering the secondary market price. Since lowering the secondary market price reduces the probability of diversion, such policies should follow a similar trajectory as PDMPs: decreases in prescriptions for diversion (here driven by a lowering of the incentives for patients to resell) will be met with increases in prescriptions for personal consumption among patients without a legitimate medical need. This again highlights the potential for the effectiveness of policies targeting a single market to be eroded by feedback across the two markets and suggests the need for policies to target both the reallocation of prescriptions by patients and overprescribing by physicians.

7 Discussion and conclusion

Despite a recent wave of literature examining the opioid epidemic, the general forces underlying the crisis are not well understood. In particular, while the opioid epidemic is borne from legal activity, surprisingly little is known about why physicians continue to prescribe these medications in such large quantities. Furthermore, while it is widely acknowledged that the presence of a secondary market helps fuel non-medical use, little attention has been devoted to understanding how this market influences the prescribing practices of physicians. This paper contributes to our understanding of the mechanisms driving the epidemic by analyzing the behavior of patients, physicians, and the interactions between the two across both primary and secondary markets.

Policies to address the epidemic are complicated by the 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: while reducing the supply of drugs with no legitimate medical purpose is an uncontroversial policy objective, there is no agreement among the medical community, policy makers, and the public about the optimal level of opioid prescriptions. This paper provides a framework that can be used to quantify the health impacts of prescription opioids under alternative prescribing regimes, providing valuable information that can help inform policy. My results demonstrate that at least 20% of opioid prescriptions are currently written for patients who are harmed by the medications, suggesting that the current level of prescriptions is not optimal from a public health perspective.

While the trade-off between legitimate and illegitimate use of prescription opioids is widely recognized, this paper uncovers another trade-off that further complicates the design of policies to address the epidemic. In particular, while reducing activity on the secondary market will reduce the medical harm caused by the reallocation of legally prescribed opioids to addicts, policies that target the secondary market will have the unintended consequence of *increasing* unnecessary prescribing by physicians. 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 prescription opioids being consumed by patients without a legitimate medical need. It follows that policies to address the epidemic should not be one dimensional: Rather, policies should simultaneously target both the primary and secondary markets. Estimates demonstrate that such policies have potential gains from accrued health benefits of at least $18 billion per year, an increase of $33 billion over the status quo.

While cracking down on the secondary market is an accepted policy lever, policies that target the primary market remain controversial. In addition to limiting physician autonomy, critics argue that reducing the legal supply of opioid prescriptions will not quell the epidemic since users will just switch to heroin or illicit fentanyl. As shown by Alpert et al. (2016), as much as 80% of the increase in heroin mortality since 2010 can be attributed to the OxyContin reformulation, suggesting that users are willing to substitute to heroin when the legal opioid supply is disrupted. It is therefore likely that deaths from non-prescription opioids would rise if physicians became less willing to prescribe opioids. However, these increases would likely be temporary. Eighty percent of heroin users misused prescription opioids before switching to heroin (Muhuri et al., 2013), so reducing access to prescription opioids should reduce the size of the next generation of opioid addicts. Reducing the supply of prescription opioids by reigning in unnecessary prescribing therefore has the potential to change the trajectory of the epidemic by making it less likely that opioid addiction begins. Identifying policies that can limit addiction among the next generation while mitigating harm for current users is a fruitful area for future research.

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A Additional model details

A.1 Proofs

Consider a single geographic market c. Recalling the notation introduced in Section 4, let κ_j^{SM*} (κ_j^*) denote physician j's threshold with (without) a secondary market and let $\bar{h}^{SM}$ denote the average health impact on the secondary market (location subscripts suppressed for ease of notation). Furthermore, recall that a physician sets her optimal threshold

- without a secondary market such that

$$h\left(\kappa_j^*\right) = -\frac{R_j}{\beta_{b_j}} \tag{A.1}$$

- with a secondary market such that

$$\left(1 - G\left(p - h\left(\kappa_j^{SM*}\right)\right)\right) \cdot h\left(\kappa_j^{SM*}\right) + G\left(p - h\left(\kappa_j^{SM*}\right)\right) \cdot \bar{h}^{SM} = -\frac{R_j}{\beta_{b_j}} \tag{A.2}$$

I begin with two lemmas before proceeding to the proofs of Theorems 1 and 2.

Lemma 1: *Physicians with*

1. $h(\kappa_j^*) < \bar{h}^{SM}$ *are more lenient in the presence of a secondary market (i.e., $h(\kappa_j^*) < \bar{h}^{SM} \Rightarrow \kappa_j^{SM*} < \kappa_j^*$)*

2. $h(\kappa_j^*) = \bar{h}^{SM}$ *do not change their optimal prescribing behavior in the presence of a secondary market (i.e., $h(\kappa_j^*) = \bar{h}^{SM} \Rightarrow \kappa_j^{SM*} = \kappa_j^*$)*

3. $h(\kappa_j^*) > \bar{h}^{SM}$ *are less lenient in the presence of a secondary market (i.e., $h(\kappa_j^*) > \bar{h}^{SM} \Rightarrow \kappa_j^{SM*} > \kappa_j^*$)*

Proof: Combining equations (A.1) and (A.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 $G\left(p - h\left(\kappa_j^{SM*}\right)\right) \in [0,1]$, $h\left(\kappa_j^*\right)$ is simply 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 $h\left(\kappa_j^{SM*}\right) < h(\kappa_j*)$. Since $h'(\kappa) > 0$ (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 2: *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 $\kappa_j^{SM*} < \kappa_j^* \ \forall \ j \in J$. Since $h'(\kappa) > 0$ (by assumption), it follows that $h\left(\kappa_j^{SM*}\right) < h\left(\kappa_j^*\right) \ \forall \ j \in J$. By Lemma 1, $h\left(\kappa_j^{SM*}\right) < h\left(\kappa_j^*\right) \ \forall \ j \in J \ \Rightarrow h\left(\kappa_j^*\right) < \bar{h}^{SM} \ \forall \ j \in J$. This implies that $\exists$ at least one patient i with $\kappa_i > \kappa_j^* \ \forall \ j \in J$ who buys on the secondary market. However, this violates optimal patient behavior: it is cheaper to obtain a prescription opioid from a physician than from the secondary market, 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 $\kappa_j^{SM*} > \kappa_j^*$. ∎

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

Proof: As noted in Section 4, 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 $\frac{|I|}{|J|} \cdot \int_{\kappa_j^*}^{\infty} \int_{-\infty}^{\tau^d + \tau^o - h(k)} f(k)g(\gamma)d\gamma dk$ more prescriptions in the presence of a secondary market. However, since the physician alters her optimal threshold, her prescriptions further change by $\frac{|I|}{|J|} \cdot \int_{\kappa_j^{SM*}}^{\kappa_j^*} f(k)dk$. 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., $\kappa_j^* < \kappa_j^{SM*}$, then 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:

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

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

Theorem 2: *If the health impact function is approximately linear between $[\underline{\kappa}^*, \bar{\kappa}^{SM*}]$, the presence of a secondary market increases prescribing differences between strict and lenient prescribers within a given geographic market.*

Proof: Denote the optimal threshold of the most lenient (most strict) prescriber in the absence of a secondary market by $\underline{\kappa}^*$ ($\bar{\kappa}^*$). Similarly, denote the optimal threshold of the most lenient (most strict) prescriber in the presence of a secondary market by $\underline{\kappa}^{SM*}$ ($\bar{\kappa}^{SM*}$). We aim to determine under which conditions $\bar{\kappa}^{SM*} - \underline{\kappa}^{SM*} > \bar{\kappa}^* - \underline{\kappa}^*$.

From Lemma 2, 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), prescribing differences between strict and lenient prescribers necessarily increase. To see this, first note that if at least one physician becomes more strict, the most strict physician will become more strict; that is, $\bar{\kappa}^{SM*} > \bar{\kappa}^*$. Furthermore, if at least one physician becomes more lenient, the most lenient physician will become more lenient; that is, $\underline{\kappa}^{SM*} < \underline{\kappa}^*$. Combining these expressions, we have that $\bar{\kappa}^{SM*} - \underline{\kappa}^{SM*} > \bar{\kappa}^* - \underline{\kappa}^{SM*} > \bar{\kappa}^* - \underline{\kappa}^*$.

Now consider case (1) (i.e., all physicians become more strict in the presence of a secondary market). From optimal physician behavior (equations (A.1) and (A.2)), we have that

$$\max_{j \in J}\left(-\frac{R_j}{\beta_{b_j}}\right) - \min_{j \in J}\left(-\frac{R_j}{\beta_{b_j}}\right) = h(\bar{\kappa}^*) - h(\underline{\kappa}^*)$$

and

$$\max_{j \in J}\left(-\frac{R_j}{\beta_{b_j}}\right) - \min_{j \in J}\left(-\frac{R_j}{\beta_{b_j}}\right) = \left[\left(1 - G\left(p - h\left(\bar{\kappa}^{SM*}\right)\right)\right) \cdot h\left(\bar{\kappa}^{SM*}\right) + G\left(p - h\left(\bar{\kappa}^{SM*}\right)\right) \cdot \bar{h}^{SM}\right]$$
$$- \left[\left(1 - G\left(p - h\left(\underline{\kappa}^{SM*}\right)\right)\right) \cdot h\left(\underline{\kappa}^{SM*}\right) + G\left(p - h\left(\underline{\kappa}^{SM*}\right)\right) \cdot \bar{h}^{SM}\right]$$

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Therefore, we know that

$$h(\bar{\kappa}^*) - h(\underline{\kappa}^*) = h(\bar{\kappa}^{SM*}) - h(\underline{\kappa}^{SM*})$$
$$+ G\left(p - h(\bar{\kappa}^{SM*})\right) \cdot \left[\bar{h}^{SM} - h(\bar{\kappa}^{SM*})\right]$$
$$+ G\left(p - h(\underline{\kappa}^{SM*})\right) \cdot \left[h(\underline{\kappa}^{SM*}) - \bar{h}^{SM}\right]$$

Since all physicians become more strict, $\bar{\kappa}^{SM*} > \bar{\kappa}^*$ and $\underline{\kappa}^{SM*} > \underline{\kappa}^*$. Since $\kappa_j^{SM*} > \kappa_j^* \Leftrightarrow$ $h(\kappa_j^*) > \bar{h}^{SM}$ (Lemma 1) and $h'(\kappa) > 0$ (by assumption), it follows that $\bar{h}^{SM} < h(\bar{\kappa}^*) < h(\bar{\kappa}^{SM*})$ and $\bar{h}^{SM} < h(\underline{\kappa}^*) < h(\underline{\kappa}^{SM*})$. Therefore, since $G\left(p - h(\kappa_j^{SM*})\right) \in [0,1]$, we have that $G\left(p - h(\bar{\kappa}^{SM*})\right) \cdot \left[\bar{h}^{SM} - h(\bar{\kappa}^{SM*})\right] \leq 0$ and $G\left(p - h(\bar{\kappa}^{SM*})\right) \cdot \left[h(\underline{\kappa}^{SM*}) - \bar{h}^{SM}\right] \geq 0$.

