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Doctoral Dissertations, 2011-2026 Economics

2018

The Economics of Physician Behavior

Schnell, Molly Kathleen

Princeton, NJ : Princeton University

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THE ECONOMICS OF PHYSICIAN BEHAVIOR

Molly Kathleen Schnell

A DISSERTATION

PRESENTED TO THE FACULTY

OF PRINCETON UNIVERSITY

IN CANDIDACY FOR THE DEGREE

OF DOCTOR OF PHILOSOPHY

RECOMMENDED FOR ACCEPTANCE

BY THE DEPARTMENT OF ECONOMICS

ADVISORS: Janet Currie & Jakub Kastl

June 2018

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Abstract

Physicians form the core of healthcare markets, with their behavior determining outcomes and costs. My dissertation consists of three chapters that examine the economics of physician behavior. In particular, I examine how the organization of markets, human capital development, and financial incentives influence the treatment decisions that physicians make.

In Chapter 1, I examine how the presence of an illegal, secondary market for prescription opioids influences both the prescribing practices of physicians and the equilibrium allocation of these prescriptions. To do so, I develop and estimate a model of physician behavior in the presence of a secondary market with patient search. Estimates demonstrate that cracking down on the secondary market, while useful in controlling the allocation of prescription opioids, will have the unintended consequence of inducing physicians to be even more lenient in their prescribing.

In Chapter 2, Janet Currie and I consider the role that education plays in determining a physician's prescribing habits. Using comprehensive prescription data, we uncover a striking relationship between opioid prescribing and medical school rank. Even within the same specialty and practice location, physicians who completed their initial training at top medical schools write significantly fewer opioid prescriptions than physicians from lower ranked schools. Additional evidence suggests that some of this gradient represents a causal effect of education rather than patient selection across physicians or physician selection across medical schools.

Finally, in Chapter 3, Diane Alexander and I examine how the amount a physician is paid influences who they are willing to see. To do so, we exploit large, exogenous changes in Medicaid reimbursement rates to quantify the impact of physician payment on access to treatment and health. We find that increasing Medicaid payments to primary care doctors is associated with improvements in access, better self-reported health, and fewer school days missed among beneficiaries.

Acknowledgments

I owe my deepest gratitude to my advisors, Janet Currie and Jakub Kastl. This dissertation would not have been possible without their frequent and profound feedback and seemingly endless support. I am humbled by how generous they have been with their time and energy. I also thank Bo Honoré and Eduardo Morales for their careful reading of my work and their commitment to helping me tie up loose ends in the eleventh hour. I further thank Diane Alexander, a great friend and frequent coauthor, for always reminding me that research can and should be fun.

I am grateful to participants in the Center for Health and Wellbeing working group, the Industrial Organization student workshop, and the Fellowship of Woodrow Wilson Scholars for conversations and suggestions that have greatly improved my work at all stages. I would particularly like to acknowledge Nick Buchholz, Anne Case, Angus Deaton, Jan De Loecker, Henry Farber, Marc Fleurbaey, Thomas Fujiwara, Myrto Kalouptsidi, Ilyana Kuziemko, Bentley MacLeod, Steve Redding, and Tom Vogl. I also thank Justine Conoline, Laura Hedden, and Gabriella Herrera for always ensuring that things run smoothly; my life would have been much more difficult without their support.

I thank my classmates for their companionship and support throughout the past six years. I would especially like to thank Giulia Brancaccio, Emily Cuddy, Júlia Fonseca, Clara Santamaría, and Jenny Shen for their constant encouragement and unbeatable friendship. An extra special thanks is reserved for my roommates, Giulia Brancaccio and Clara Santamaría, who put up with me in the lead up to the market. I thank my parents, Mary and Steve Schnell, for their love and free psychological support. Thank you for helping me keep things in perspective. I thank my sister, Kerry Sheets, for her friendship, encouragement, and invaluable insights into how physicians think. Most of all, I thank Janet Currie for introducing me to Hannes Schwandt, whose perpetual optimism and unwavering support will remain with me long past graduate school.

Contents

Abstract iii

Acknowledgments iv

List of Tables viii

List of Figures x

1 Physician Behavior in the Presence of a Secondary Market: The Case of Prescription Opioids 1

1.1 Introduction 1

1.2 Data 7

1.2.1 Physician-level data 8

1.2.2 Market-level data 10

1.3 Physician preferences 13

1.4 Model 20

1.4.1 Set-up 20

1.4.2 Without a secondary market 24

1.4.3 With a secondary market 28

1.4.4 Discussion 38

1.5 Empirical strategy 40

1.5.1 Estimation 41

1.5.2 Robustness 44

1.6 Results 45

1.6.1 Model estimates . . . 45
1.6.2 Shutting down the secondary market . . . 48
1.6.3 Maximal health benefits . . . 50
1.6.4 Policy discussion . . . 51
1.7 Discussion and conclusion . . . 52
References . . . 55
1.A Additional model details . . . 61
1.A.1 Proofs . . . 61
1.A.2 With a secondary market and patient search . . . 65
1.A.3 Estimation algorithm . . . 68
1.A.4 Supplementary diagrams . . . 71
1.B Data appendix . . . 75
1.B.1 Reimbursement . . . 75
1.B.2 Pain and taste distributions . . . 81
1.C Supplementary tables and figures . . . 85

2 Addressing the Opioid Epidemic: Is There a Role for Physician Education? 91
2.1 Introduction . . . 91
2.2 Data . . . 95
2.3 Opioid prescriptions and medical school rankings . . . 99
2.4 Empirical strategy . . . 101
2.5 The role of training . . . 107
2.5.1 Gradient conditional on specialty and practice location . . . 107
2.5.2 Prescribing gradient across specialties . . . 112
2.5.3 Prescribing gradient across cohorts . . . 114
2.6 Robustness . . . 115
2.7 Discussion and conclusions . . . 119
References . . . 121

2.A Supplementary figures . . . 126
2.B Supplementary tables . . . 136

3 Physician Payments and Access to Care: Evidence from Medicaid 145

3.1 Introduction . . . 145
3.2 Data . . . 150
3.2.1 Medicaid reimbursement rates . . . 150
3.2.2 National Health Interview Survey . . . 155
3.2.3 National Assessment of Educational Progress . . . 160
3.3 Empirical strategy . . . 162
3.4 Results . . . 163
3.5 Robustness . . . 171
3.5.1 The fee increase and the 2014 Medicaid expansion . . . 171
3.5.2 Robustness of the fee variable . . . 176
3.5.3 Alternative empirical specification: difference-in-difference . . . 177
3.6 Conclusion . . . 179
References . . . 181
3.A Data appendix . . . 185
3.A.1 Outcomes . . . 185
3.A.2 Medicaid fees . . . 187
3.B Results by duration expectations . . . 190
3.C Supplementary tables and figures . . . 192

List of Tables

1.1 Summary statistics: physician-level variables by specialty categories 10

1.2 Summary statistics: market-level variables 13

1.3 Summary statistics: physician altruism 18

1.4 Drug-related mortality and local composition of physician altruism 19

1.5 Parameters to be estimated 40

1.6 Moments used for estimation 42

1.7 Parameter estimates 45

1.8 Reimbursement components across specialties 76

1.9 CPT codes considered for reimbursement 77

1.10 Sources of misused prescription opioids in NSDUH 85

1.11 Opioid prescriptions across specialties 86

1.12 Office visit reimbursement rates across specialties 87

2.1 Opioid prescriptions and practice characteristics by medical school rank . . 103

2.2 Opioid prescriptions by medical school rank 109

2.3 Opioid prescriptions by medical school rank across specialties 113

2.4 Opioid prescriptions by medical school rank across cohorts 115

2.5 Composite medical school rankings 136

2.6 Summary statistics: prescription data 137

2.7 Summary statistics: county-level prescriptions and mortality 137

2.8 Opioid prescriptions by detailed medical school rank 138

2.9 Opioid prescriptions by detailed medical school rank: GPs 139
2.10 Opioid prescriptions by physician specialty 140
2.11 Opioids by rank controlling for specialty and practice county 141
2.12 Opioids by rank controlling for specialty and practice county: GPs 142
2.13 Opioids by medical school rank across cohorts: pain specialists 143
2.14 Opioids by medical school rank excluding university-affiliated zip codes . . 143
2.15 Opioid prescriptions and deaths involving drugs 144

3.1 Summary statistics: outcome measures 156
3.2 Summary statistics: individual and county controls 159
3.3 Effects of physician reimbursement on access and health 165
3.4 Effects of physician reimbursement on school absences: grade 4 169
3.5 Effects of physician reimbursement: difference-in-difference specification . 178
3.6 Overview of data sources used for outcome measures 185
3.7 Medicaid enrollment and managed care to fee-for-service payment ratios . . 187
3.8 Overview of Medicaid rate data 189
3.9 Effects of physician reimbursement by duration expectations 191
3.10 Effects of physician reimbursement on school absences: grade 8 198
3.11 Effects of physician reimbursement on test scores: grade 4 199
3.12 Effects of physician reimbursement on test scores: grade 8 200
3.13 Effects of physician reimbursement: imputing with mean fee ratio 201
3.14 Effects of physician reimbursement: states in GAO report 202
3.15 Effects of physician reimbursement: primary care shortage areas 203

List of Figures

1.1 OxyContin prescriptions nationally 14

1.2 Example physicians 16

1.3 Equilibrium allocation: with secondary market and without patient search . 30

1.4 Opioid prescriptions and secondary market prevalence 35

1.5 Estimated health impact function 46

1.6 Estimated distributions of tastes 47

1.7 Optimal physician thresholds: with and without a secondary market 49

1.8 Equilibrium allocation: with secondary market and patient search 67

1.9 Equilibrium allocation: without secondary market or patient search 71

1.10 Equilibrium allocation: without secondary market and with patient search . 72

1.11 Equilibrium market shares: without secondary market and with patient search 73

1.12 Equilibrium market shares: with secondary market and patient search . . . 74

1.13 Average pain severity across age-gender-race cells 82

1.14 Example distributions of average pain severities 82

1.15 Prescription opioid misuse rates across age-gender-race cells 84

1.16 Example distributions of prescription opioid misuse rates 84

1.17 Homepage of StreetRx.com 87

1.18 Discussion of price dispersion on Bluelight.com 88

1.19 Average copayment for OxyContin over time 88

1.20 Percent of opioid scripts for OxyContin by physician altruism groups 89

1.21 Average copayment for opioid products by physician altruism over time . . 89
1.22 Change in use of opioid drug classes surrounding OxyContin reformation . 90

2.1 Opioid prescriptions by medical school rank 100
2.2 Opioids by rank controlling for specialty and practice county 108
2.3 Opioids by school region controlling for specialty and practice county . . . 111
2.4 Opioids by medical school rank: levels versus rates in Medicare Part D . . . 117
2.5 Physicians and medical schools across rankings and world regions 126
2.6 Persistence across medical school rankings over time 127
2.7 Opioid prescriptions by medical school rank: all physicians 128
2.8 Opioid prescriptions by medical school rank: general practitioners 129
2.9 Opioid prescriptions by US rankings and regions of foreign schools 130
2.10 Opioids by rank controlling for specialty and practice address 131
2.11 Opioid prescriptions by medical school rank across specialties 132
2.12 Opioid prescriptions by medical school rank: oncology and nephrology . . 133
2.13 Opioid prescriptions by medical school rank across graduation cohorts . . . 134
2.14 Opioids by medical school rank excluding university-affiliated zip codes . . 135

3.1 Maps of state-level Medicaid fees for new patient primary care services . . 152
3.2 State-level Medicaid fees for new patient primary care services over time . 153
3.3 Distribution of school absences by grade and subject 161
3.4 Before-after differences by size of fee increase 164
3.5 Heterogeneous effects of physician reimbursement 173
3.6 Heterogeneous effects of physician reimbursement: adult subsample 174
3.7 State-level Medicaid Managed Care penetration over time 192
3.8 States extending Medicaid primary care rate increase past 2014 193
3.9 Distribution of school absences by free lunch eligibility 194
3.10 Average test scores by school absences 195

3.11 Heterogeneous effects of physician reimbursement: child subsample 196
3.12 Event time figures by size of fee increase 197

Chapter 1

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

1.1 Introduction

Every day, over 40 Americans die from a drug overdose involving a prescription opioid (CDC, 2017). 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

*Materials from this chapter were presented at the 2016 Conference of the American Society of Health Economists, the 2016 European Health Economics Association Conference, the 2016 Population Health Science Workshop at Boston University, the 2016 and 2017 Becker Friedman Institute Emerging Scholars Roundtables, the 2017 CEPR Applied IO Summer School, the 2017 Barcelona GSE Summer Forum (Applied IO), and the 2017 European Association of Labour Economists Conference. I thank Giulia Brancaccio, Nick Buchholz, Janet Currie, Angus Deaton, Bo Honoré, Jakub Kastl, Ilyana Kuziemko, Bentley MacLeod, Eduardo Morales, Nicholas Papageorge, Clara Santamaría, Otto Toivanen, Atheendar Venkataramani, and seminar participants at Bocconi, Booth, Columbia, Dartmouth, Duke Fuqua, HBS, Hebrew U, Kellogg, LSE, MIT, MSR, UMN SPH, NYU, Northwestern, Princeton, Stanford GSB, Tel Aviv, UCL, UChicago, UPenn, UZH, Wharton, Wisconsin, Yale, and Yale SOM. Generous financial support from the Center for Health and Wellbeing at Princeton University and the Becker Friedman Institute at the University of Chicago is gratefully acknowledged. The statements, findings, conclusions, views, and opinions contained and expressed herein are not necessarily those of QuintilesIMS or any of its affiliated or subsidiary entities.

[1] In 2017, deaths from drug overdoses in the US 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).

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 the legal, primary market and the illegal, secondary market 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 interlinked markets. I estimate my model using detailed data on the number of opioid prescriptions written by each physician in the US from 2006–2014, unique data documenting street prices for prescription opioids across the US, 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.

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

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

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 1.10).[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

[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, Haegerich and Chou, 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.

revenue. If a patient receives a prescription from a physician, she can either consume the medication—and receive utility from this consumption that is increasing in her level of pain and taste for opioids—or resell the prescription on the secondary market.

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 all 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 US.

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 US.[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

[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. (2018) 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.

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 1.2 introduces the data sets that I use. In Section 1.3, I exploit the reformulation of OxyContin to estimate physician preferences and document heterogeneity in altruism across physicians. In Section 1.4, I present a model of the primary and secondary markets for opioids and formalize the forces influencing optimal patient and physician behavior. Section 1.5 discusses estimation. Results and counterfactuals are presented in Section 1.6. Section 1.7 provides a discussion and concludes.

1.2 Data

I use six main data sets that together describe the primary and secondary markets for prescription opioids across the US. The features of each data set that are most relevant for my analysis are described below. Additional details are provided in Appendix 1.B.

[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.

1.2.1 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 US 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 US 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 1.3, 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 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

[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.

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 1.4, 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 1.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 1.1. 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

Table 1.1: Summary statistics: physician-level variables by specialty categories

			Monthly opioid scripts			Office visit reimbursement		
	% opioids	N phys.	Mean	Std. Dev.	Range	Mean	Std. Dev.	Range
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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 1.11 and 1.12.

(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.

1.2.2 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 1.4 requires an average resell price for an opioid prescription across the US. 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, $\left(\overline{\frac{days}{script}}\right)$ denote the average number of days supplied per opioid script, $\left(\overline{\frac{pills}{day}}\right)$ the average number of pills per day supplied, and $\left(\overline{\frac{MME}{pill}}\right)$ the average number of MME per pill, the expected resell price for an opioid prescription in commuting zone c, p_c, is given by

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

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

[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).

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 population. 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 1.B.2.

Summary statistics Summary statistics for the ten largest commuting zones are provided in Table 1.2. 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

Table 1.2: 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 1.3.

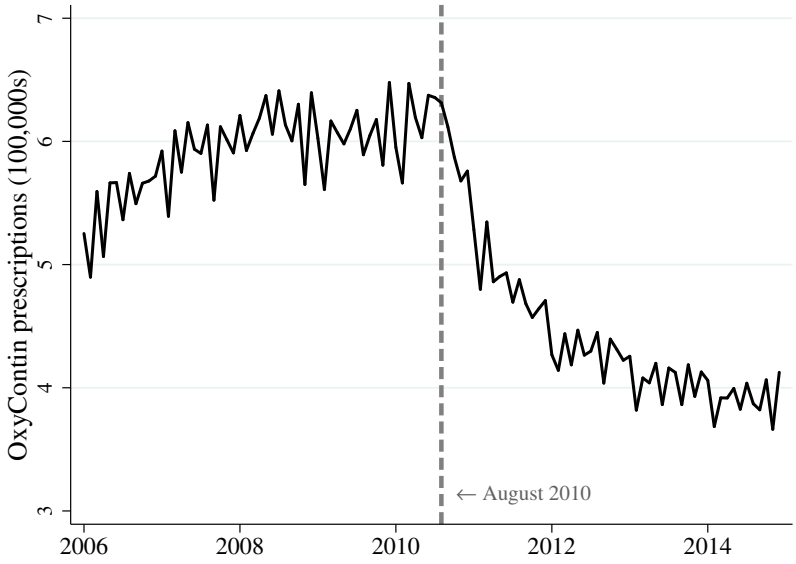
likewise differ across locations, with patients being able to resell their prescriptions for over $350 more in Chicago than Atlanta (column (2)).[14] Pain severities and misuse rates also vary across commuting zones, with nearly 4% of the population misusing prescription opioids on average (columns (4)-(6)).

1.3 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

[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 1.18.

Figure 1.1: OxyContin prescriptions nationally



Notes: The above figure presents the number of OxyContin prescriptions filled in US 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 1.19 for average copayments for OxyContin over the same time period.

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 1.1, the reformulation was associated with a significant drop in the number of prescriptions for OxyContin across the US. While there were over 635,000 OxyContin prescriptions in July 2010, OxyContin prescriptions fell by over 25% to only 469,000 per

[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).