Now, suppose $G\left(p - h(\bar{\kappa}^{SM*})\right) \cdot \left[\bar{h}^{SM} - h(\bar{\kappa}^{SM*})\right] + G\left(p - h(\bar{\kappa}^{SM*})\right) \cdot \left[h(\underline{\kappa}^{SM*}) - \bar{h}^{SM}\right] \leq$ 0. This implies that $h(\bar{\kappa}^*) - h(\underline{\kappa}^*) < h(\bar{\kappa}^{SM*}) - h(\underline{\kappa}^{SM*})$. Note that if $h'(\kappa) > 0$ and $h''(\kappa) = 0$, it follows that $\bar{\kappa}^* - \underline{\kappa}^* < \bar{\kappa}^{SM*} - \underline{\kappa}^{SM*}$. If $h'(\kappa) \geq 0$ and $h''(\kappa) < 0$, this will still imply that $\bar{\kappa}^* - \underline{\kappa}^* < \bar{\kappa}^{SM*} - \underline{\kappa}^{SM*}$ as long as $h''(\kappa)$ is sufficiently large (i.e., the health impact function is not too flat) over the relevant range. In particular, as long as $max_{x \in [\underline{\kappa}^*, \bar{\kappa}^{SM*}]} - f''(x) < \frac{\bar{\kappa}^{SM*} - \underline{\kappa}^{SM*}}{\bar{\kappa}^* - \underline{\kappa}^*}$, it follows that $\bar{\kappa}^* - \underline{\kappa}^* < \bar{\kappa}^{SM*} - \underline{\kappa}^{SM*}$. ∎

A.2   With a secondary market and patient search

A.2.1   Physician optimality

In the presence of a secondary market with patient search on the primary market, doctor j in geographic market c chooses her threshold severity to solve the following problem:

- If $\kappa_{j,c}^* \geq \tilde{P}_c$,

$$\max_{\kappa_{j,c}} \; \beta_{j,c} \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{p_c-h(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ \beta_{j,c} \cdot \sum_{n=1}^{j-1} \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} \int_{p_c-h(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ \beta_{j,c} \cdot (\bar{h}_c^{SM}) \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{-\infty}^{p_c-h(k)} f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ \beta_{j,c} \cdot (\bar{h}_c^{SM}) \cdot \sum_{n=1}^{j-1} \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} \int_{-\infty}^{p_c-h(k)} f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ R_{j,c} \cdot \left(\frac{|I_c|}{|J_c|} \cdot \int_{\kappa_{j,c}}^{\infty} f_c(k) dk + \sum_{n=1}^{j-1} \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} f_c(k) dk \right] \right)$$

- If $\kappa_{j,c}^* < \tilde{P}_c$,

$$\max_{\kappa_{j,c}} \; \beta_{j,c} \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{p_c-h(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ \beta_{j,c} \cdot \sum_{n=j_{p,c}}^{j-1} \cdot \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} \int_{T_c(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ \beta_{j,c} \cdot \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa_{j,c}^*}^{\tilde{P}_c} \int_{T_c(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ \beta_{j,c} \cdot \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\tilde{P}_c}^{\kappa_{n,c}^*} \int_{p_c-h(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ \beta_{j,c} \cdot (\bar{h}_c^{SM}) \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{-\infty}^{p_c-h(k)} f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ \beta_{j,c} \cdot (\bar{h}_c^{SM}) \cdot \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{1}{(|J_c| - n + 1)(|J_c| - n)} \cdot \left(\int_{\tilde{P}_c}^{\kappa_{n,c}^*} \int_{-\infty}^{p_c-h(k)} f_c(k) g_c(\gamma) d\gamma dk \right) \right]$$

$$+ R_{j,c} \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} f_c(k) dk \right]$$

$$+ R_{j,c} \cdot \sum_{n=j_{p,c}}^{j-1} \cdot \left[\frac{1}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} \int_{T_c(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk \right]$$

$$+ R_{j,c} \cdot \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{1}{(|J_c| - n + 1)(|J_c| - n)} \cdot \left(\int_{\kappa_{j,c}^*}^{\tilde{P}_c} \int_{T_c(k)}^{\infty} f(k) g_c(\gamma) d\gamma dk + \int_{\tilde{P}_c}^{\kappa_{n,c}^*} f_c(k) dk \right) \right]$$

Taking the derivate with respect to $\kappa_{j,c}$ and setting equal to zero yields:

$$-\beta_{j,c}\left[W_{j,c}\cdot h(\kappa_{j,c}^*)+(1-W_{j,c})\cdot\left(\bar{h}_c^{SM}\right)^*\right]=R_{j,c}$$

where

$$W_{j,c}=\frac{[1-G_c(p_c-h(\kappa_{j,c}^*))]\cdot\frac{|I_c|}{|J_c|}+[1-G_c(T_c(\kappa_{j,c}^*))]\cdot\sum_{n=1}^{j-1}\cdot\left[\frac{1}{(|J_c|-n+1)(|J_c|-n)}\right]}{\frac{|I_c|}{|J_c|}+[1-G_c(T_c(\kappa_{j,c}^*))]\cdot\sum_{n=1}^{j-1}\left[\frac{1}{(|J_c|-n+1)(|J_c|-n)}\right]}$$

$$1-W_{j,c}=\frac{\frac{|I_c|}{|J_c|}\cdot G_c(p_c-h(\kappa_{j,c}^*))}{\frac{|I_c|}{|J_c|}+[1-G_c(T_c(\kappa_{j,c}^*))]\cdot\sum_{n=1}^{j-1}\left[\frac{1}{(|J_c|-n+1)(|J_c|-n)}\right]}$$

A.2.2 Equilibrium allocation of opioid prescriptions

The equilibrium allocation with patient search and a secondary market in a market with two physicians is shown in Figure A.1. There are two key differences from the equilibrium allocation without patient search (Figure 3). First, when patients can search across physicians, fewer patients will buy the medication on the secondary market. Since the cost of accessing the medication from a physician is cheaper $\left(p_c>\tau_c^d+\tau_c^o\right)$, those with a high enough probability of getting a prescription from a physician (i.e., high enough pain) will search for a physician rather than turning to the secondary market. Second, when patients can search across physicians, some patients will search with the intention of reselling their prescriptions. This rationalizes the behavior of secondary market retailers who are known to shop doctors in order to resell opioid prescriptions.

Figure A.1: Equilibrium allocation of opioid prescriptions: with secondary market and search
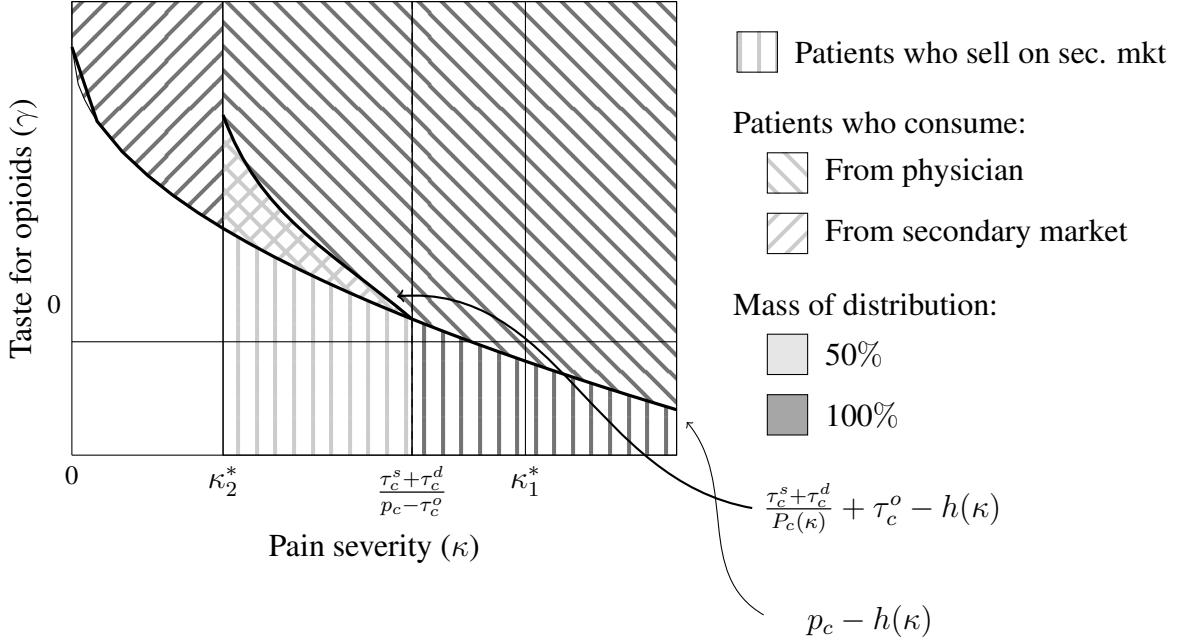
Notes: The above figure displays the equilibrium allocation of opioid prescriptions with a secondary market and patient search in a market with two physicians. As highlighted in the text, all patients with high enough pain $\left(\kappa_i \geq \frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} + \tau_{c_i}^o} \right)$ will search in the presence of a secondary market to either resell (if $\gamma_i < p_{c_i} - h(\kappa_i)$) or to consume (if $\gamma_i \geq p_{c_i} - h(\kappa_i)$). However, those with less severe pain $\left(\kappa_i < \frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} + \tau_{c_i}^o} \right)$ will only search if they have a high enough combination of pain and tastes $\left(P_{c_i}(\kappa_i) \neq 0 \text{ and } \gamma_i \geq \frac{\tau_{c_i}^s + \tau_{c_i}^d}{P_{c_i}(\kappa_i)} + \tau_{c_i}^o - h(\kappa_i) \right)$.