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 either 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]

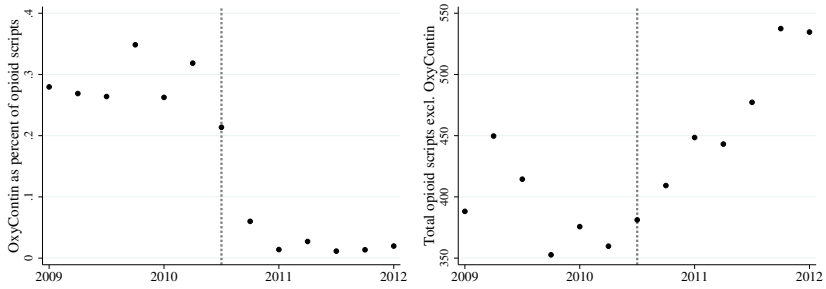
As shown in Figure 1.2, physician-level responses to the reformulation of OxyContin were not identical. The left figure in each subplot shows an individual physician's quarterly percent of opioid prescriptions for OxyContin, and the right figure shows the same physician's prescriptions for all opioids 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 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.

[16] As new drugs are often more expensive than their predecessors, the pattern observed in Figure 1.1 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 1.19).

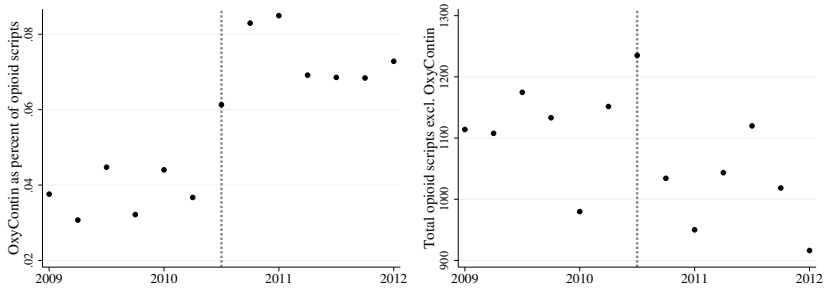
[17] Physicians who switched their patients away from OxyContin following the reformulation switched their patients to a variety of opioid products without abuse-deterrent properties (Figure 1.22). Furthermore, while the average copayment of patients seen by low-altruism physicians decreased as their physician switched them away from OxyContin, 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 1.21).

Figure 1.2: 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 of

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

months, respectively, I calculate

$$b_j^n = \frac{\sum_{m \in M_1} Share_{jm} - \sum_{m \in M_0^n} Share_{jm}}{\sum_{m \in M_0^n} Share_{jm}} \; for \; n \in \{1, 2\} \tag{1.1}$$

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 (1.1), 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 1.3, 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 US. 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

Table 1.3: 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.

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.

Locations differ in their composition of physician altruism types (columns (7)–(8) of Table 1.2).[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 1.4, 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 1.4 are standardized. Looking first to the results for deaths involving drugs (columns (1)–(4)), we see that a one standard deviation increase

[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.

Table 1.4: 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.

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 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.

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.

1.4 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 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.

1.4.1 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

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

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

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

where $\bar{h}_c^{SM}$ 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)

[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.

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, 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.

1.4.2 Without a secondary market

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 $\left(\frac{|I_{c_j}|}{|J_{c_j,g_j}|}\right)$ 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 $\frac{|I_{c_j}|}{|J_{c_j}|}$ patients.

In the absence of a secondary market, any patient for whom $h(\kappa_i) + \gamma_i \geq \tau^d_{c_i} + \tau^o_{c_i}$ 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 $\left(h(\kappa_i) + \gamma_i \geq \tau^d_{c_i} + \tau^o_{c_i}\right)$ 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:

$$\begin{aligned}\max_{\kappa_j} \ \beta_{b_j} \cdot \frac{|I_{c_j}|}{|J_{c_j}|} \cdot \int_{\kappa_j}^{\infty} \int_{\tau^d_{c_j}+\tau^o_{c_j}-h(k)}^{\infty} h(k) f_{c_j}(k) g_{c_j}(\gamma) d\gamma dk \\ + R_j \cdot \frac{|I_{c_j}|}{|J_{c_j}|} \cdot \int_{\kappa_j}^{\infty} \int_{\tau^d_{c_j}+\tau^o_{c_j}-h(k)}^{\infty} f_{c_j}(k) g_{c_j}(\gamma) d\gamma dk \end{aligned} \tag{1.2}$$

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 (1.2) 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*

$$-\beta_{b_j} \cdot h\left(\kappa_j^*\right) = R_j \tag{1.3}$$

Equation (1.3) 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.

With patient search

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

$$\underbrace{\frac{1}{|J_{c_i}|} \sum_{j \in J_{c_i}} \mathbb{1}\{\kappa_j^* \leq \kappa_i\}}_{\equiv P_{c_i}(\kappa_i)} \cdot [h(\kappa_i) + \gamma_i] \tag{1.4}$$

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

$$\tau_{c_i}^s + \tau_{c_i}^d + P_{c_i}(\kappa_i) \cdot \tau_{c_i}^o \tag{1.5}$$

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

$$T_{c_i}(\kappa_i) = \frac{\tau^s_{c_i} + \tau^d_{c_i}}{P_{c_i}(\kappa_i)} + \tau^o_{c_i} - h(\kappa_i) \tag{1.6}$$

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

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

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]

$$q^*_{j,c} = \frac{1}{|J_c|} \cdot \left[\int_{\kappa^*_{j,c}}^{\infty} f_c(k)dk + \int_0^{\kappa^*_{j,c}} \int_{-\infty}^{T_c(k)} f_c(k)g_c(\gamma)d\gamma dk \right] + \sum_{n=1}^{j-1} \left[\frac{1}{\left(|J_c|-n+1\right)\left(|J_c|-n\right)} \cdot \int_{\kappa^*_{j,c}}^{\kappa^*_{n,c}} \int_{T_c(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right] \tag{1.7}$$

Assume physicians take the optimal thresholds of the other physicians in their market as given. With patient search and without a secondary market, physician j in geographic market c then chooses her threshold severity to solve the following problem:

$$\begin{aligned} \max_{\kappa_{j,c}} \; & \beta_{b_j,c} \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{\tau^d_c+\tau^o_c-h(k)}^{\infty} h(k)f_c(k)g_c(\gamma)d\gamma dk \right] \\ & + \beta_{b_j,c} \cdot \sum_{n=1}^{j-1} \left[\frac{|I_c|}{\left(|J_c|-n+1\right)\left(|J_c|-n\right)} \cdot \int_{\kappa_{j,c}}^{\kappa^*_{n,c}} \int_{T_c(k)}^{\infty} h(k)f_c(k)g_c(\gamma)d\gamma dk \right] \\ & + R_{j,c} \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{\tau^d_c+\tau^o_c-h(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right] \\ & + R_{j,c} \cdot \sum_{n=1}^{j-1} \left[\frac{|I_c|}{\left(|J_c|-n+1\right)\left(|J_c|-n\right)} \cdot \int_{\kappa_{j,c}}^{\kappa^*_{n,c}} \int_{T_c(k)}^{\infty} f_c(k)g_c(\gamma)d\gamma dk \right] \end{aligned} \tag{1.8}$$

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.

[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 1.11 for a market with two physicians.

Taking the derivative of equation (1.8) 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*

$$-\beta_{b_j,c} \cdot h(\kappa^*_{j,c}) = R_{j,c} \tag{1.9}$$

As in Result 1a, the uniqueness of this threshold is guaranteed by the strict monotonicity of the health impact function. Comparing equations (1.9) and (1.3), 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]

1.4.3 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 that the resale price (p_c) outweighs the cost of accessing an opioid prescription $\left(\tau^d_c + \tau^o_c\right)$, 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.

[23]The equilibrium allocation of opioid prescriptions with search and without a secondary market is shown pictorially in Figure 1.10 for a market with two physicians.

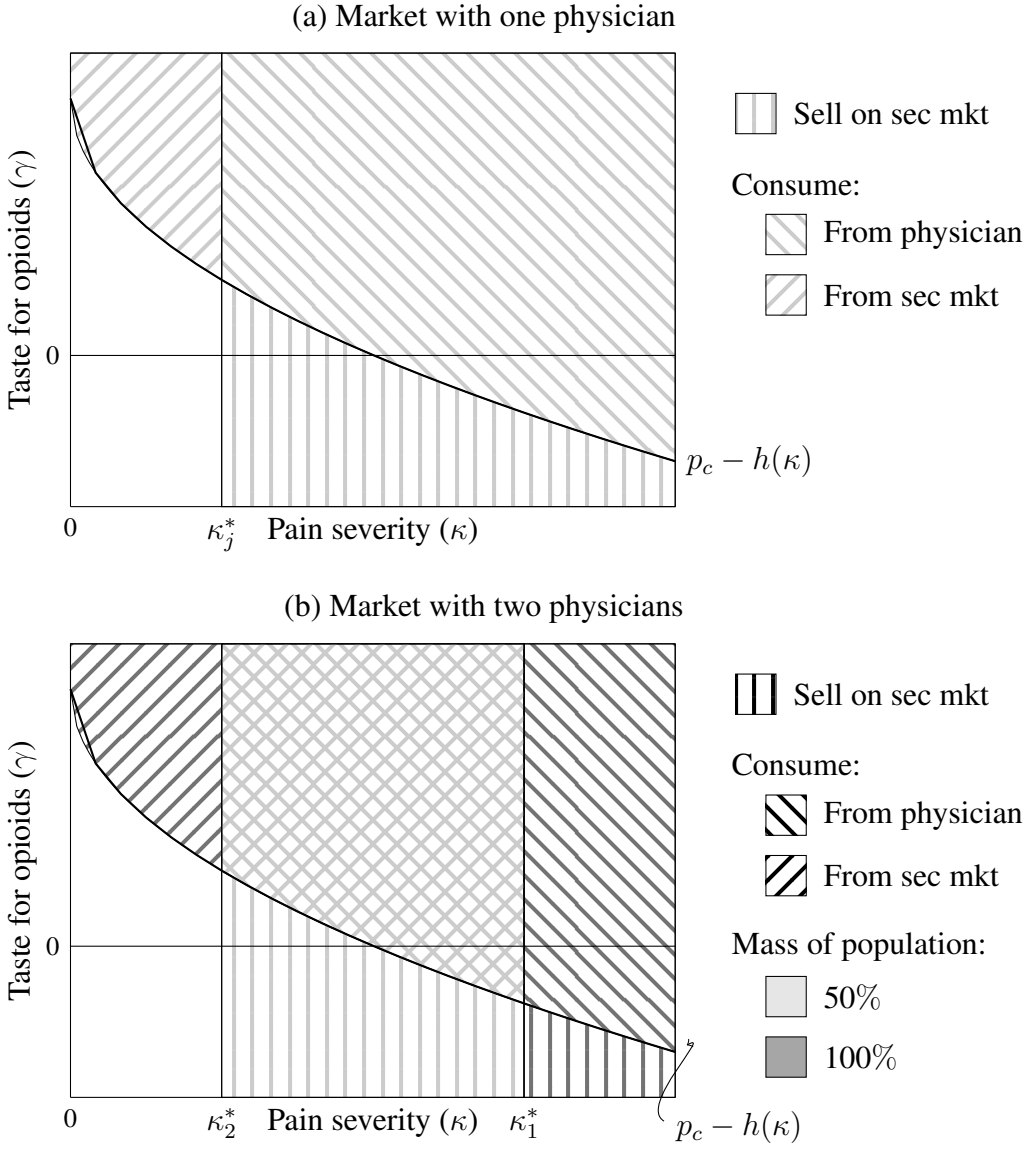
Before analyzing how the presence of a secondary market influences physician behavior, let us first consider how a secondary market influences the equilibrium allocation of prescriptions. Again begin under the assumption that patients cannot search for physicians.

Without patient search

The reallocation of prescriptions across patients with a secondary market (and no patient search) is shown pictorially in Figure 1.3. 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).

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

Figure 1.3: Equilibrium allocation: with secondary market and without patient search



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)).

threshold severity κ_j^* to solve

$$\begin{aligned}\max_{\kappa_j} \quad & \beta_{b_j} \cdot \frac{\left|I_{c_j}\right|}{\left|J_{c_j}\right|} \cdot \int_{\kappa_j}^{\infty} \int_{p_{c_j}-h(k)}^{\infty} h(k) f_{c_j}(k) g_{c_j}(\gamma) d\gamma dk \\ & + \beta_{b_j} \cdot \frac{\left|I_{c_j}\right|}{\left|J_{c_j}\right|} \cdot \bar{h}_{c_j}^{SM} \cdot \int_{\kappa_j}^{\infty} \int_{-\infty}^{p_{c_j}-h(k)} f_{c_j}(k) g_{c_j}(\gamma) d\gamma dk \\ & + R_j \cdot \frac{\left|I_{c_j}\right|}{\left|J_{c_j}\right|} \cdot \int_{\kappa_j}^{\infty} f_{c_j}(k) dk \end{aligned} \tag{1.10}$$

where $\bar{h}_c^{SM} = \frac{\sum_{j \in J_c} \int_0^{\kappa_j^*} \int_{p_c - h(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk}{\sum_{j \in J_c} \int_0^{\kappa_j^*} \int_{p_c - h(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk}$ 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 (1.10) 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*

$$-\beta_{b_j} \cdot \left[(1 - G_{c_j}(p_{c_j} - h(\kappa_j^*))) \cdot h(\kappa_j^*) + G_{c_j}(p_{c_j} - h(\kappa_j^*)) \cdot \bar{h}_{c_j}^{SM} \right] = R_j \tag{1.11}$$

[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.

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 (1.3)). In the presence of 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 (1.11) holds $\forall\ j \in J_c$)

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

$$\sum_{j \in J_c} \int_{\kappa_j^*}^{\infty} \int_{-\infty}^{p_c - h(k)} f_c(k) g_c(\gamma) d\gamma dk = \sum_{j \in J_c} \int_{0}^{\kappa_j^*} \int_{p_c - h(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk \tag{1.12}$$

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 1.A for formal statements and proofs.

First, consider how an individual physician responds to the presence of a secondary market (Lemma 1 in Appendix 1.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 1.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.

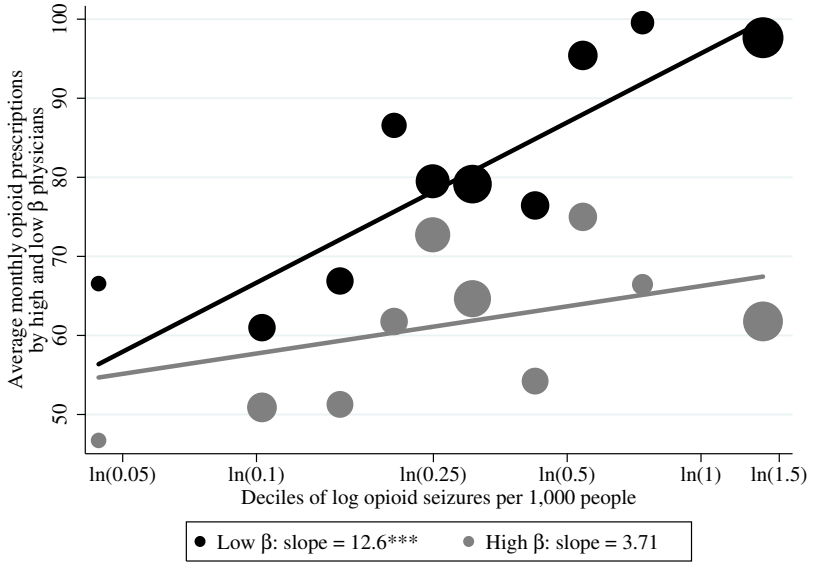
How does the presence of a secondary market for prescription opioids affect the total number of prescriptions written by physicians on the primary market? If all physicians become more strict, supply contracts. If some physicians become more strict and some physicians become more lenient, the supply 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 1.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 1.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 inducing 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.

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 US, 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

Figure 1.4: 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.

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 1.4 plots average opioid prescriptions written by high- and low-altruism physicians in counties across the US 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.

With patient search

When a secondary market for opioids exists, the marginal cost of search remains as before (equation (1.5)). 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 (1.4). 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 $\Leftrightarrow$

$$P_{c_i}(\kappa_i) \cdot [h(\kappa_i) + \gamma_i] \geq \tau^s_{c_i} + \tau^d_{c_i} + P_{c_i}(\kappa_i) \cdot \tau^o_{c_i} \tag{1.13}$$

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

$$P_{c_i}(\kappa_i) \cdot p_{c_i} \geq \tau^s_{c_i} + \tau^d_{c_i} + P_{c_i}(\kappa_i) \cdot \tau^o_{c_i} \tag{1.14}$$

Rearranging the inequality in equation (1.14), we see that patients with $p_{c_i} > h(\kappa_i) + \gamma_i$ and $\kappa_i \geq P^{-1}_{c_i}\left(\frac{\tau^s_{c_i}+\tau^d_{c_i}}{p_{c_i}-\tau^o_{c_i}}\right)$ will search to resell. Furthermore, since the inequality in equation (1.13) always holds for patients with $h(\kappa_i) + \gamma_i \geq p_{c_i}$ and $\kappa_i \geq P^{-1}_{c_i}\left(\frac{\tau^s_{c_i}+\tau^d_{c_i}}{p_{c_i}-\tau^o_{c_i}}\right)$, it follows that *all* patients with $\kappa_i \geq P^{-1}_{c_i}\left(\frac{\tau^s_{c_i}+\tau^d_{c_i}}{p_{c_i}-\tau^o_{c_i}}\right)$ find it optimal to search.[25] As this observation will be helpful in deriving physician market shares and subsequently optimal physician behavior, let

$$\tilde{P}_c \equiv P^{-1}_c\left(\frac{\tau^s_c + \tau^d_c}{p_c - \tau^o_c}\right)$$

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

[25]The probability that a physician's patient resells therefore depends on whether $\kappa_i \lesseqgtr P^{-1}_{c_i}\left(\frac{\tau^s_{c_i}+\tau^d_{c_i}}{p_{c_i}-\tau^o_{c_i}}\right)$. 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 $\kappa_i \geq P^{-1}_{c_i}\left(\frac{\tau^s_{c_i}+\tau^d_{c_i}}{p_{c_i}-\tau^o_{c_i}}\right)$ and another for patients with $\kappa_i < P^{-1}_{c_i}\left(\frac{\tau^s_{c_i}+\tau^d_{c_i}}{p_{c_i}-\tau^o_{c_i}}\right)$. However, there is 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.

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 (1.13) 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 (1.6).

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 whose threshold is closest from below to the pain level $\tilde{P}_c$.[26] The equilibrium market share for doctor j in geographic market c is given by[27]

$$q^*_{j,c} = \begin{cases} \frac{1}{|J_c|} \cdot \left[\int_{\kappa^*_{j,c}}^{\infty} f_c(k)dk + \int_0^{P^*_c} \int_{-\infty}^{T_c(k)} f_c(k) g_c(\gamma) d\gamma dk \right] & \text{if } \kappa^*_{j,c} \geq \tilde{P}_c \\ + \sum_{n=1}^{j-1} \cdot \left[\frac{1}{(|J_c|-n+1)(|J_c|-n)} \cdot \int_{\kappa^*_{j,c}}^{\kappa^*_{n,c}} f_c(k)dk \right] & \\ \frac{1}{|J_c|} \cdot \left[\int_{\kappa^*_{j,c}}^{\infty} f_c(k)dk + \int_0^{\kappa^*_{j,c}} \int_{-\infty}^{T_c(k)} f_c(k) g_c(\gamma) d\gamma dk \right] & \text{if } \kappa^*_{j,c} < \tilde{P}_c \\ + \sum_{n=j_{p,c}}^{j-1} \cdot \left[\frac{1}{(|J_c|-n+1)(|J_c|-n)} \cdot \int_{\kappa^*_{j,c}}^{\kappa^*_{n,c}} \int_{T_c(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk \right] & \\ + \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{1}{(|J_c|-n+1)(|J_c|-n)} \cdot \left(\int_{\kappa^*_{j,c}}^{P^*_c} \int_{T_c(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk + \int_{P^*_c}^{\kappa^*_{n,c}} f_c(k)dk \right) \right] & \end{cases} \tag{1.15}$$

[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.

[27] These market shares are shown pictorially in Figure 1.12 for a market with two physicians.

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 1.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.

1.4.4 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 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.

1.5 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 1.5.

Table 1.5: Parameters to be estimated

Parameters	#	Description
$G_c(\gamma) \sim \mathcal{N}(\mu_c, \sigma_c^2)$	2· 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 1.2), 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 1.3).

Recall the optimality condition for each physician first displayed in equation (1.11). Adding explicit notation for the parameters on which each component depends, the opti-

[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.

mality condition for physician j becomes

$$-\beta_{b_j}\cdot\Big[(1-G_{c_j}(p_{c_j}-h(\kappa_j^*:\boldsymbol{\theta})))\cdot h(\kappa_j^*:\boldsymbol{\theta})+G_{c_j}(p_{c_j}-h(\kappa_j^*:\boldsymbol{\theta}))\cdot\bar{h}_{c_j}^{SM}\Big]=R_j \tag{1.16}$$

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

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 $\left(\left\{\bar{h}_c^{SM}\right\}_{\forall c}\right)$, 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 $\left\{\bar{h}_c^{SM}\right\}_{\forall c}$ as nuisance parameters to be estimated.[30] There are therefore $4\cdot C+6$ parameters to be estimated.

1.5.1 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 1.6. As outlined in Appendix 1.A.3, for a given set of parameter values $\left\{\left\{\tilde{\tau_c^s},\mu_c,\sigma_c^2,\bar{h}_c^{SM}\right\}_{\forall c},\boldsymbol{\theta},\boldsymbol{\beta}\right\}$, I first solve equation (1.16) 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 (1.15)), I can then compute (1) the number of prescriptions written by each physician, (2) the share of each physician's

[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 $\left\{\bar{h}_c^{SM}\right\}_{\forall c}$ as free parameters that are simply matched to functions of the other parameters in estimation.

Table 1.6: 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 sec. mkt. 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
$m_{4,c} = \eta_c - \frac{1}{\lvert I_c \rvert} \sum_{j \in J_c} N_j^{\text{buy}}$	C	Misuse rate from sec. mkt. in czone c
$m_{5,b} = \frac{1}{\lvert J_b \rvert} \cdot \sum_{j \in J_b} Q_j - \frac{1}{\lvert J_b \rvert} \cdot \sum_{j \in J_b} \left(N_j^{\text{consume}} + N_j^{\text{sell}} \right)$	3	Avg. Rx per phys. in altruism group b
$m_{6,g} = \frac{1}{\lvert J_g \rvert} \cdot \sum_{j \in J_g} Q_j - \frac{1}{\lvert J_g \rvert} \cdot \sum_{j \in J_g} \left(N_j^{\text{consume}} + N_j^{\text{sell}} \right)$	3	Avg. Rx per phys. 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 1.5 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 1.A.3. I estimate the model on the ten largest commuting zones (listed in Table 1.2), resulting in 46 moments and 46 parameters.

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 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).

Identification While all of the moments listed in Table 1.6 are used to jointly identify the parameters listed in Table 1.5, 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.

1.5.2 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 1.1, 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 Oxy-Contin 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 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

[31] As noted in Section 1.3, 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.

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.

1.6 Results

1.6.1 Model estimates

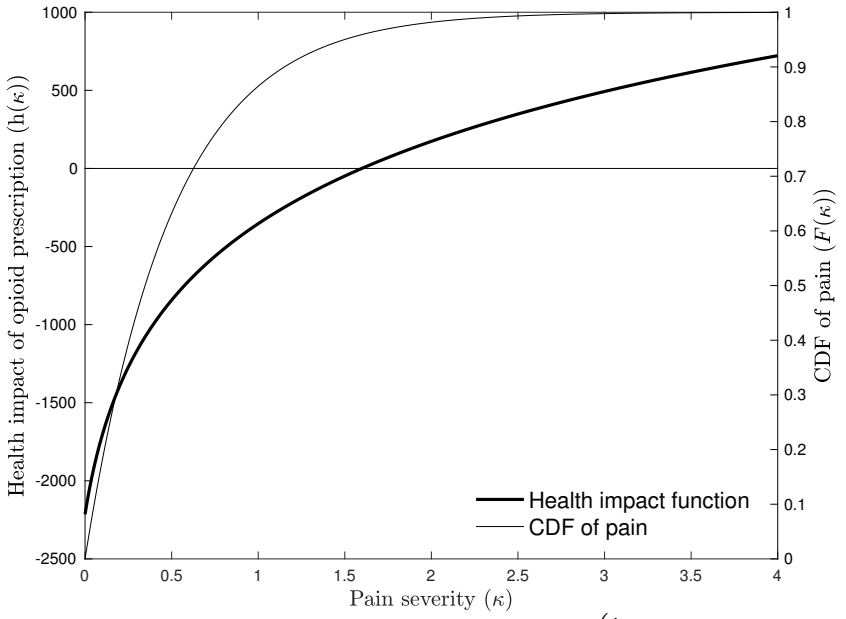
Estimation results are provided in Table 1.7. Looking first to the results for relative utility weights, we see that the ordering of altruism groups by the average weight physicians place on their health impact accords with the intuition previously introduced. In particular, low-altruism physicians place 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 1.7: 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 1.5. These estimates reflect the parameters in ten commuting zones: Los Angeles, Chicago, Houston, Philadelphia, Washington DC, Boston, Detroit, San Francisco, Atlanta, and Dallas.

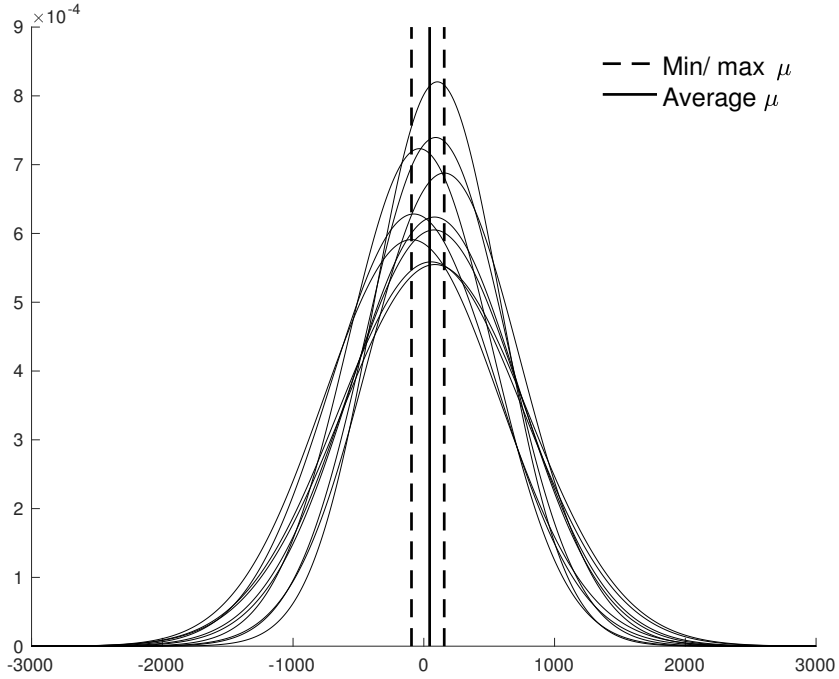
Figure 1.5: Estimated health impact function



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 1.5. 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 1.2)—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, Haegerich and Chou, 2016). In fact, the health impact function depicted in Figure 1.5 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 1.6: 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 1.2).

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 1.5 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 1.6, 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.

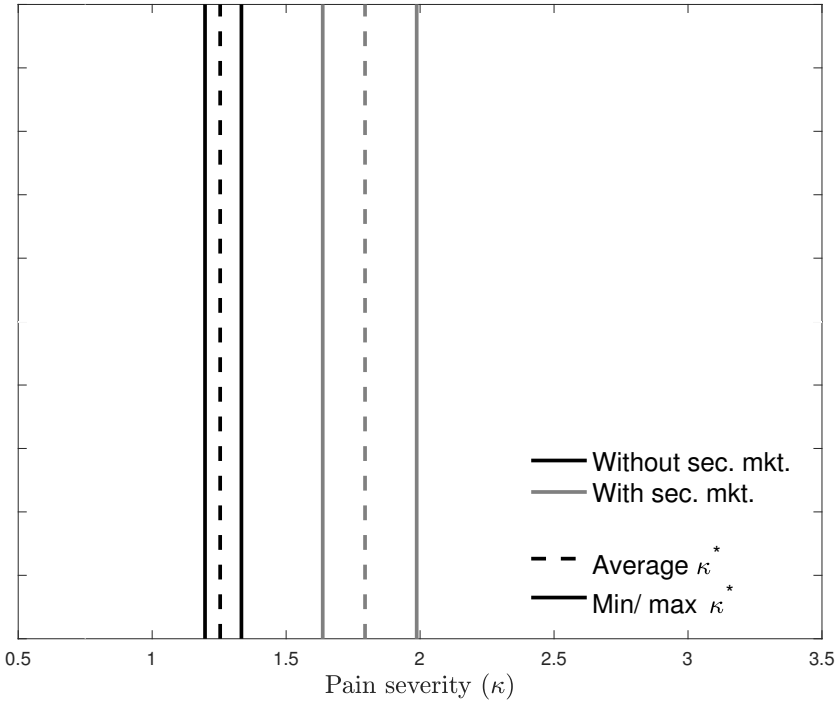
Turning to the estimates for search costs, we see that the cost of searching for a physician varies between \$90–\$180 across commuting zones. By benchmarking these estimates to resale prices on the secondary market, we see that estimated search costs vary between 12%–28% of secondary market prices. 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.

1.6.2 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 1.6.1 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 (1.9) (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, $\hat{\boldsymbol{\theta}}$, I then invert the health impact at each physician's threshold to obtain their optimal threshold. This distribution of thresholds gives us the empirical

Figure 1.7: 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 1.2).

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 (1.7)), 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 1.7 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 1.4 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.

1.6.3 Maximal health benefits

What are the maximal health benefits that can be gained from prescription opioid use across the US? Recall from Section 1.4 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 1.6.2, 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.

1.6.4 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.

1.7 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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Appendix

1.A Additional model details

1.A.1 Proofs

Consider a single geographic market c. Recalling the notation introduced in Section 1.4, 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

$$h\left(\kappa_j^*\right) = -\frac{R_j}{\beta_{b_j}} \tag{1.17}$$

- with a secondary market such that

$$\left(1 - G\left(p - h\left(\kappa_j^{SM*}\right)\right)\right) \cdot h\left(\kappa_j^{SM*}\right) + G\left(p - h\left(\kappa_j^{SM*}\right)\right) \cdot \bar{h}^{SM} = -\frac{R_j}{\beta_{b_j}} \tag{1.18}$$

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 (1.17) and (1.18), 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 1.4, 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:

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

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 (1.17) and (1.18)), 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

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

Therefore, we know that

$$\begin{aligned} h(\bar{\kappa}^*) - h(\underline{\kappa}^*) \; &= h\left(\bar{\kappa}^{SM*}\right) - h\left(\underline{\kappa}^{SM*}\right) \\ &\quad + G\left(p - h\left(\bar{\kappa}^{SM*}\right)\right) \cdot \left[\bar{h}^{SM} - h\left(\bar{\kappa}^{SM*}\right)\right] \\ &\quad + G\left(p - h\left(\underline{\kappa}^{SM*}\right)\right) \cdot \left[h\left(\underline{\kappa}^{SM*}\right) - \bar{h}^{SM}\right] \end{aligned}$$

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 $G\left(p - h\left(\kappa_j^{SM*}\right)\right) \in [0, 1]$, we have that $G\left(p - h\left(\bar{\kappa}^{SM*}\right)\right) \cdot \left[\bar{h}^{SM} - h\left(\bar{\kappa}^{SM*}\right)\right] \leq 0$ and $G\left(p - h\left(\bar{\kappa}^{SM*}\right)\right) \cdot \left[h\left(\underline{\kappa}^{SM*}\right) - \bar{h}^{SM}\right] \geq 0$.

Now, suppose that

$$G\left(p - h\left(\bar{\kappa}^{SM*}\right)\right) \cdot \left[\bar{h}^{SM} - h\left(\bar{\kappa}^{SM*}\right)\right] + G\left(p - h\left(\bar{\kappa}^{SM*}\right)\right) \cdot \left[h\left(\underline{\kappa}^{SM*}\right) - \bar{h}^{SM}\right] \leq 0$$

This implies that $h(\bar{\kappa}^*) - h(\underline{\kappa}^*) < h\left(\bar{\kappa}^{SM*}\right) - h\left(\underline{\kappa}^{SM*}\right)$. 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 $\bar{\kappa}^* - \underline{\kappa}^* < \bar{\kappa}^{SM*} - \underline{\kappa}^{SM*}$. ■

1.A.2 With a secondary market and patient search

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 $\kappa^*_{j,c} \geq \tilde{P}_c$,

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

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

$$
\begin{aligned}
\max_{\kappa_{j,c}} \; & \beta_{j,c} \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{p_c - h(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right] \\
& + \beta_{j,c} \cdot \sum_{n=j_{p,c}}^{j-1} \cdot \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa^*_{j,c}}^{\kappa^*_{n,c}} \int_{T_c(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right] \\
& + \beta_{j,c} \cdot \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa^*_{j,c}}^{\tilde{P}_c} \int_{T_c(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right] \\
& + \beta_{j,c} \cdot \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{|I_c|}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\tilde{P}_c}^{\kappa^*_{n,c}} \int_{p_c - h(k)}^{\infty} h(k) f_c(k) g_c(\gamma) d\gamma dk \right] \\
& + \beta_{j,c} \cdot \left(\bar{h}^{SM}_c \right) \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} \int_{-\infty}^{p_c - h(k)} f_c(k) g_c(\gamma) d\gamma dk \right] \\
& + \beta_{j,c} \cdot \left(\bar{h}^{SM}_c \right) \cdot \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{1}{(|J_c| - n + 1)(|J_c| - n)} \cdot \left(\int_{\tilde{P}_c}^{\kappa^*_{n,c}} \int_{-\infty}^{p_c - h(k)} f_c(k) g_c(\gamma) d\gamma dk \right) \right] \\
& + R_{j,c} \cdot \frac{|I_c|}{|J_c|} \cdot \left[\int_{\kappa_{j,c}}^{\infty} f_c(k) dk \right] \\
& + R_{j,c} \cdot \sum_{n=j_{p,c}}^{j-1} \cdot \left[\frac{1}{(|J_c| - n + 1)(|J_c| - n)} \cdot \int_{\kappa^*_{j,c}}^{\kappa^*_{n,c}} \int_{T_c(k)}^{\infty} f_c(k) g_c(\gamma) d\gamma dk \right] \\
& + R_{j,c} \cdot \sum_{n=1}^{j_{p,c}-1} \cdot \left[\frac{1}{(|J_c| - n + 1)(|J_c| - n)} \cdot \left(\int_{\kappa^*_{j,c}}^{\tilde{P}_c} \int_{T_c(k)}^{\infty} f(k) g_c(\gamma) d\gamma dk + \int_{\tilde{P}_c}^{\kappa^*_{n,c}} f_c(k) dk \right) \right]
\end{aligned}
$$

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

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

where

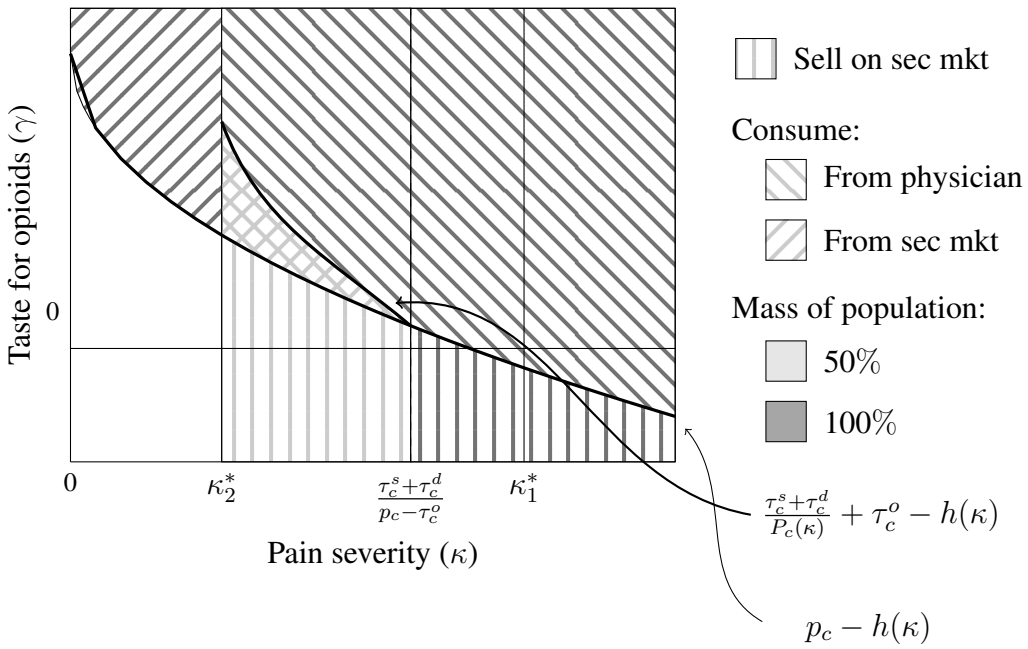
$$
W_{j,c} = \frac{[1 - G_c(p_c - h(\kappa^*_{j,c}))] \cdot \frac{|I_c|}{|J_c|} + [1 - G_c(T_c(\kappa^*_{j,c}))] \cdot \sum_{n=1}^{j-1} \cdot \left[\frac{1}{(|J_c| - n + 1)(|J_c| - n)} \right]}{\frac{|I_c|}{|J_c|} + [1 - G_c(T_c(\kappa^*_{j,c}))] \cdot \sum_{n=1}^{j-1} \left[\frac{1}{(|J_c| - n + 1)(|J_c|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

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

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 1.8. There are two key differences from the equilibrium allocation without patient search (Figure 1.3). 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 1.8: Equilibrium allocation: with secondary market and patient 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 will search in the presence of a secondary market to either resell or to consume. However, those with less severe pain will only search if they have a high enough combination of pain and tastes to justify consuming.