A.3 Estimation algorithm

1. Begin with starting values for the parameters $\left\{ \left\{ \tilde{\tau}_c^s, \mu_c, \sigma_c^2, \bar{h}_c^{SM} \right\}_{\forall c}, \boldsymbol{\theta}, \boldsymbol{\beta} \right\}$

2. Given $\left\{ \left\{ \mu_c, \sigma_c^2, \bar{h}_c^{SM} \right\}_{\forall c}, \boldsymbol{\theta}, \boldsymbol{\beta} \right\}$,

   (a) Solve equation (16) to obtain the health impact at each physician's optimal threshold:
   $$\left\{ h(\kappa_j^* : \boldsymbol{\theta}) \right\}_{\forall j}$$

   (b) Using $\boldsymbol{\theta}$, invert the health impact at each physician's threshold to obtain their optimal threshold: $\left\{ \kappa_j^* \right\}_{\forall j}$

3. Using these optimal thresholds and the search costs $\{ \tilde{\tau}_c^s \}_{\forall c}$,

(a) Solve for the empirical distribution of prescription probabilities in each commuting zone: $P_c(\kappa) = \frac{1}{|J_c|} \sum_{j \in J_c} \mathbb{1}\{\kappa_j^* \leq \kappa\}$

(b) Solve for the level of pain above which all patients search in each commuting zone: $\tilde{P}_c = P_c^{-1}\left(\frac{\tilde{\tau}_c^s}{p_c - \tau_c^o}\right)$ (where $\{\tau_c^o\}_{\forall c}$ is the average opioid copayment in commuting zone c as reported in the QuintilesIMS data)

4. Order physicians within each commuting zone by optimal thresholds and assign patients to physicians using equation (15)

5. Compute:

(a) The number of each physician's patients who get a prescription from the physician and consume, $N_{j,c}^{consume}$:

$$
N_{j,c}^{consume} =
\begin{cases}
\frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}^*}^{\infty} \int_{p_c-h(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right] \\
\quad + \sum_{n=1}^{j-1} \cdot \left[\frac{|I_c|}{(|J_c|-n+1)(|J_c|-n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} \int_{p_c-h(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right] & \text{if } \kappa_{j,c}^* \geq \tilde{P}_c \\[2em]
\frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}^*}^{\infty} \int_{p_c-h(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right] \\
\quad + \sum_{n=j_{p,c}}^{j-1} \cdot \left[\frac{|I_c|}{(|J_c|-n+1)(|J_c|-n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} \int_{T_c(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right] & \text{if } \kappa_{j,c}^* < \tilde{P}_c \\
\quad + \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{|I_c|}{(|J_c|-n+1)(|J_c|-n)} \cdot \left(\int_{\kappa_{j,c}^*}^{\tilde{P}_c} \int_{T_c(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right) \right] \\
\quad + \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{|I_c|}{(|J_c|-n+1)(|J_c|-n)} \cdot \left(\int_{\tilde{P}_c}^{\kappa_{n,c}^*} \int_{p_c-h(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right) \right]
\end{cases}
$$

(b) The number of each physician's patients who get a prescription from the physician and resell on the secondary market, $N_{j,c}^{sell}$:

$$
N_{j,c}^{sell} =
\begin{cases}
\frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}^*}^{\infty} \int_{-\infty}^{p_c-h(k)} f_c(k)g_c(\gamma)d\gamma dk \right] \\
\quad + \sum_{n=1}^{j-1} \cdot \left[\frac{|I_c|}{(|J_c|-n+1)(|J_c|-n)} \cdot \int_{\kappa_{j,c}^*}^{\kappa_{n,c}^*} \int_{-\infty}^{p_c-h(k)} f_c(k)g_c(\gamma)d\gamma dk \right] & \text{if } \kappa_{j,c}^* \geq \tilde{P}_c \\[2em]
\frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}^*}^{\infty} \int_{-\infty}^{p_c-h(k)} f_c(k)g_c(\gamma)d\gamma dk \right] \\
\quad + \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{|I_c|}{(|J_c|-n+1)(|J_c|-n)} \cdot \int_{\tilde{P}_c}^{\kappa_{n,c}^*} \int_{-\infty}^{p_c-h(k)} f_c(k)g_c(\gamma)d\gamma dk \right] & \text{if } \kappa_{j,c}^* < \tilde{P}_c
\end{cases}
$$

(c) The number of each physician's patients who buy a prescription on the secondary mar-

ket, $N_{j,c}^{buy}$:

$$N_{j,c}^{buy} = \begin{cases} \frac{|I_c|}{|J_c|} \cdot \left[\int_0^{\tilde{P}_c} \int_{p_c - h(k)}^{T_c(k)} f_c(k) g_c(\gamma) d\gamma dk \right] & \text{if } \kappa_{j,c}^* \geq \tilde{P}_c \\ \frac{|I_c|}{|J_c|} \cdot \left[\int_0^{\kappa_{j,c}^*} \int_{p_c - h(k)}^{T_c(k)} f_c(k) g_c(\gamma) d\gamma dk \right] & if \ \kappa_{j,c}^* < \tilde{P}_c \end{cases}$$

(d) The health impact of each physician's patients who buy a prescription on the secondary market, $H_{j,c}^{buy}$:

$$N_{j,c}^{buy} = \begin{cases} \frac{|I_c|}{|J_c|} \cdot \left[\int_0^{\tilde{P}_c} \int_{p_c - h(k)}^{T_c(k)} h(k) f_c(k) g_c(\gamma) d\gamma dk \right] & \text{if } \kappa_{j,c}^* \geq \tilde{P}_c \\ \frac{|I_c|}{|J_c|} \cdot \left[\int_0^{\kappa_{j,c}^*} \int_{p_c - h(k)}^{T_c(k)} h(k) f_c(k) g_c(\gamma) d\gamma dk \right] & if \ \kappa_{j,c}^* < \tilde{P}_c \end{cases}$$

6. Let Q_j denote the number of prescriptions written by physician j (data) and η_c the percent of the population who purchase prescription opioids on the secondary market in commuting zone c (data). Using $\left\{ N_{j,c}^{consume}, N_{j,c}^{sell}, N_{j,c}^{buy}, H_{j,c}^{buy} \right\}_{\forall j}$, form $4 \cdot C + 6$ moments listed in Table 6

7. Select the set of parameters $\left\{ \left\{ \tilde{\tau}_c^s, \mu_c, \sigma_c^2, \bar{h}_c^{SM} \right\}_{\forall c}, \boldsymbol{\theta}, \boldsymbol{\beta} \right\}^*$ such that
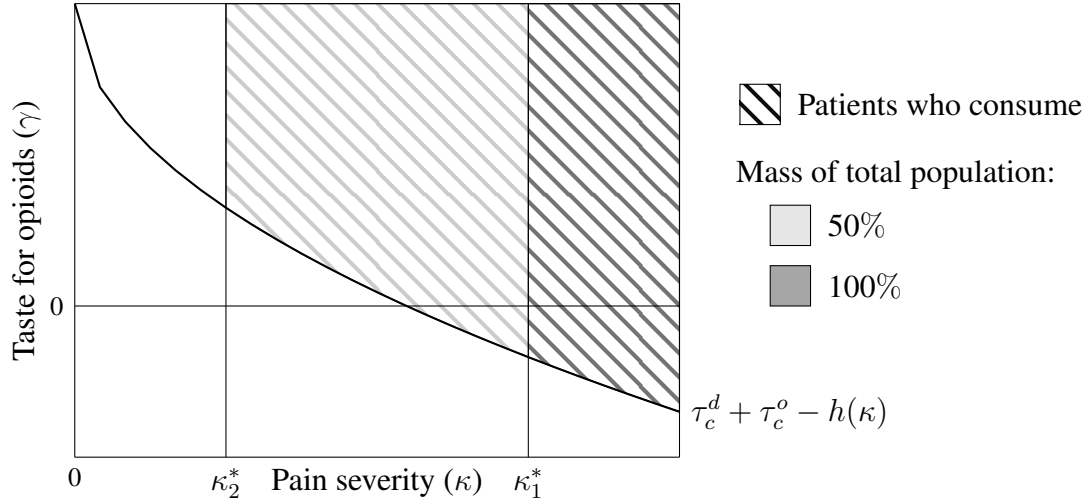
$$\left\{ \left\{ \tilde{\tau}_c^s, \mu_c, \sigma_c^2, \bar{h}_c^{SM} \right\}_{\forall c}, \boldsymbol{\theta}, \boldsymbol{\beta} \right\}^* = \min_{\left\{ \left\{ \tilde{\tau}_c^s, \mu_c, \sigma_c^2, \bar{h}_c^{SM} \right\}_{\forall c}, \boldsymbol{\theta}, \boldsymbol{\beta} \right\}} \sum_{\alpha=1}^{6} m_\alpha' \cdot m_\alpha$$

where m_{1-4} are $C \times 1$ vectors and m_{5-6} are 3×1 vectors
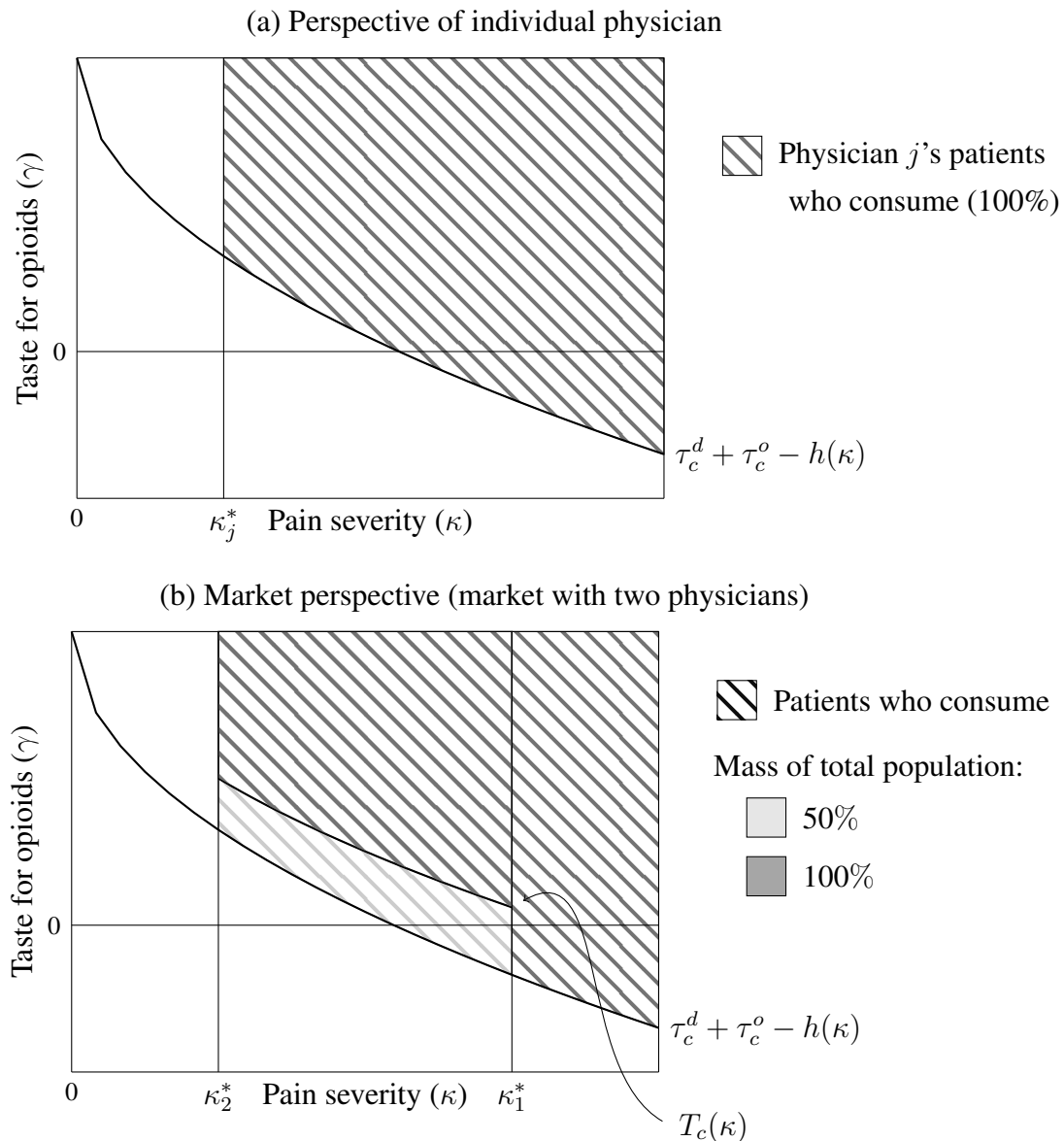
A.4 Supplementary diagrams

A.4.1 Equilibrium allocation without secondary market

Figure A.2: Equilibrium allocation of prescriptions: without secondary market or patient search

Notes: The above figure depicts the equilibrium allocation of prescriptions without a secondary market in the absence of patient search in a market with two physicians. In general, all patients for whom it is beneficial to consume and can get a prescription from any physician in their market $\left(\kappa_i \geq \max_{j \in J_{c_i}} \kappa_j^*\right)$ will be on prescription opioids. For patients who can obtain a prescription from all but $n < |J_c|$ physicians in their market, $\frac{|J_c|-n}{|J_c|}$ of the patients will be on prescription opioids.

Figure A.3: Equilibrium allocation of prescriptions: without secondary market and with patient search

(a) Perspective of individual physician

Taste for opioids (γ)

Physician j's patients who consume (100%)

$\tau_c^d + \tau_c^o - h(\kappa)$

0

κ_j^* Pain severity (κ)

(b) Market perspective (market with two physicians)

Taste for opioids (γ)

Patients who consume

Mass of total population:
- 50%
- 100%

$\tau_c^d + \tau_c^o - h(\kappa)$

$T_c(\kappa)$

0

κ_2^* Pain severity (κ) κ_1^*

Notes: The above figures display the equilibrium allocation of opioid prescriptions in a market with two physicians with patient search, both from the perspective of an individual physician (subfigure (a)) and from a market perspective (subfigure (b)). From the perspective of an individual physician, all of her patients who can get a prescription $\left(\kappa_i \geq \kappa_j^*\right)$ and for whom the benefit of consuming the medication outweighs the cost $\left(h(\kappa_i) + \gamma_i \geq \tau_{c_i}^d + \tau_{c_i}^o\right)$ will show up at her office and get an opioid script. From a market perspective, this means that all patients with pain above the most stringent physician's threshold who find it beneficial to consume opioids will do so since they can get a prescription from whichever physician they are originally assigned. However, due to patient search, patients who are initially assigned to a physician from whom they cannot get a prescription but find it beneficial to search will be on prescription opioids in equilibrium. In a market with two physicians, all of the patients who cannot get a prescription from physician 1 $\left(\kappa_i < \kappa_1^*\right)$ but who find it beneficial to search $\left(\gamma_i \geq T_{c_i}(\kappa_i)\right)$ will access prescription opioids on the primary market from physician 2 in equilibrium. See Figure A.2 for the equilibrium allocation of prescriptions in the absence of patient search.
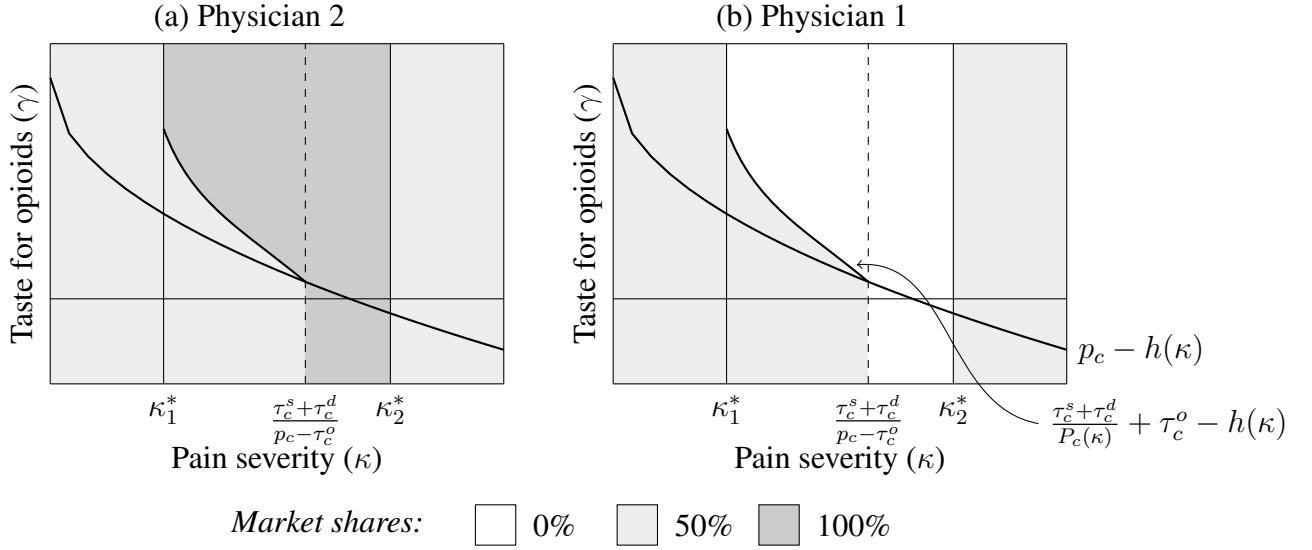
A.4.2 Market shares

Figure A.4: Equilibrium market shares: without secondary market and with patient search

(a) Physician 2 — (b) Physician 1

Market shares: ☐ 0%   50%   ▨ 100%
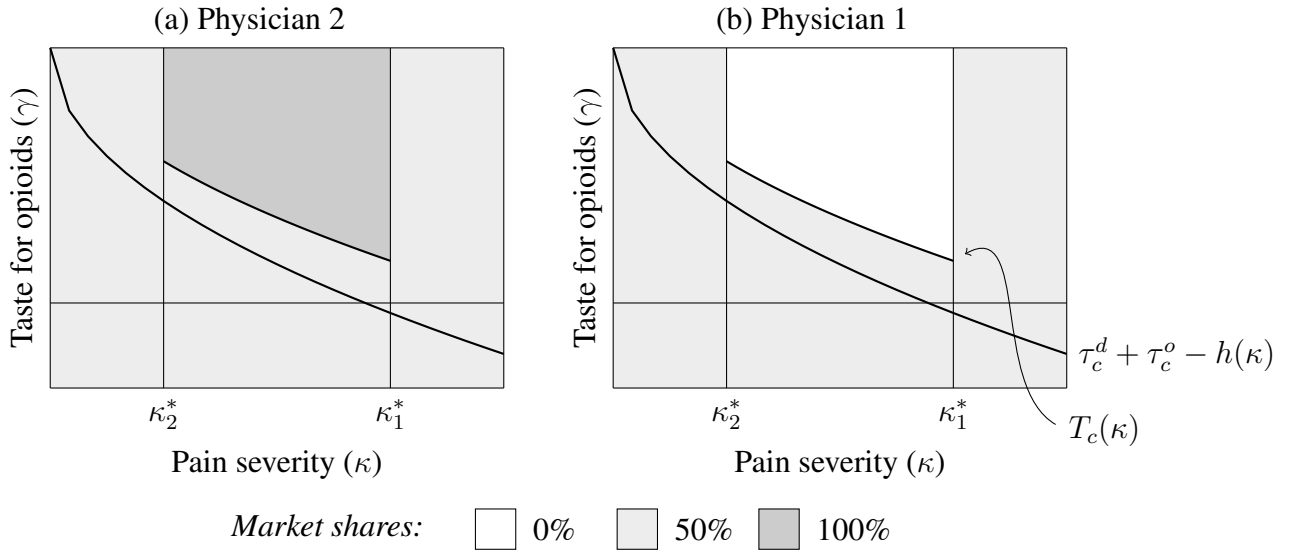
Notes: The above figures depict the market shares for a market with two physicians in the absence of a secondary market. Without patient search, each physician would be assigned half of all patients throughout the pain and taste distributions (that is, both figures would be entirely light gray). With patient search, however, the physician who is more lenient in her prescribing will see 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 ($\gamma_i < T_{c_i}(\kappa_i)$), 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 ($\gamma_i \geq T_{c_i}(\kappa_i)$). Rather, these patients will keep searching until they find physician 2, so physician 2 sees all of these patients in equilibrium.

Figure A.5: Equilibrium market shares: with secondary market and patient search

(a) Physician 2   (b) Physician 1

Market shares: □ 0% ▢ 50% ▨ 100%

Notes: The above figures depict the market shares for a market with two physicians in the presence of a secondary market. Without patient search, each physician would be assigned half of all patients throughout the pain and taste distributions (that is, both figures would be entirely light gray). With patient search, however, the physician who is more lenient in her prescribing will see 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 $\left(\gamma_i < \frac{\tau_{c_i}^s + \tau_{c_i}^d}{P_{c_i}(\kappa)} + \tau_{c_i}^o - h(\kappa_i) \ \& \ \kappa_i < \frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} - \tau_{c_i}^o}\right)$, 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 $\left(\gamma_i \geq \frac{\tau_{c_i}^s + \tau_{c_i}^d}{P_{c_i}(\kappa)} + \tau_{c_i}^o - h(\kappa_i) \ \mid \ \kappa_i \geq \frac{\tau_{c_i}^s + \tau_{c_i}^d}{p_{c_i} - \tau_{c_i}^o}\right)$. Rather, these patients will keep searching until they find physician 2, so physician 2 sees all of these patients in equilibrium.