1.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 (1.16) 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: $P_c(\kappa) = \frac{1}{|J_c|}\sum_{j \in J_c} \mathbb{1}\left\{\kappa_j^* \leq \kappa\right\}$

   (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 (1.15)

5. Compute:

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

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

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

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

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

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

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

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

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 1.6

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

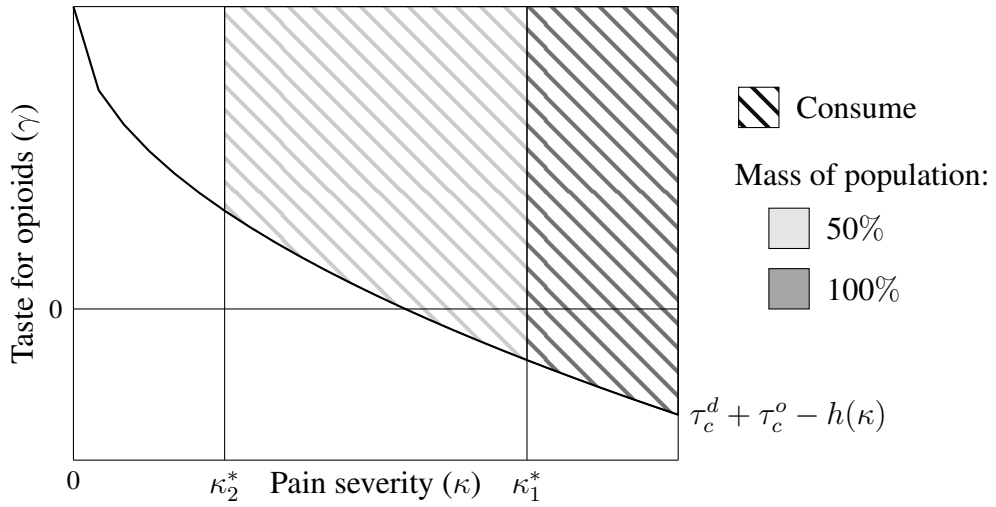
$$\left\{ \left\{ \tilde{\tau_c^s}, \mu_c, \sigma_c^2, \bar{h}_c^{SM} \right\}_{\forall c}, \boldsymbol{\theta}, \boldsymbol{\beta} \right\}^* = \min_{\left\{ \left\{ \tilde{\tau_c^s}, \mu_c, \sigma_c^2, \bar{h}_c^{SM} \right\}_{\forall c}, \boldsymbol{\theta}, \boldsymbol{\beta} \right\}} \sum_{\alpha=1}^{6} m'_\alpha \cdot m_\alpha$$

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

1.A.4 Supplementary diagrams

Equilibrium allocation without secondary market

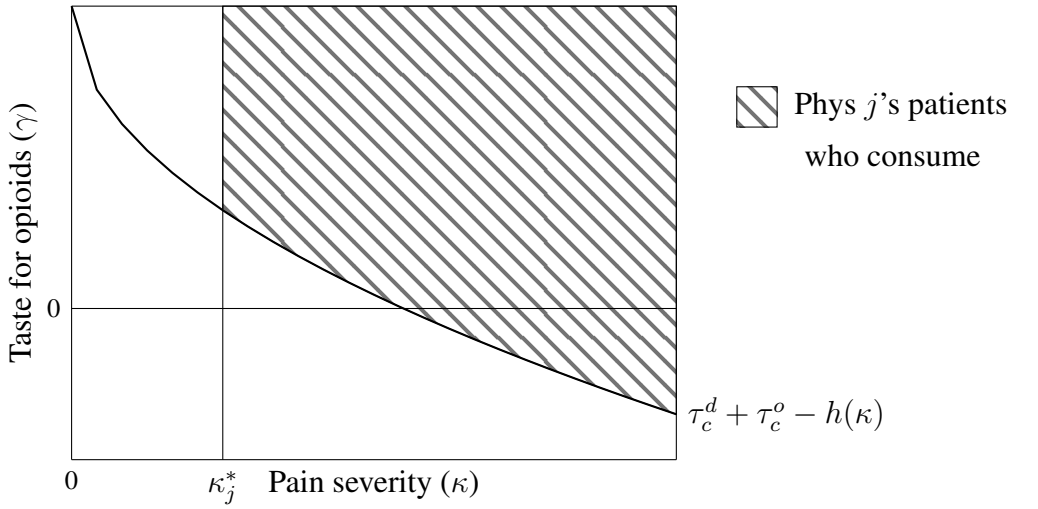
Figure 1.9: Equilibrium allocation: without secondary market or patient search



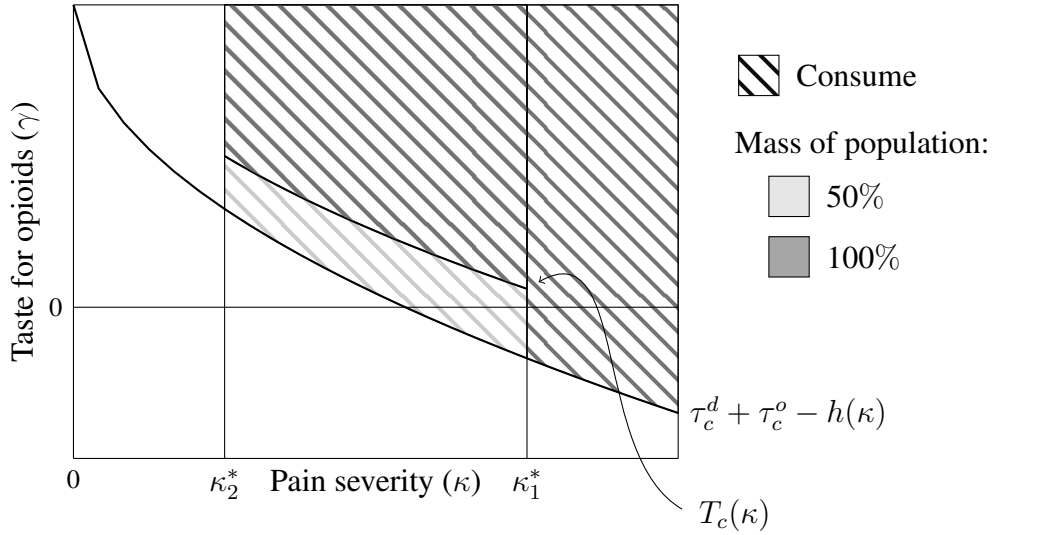
Notes: The above figure depicts the equilibrium allocation of prescriptions without a secondary market in the absence of patient search in a market with two physicians. In general, all patients for whom it is beneficial to consume and can get a prescription from any physician in their market $\left(\kappa_i \geq \max_{j \in J_{c_i}} \kappa_j^*\right)$ 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 1.10: Equilibrium allocation: without secondary market and with patient search

(a) Perspective of individual physician



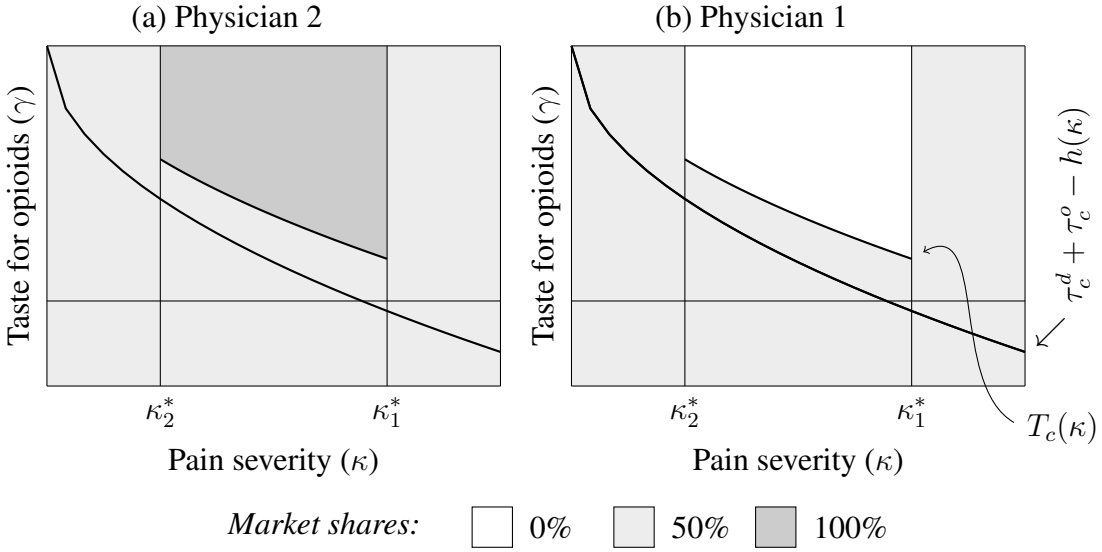
(b) Market perspective (market with two physicians)



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 $(\kappa_i < \kappa_1^*)$ but who find it beneficial to search $(\gamma_i \geq T_{c_i}(\kappa_i))$ will access prescription opioids on the primary market from physician 2 in equilibrium. See Figure 1.9 for the equilibrium allocation of prescriptions in the absence of patient search.

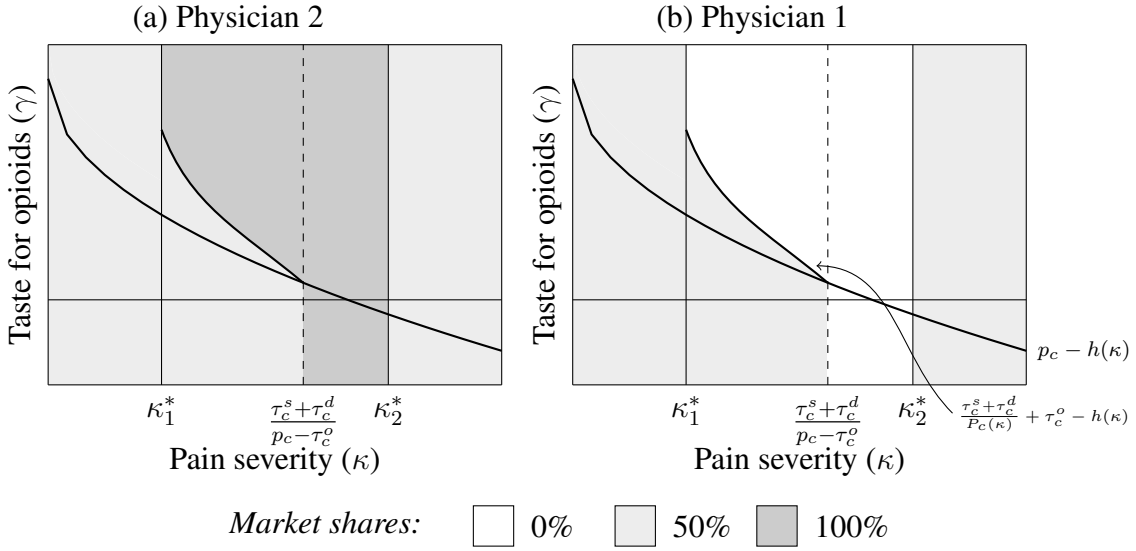
Market shares

Figure 1.11: Equilibrium market shares: without secondary market and with patient search



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 1.12: Equilibrium market shares: with secondary market and patient search



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.

1.B Data appendix

1.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.

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.

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); (2) state-level Medicaid fee-for-service (FFS) to Medicare payment ratios from the Kaiser Family Foundation; (3)

Table 1.8: 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.

Table 1.9: 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.

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 1.9.

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

$$R_{ls}^{Medicare} = \sum_{\Omega} R_{lc}^{Medicare} \cdot S_{sc} \qquad \text{with } \sum_{\Omega} S_{sc} = 1 \; \forall \; s \tag{1.19}$$

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 (1.19)) with state-specialty-specific Medicaid FFS to Medicare payment ratios from the Kaiser Family Foundation.[32] 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 $R_{ls}^{MFFS} = R_{ls}^{Medicare} \cdot \frac{R_{ls}^{MFSS}}{R_{ls}^{Medicare}}$.

[32]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.

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)).[33] 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.[34,35]

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

$$R_{ls}^{Medicaid} = F_l^{FFS} \cdot R_{ls}^{FFS} + \left(1 - F_l^{FFS}\right) \cdot R_{ls}^{MMC} \tag{1.20}$$

[33]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.

[34]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.

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

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,[36] 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.

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 1.B.1, where the weights for each given provider are given by the physician-level insurance compositions introduced in Section 1.B.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 specialty s in state l is given by

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

[36] 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.

1.B.2 Pain and taste distributions

Pain severities

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

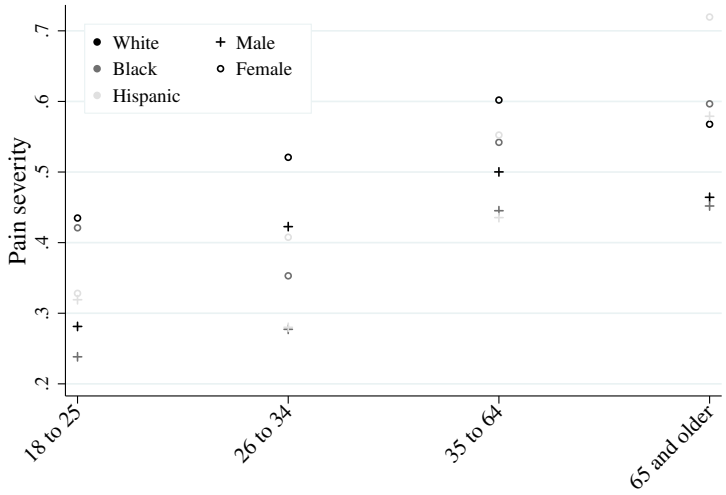
> "During the past three months, did you have neck pain? Lower back pain? Facial ache or pain in the jaw muscles or the joint in front of the ear?"

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 1.2, 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 1.13 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 1.14, these differences across

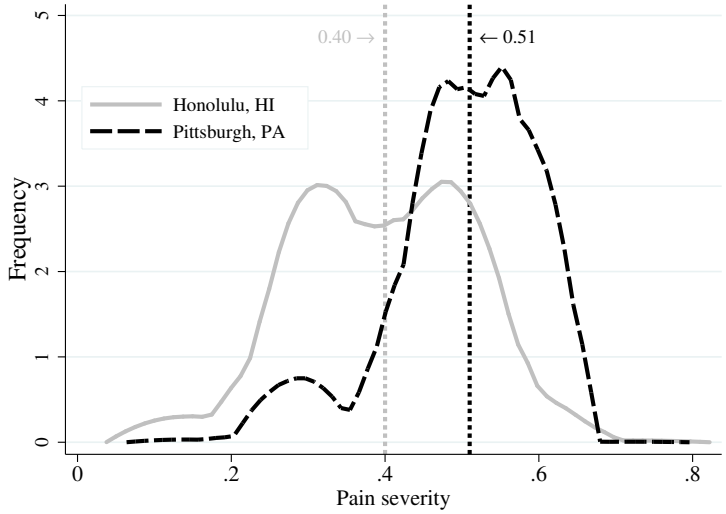
Figure 1.13: Average pain severity across age-gender-race cells



Notes: The above figure presents average pain severities within age-gender-race cells from the 2014 NHIS.

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 1.14: 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.

Prescription opioid misuse rates

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

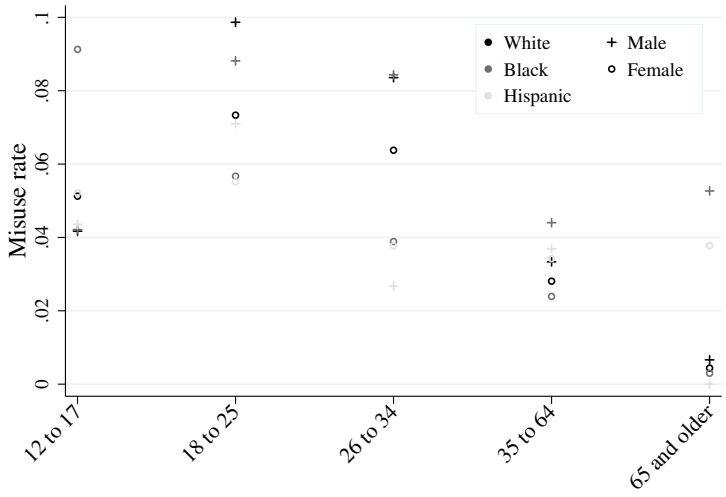
> 1. "How long has it been since you last used any prescription pain reliever that was not prescribed for you or that you took only for the experience or feeling it caused?"
>
> 2. "Now think about the last time you used a prescription pain reliever that was not prescribed for you or that you took only 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.[37] Differences across demographic groups are robust to the use of different time frames over which misuse is defined.

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 1.15, 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 1.16).

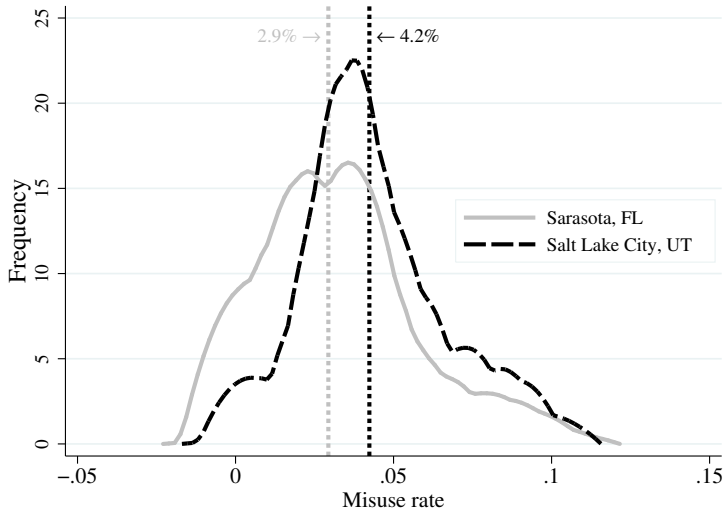
[37]The response options for Question (2) are listed in Table 1.10.

Figure 1.15: 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 1.16: 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.

1.C Supplementary tables and figures

Table 1.10: 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 1.11: Opioid prescriptions across specialties

			Monthly opioid prescriptions per physician					
	% of opioids	N providers	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

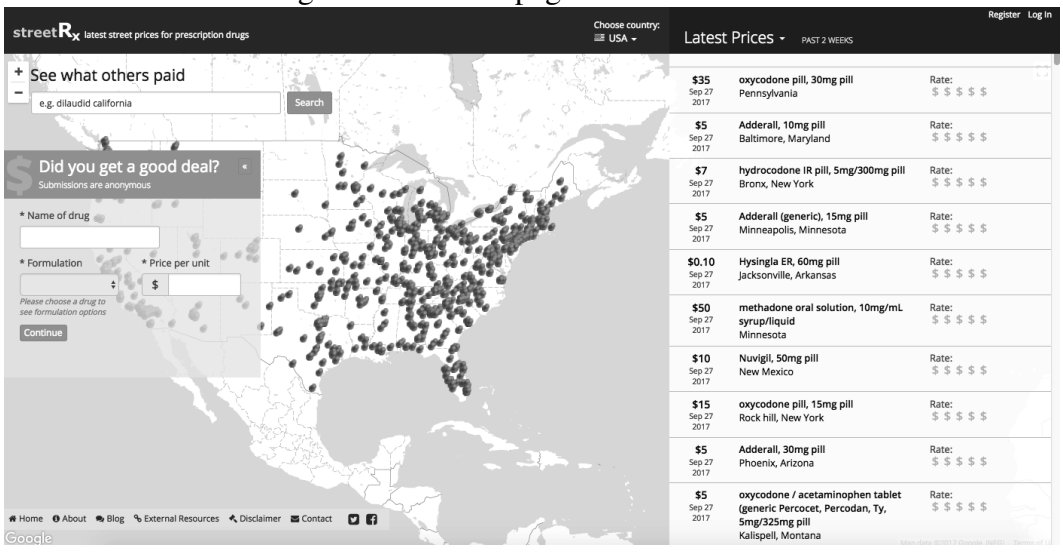
Notes: The above table provides summary statistics for opioid prescriptions by physician specialty in 2014.

Table 1.12: 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

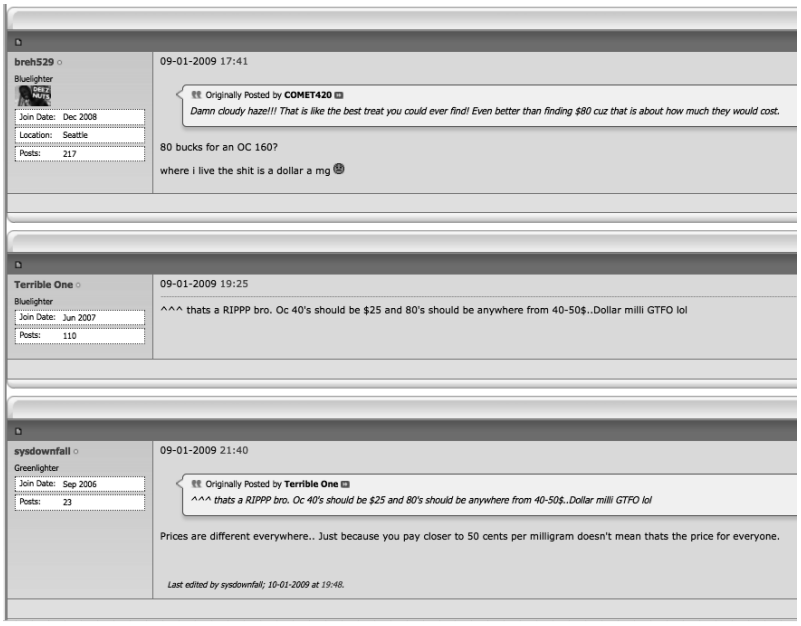
Notes: The above table provides summary statistics for office visit reimbursement rates by physician specialty in 2014.

Figure 1.17: Homepage of StreetRx.com



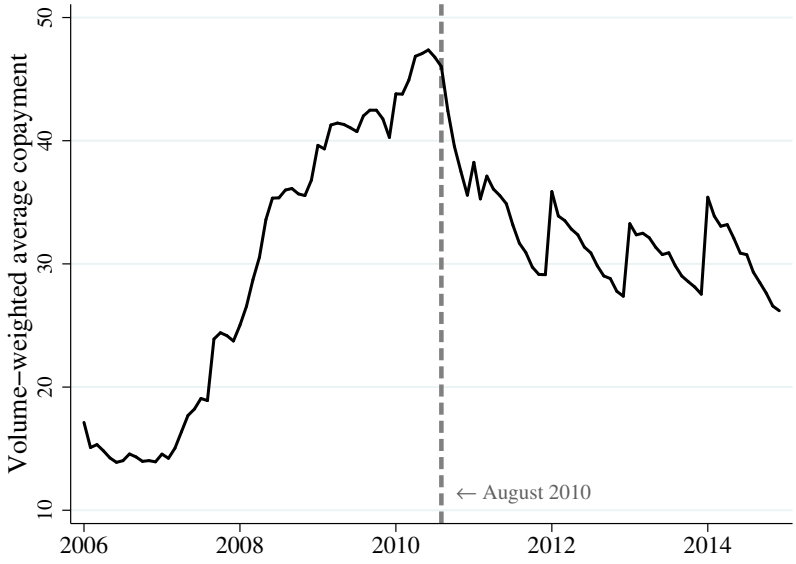
Notes: The above picture is a screenshot of the homepage of StreetRx.com. Visitors to the site can enter a prescription and location to get an overview of location-drug-specific prices ("See what others paid") or enter the price they paid per unit for a given formulation ("Did you get a good deal?").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

Figure 1.18: Discussion of price dispersion on Bluelight.com



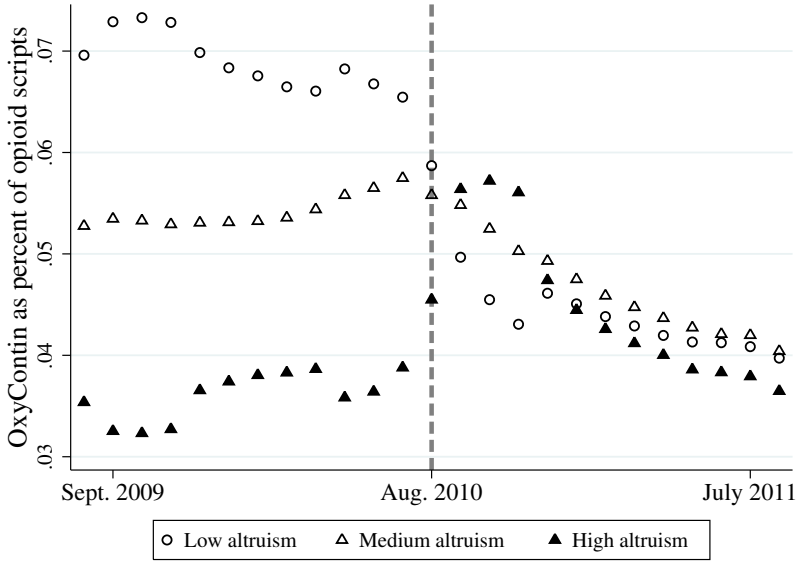
Notes: The above picture is a screenshot from Bluelight.com—a forum on which users discuss various topics related to drug use. The above conversation highlights that there is significant price dispersion across locations and that users are aware of these differences.

Figure 1.19: Average copayment for OxyContin over time



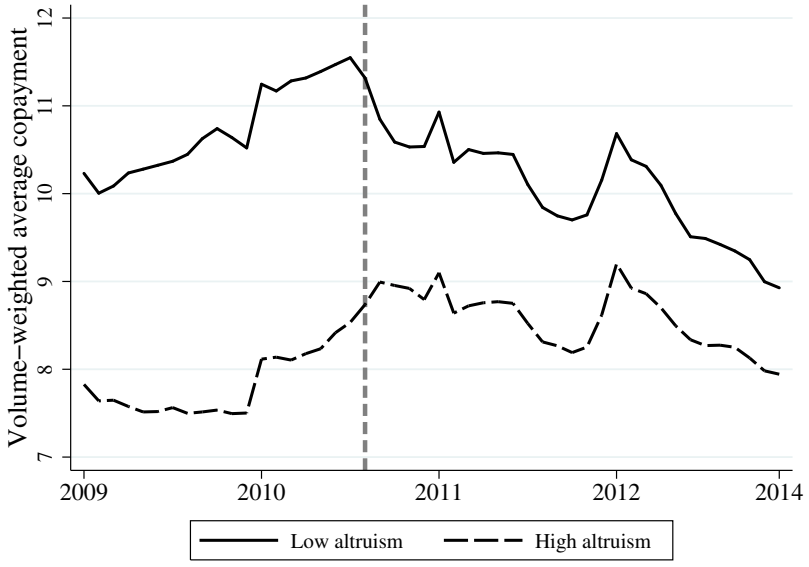
Notes: The above figure presents volume-weighted average copayments for OxyContin prescriptions filled in all retail pharmacies across the US in each month as reported by QuintilesIMS. The vertical line denotes the month in which the original formulation of OxyContin stopped shipping and the reformulated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

Figure 1.20: 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.

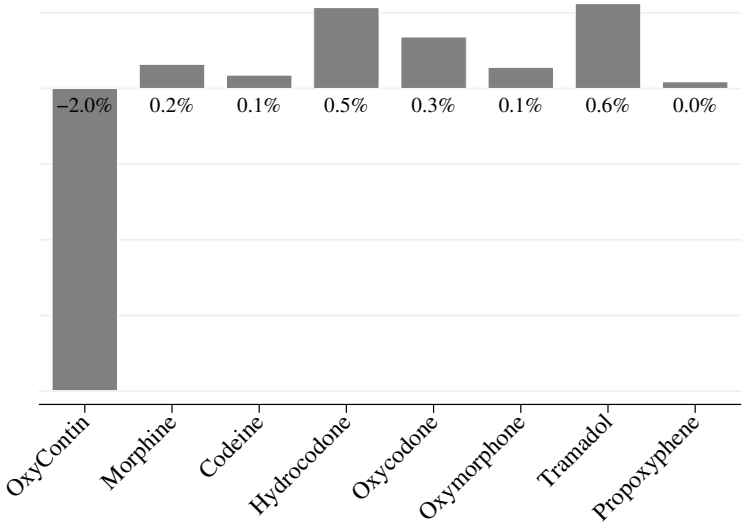
Figure 1.21: Average copayment for opioid products by physician altruism over time



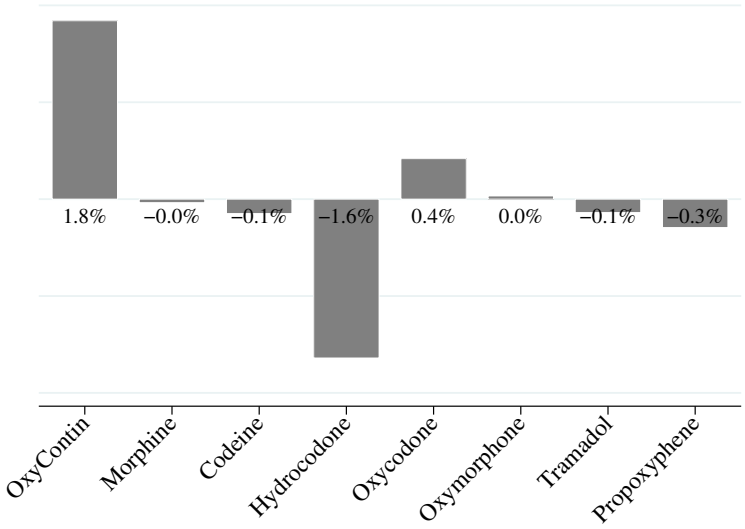
Notes: The above figure presents volume-weighted average copayments for all opioid prescriptions filled at retail pharmacies by patients seeing either a low-altruism (solid line) or high-altruism (dashed line) physician. The vertical line denotes the month in which the original formulation of OxyContin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

Figure 1.22: 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.

Chapter 2

Addressing the Opioid Epidemic: Is There a Role for Physician Education?*

2.1 Introduction

Between 2000 and 2014, drug overdoses involving opioids rose 200%, fueling widespread concern about an opioid epidemic and spurring calls for changes in public policy (Chen et al., 2014; Dart et al., 2015; Rudd et al., 2016). A distinguishing feature of the current epidemic of drug abuse is that many overdoses and deaths can be attributed to legal opioids that were prescribed by a physician. The clinical use of opioids in the United States has quadrupled since 1999, contributing to the rise in drug overdoses, emergency room visits, and admissions for drug treatment. Despite significant efforts to restrict the prescribing of opioids over the past decade, prescription opioid abuse and drug overdoses due to prescription opioids have continued to rise (Health and Human Services, 2014; Meara et al., 2016).

Recent evidence suggests that doctors play a key role in the opioid epidemic. While prescription drug monitoring programs (PDMPs)—prescription databases that allow physi-

*This chapter is joint work with Janet Currie and has been accepted for publication in the *American Journal of Health Economics*. Materials from this chapter were presented at the 2016 Population Health Sciences Research Workshop. We thank Michael Barnett, Amitabh Chandra, Angus Deaton, Jonathan Skinner, Atheendar Venkataramani, and seminar participants at Johns Hopkins Center for Innovative Medicine. Generous financial support from the Center for Health and Wellbeing at Princeton University is gratefully acknowledged. The statements, findings, conclusions, views, and opinions contained and expressed herein are not necessarily those of QuintilesIMS or any of its affiliated or subsidiary entities.

cians to check for signs of opioid abuse before prescribing—have little effect on average (Paulozzi et al., 2011; Reifler et al., 2012; Haegerich et al., 2014; Meara et al., 2016), research shows that they are more effective when states require physicians to consult them (Dowell, Zhang, Noonan and Hockenberry, 2016; Buchmueller and Carey, 2017; Dave et al., 2017). Furthermore, among patients treated in the same emergency room, Barnett et al. (2017) demonstrate that those who happen to be treated by a physician with a higher propensity to prescribe opioids are more likely to be dependent on opioids 12 months later. Despite being the gatekeepers of the legal opioid supply, very little is known about why some physicians are more likely to prescribe opioids than others[1] or about what role physician training can play in bringing the epidemic under control.

In this paper, we use comprehensive data on all opioid prescriptions written by doctors in the US between 2006 and 2014 to examine the relationship between opioid prescribing and training. In particular, we ask how the number of opioid prescriptions written yearly by individual physicians varies with a key feature of the school where they received their initial medical training: the rank of the medical school.[2] As general practitioners (GPs) account for 48% of opioid prescriptions written by physicians in our sample, we examine the relationship between medical school rank and opioid prescriptions both across all physicians and separately for GPs.[3]

We find that where a doctor received his/her initial training matters in terms of predicting how likely they are to prescribe opioids: physicians trained at the lowest ranked US medical schools prescribe nearly three times as many opioids per year as physicians trained at the top medical school. This striking inverse relationship reflects two factors: (1) physicians from lower ranked medical schools are more likely to write any opioid pre-

[1]Recent evidence documents differences in opioid prescribing by medical specialty (Volkow et al., 2011; Ringwalt et al., 2014; Levy et al., 2015).

[2]Our data does not include information on the number of patients seen by each physician. Using data for Medicare Part D, we demonstrate that our results are robust to using opioid prescription rates (total prescriptions/ number of unique patients) in the Medicare population.

[3]We define GPs as physicians in general practice, family practice, and internal medicine. Results are quite similar if we exclude internal medicine.

scriptions; and (2) conditional on being an opioid prescriber, physicians for lower ranked medical schools write more opioid prescriptions on average. This prescribing gradient is particularly pronounced among GPs. Our results demonstrate that if all GPs prescribed like those from the top ranked school, we would have had 56.5% fewer opioid prescriptions and 8.5% fewer deaths over the period 2006 to 2014.

Differences in the propensity to prescribe opioids across medical schools need not reflect a causal effect of training. If physicians from lower ranked medical schools systematically see patients with a greater need for opioids, then at least part of the relationship between medical school rank and prescribing will reflect patient sorting across physicians. Furthermore, if people who have a higher probability of getting into selective medical schools are systematically less likely to write opioid prescriptions ex ante, then the prescribing gradient will also reflect selection into medical schools. While we cannot definitively quantify the role of training, we provide three additional sets of analyses that suggest that selection alone cannot account for the differences in prescribing habits that we observe across medical school ranks.

First, we demonstrate that the relationship between opioid prescriptions and medical school rank persists conditional on physician specialty and county of practice.[4] It is therefore unlikely that differences in patient need across physicians can account for the entirety of the prescribing gradient. Second, we demonstrate that the prescribing gradient is flatter among physicians in specialties that receive specific training in the use of opioids after medical school. If physicians who go on to prescribe fewer opioids select into higher ranked medical schools (or if patients with a high need for opioids sort towards physicians from lower ranked schools), then the prescribing gradient should not be dependent on subsequent training in pain management. Finally, we demonstrate that the prescribing gradient is flatter in more recent cohorts. Since selectivity at top medical schools has been increasing over

[4]Taking this analysis a step further, we also demonstrate that a prescribing gradient exists among specialists who practice in the exact same hospital or clinic.

time, a story of selection would instead imply that the relationship should be stronger in more recent cohorts.

This paper contributes to a growing empirical literature on policies to address the opioid epidemic. In addition to the introduction of PDMPs,[5] researchers have examined the impact of the introduction of abuse-deterrent opioids (Cicero and Ellis, 2012; Alpert et al., 2016; Evans et al., 2018), the strengthening of pain clinic laws (Kennedy-Hendricks et al., 2016; Meinhofer, 2016), and improvements in access to opioid antagonists such as naloxone (Mueller et al., 2015; Rees et al., 2017) on opioid abuse and related health outcomes. To the best of our knowledge, this is the first study to examine whether additional physician training is likely to have a significant role to play in addressing the opioid epidemic.