B Data Appendix

B.1 Reimbursement

The QuintilesIMS data contain no information on physician revenue. However, it does contain information on the type of insurance each physician's patients use to pay for their opioid prescriptions. Under the assumption that the distribution of insurance types used to pay for opioid prescriptions is representative of a physician's practice, I combine the insurance composition facing each physician with estimated reimbursement rates at the insurance type-state-specialty level to calculate physician-specific reimbursement rates. Variation in reimbursement rates across physicians therefore comes from variation in the state of practice, physician specialty, and composition of patient insurance types. The process used to construct these reimbursement rates is described

below.

Table A.1: Reimbursement components across specialties

| | Panel A: QuintilesIMS Data | | | | | Panel B: Medicare Data | | | | |
| | Insurance used for opioids | | | | | Locations of provided care | | | | |
	N providers	Third party	Medicaid	Medicare	Cash	N providers	Office	Hospital	ED	Other
Primary										
General & Family Practice	80,679	62.84	4.91	26.22	6.03	81,246	73.64	11.31	2.2	12.86
Internal Medicine	58,211	55.92	3.57	35.94	4.57	88,693	47.1	34.11	1.31	17.48
Total	138,890	60.22	4.41	29.89	5.48	169,939	57.04	25.57	1.64	15.75
Medical										
Anesthesiology	2,693	70.88	4.13	20.93	4.07	2,778	87.38	4.49	0.61	7.53
Emergency Medicine	26,995	65.33	7.47	12	15.2	38,340	8.94	2.47	86.44	2.15
Hematology & Oncology	9,865	54.51	5.58	36.65	3.25	15,154	78.94	19.75	0.11	1.2
Internal Medicine	18,642	59.41	3.31	33.47	3.81	49,841	53.27	42.18	2.24	2.31
Obstetrics & Gynecology	21,086	78.55	10.39	3.38	7.68	16,200	97.68	0.73	0.32	1.26
Pain Medicine	2,972	72.56	2.81	21.15	3.48	3,226	88.52	3.51	0.02	7.95
Physical Medicine & Rehab.	5,044	72.82	3.47	19.81	3.89	6,320	36.53	46.42	0.02	17.04
Psychiatry & Neurology	8,547	73.33	4.12	16.99	5.56	20,006	53.34	38.36	0.53	7.77
Other	3,287	66.01	2.84	23.27	7.88	9,044	98.1	0.64	0.11	1.15
Total	99,131	68.76	4.97	19.55	6.72	160,909	52.96	29.33	13.93	3.78
Surgical										
Surgery	50,873	69.02	3.79	21.03	6.16	53,178	82.79	14.14	0.85	2.22
Other	14,694	68.55	4.77	21.62	5.06	23,761	94.6	4.77	0.06	0.57
Total	65,567	68.97	3.9	21.09	6.03	76,939	87.93	10.06	0.5	1.5
Total	303,588	64.46	4.5	25.07	5.97	407,787	59.08	25.25	6.55	9.12

Notes: The above table provides summary statistics in 2014 for the components used to construct office visit reimbursement rates by specialty.

B.1.1 Physician-level insurance compositions

The QuintilesIMS data include both the percentage of each physician's opioid prescriptions that were paid for with Medicaid, third-party insurance, or cash and the percentage of each physician's opioid prescriptions written for patients within different age bins. Assuming that all patients 65+ are covered by Medicare, I compute the percentage of a physician's patients in four categories: Medicaid (under 65, paid with Medicaid), Medicare (65+), private insurance (under 65, paid with third party), and no insurance (under 65, paid with cash). By construction, these categories sum to one for each physician.

B.1.2 Insurance-specific reimbursement rates

To construct reimbursement rates under different insurance types, I use four additional data sets: (1) publicly available Medicare claims at the CPT code-provider level from the Centers for Medicare and Medicaid Services (CMS)[32]; (2) state-level Medicaid fee-for-service (FFS) to Medicare payment ratios from the Kaiser Family Foundation[33]; (3) state-level payment ratios for Medicaid FFS, Medicaid managed care (MC), and private insurance from the Government Accountability Office (GAO); and (4) the percent of Medicaid beneficiaries enrolled in Medicaid MC in each state-year from CMS.

Medicare To calculate reimbursement rates under Medicare, I combine state-specific reimbursement rates for individual CPT codes with specialty-specific distributions of CPT billing frequencies in Medicare. Throughout I consider CPT codes associated with evaluation and management services (E/M) provided in an office, hospital, or emergency department (ED). This set of CPT codes is denoted by Ω and is provided in Table A.2.

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[32]Available at https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Physician-and-Other-Supplier.html; last accessed August 29, 2017.

[33]Available at http://www.kff.org/medicaid/state-indicator/medicaid-to-medicare-fee-index; last accessed August 29, 2017.

Table A.2: CPT codes considered for reimbursement

CPT Code	Description
Office visits	
99201	Office or other outpatient visit, new patient, 10 minutes
99202	Office or other outpatient visit, new patient, 20 minutes
99203	Office or other outpatient visit, new patient, 30 minutes
99204	Office or other outpatient visit, new patient, 45 minutes
99205	Office or other outpatient visit, new patient, 60 minutes
99211	Office or other outpatient visit, established patient, 5 minutes
99212	Office or other outpatient visit, established patient, 10 minutes
99213	Office or other outpatient visit, established patient, 15 minutes
99214	Office or other outpatient visit, established patient, 25 minutes
99215	Office or other outpatient visit, established patient, 40 minutes
Hospital care	
99221	Initial hospital inpatient care, 30 minutes
99222	Initial hospital inpatient care, 50 minutes
99223	Initial hospital inpatient care, 70 minutes
99231	Subsequent hospital inpatient care, 15 minutes
99232	Subsequent hospital inpatient care, 25 minutes
99233	Subsequent hospital inpatient care, 35 minutes
Emergency care	
99281	Emergency department visit, self-limited or minor
99282	Emergency department visit, low severity
99283	Emergency department visit, moderate severity
99284	Emergency department visit, high severity but no immediate threat
99285	Emergency department visit, high severity and immediate threat
99291	Critical care, first 30-74 minutes
99292	Critical care, each additional 30 minutes

Notes: The above table lists the CPT codes considered when measuring office visit reimbursement rates.

Let S_{sc} denote the share of specialty s's Medicare E/M claims represented by CPT code c and $R_{lc}^{Medicare}$ denote the average Medicare allowed amount for CPT code c in state l. The Medicare reimbursement rate for a physician with specialty s practicing in state l is given by

$$R_{ls}^{Medicare} = \sum_{\Omega} R_{lc}^{Medicare} \cdot S_{sc} \qquad \text{with} \sum_{\Omega} S_{sc} = 1 \ \forall \ s \qquad (A.3)$$

Medicaid To calculate Medicaid reimbursement rates, I adopt a similar approach as that used in Alexander and Schnell (2017). In particular, since providers are often reimbursed different amounts depending on whether the beneficiary is enrolled in Medicaid FFS or Medicaid MC, I take a beneficiary-weighted average across reimbursement rates for Medicaid FFS and Medicaid MC in each state. Let R_{ls}^{MFSS} and R_{ls}^{MMC} denote the reimbursement rates for specialty s in state l

under Medicaid FFS and Medicaid MC, respectively.

To construct Medicaid FFS reimbursement rates, I combine state-specialty-specific reimbursements under Medicare (equation (A.3)) with state-specialty-specific Medicaid FFS to Medicare payment ratios from the Kaiser Family Foundation.[34] For each state, the Kaiser Family Foundation provides different Medicaid FFS to Medicare reimbursement ratios for primary care, obstetric care, and other services. I consider the primary care ratio to be relevant for physicians in general and family practice, general internal medicine, and pediatric medicine; the obstetric care ratio to be relevant for physicians in gynecology and obstetrics; and the "other services" ratio to be relevant for all other remaining specialties. Letting $\frac{R_{ls}^{MFSS}}{R_{ls}^{Medicare}}$ denote the Medicaid FFS to Medicare payment ratio for specialty s in state l, the state-specialty-specific Medicaid FFS reimbursement is then easily computed as $R_{ls}^{MFFS} = R_{ls}^{Medicare} \cdot \frac{R_{ls}^{MFSS}}{R_{ls}^{Medicare}}$.

The Kaiser Family Foundation only provides Medicaid-to-Medicare payment ratios for Medicaid FFS. However, the GAO provides payment ratios for Medicaid FFS to Medicaid MC in select states by place of care (Yocom (2014)).[35] Breaking the relevant CPT codes into three categories based on place of service (office, hospital, or ED), the Medicaid MC reimbursement rate for a physician with specialty s practicing in state l is given by

$$R_{ls}^{MMC} = \sum_{L=\{Off,Hosp,ED\}} \left[\sum_{\Omega_L} R_{lc}^{Medicare} \cdot S_{sc} \cdot \left(\frac{R_{ls}^{MFSS}}{R_{ls}^{Medicare}} \right) \left(\frac{R_{lc}^{MMC}}{R_{lc}^{MFSS}} \right) \right]$$

with

$$\Omega = \Omega_{Office} \cap \Omega_{Hospital} \cap \Omega_{ED}$$

where $\frac{R_{lc}^{MMC}}{R_{lc}^{MFSS}}$ represents the GAO Medicaid MC to Medicaid FFS ratio and all other variables are defined as above.[36,37]

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[34]These payment ratios are for 2016. Because Section 1202 of the Affordable Care Act federally mandated that states achieve parity between Medicaid and Medicare payments for primary care services for 2013 and 2014, I impute the Medicaid-to-Medicare payment ratio for physicians in family medicine, general internal medicine, and pediatric medicine to be one in 2014. Since Alaska and Montana were unaffected by the fee bump (they reimburse physicians more under Medicaid than Medicare), their payment ratios are greater than one for primary care services in 2014.

[35]The payment ratios in the latest report were computed using data from 2010. Although the ratios could have changed by 2014, it is likely that the pronounced differences across states still provide meaningful variation in 2014.

[36]Because the primary care rate increase applied to Medicaid FFS and Medicaid MC, I impute the Medicaid FFS-to-MC ratio for physicians in family practice, general internal medicine, and pediatric medicine to be one in 2014.

[37]The GAO report only includes the Medicaid FFs-to-MC ratio for 20 states. Following Alexander and Schnell (2017), I impute the location-specific ratio for states not included in the report using the median across the included

Finally, while the IMS data identify the fraction of a physician's patients who paid with Medicaid, it does not identify the fraction of a physician's Medicaid patients enrolled in Medicaid FFS or Medicaid MC. To create a composite Medicaid reimbursement rate for each specialty and state, I take a weighted average across R_{ls}^{FFS} and R_{ls}^{MMC}, where the weights represent the fraction of each state's Medicaid beneficiaries enrolled in each program. Letting F_l^{FFS} denote the fraction of Medicaid beneficiaries enrolled in Medicaid FFS in state l, the composite Medicaid payment for a physician in specialty s in state l is given by

$$R_{ls}^{Medicaid} = F_l^{FFS} \cdot R_{ls}^{FFS} + \left(1 - F_l^{FFS}\right) \cdot R_{ls}^{MMC} \tag{A.4}$$

Private The method for computing state-specialty specific reimbursement rates under private insurance is analogous to the method used for computing Medicare MC rates introduced above. That is, letting $\frac{R_{lc}^{Private}}{R_{lc}^{MFSS}}$ represent the GAO private insurance to Medicaid FFS ratio,[38] the private insurance reimbursement rate for a physician with specialty s practicing in state l is given by

$$R_{ls}^{Private} = \sum_{L=\{Off,Hosp,ED\}} \left[\sum_{\Omega_L} R_{lc}^{Medicare} \cdot S_{sc} \cdot \left(\frac{R_{ls}^{MFSS}}{R_{ls}^{Medicare}} \right) \left(\frac{R_{lc}^{Private}}{R_{lc}^{MFSS}} \right) \right]$$

Since the primary care rate increase did not apply to private insurance, I do not impute the Medicaid-to-Medicare ratio with a one for primary care when using it as a stepping stone to compute private insurance rates.

B.1.3 Physician-specific reimbursement rates

To construct a single reimbursement rate facing each provider, I take a weighted average across the insurance-state-specialty specific reimbursement rates introduced in Section B.1.2, where the weights for each given provider are given by the physician-level insurance compositions introduced in Section B.1.1. That is, letting S_{jy}^I denote the percentage of physician j's patients with insurance type $I \in \{Medicaid, Medicare, Private, None\}$, the reimbursement rate for physician j with

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states. Results are robust to a variety of other imputation techniques.

[38]The GAO report includes the private insurance to Medicaid FFs ratio for 32 states. I impute the location-specific ratio for states not included in the report using the median across the included states. Results are robust to a variety of other imputation techniques.

specialty s in state l is given by

$$R_{jls} = \sum_I S_j^I \cdot R_{ls}^I \qquad \text{with} \sum_I S_j^I = 1 \ \forall \ j$$

B.2 Pain and taste distributions

B.2.1 Pain severities

To measure differences in pain across the United States, I consider responses to the following questions from the 2014 NHIS:

> "During the past three months, did you have neck pain? Lower back pain? Facial ache
> or pain in the jaw muscles or the joint in front of the ear?"

When introducing these questions, the interviewer tells the respondent that each question refers to pain in the last three months that lasted a whole day or more. Respondents are told not to report pain that is "fleeting or minor." I define severity of pain as the sum of a respondent's "yes" answers: that is, if the respondent has neck pain and lower back pain but no facial pain, the respondent would receive a pain score of two out of three. Differences across demographic groups are robust to using either a dummy equal to one if the respondent reports pain in either the neck, lower back, or face, or to focusing on a specific area of pain.

If the NHIS were representative at the commuting zone-level, I would use commuting zone-specific responses to this sequence of questions to approximate pain distributions in each commuting zone. Unfortunately, only region identifiers are included in the NHIS. To capture variation in pain levels across commuting zones, I compute the average pain severity nationally in age-gender-race bins and combine these averages with commuting zone-level demographics from the 5-year pooled (2010–2014) ACS. As noted in Section 2, variation across areas in pain levels therefore comes from differences in age-gender-race profiles: if two commuting zones have the same proportion of their population in each age-gender-race bin, they will have the same distribution of pain severities.

Figure A.6 displays average pain severities by age-gender-race bins. Unsurprisingly, pain increases over the lifecycle. Consistent with previous studies, women and whites report more pain

than men and minorities. As shown in Figure A.7, these differences across age-gender-race cells translate into differences in average pain severities across commuting zones. For example, average pain in Pittsburgh, a predominately white commuting zone, is higher than in Honolulu, a commuting zone with a higher share of young, minority residents.

Figure A.6: Average pain severity across age-gender-race cells
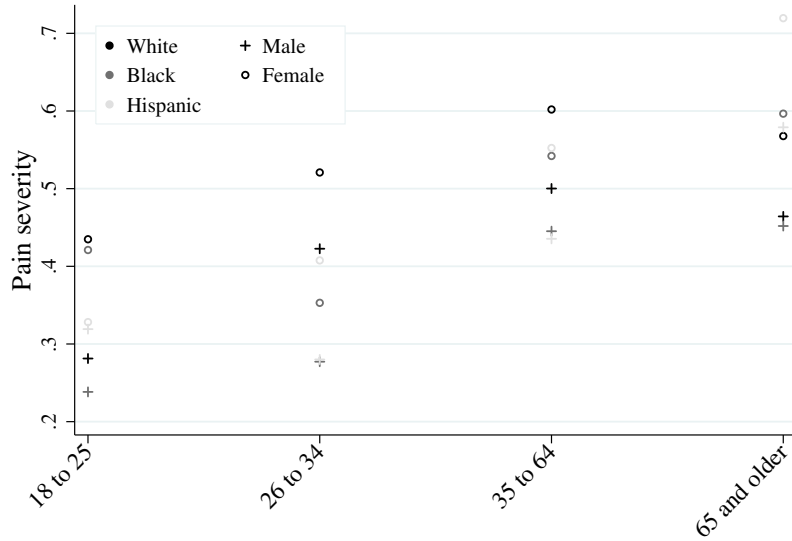
Notes: The above figure presents average pain severities within age-gender-race cells from the 2014 NHIS.

Figure A.7: Example distributions of average pain severities
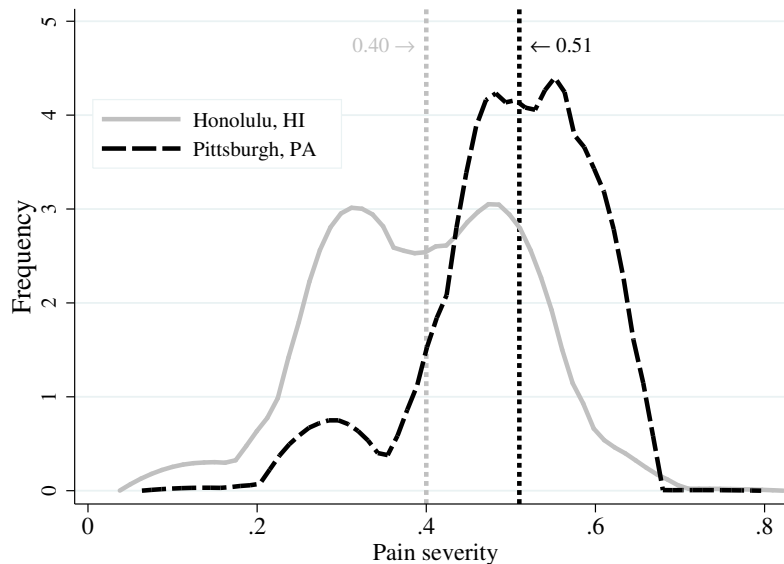
Notes: The above figure depicts the distribution of average pain severities in example commuting zones. The dotted lines denote the centers of each distribution. These distributions are constructed by combining responses regarding pain from the 2014 NHIS in age-gender-race cells nationally with location-specific demographics from the 2010–2014 ACS.

B.2.2 Prescription opioid misuse rates

To measure differences in opioid misuse across the United States, I consider responses to the following two questions from the 2014 NSDUH:

1. "How long has it been since you last used any prescription pain reliever that was not prescribed for you or that you took only for the experience or feeling it caused?"

2. "Now think about the last time you used a prescription pain reliever that was not prescribed for you or that you took only for the experience or feeling it caused. How did you get this prescription pain reliever?"

I define opioid misuse from the secondary market as the interaction between a response to Question (1) denoting opioid misuse in the past 12 months and a response to Question (2) indicating that the respondent purchased the medication.[39] Differences across demographic groups are robust to the use of different time frames over which misuse is defined.

[39]The response options for Question (2) are listed in Table A.3.

Using individual-level demographics provided in the NSDUH, I compute national averages of opioid misuse from the secondary market within age-gender-race cells. Merging these misuse rates with commuting zone-level demographics from the ACS, I compute the fraction of the population in each commuting zone who purchases an opioid prescription to misuse. As shown in Figure A.8, non-medical use of prescription opioids is highest among young, white males, with misuse rates generally decreasing over the lifecycle. Therefore, commuting zones with higher shares of young, white residents are identified to have higher prescription misuse rates (Figure A.9).

Figure A.8: Prescription opioid misuse rates across age-gender-race cells
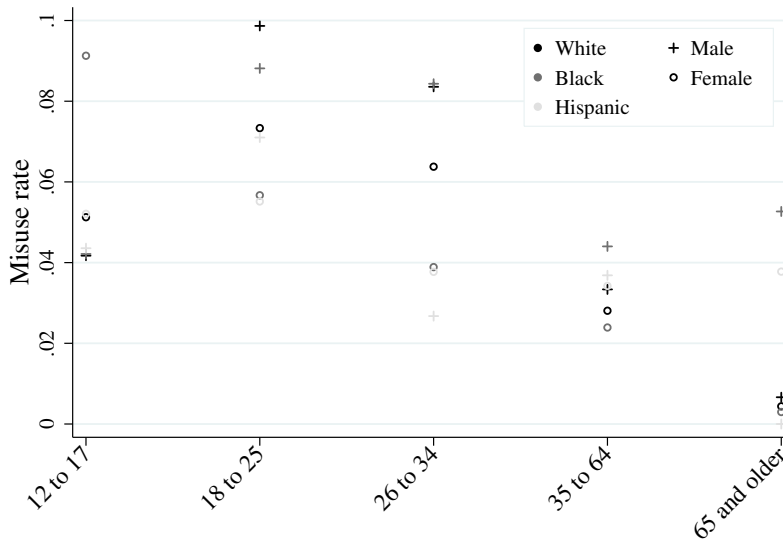
Notes: The above figure presents prescription opioid misuse rates within age-gender-race cells from the 2014 NSDUH.