This paper further contributes to a large literature in health economics on the determinants of physician practice style. While a physician's network is known to influence how they practice (Coleman et al., 1957; Soumerai et al., 1998; Epstein and Nicholson, 2009; Lucas et al., 2010), the rank of a physician's initial medical school is one aspect of a physician's network that has received surprisingly little attention. A notable exception is Doyle et al. (2010), who demonstrate that patients randomly assigned to a doctor who attended a higher ranked medical school have less expensive stays but no difference in health outcomes compared to patients who instead see physicians from a lower ranked program.[6]

Finally, we contribute to a literature on the impacts of selectivity in higher education on subsequent outcomes. While the literature on the effects of university rank highlights that at least some of the "effect" of going to a higher ranked school is the result of selection into schools rather than a consequence of any difference in the education received, the evidence suggests that there are economic returns to attending more selective institutions

[5] See Haegerich et al. (2014) for a review of earlier studies and Meara et al. (2016), Dowell, Zhang, Noonan and Hockenberry (2016), Patrick et al. (2016), Bao et al. (2016), Buchmueller and Carey (2017), and Dave et al. (2017) for more recent work.

[6] Although not focused on practice style, Hartz et al. (1999) find that surgeons who trained at prestigious residency or fellowship programs are more likely to be regarded as a "best doctor" by other physicians in the same market.

(Brewer et al., 1999; Dale and Krueger, 2002; Hoekstra, 2009; Hoxby, 2016). Our work demonstrates that the value-added of attending a selective medical school may include broader public health benefits resulting from differences in clinical practice as a result of the training received.

The paper proceeds as follows. Section 2.2 introduces the data. Section 2.3 asks how the number of annual opioid prescriptions written by individual physicians varies with the rank of the medical school where they were initially training. Section 2.4 introduces three sets of empirical exercises that can be used to probe whether a causal effect of training contributes to the prescribing gradient that we observe. Section 2.5 provides the results from these ancillary analyses. Section 2.6 discusses limitations of our study and provides a variety of robustness checks to help mitigate these concerns. Section 2.7 provides a discussion and conclusions.

2.2 Data

To examine the relationship between opioid prescribing and training, we combine prescription data from QuintilesIMS with medical school rankings from US News and World Report and a new dataset documenting the countries of over 900 foreign medical schools. This data is supplemented with locations of teaching hospitals from the American Hospital Association's (AHA) annual surveys, physician-level opioid prescription rates from the Centers for Medicare and Medicaid Services' (CMS) 2014 provider utilization and payment data, county-level characteristics from the five-year pooled 2008-2012 American Community Survey (ACS), and county-level mortality from the US Mortality Files.

Our primary prescription data was purchased from QuintilesIMS, a public company specializing in pharmaceutical market intelligence. This dataset contains the number of prescriptions filled for opioid analgesics at US retail pharmacies in each year from 2006 to 2014 at the prescriber level. In addition to the number of prescriptions, the QuintilesIMS

data contain information on each prescriber provided by the American Medical Association (AMA). In particular, we know each prescriber's specialty, current practice address as of 2014, the medical school where they obtained their first medical degree, and the year in which they graduated from medical school. We use ArcGIS to extract each provider's county of practice from their practice address. To create the sample of physicians used in the paper, we keep active physicians who graduated from medical school before 2006 and are not missing any information necessary for our analysis.[7]

We therefore have nine observations for every physician in our sample—one for each year between 2006 and 2014. Altogether, 2.16 billion opioid prescriptions were written between 2006 and 2014; 72.9% of these were written by the 742,297 physicians in our cleaned sample.[8] Although GPs (here defined as physicians in general practice, family practice, and internal medicine) make up only 27.4% of our sample, they wrote 48.2% of all opioids prescribed by physicians between 2006 and 2014 (35.1% of all opioid prescriptions). See Table 2.6 for an overview of these summary statistics.

There was a continuous increase in the number of opioid prescriptions from 2.04 million in 2006 to 2.6 million in 2012 and then a slight moderation. Nevertheless, in 2014 the average physician still wrote 221.7 opioid prescriptions. This figure includes zeros—in 2014, 28.3% of physicians did not write any opioid prescriptions. Among physicians in general practice, these statistics are even more striking: only 16.2% of GPs wrote no opioid prescriptions in 2014 with opioid-prescribing GPs writing 480.3 prescriptions on average.

[7] In particular, we keep prescribers whose status is listed as "active" in 2014 (94.20% of prescribers) and who list a specialty that requires either the degree of medical doctor (MD) or doctor of osteopathic medicine (DO). We exclude physicians whose medical school is not provided or whose medical school name is ambiguous (2.29% of active physicians have missing medical school; 0.12% of active physicians list "University of Medicine" or "College of Medical Sciences" as their medical school). We also exclude prescribers who list a P.O. Box, a home address, or an address of unknown type (0.49% of remaining physicians) in place of an office address as well as physicians whose offices are in US territories (0.06% of remaining physicians). Finally, to avoid including physicians who are still doing a residency or other training, we exclude physicians who graduated medical school in 2006 or later (15.93% of remaining physicians). Note that we purchased data from QuintilesIMS for both anti-depressant and opioid prescriptions. Of physicians who appear in the AMA data set, only 0.45% do not appear in our Quintiles IMS prescription data.

[8] 19.1% of the remaining prescriptions were written by non-physician providers including dentists, nurse practitioners, and physician assistants. We exclude non-physician providers from our analysis since our data includes no information on where they were trained.

In order to rank medical schools, we use US News and World Report's "Best Medical Schools: Research Rankings." Although medical school rankings change from year to year, we construct a composite medical school rank to use in our analyses.[9] In particular, we take the average of a school's non-missing rankings from 2010 to 2017 and then re-rank schools according to this average rank (assigning a rank of "1" to the school with the lowest average rank, "2" to the school with the next lowest average rank, and so on).[10] Refer to Table 2.5 for a list of these composite rankings.

There are 92 ranked medical schools and 55 unranked US medical schools in these data. We divide unranked schools by whether they grant the degree of medical doctor (MD) or doctor of osteopathic medicine (DO) (35 and 20 medical schools, respectively).

We group foreign medical schools based on the UN's "Classification of Countries by Major Area and Region of the World." While the QuintilesIMS data does not provide information on the location of each medical school, we googled all medical schools with 10 or more opioid prescribers in the main sample and recorded the country of the school's primary campus (902 medical schools). Foreign medical schools with fewer than 10 opioid prescribers in the main sample are labeled as "Uncategorized" (695 medical schools). Refer to Figure 2.5 for the distribution of medical schools and physicians in our data across world regions.

While the QuintilesIMS data contain information representative of all opioid prescriptions filled at US retail pharmacies, it is not without limitations. As of 2014, they directly surveyed 86% of retail pharmacies, with the remaining prescriptions imputed to add to industry totals using a patented projection method. The fraction of pharmacies directly surveyed has increased slightly since 2006. Since hospital pharmacies are not included in the data, prescriptions of specialists who practice primarily in hospitals (such as surgeons)

[9] Figure 2.6 shows how our composite ranking compares to annual rankings from 2010 to 2017. There is a high correlation between the rankings of medical schools over time, with pairwise correlation coefficients all greater than 0.96 across annual rankings from 2010 to 2017.

[10] We exclude schools that are ranked in only one or two years over the sample (eight medical schools). Of the remaining medical schools, each school is ranked in 7.4 years on average.

may be under-represented. This is one motivation for looking at the relationship between prescribing and rank by specialty as discussed further below. Also, the QuintilesIMS Xponent data we purchased contains no information on the number of patients seen by each physician or about the strength or number of pills included in each prescription. We use three additional datasets to verify that these data shortcomings are unlikely to drive our results.

First, using the AHA's annual surveys from 2007 to 2013, we demonstrate that our results are robust to excluding physicians who practice in a zip code containing a university-affiliated hospital. We consider a zip code as containing a university-affiliated hospital if it contained a hospital that reported a university affiliation to the AMA in any year between 2007 and 2013. According to this measure, 9.4% of zip codes with any physicians in our data include a university-affiliated hospital.

Second, using publicly available data from CMS's Medicare Part D provider utilization and payment data files, we demonstrate that our results are consistent to using opioid prescription rates as opposed to prescription levels in the Medicare population. While this data does not include information on each physician's medical school, we merge the Medicare Part D data with CMS's publicly available Physician Compare database to extract this information.[11]

Finally, using county-level deaths from the US Vital Statistics Mortality Files, we demonstrate that the number of opioid prescriptions correlate with deaths involving drugs. To measure "deaths involving drugs," we include all deaths where either the underlying cause of death or a condition contributing to death indicates accidental poisoning by and exposure to drugs (ICD-10 codes X40-X44); intentional self-poisoning by exposure to drugs (ICD-10 codes X60-X64); poisoning by and exposure to drugs (ICD-10 codes Y10-Y14); and poisoning by, adverse effects of, or under dosing of drugs excluding anesthetics

[11]This merge is not perfect. According to CMS, clinicians are only listed on Physician Compare if they are in "approved" status in the Medicare enrollment system (PECOS), have a specialty and at least one practice address listed, and have submitted at least one Medicare fee-for-service claim within the past 12 months.

(ICD-10 codes T40, T42, T43). We further include deaths where drug dependence, excluding alcohol or tobacco, is indicated on the death certificate (ICD-10 codes F11-F16, F18, F19).[12] Summary statistics for the annual, county-level mortality measures that we use are provided in Table 2.7. There was a clear upward trend in deaths due to drugs between 2006 and 2014 from 12.9 to 17.4 per 100,000—a trend that has received a great deal of recent attention (Case and Deaton, 2015).

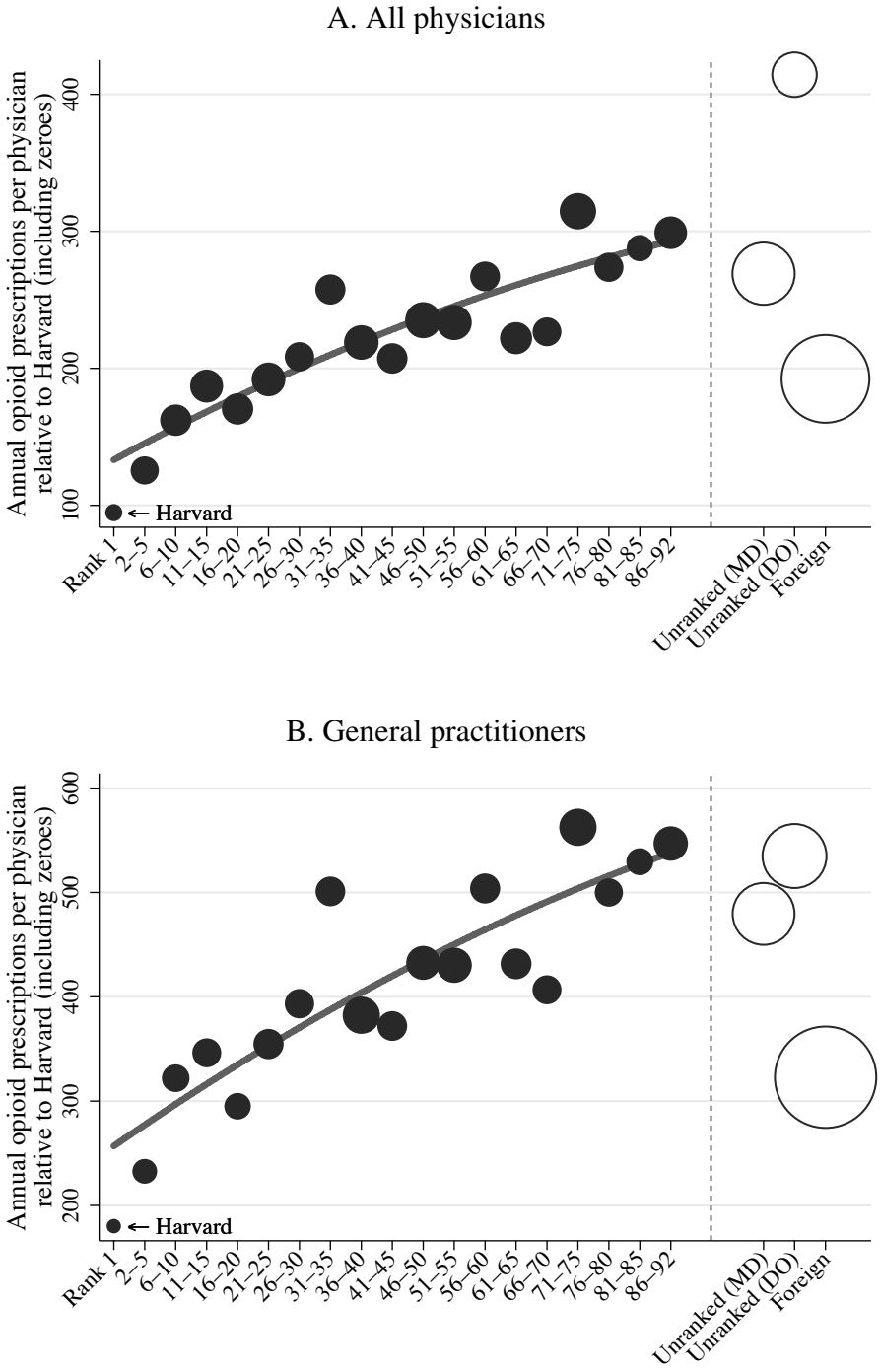
2.3 Opioid prescriptions and medical school rankings

We are interested in whether the propensity to prescribe opioids is associated with the rank of the medical school where a physician attained his/her initial medical education. We consider three outcomes: (1) the number of opioid prescriptions written annually by each physician including physician-years with no opioid prescriptions, (2) the number of opioid prescriptions excluding physician-years with no opioid prescriptions, and (3) an indicator denoting physician-years with at least one opioid prescription. As GPs account for nearly half of the opioid prescriptions written in the sample (Table 2.6), we look at all physicians as well as GPs separately. For ease of presentation, we present graphs summarizing the empirical findings as well as tables with regression output.

Figure 2.1 shows the average number of opioid prescriptions written yearly per physician by medical school rank, both among all physicians (Subfigure A) and among GPs (Subfigure B). We see that a higher medical school rank is associated with fewer opioid prescriptions: on average, physicians from the lowest ranked US medical schools write three times as many opioid prescriptions as physicians trained at Harvard Medical School, the top ranked school. While GPs trained at Harvard write an average of 180.2 opioid prescriptions per year, GPs from the lowest ranked US medical schools write an average of nearly 550 opioid prescriptions per year (Table 2.9).

[12] Our results are robust to only including deaths where a drug overdose is listed as the cause of death.

Figure 2.1: Opioid prescriptions by medical school rank



Notes: The above figures depict the average number of opioid prescriptions written yearly per physician by medical school rank. Subfigure A includes all physicians; Subfigure B only includes GPs (physicians in general practice, family practice, and internal medicine). Physician-years with zero opioid prescriptions are included. The size of the marker indicates the number of physician-year observations in a given bin. Refer to Tables 2.8 and 2.9 for the underlying averages for all physicians and GPs, respectively.

This striking inverse relationship between the number of annual opioid prescriptions and medical school rank reflects two factors: (1) physicians from higher ranked medical schools are less likely to write any opioid prescriptions; and (2) conditional on writing any opioid prescription, physicians from higher ranked medical schools write fewer opioid prescriptions on average. Only 65% of physicians trained at Harvard Medical School wrote at least one opioid prescription in a given year between 2006 and 2014 compared to nearly 80% of physicians from the lowest ranked medical schools (see Figure 2.7 and Table 2.8 for all physicians and Figure 2.8 and Table 2.9 for the analogous information for GPs). Conditional on prescribing opioids, the behavior of physicians likewise varies with medical school rank: on average, opioid prescribers from the lowest ranked medical schools write over 160% more opioid prescriptions per year than opioid prescribers from Harvard (146.4 versus 381.6; see Table 2.8).

Turning to the results for physicians trained at unranked medical schools, we see from Figure 2.1 that foreign doctors have similar prescribing habits as physicians trained at mid-tier US schools, while MDs from unranked US schools are closer to the average for physicians from the lowest ranked schools. This is true both among all physicians (Subfigure A) and among GPs (Subfigure B). Comparing the prescribing habits of DOs to MDs, we see that DOs in general practice prescribe similarly to GPs trained at the lowest ranked US schools. However, at an average of over 400 opioid prescriptions annually per physician, DOs across all specialties write more opioid prescriptions per prescriber than MDs trained either domestically or abroad.

2.4 Empirical strategy

The striking inverse relationship between opioid prescribing and medical school rank documented in Section 2.3 begs the question of why such a relationship exists. It is possible that medical schools have differing approaches to the tradeoff between pain management and

addiction and instill different beliefs among their graduates about the appropriate clinical use of opioids. However, a prescribing gradient across medical school rankings need not reflect a causal effect of training. There are two key threats to attributing the raw prescribing gradient to differences in training:

1. If physicians from lower ranked medical schools are systematically more likely to see patients with a greater need for opioids, then at least part of the relationship between medical school rank and prescribing will reflect **patient sorting across physicians**.[13]

2. If physicians who have a higher probability of getting into a higher ranked medical school have a lower propensity to prescribe opioids ex ante, then at least part of the relationship between medical school and prescribing will reflect **physician sorting across medical schools**.

While we do not have the data necessary to test whether physicians select into medical schools based on their outlooks towards opioids (or, more realistically, whether physicians select into medical schools based on characteristics that are correlated with their outlooks towards opioids), we can examine whether physicians from lower ranked medical schools are more likely to encounter patients with a greater medical need for opioids. In particular, we can examine whether physicians from lower ranked medical schools are systematically more likely to practice in specialties and/or locations where patient need for opioids may be higher.

As shown in Table 2.1, there are differences in both the specialties and practice locations chosen across medical school rankings. The eight specialties shown in the table are the top eight opioid-prescribing specialties (Table 2.10) and together account for 84% of opioid

[13]Note that only a particular type of patient sorting threatens a causal interpretation of the relationship between opioid prescribing and medical school rank. If patients sort towards physicians from lower ranked medical schools based on *medical need*, then the relationship between opioid prescribing and medical school rank cannot be attributed (at least entirely) to a causal effect of training. If, however, patients sort towards physicians from lower ranked medical schools based on a *desire to misuse or abuse opioids* (for example because physicians from low-ranked schools are known to be more lenient prescribers), then this endogenous sorting is a consequence of the differences in prescribing practices that we want to capture.

prescriptions in our sample. The table makes clear that while as a group, GPs prescribe the most opioids, this is because they are the most numerous practitioners. Not surprisingly, other specialties, such as those in pain medicine, prescribe much more on a per capita basis.