Figure A.9: Example distributions of prescription opioid misuse rates
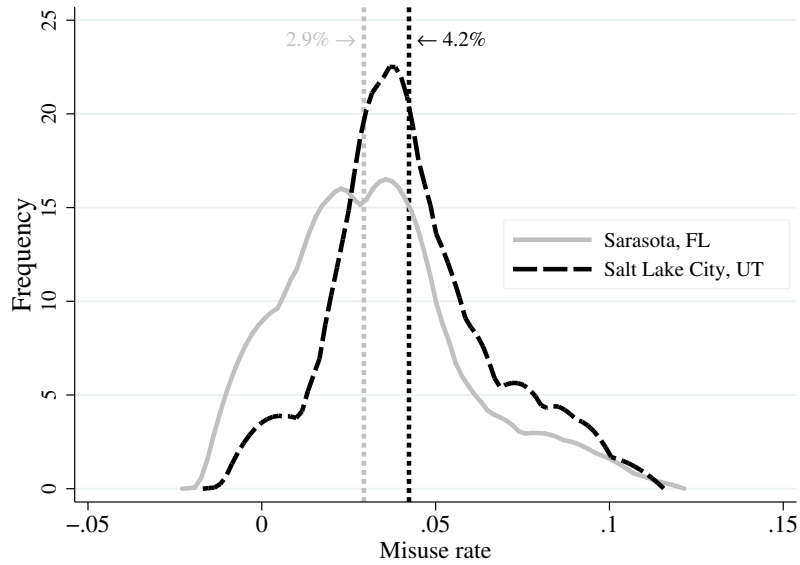
Notes: The above figure depicts the distribution of average misuse rates in example commuting zones. The dotted lines denote the centers of each distribution. These distributions are constructed by combining responses regarding prescription opioid misuse from the 2014 NSDUH in age-gender-race cells nationally with location-specific demographics from the 2010–2014 ACS.

C Supplementary Tables and Figures

Table A.3: Sources of misused prescription opioids in NSDUH

	Sources of misused prescription opioids	
	(1) Unweighted	(2) Weighted
Primary market		
From one doctor	22.95	28.34
From more than one doctor	3.58	3.71
Total	26.53	32.05
Secondary market		
Bought from friend or relative	10.12	16.45
Bought from drug dealer or other stranger	5.08	11.60
Total	15.20	28.05
Other		
Got from friend or relative for free	48.45	32.14
Took from friend of relative without asking	5.18	2.90
Stole from office, clinic, hospital, or pharmacy	0.18	0.13
Wrote fake prescription	0.12	0.14
Got some other way	4.34	4.60
Total	58.27	39.90

Notes: The above table lists the frequency of response options to questions concerning sources of misused prescription opioids on the 2014 NSDUH. If a respondent reports having used a prescription pain reliever they were not prescribed "only for the experience or feeling it caused," the respondent is then asked to report how they obtained the last prescription pain reliever they misused. "Weighted" frequencies adjust responses for the number of times a given respondent reported misusing prescription pain relievers in the past year.

Table A.4: Opioid prescriptions across specialties

|	% of opioids	N providers	Monthly opioid prescriptions per physician					
			Mean	Std. Dev.	Range	p25	p50	p75
Primary								
General & Family Practice	31.6	80,679	54.8	71.8	[1,2043]	13.3	31.9	68.6
Internal Medicine	19.2	58,211	46.1	66.3	[1,2040]	10.2	25.4	57.1
Total	50.8	138,890	51.1	69.7	[1,2043]	11.9	29.1	63.7
Medical								
Anesthesiology	3.8	2,693	197.4	304	[1,4982]	17.7	82.9	253.1
Emergency Medicine	6.8	26,995	35.4	34.9	[1,1167]	14.2	27	46.1
Hematology & Oncology	1.6	9,865	22.9	25.8	[1,798]	7.9	15.8	29.2
Internal Medicine	3.8	18,642	28.4	59.8	[1,2010]	4.5	9.8	25.7
Obstetrics & Gynecology	2.5	21,086	16.9	19.7	[1,1230]	6.8	12.3	21.1
Pain Medicine	5.8	2,972	273.7	328.1	[1,3371]	58.4	161.6	371.4
Physical Medicine & Rehab.	4.6	5,044	128	205.8	[1,4397]	14.4	47.4	152.1
Psychiatry & Neurology	2.1	8,547	34.1	86.7	[1,1795]	4.6	11.1	28.6
Other	0.5	3,287	22.8	49.6	[1,1138]	4.4	9.3	21.2
Total	31.6	99,131	44.6	112.5	[1,4982]	7.5	16.9	37.8
Surgical								
Surgery	15.6	50,873	42.9	53.1	[1,2209]	12.8	27.4	55.1
Other	2	14,694	18.8	18.2	[1,534]	7.8	14.7	24.7
Total	17.6	65,567	37.5	48.6	[1,2209]	11.2	23	46.5
Total	100	303,588	46.1	83	[1,4982]	9.9	23	51.4

Notes: The above table provides summary statistics for opioid prescriptions by physician specialty in 2014.

Table A.5: Office visit reimbursement rates across specialties

|	N providers	Mean	Std. Dev.	Range	p25	p50	p75
Primary							
General & Family Practice	80,679	102.3	25.2	[72,277]	86.9	99.5	108.4
Internal Medicine	58,211	103.8	17.1	[77,256]	93.4	101.9	108.2
Total	138,890	102.9	22.2	[72,277]	89.3	100.3	108.3
Medical							
Anesthesiology	2,693	139.7	37.5	[77,412]	113.8	131.8	154.4
Emergency Medicine	26,995	288.4	134.3	[123,1321]	206.4	250.1	300.9
Hematology & Oncology	9,865	125	25.6	[80,299]	108.6	118.1	133.1
Internal Medicine	18,642	132.3	29	[73,422]	113.9	127	142.2
Obstetrics & Gynecology	21,086	122.5	37.8	[52,258]	92.1	115.2	142.1
Pain Medicine	2,972	121.7	28.6	[74,272]	101.9	116.2	132.4
Physical Medicine & Rehab.	5,044	117.5	29.1	[73,333]	101.4	111.9	122.1
Psychiatry & Neurology	8,547	129.5	32.9	[68,356]	110.6	122.6	138
Other	3,287	99.7	26.7	[62,236]	81.4	92.2	110.4
Total	99,131	169.8	104.7	[52,1321]	111.7	132.8	194.8
Surgical							
Surgery	50,873	122.3	30.5	[68,320]	103.1	113.7	133.5
Other	14,694	120.2	30.1	[70,291]	100.4	112.3	132
Total	65,567	121.9	30.4	[68,320]	102.3	113.4	133.2
Total	303,588	128.9	69.8	[52,1321]	96.9	108.5	132.6

Notes: The above table provides summary statistics for office visit reimbursement rates by physician specialty in 2014.

Figure A.10: Homepage of StreetRx.com
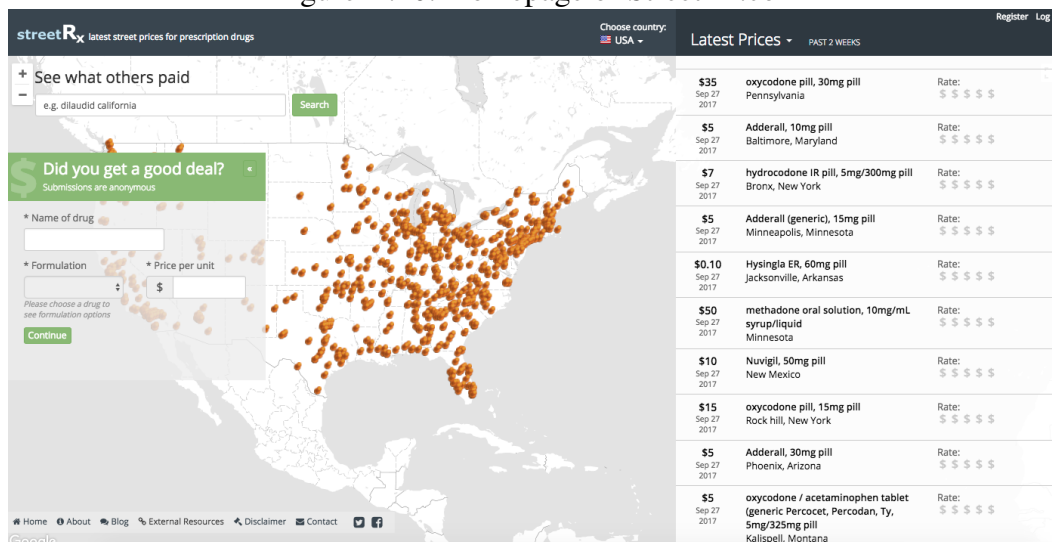
Notes: The above picture is a screenshot of the homepage of StreetRx.com. Visitors to the site can enter a prescription and location to get an overview of location-drug-specific prices ("See what others paid") or enter the price they paid per unit for a given formulation ("Did you get a good deal?"). The panel on the right of the screen provides a real-time display of data being captured.

Figure A.11: Average copayment for OxyContin over time


← August 2010
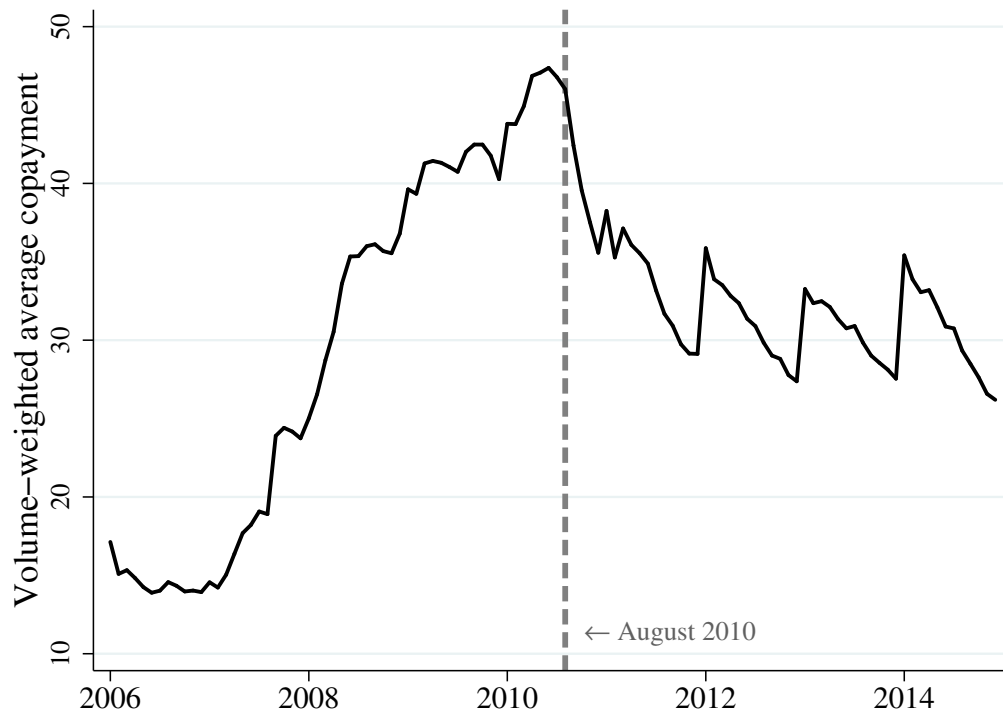
Notes: The above figure presents volume-weighted average copayments for OxyContin prescriptions filled in all retail pharmacies across the United States in each month as reported by QuintilesIMS. The vertical line denotes the month in which the original formulation of OxyContin stopped shipping and the reformulated version began shipping.

Figure A.12: Percent of opioid scripts for OxyContin by physician altruism groups
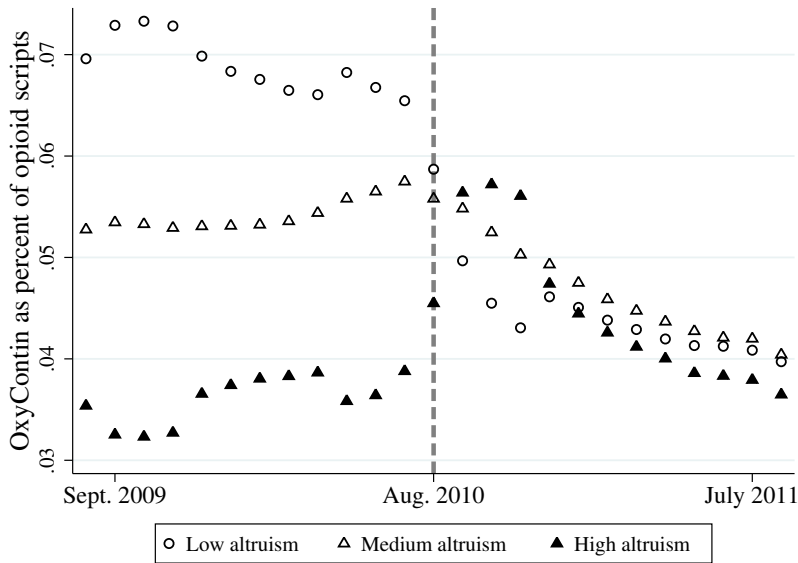
Notes: The above figure depicts the weighted-average percent of opioid prescriptions for OxyContin monthly across physicians within the three groupings of physician altruism. The vertical line denotes the quarter in which the original formulation of OxyContin stopped shipping and the reformulated version began shipping.

Figure A.13: Average copayment for opioid products by physician altruism over time
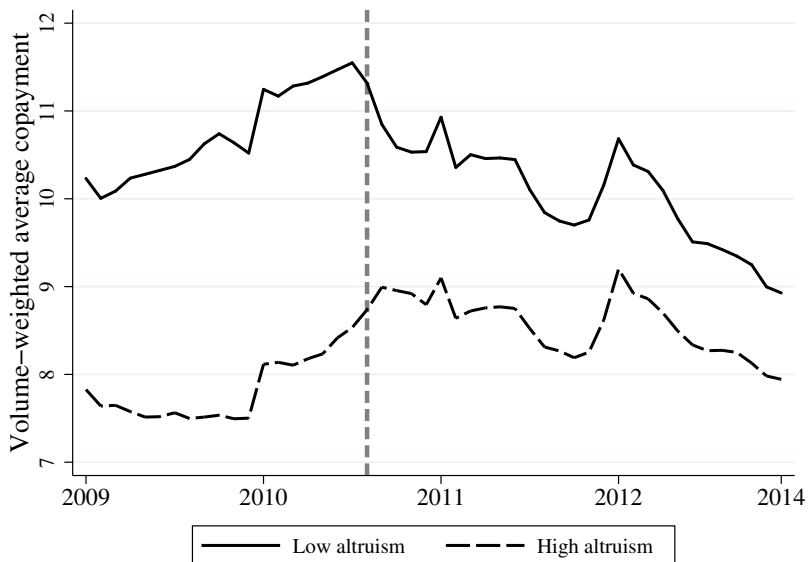
Notes: The above figure presents volume-weighted average copayments for all opioid prescriptions filled at retail pharmacies by patients seeing either a low-altruism (solid line) or high-altruism (dashed line) physician. The vertical line denotes the month in which the original formulation of OxyContin stopped shipping and the reformulated version began shipping.

Figure A.14: Change in use of opioid drug classes surrounding OxyContin reformation

(a) Low-altruism
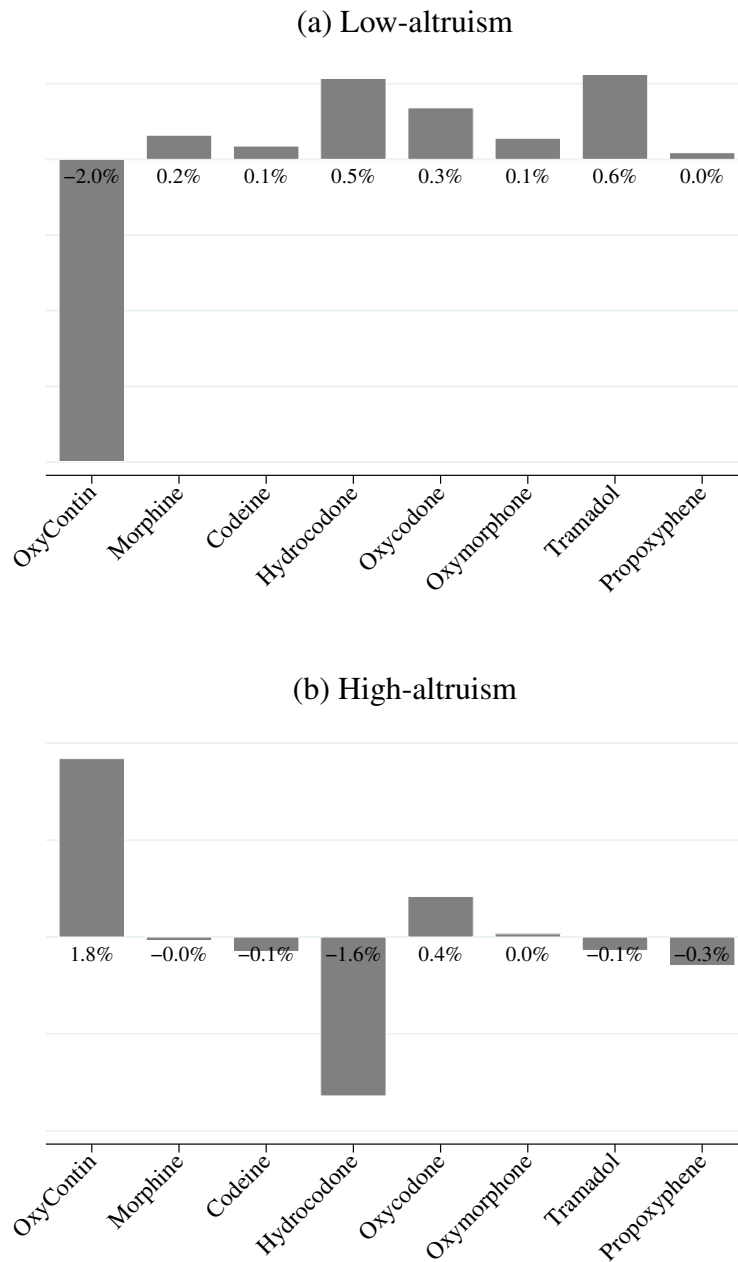
(b) High-altruism

Notes: The above figure presents the percent change in total opioid prescriptions written for different opioid classes by low-altruism physicians (Subfigure A) and high-altruism physicians (Subfigure B) from July 2010 to October 2010. Only opioid drug classes in which either low- or high-altruism physicians experienced a percent change of over 0.1% in absolute value are included.

Figure A.15: Discussion of price dispersion on Bluelight.com
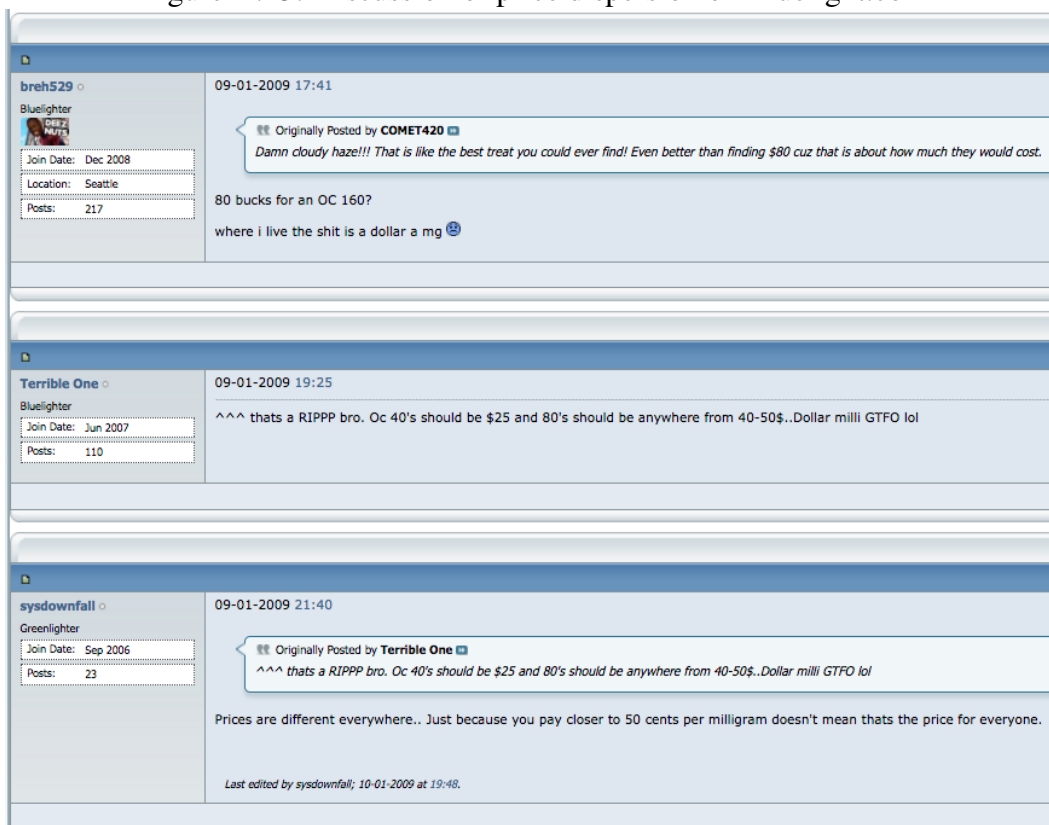
Notes: The above picture is a screenshot from Bluelight.com—a forum on which users discuss various topics related to drug use. The above conversation highlights that there is significant price dispersion across locations and that users are aware of these differences.