Table 2.1: Opioid prescriptions and practice characteristics by medical school rank

		U.S. Ranked			U.S. Unranked		
	Full sample	Top 30	31-60	61-92	M.D.	D.O.	Foreign
N physicians	742,297	134,119	142,822	127,007	96,644	49,376	192,329
N physician-years (9 years/ physician)	6,680,673	1,207,071	1,285,398	1,143,063	869,796	444,384	1,730,961
Opioid prescriptions							
Total (100 million)	15.7	2.1	3.0	3.1	2.3	1.8	3.3
Average per physician-year	235.7	172.4	235.3	273.7	269.0	414.3	192.3
including zeroes	(1.4)	(2.4)	(2.9)	(3.6)	(4.1)	(7.2)	(2.7)
Average per physician-year	319.0	240.3	309.5	356.2	348.6	501.7	283.1
excluding zeroes	(1.8)	(3.2)	(3.7)	(4.5)	(5.2)	(8.4)	(3.8)
Zeroes (% physician-years)	26.1	28.3	24.0	23.2	22.8	17.4	32.1
Specialties (% physicians)							
General practice	27.4	19.2	24.5	25.0	24.2	50.7	32.6
Orthopaedic surgery	3.3	4.7	4.2	3.9	3.7	2.8	1.1
Emergency medicine	4.5	4.3	5.7	5.5	5.7	8.2	1.5
Pain medicine	0.5	0.3	0.5	0.5	0.5	0.6	0.7
Physical medicine & rehabilitation	1.1	0.7	1.0	1.1	1.3	1.8	1.2
Obstetrics & gynecology	5.4	5.2	5.9	6.5	7.1	4.5	3.6
Anesthesiology	4.4	3.9	4.7	4.8	4.4	3.9	4.3
General surgery	4.0	4.3	4.3	4.6	4.4	2.7	3.5
County of practice (avg across phys-yrs)							
Pop density (People/1000 sq miles)	3.6	4.9	3.0	2.3	3.6	2.0	4.5
Percent white	71.0	69.2	72.2	72.6	70.0	76.8	69.4
Percent HS or less	40.0	37.7	39.0	40.0	40.7	42.1	41.6
Percent unemployed	9.3	9.2	9.2	9.1	9.2	9.4	9.7
Median household income	53.7	55.8	54.4	52.4	52.8	51.9	53.4
Percent poverty	13.9	13.7	13.6	13.9	14.1	13.6	14.0
Percent uninsured	14.4	13.9	14.1	14.1	14.8	14.0	14.9
Zipcode of practice (% physicians)							
Contains university-affiliated hosp	45.0	51.1	45.4	44.9	43.7	30.6	44.9

Notes: Standard errors are displayed in parentheses and are clustered by physician. The displayed specialties are the top 8 specialties out of the 57 with the most opioid prescriptions collectively from 2006-2014 (Table 2.10). The prescription statistics are raw averages; that is, they do not control for physician specialty or county of practice.

While only 20% of doctors from the top 30 medical schools are in general practice, over 50% of DOs are GPs. Furthermore, while doctors from the top 30 schools tend to

practice in places with greater population density, lower percentages of white inhabitants, and higher education levels (that is, in more urban settings), DOs practice in areas with low population density, a high percentage of white inhabitants, and the highest percentage of less educated residents. If, for example, GPs who practice in more rural settings see patients with a greater need for opioids, then the patterns documented in Figures 2.1, 2.7, and 2.8 could reflect differences in the specialties and practice locations chosen across medical school rankings.

In the following section, we provide three sets of additional analyses that together provide evidence that neither patient sorting across physicians nor physician sorting across medical schools can account for all of the prescribing gradient that we observe. First, to control for differences in patient need, we replicate the analysis from Section 2.3 conditional on specialty and county of practice fixed effects. In particular, we estimate regressions of the following form:

$$Y_{itc} = \beta Rank_i + \delta Specialty_i + \alpha_c + \gamma_t + \epsilon_{itc} \tag{2.1}$$

where Y_{itc} denotes the number of opioid prescriptions written by doctor i in year t in county c; $Specialty_i$, α_c, and γ_t denote specialty, county, and year fixed effects, respectively; and ϵ_{itc} is an error term. In some specifications, county fixed effects are replaced with either exact practice address fixed effects or a vector of county characteristics. $Rank_i$ is a vector of indicators for medical school rank group. Harvard is the top ranked medical school, followed by schools ranked 2-5, 6-10, etc. Including this vector of indicators allows the effect of school rank to be non-linear. We further include separate indicators for unranked schools that grant MDs, unranked schools that grant DOs, and foreign schools. With the inclusion of county and specialty fixed effects, the parameters of interest—the vector β—are identified using variation in the number of prescriptions written by physicians

within the same specialty who practice in the same county but who attended different medical schools. Standard errors are clustered by physician.

While Equation (2.1) is useful for graphical analyses (the vector β can be plotted to visualize the prescribing gradient), we would like a parsimonious way to examine how the prescribing gradient changes when we include different controls. Hence, we also estimate equations similar to Equation (2.1) where we replace indicators for medical school rank bins with a quadratic in continuous medical school rank. That is, we estimate equations of the form:

$$Y_{itc} = \beta_1 Rank_i + \beta_2 Rank_i^2 + \delta Specialty_i + \alpha_c + \gamma_t + \epsilon_{itc} \tag{2.2}$$

where $Rank_i$ is a continuous measure of medical school rank (graduates of Harvard receive a value of 1, graduates of Johns Hopkins receive a value of 2, etc.) and all other variables are defined as in Equation (2.1). We include a quadratic in medical school rank because results from Equation (2.1) suggest that the relationship between medical school rank and annual opioid prescriptions is approximately quadratic. As there in no ordinal ranking for physicians who trained at unranked US medical schools or foreign institutions, we only include physicians who graduated from ranked US medical schools in these regressions. As before, standard errors are clustered by physician.

Next, instead of residualizing the number of prescriptions from specialty fixed effects, we examine whether the prescribing gradient is different across physicians in different specialties. If the prescribing gradient is driven entirely by patient sorting across physicians or physician selection into medical schools, then we would expect the prescribing gradient to be similar across specialties. If, however, there is a causal effect of training, then we would expect the prescribing gradient to be weaker in specialties that receive subsequent training in pain management.

To estimate the prescribing gradient across different specialties, we estimate Equations (2.1) and (2.2) separately for the top eight opioid-prescribing specialties.[14] The eight specialties with the most opioid prescriptions over our sample period are general practice, orthopaedic surgery, emergency medicine, pain medicine, physical medicine and rehabilitation, obstetrics and gynecology, anesthesiology, and general surgery (see Table 2.10). Of these specialties, those in pain medicine, physical medicine and rehabilitation, and anesthesiology prescribe the most on a per physician basis and have the most detailed subsequent training in the use of pain medicine.

Finally, we examine whether the prescribing gradient is different across graduation cohorts. While medical school rankings have been quite stable over time, the degree of selectivity at top schools has been increasing as the market for higher education has become national (and international) rather than being regionally segmented (Hoxby, 2009). Hence, if the effect of medical school rank is due to the selection of more qualified people into higher ranked schools, then we should see the effect of rank increase in more recent cohorts with increasing selectivity. Conversely, if the effect of rank is due to differences in training offered at different schools, and if training standards tend to diffuse downwards from the top schools over time, then the effect of rank should be less important in more recent cohorts. To examine whether the prescribing gradient is stronger in more selective cohorts, we estimate Equations (2.1) and (2.2) separately for four broad cohorts: those who graduated before 1975, between 1976 and 1985, between 1986 and 1995, and after 1996.

[14] When these equations are estimated on a single specialty, specialty fixed effects are excluded. However, when we estimate these equations only on GPs, we include sub-specialty fixed effects to account for differences across the three categories of sub-specialties we include in our definition of GPs (general practice, family practice, and internal medicine).

2.5 The role of training

We now implement the three sets of empirical exercises introduced in Section 2.4 to investigate whether there is evidence that the prescribing gradient we uncover in Section 2.3 is driven—at least in part—by a causal effect of training.

2.5.1 Gradient conditional on specialty and practice location

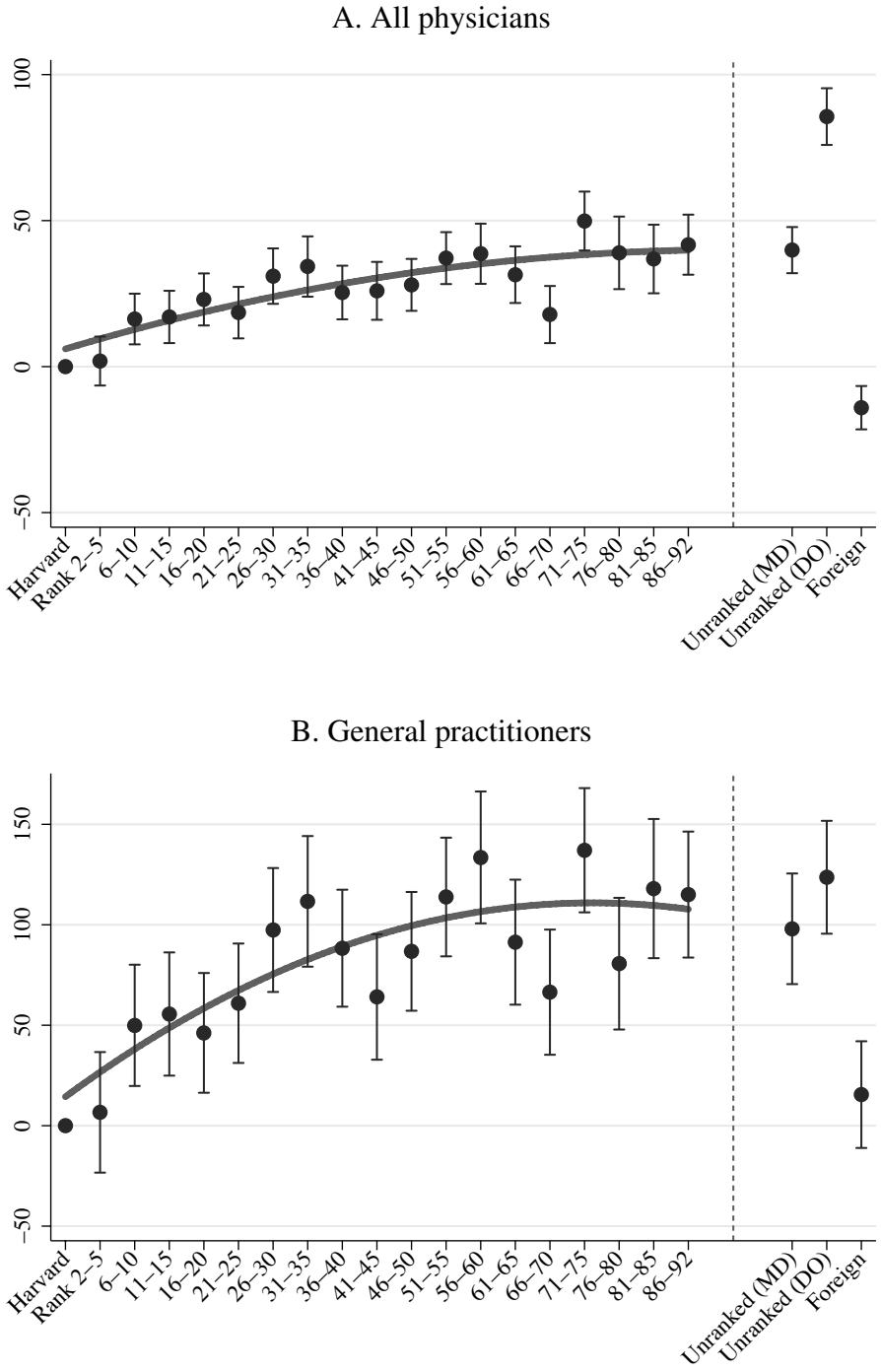
Figure 2.2 provides coefficient estimates and 95% confidence intervals on indicators for medical school rank bins from estimation of Equation (2.1), both for all physicians (Subfigure A) and for GPs (Subfigure B). The figures are scaled so that the coefficients on the highest ranked medical school (Harvard) are set to zero, and all other schools are compared to it. A comparison of Figures 2.1 and 2.2 demonstrates that controlling for differences in specialties and practice locations moderates the relationship between medical school rank and opioid prescribing. However, even within the same specialty and county of practice, the relationship between medical school rank and opioid prescriptions remains highly statistically significant. This is particularly true among GPs, for whom the average number of opioid prescriptions written yearly per physician rises steeply with medical school rank until around the rank of 60, where the curve flattens out.[15]

A comparison of specifications with and without controls is shown more formally in Table 2.2. Here, we provide results for variants of Equation (2.2) estimated on all physicians (Panel A) and using GPs alone (Panel B). Looking to the results for all physicians first, we see that a regression of annual opioid prescriptions on medical school rank yields a best fit line of $y = 117.07 + 2.44x$–$0.01x^2$ (column (1)). Controlling for specialty (column (2)), reduces the derivative of y with respect to x by about half, as does controlling for county-level demographics from the ACS (column (3)).[16] Comparing columns (3) and (4), we see that the estimates are very similar whether we control for observable differences

[15]Tables 2.11 and 2.12 show the regression output underlying Figure 2.2.

[16]Controls include population density; percent male; percent in 12 age bins; percent white, black, and Hispanic; percent in seven education categories; percent unemployed; percent in 16 income categories;

Figure 2.2: Opioids by rank controlling for specialty and practice county



Notes: The above figures depict the coefficient estimates on indicators for medical school rank bins from regressions of opioid prescriptions at the physician-year level on medical school rank bin indicators with year, specialty, and county fixed effects (Equation (2.1)). Subfigure A includes all physicians; Subfigure B only includes GPs (physicians in general practice, family practice, and internal medicine). Physician-years with zero opioid prescriptions are included. The bars denote 95% confidence intervals; standard errors are clustered by physician. Refer to online appendix Tables 2.11 and 2.12 for the underlying coefficient estimates for all physicians and GPs, respectively.

Table 2.2: Opioid prescriptions by medical school rank

A. All physicians	Annual opioid prescriptions (including zeroes)					
	(1)	(2)	(3)	(4)	(5)	(6)
Medical rank	2.439***	1.243***	1.524***	1.502***	0.635***	0.263***
	(0.120)	(0.110)	(0.119)	(0.118)	(0.109)	(0.097)
(Medical rank)^2	-0.007***	0.001	-0.008***	-0.010***	-0.003***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	117.071***	71.847**	-9.1e3***	164.871***	111.570***	232.763***
	(2.074)	(30.845)	(623.952)	(2.120)	(31.767)	(39.732)
Specialty FEs	No	Yes	No	No	Yes	Yes
County demographics	No	No	Yes	No	No	No
County FEs	No	No	No	Yes	Yes	No
Practice address FEs	No	No	No	No	No	Yes
N (physician-years)	3,635,532	3,635,532	3,635,532	3,635,532	3,635,532	3,635,532
R^2	0.006	0.147	0.039	0.064	0.194	0.525

B. General practitioners	Annual opioid prescriptions (including zeroes)					
	(1)	(2)	(3)	(4)	(5)	(6)
Medical rank	4.147***	2.995***	2.644***	2.784***	2.418***	1.441***
	(0.309)	(0.307)	(0.301)	(0.292)	(0.292)	(0.257)
(Medical rank)^2	-0.011***	-0.003	-0.015***	-0.021***	-0.018***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	202.380***	321.419***	-8.3e3***	295.736***	354.644***	362.420***
	(5.818)	(6.521)	(1297.679)	(5.712)	(6.264)	(5.713)
Specialty FEs	No	Yes	No	No	Yes	Yes
County demographics	No	No	Yes	No	No	No
County FEs	No	No	No	Yes	Yes	No
Practice address FEs	No	No	No	No	No	Yes
N (physician-years)	832,005	832,005	832,005	832,005	832,005	832,005
R^2	0.014	0.029	0.096	0.174	0.178	0.636

Notes: The above table presents output from regressions of opioid prescriptions at the physician-year level on a quadratic in medical school rank (variants of Equation (2.2)). All specifications include year fixed effects. Standard errors are clustered by physician. Panel A includes all physicians; Panel B only includes GPs (physicians in general practice, family practice, and internal medicine). Column (3) includes the following county-level controls: population density; percent male; percent in 12 age bins; percent white, black, and Hispanic; percent in seven education categories; percent unemployed; percent in 16 income categories; percent poverty for three different age ranges; percent with public and private health insurance; and median age of housing stock.

across counties or for both observable and unobservable differences across counties using county fixed effects. Finally, column (5) shows estimates from a specification similar to that depicted in Figure 2.2 in that it includes both county and specialty fixed effects: here, the best fit line is given by $y = 111.57 + 0.64x$–$0.003x^2$. Taking into account differences in specialties and counties of practice across medical school rankings, doctors from the lowest ranked schools still write on average over 33 more opioid prescriptions per year than doctors from the highest ranked schools.

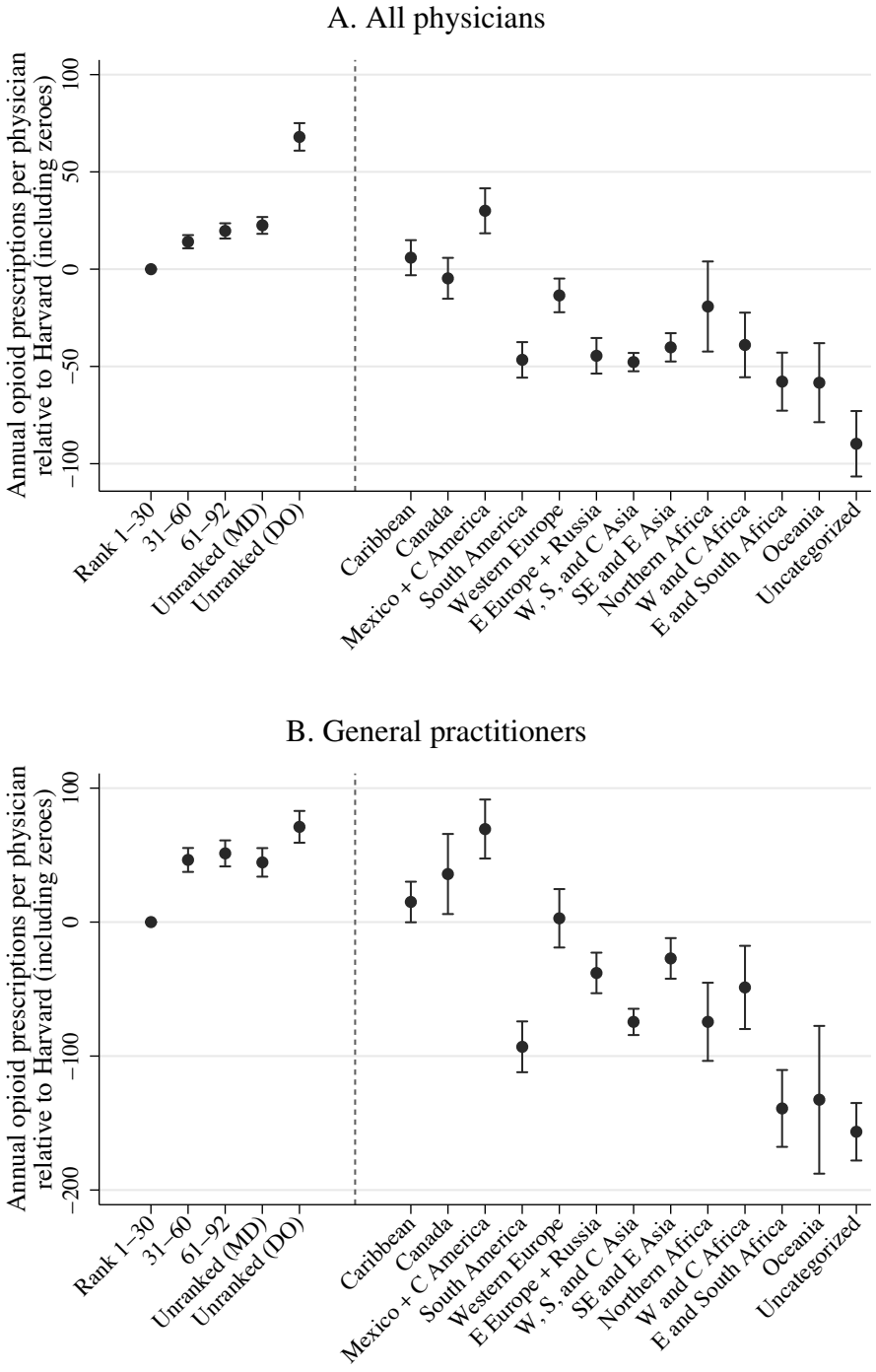
While the prescribing gradient among GPs is also attenuated when we control for specialty and county of practice, we see from the regression output in Panel B of Table 2.2 that a significant gradient persists among GPs practicing in the same county. Conditional on specialty and county of practice, GPs from the lowest ranked schools write on average over 70 more opioid prescriptions per year than GPs from the highest ranked schools (column (5)).

Turning to the coefficients on unranked medical schools in Figure 2.2, we see that among all physicians (Subfigure A), DOs write more prescriptions per prescriber than all other doctors even when we control for differences in specialties and practice locations. Furthermore, conditional on these controls, MDs trained at unranked US medical schools still prescribe similarly to physicians from the lowest third of ranked US medical schools, both among all physicians and among GPs. However, unlike in Figure 2.1, foreign-trained doctors actually write fewer opioid prescriptions than US-trained doctors once we control for specialty and county of practice.

The behavior of foreign-trained doctors is probed further in Figure 2.3. Here, we plot coefficient estimates from a regression similar to the specification outlined in Equation (2.1) except that the categories for ranked US schools are collapsed and indicators are added for world region of training for foreign doctors. Conditional on specialty and county characteristics, physicians trained in most regions outside of the US write significantly

percent poverty for three different age ranges; percent with public and private health insurance; and median age of housing stock.

Figure 2.3: Opioids by school region controlling for specialty and practice county



Notes: The above figures depict the coefficient estimates on indicators for medical school rank bins for US-trained physicians and regions of training for foreign-trained physicians from regressions of opioid prescriptions at the physician-year level on medical school rank bin or region indicators with year, specialty, and county fixed effects (variants of Equation (2.1)). Subfigure A includes all physicians; Subfigure B only includes GPs. Physician-years with zero opioid prescriptions are included. The bars denote 95% confidence intervals; standard errors are clustered by physician. Refer to online appendix Tables 2.11 and 2.12 for the underlying coefficient estimates for all physicians and GPs, respectively.

fewer opioid prescriptions per year on average than physicians trained domestically. In fact, GPs trained in the Caribbean, Canada, and Mexico/Central America are the only foreign-trained GPs who on average write more opioid prescriptions per year than GPs trained at the top 30 US schools. The stark differences between physicians trained in various regions of the world suggest considerable variation in attitudes towards opioids across world regions that practitioners bring with them to the US, and provides further evidence that differences in training are likely to be important.[17]

It is possible that we are not fully controlling for medical need by controlling for physician specialty and county of practice. We can extend our analysis to compare the prescribing practices of physicians who practice in the exact same hospital or clinic by including practice address fixed effects in place of county fixed effects in Equations (2.1) and (2.2). The results of this exercise for all physicians and GPs are shown in column (6) of Table 2.2 (see also Figure S9). Even within the same practice, opioid prescribing increases with medical school rank, although the relationship is flatter than in a specification without these controls. This reduction in the relationship between medical school rank and prescribing practices within a given practice location indicates either that practices tend to hire doctors with similar propensities to prescribe opioids or that the opioid prescribing behavior of physicians is influenced by the institutions where they practice and/or the behavior of their colleagues.

2.5.2 Prescribing gradient across specialties

We next ask whether there are differences in the prescribing gradient across the top eight opioid-prescribing specialties. As discussed in Section 2.4, if differences in opioid prescribing across medical school ranks are in fact driven by differences in training, then we expect the rank of a physician's initial medical school to be a less important predictor of

[17]Figure 2.9 plots similar estimates from models without specialty and county controls both for all physicians (Subfigure A) and for GPs (Subfigure B).

opioid prescribing behavior among specialties that receive subsequent training in the use of opioids.

Table 2.3: Opioid prescriptions by medical school rank across specialties

	Annual opioid prescriptions (including zeroes)							
Specialty:	(1) General practice	(2) Ortho. surgery	(3) Emergency medicine	(4) Pain medicine	(5) Phy.med. & rehab.	(6) Ob./gyn.	(7) Anesthe-siology	(8) General surgery
Rank	2.418***	1.920**	-0.631*	-3.814	-4.467	0.658***	0.788	0.650***
	(0.292)	(0.846)	(0.368)	(9.275)	(4.110)	(0.181)	(0.865)	(0.244)
$(\text{Rank})^2$	-0.02***	-0.018*	0.013***	0.038	0.067	-0.005**	-0.003	-0.003
	(0.003)	(0.009)	(0.004)	(0.101)	(0.044)	(0.002)	(0.010)	(0.003)
Constant	354.65***	537.92***	70.70***	1507.54***	301.62	87.35***	-26.52	126.15***
	(6.264)	(20.956)	(20.580)	(207.71)	(328.58)	(22.719)	(23.612)	(20.778)
N	832,005	155,547	187,785	15,318	33,462	213,282	162,225	158,913
R^2	0.178	0.195	0.245	0.356	0.288	0.210	0.118	0.235

Notes: The above table presents output from regressions of opioid prescriptions at the physician-year level on a quadratic in medical school rank with year and county fixed effects (variants of Equation (2.2)) estimated separately across different specialties. Standard errors are clustered by physician. The displayed specialties are the 8 specialties out of 57 specialties with the most opioid prescriptions collectively from 2006-2014 (Table 2.10).

Table 2.3 provides estimates of Equation (2.2) for physicians in different specialties. As seen in Figure 2.11, there is an inverse relationship between medical school rank and opioid prescribing in most of the top eight opioid-prescribing specialties, although the relationship is generally much flatter in other specialties than that observed for GPs.[18] For pain medicine, physical medicine and rehabilitation, and anesthesiology—the specialties where all practitioners could be expected to receive specific training in the use of opioids, and which have high per physician prescribing of opioids relative to GPs[19]—we see virtually no relationship between initial medical school rank and opioid prescribing, as hypothesized above. For ER doctors, the figure indicates a relationship between rank and prescribing that is basically flat up to about rank 50 and then increases. In the quadratic regressions (Table

[18]Figure 2.12 shows similar figures for two specialties where many observers agree that opioids are often necessary for adequate pain relief: oncology and nephrology. These figures show that a relationship between medical school rank and opioid prescribing exists even among specialties where the use of opioids is uncontroversial, although the relationship is much flatter than that found for GPs.

[19]As shown in Table 2.10, physicians in pain medicine write an average of 2,040.2 opioid prescriptions per year compared to an average of 414.1 for GPs.

2.3), this concavity is captured by a negative main effect and a positive coefficient on the quadratic term, with a turnaround point right around rank 50, consistent with the figure.

2.5.3 Prescribing gradient across cohorts

We next turn to the question of cohort-level differences in the relationship between medical school rank and opioid prescribing. As discussed in Section 2.4, if the prescribing gradient is driven by physician selection into medical schools, then the gradient should be stronger in more recent cohorts due to the increasing selectivity at top medical schools.

As shown in Table 2.4, we find that that the relationship between initial medical school rank and opioid prescribing—while significant in all cohorts—has become consistently flatter over time.[20] For GPs who graduated from medical school before 1976 for instance, a regression of annual opioid prescriptions on a quadratic in continuous medical school rank with year, specialty, and county fixed effects (Equation (2.2)) yields a best fit line of $y = 354.40 + 3.55x$–$0.03x^2$ (column (2) of Panel B) compared to the best fit line of $y = 247.61 + 1.28x$–$0.01x^2$ for the cohort that graduated between 1996 and 2005 (column (5) of Panel B). This flattening gradient is inconsistent with the idea that the relationship between medical school rank and opioid prescribing is driven by selection into the top medical schools.[21]

[20] Refer to Figure 2.13 for the corresponding figures.

[21] Table 2.13 shows results for pain medicine specialists separately. Consistent with the results for pain specialists across all cohorts, there is no statistically significant association between initial medical school rank and opioid prescribing for pain specialists of any cohort.

Table 2.4: Opioid prescriptions by medical school rank across cohorts

A. All physicians	Annual opioid prescriptions (including zeroes)				
	(1)	(2)	(3)	(4)	(5)
Graduation cohort:	All	$\leq$ 1975	1976-1985	1986-1995	1996-2005
Medical rank	0.635***	1.242***	0.718***	0.481**	0.264*
	(0.109)	(0.219)	(0.242)	(0.240)	(0.143)
(Medical rank)^2	-0.003***	-0.009***	-0.003	-0.002	-0.000
	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Constant	111.570***	29.659	185.029***	220.612	417.002
	(31.767)	(21.114)	(47.655)	(159.558)	(297.311)
N (physician-years)	3,635,532	675,396	936,018	1,006,704	1,017,414
R^2	0.194	0.181	0.236	0.232	0.226
B. General practitioners	Annual opioid prescriptions (including zeroes)				
	(1)	(2)	(3)	(4)	(5)
Graduation cohort:	All	$\leq$ 1975	1976-1985	1986-1995	1996-2005
Medical rank	2.418***	3.551***	3.210***	2.073***	1.277***
	(0.292)	(0.745)	(0.613)	(0.547)	(0.410)
(Medical rank)^2	-0.018***	-0.027***	-0.026***	-0.014**	-0.009**
	(0.003)	(0.009)	(0.007)	(0.006)	(0.004)
Constant	354.644***	354.397***	437.960***	375.733***	247.608***
	(6.264)	(16.873)	(12.799)	(11.540)	(8.794)
N (physician-years)	832,005	132,849	232,596	244,278	222,282
R^2	0.178	0.256	0.261	0.241	0.264

Notes: The above table presents output from regressions of opioid prescriptions at the physician-year level on a quadratic in medical school rank with year, specialty, and county fixed effects (Equation (2.2)) estimated separately across different graduation cohorts. Standard errors are clustered by physician. Panel A includes all physicians; Panel B only includes GPs (physicians in general practice, family practice, and internal medicine).

2.6 Robustness

One limitation of these data is that they do not include information about the number of patients seen by each physician. If doctors trained at top schools are more likely to engage part-time in research or teaching and therefore see fewer patients than doctors from lower ranked medical schools, then a correlation between medical school rank and prescriptions

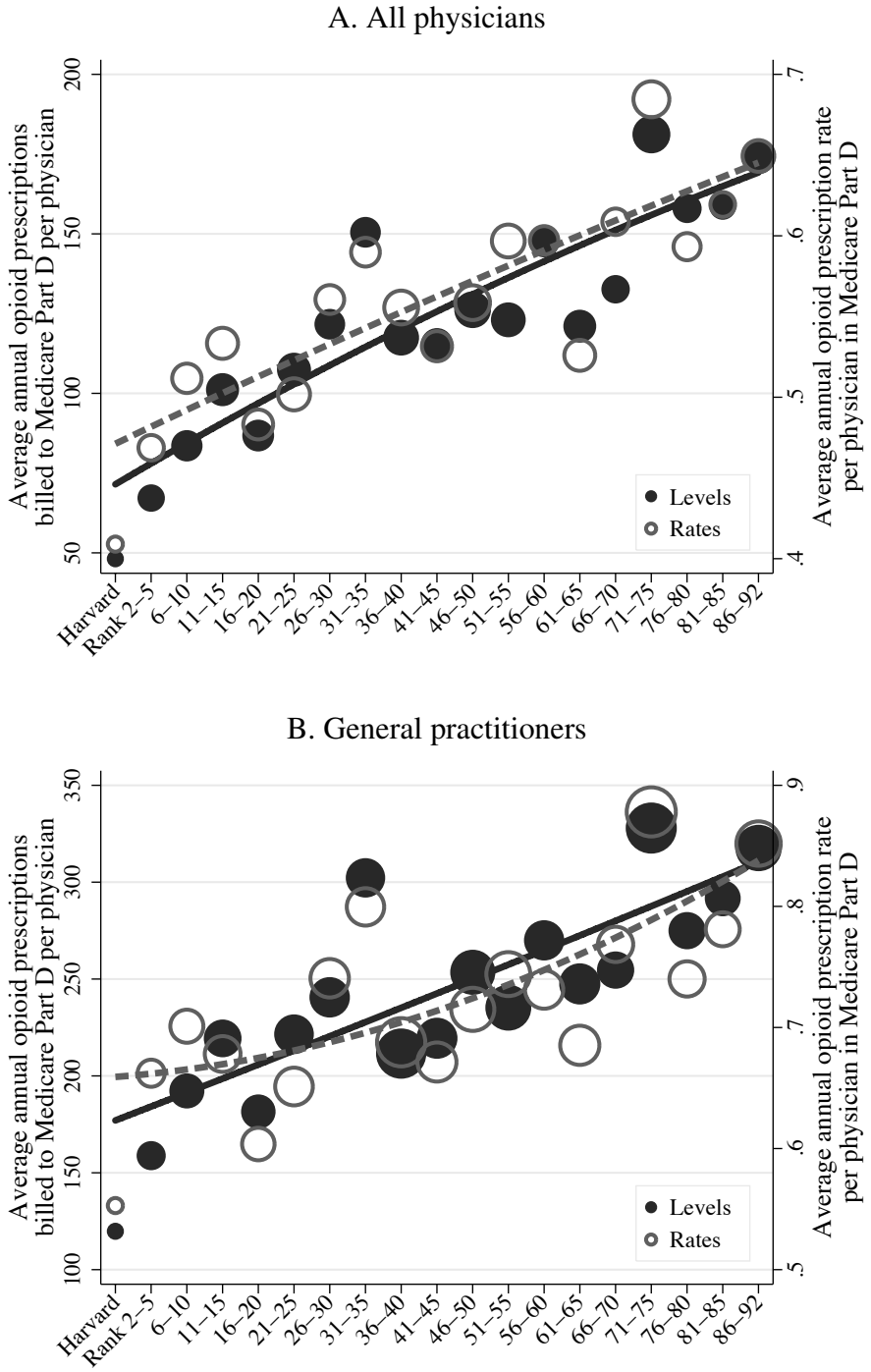
could emerge because of differences in workloads. Unfortunately, there is currently no dataset available that has patient volumes for every doctor in the US.

Despite this limitation, it is unlikely that differences in the number of patients seen can explain our findings. Recall that a strong relationship between prescribing and school rank remains throughout the distribution of medical schools ranks. In order for patient volume to explain our findings, GPs from the 30th ranked schools would have to see significantly fewer patients on average than GPs from the 40th ranked schools, for example. We do not think there is any evidence or reason to think that this is the case. Furthermore, large differences in opioid prescribing patterns exist across foreign-trained physicians—a significant share of practicing US physicians—depending on the world region in which they were trained. We are not aware of evidence suggesting that there are large differences in patient volume by region of origin.

To investigate the possibility of differential patient loads more formally, we provide two additional analysis. First, we replicate our analysis excluding physicians who practice in a zip code containing a university-affiliated hospital. If doctors from top-ranked medical schools see fewer patients on average because they are more likely to engage part-time in teaching or research, then we would expect our results to be attenuated when we exclude physicians in university-affiliated zip codes. The results for all physicians and for GPs are remarkably consistent with those discussed above (see Figure 2.14 and Table 2.14).

Second, since publicly available Medicare data includes information on both the number of Medicare beneficiaries seen and the number of opioid prescriptions written, we can verify that our results are robust to using a prescription rate (total prescriptions divided by the total number of unique patients) in the Medicare population. As shown in Figure 2.4, using total prescriptions or prescription rates paints a very similar picture: physicians who attended higher ranked medical schools prescribe significantly fewer opioids.

Figure 2.4: Opioids by medical school rank: levels versus rates in Medicare Part D



Notes: The above figures depict the (i) average number of opioid prescriptions written per physician and the (ii) average opioid prescription rate per physician in Medicare Part D in 2014. Subfigure A includes all physicians; Subfigure B only includes GPs (physicians in general practice, family practice, and internal medicine). Data on both the number of opioid prescriptions billed to Medicare Part D and the number of Medicare beneficiaries seen per physician are taken from CMS's public use Medicare files; this data is merged via NPI with CMS's Physician Compare database to extract medical school for each provider.

Another limitation of the QuintilesIMS data is that we do not know either the number or the strength of the pills included in each prescription. To the extent that physicians trained in different specialties tend to prescribe opioids of different strengths, estimating models by specialty as we have done above will help to mitigate the problem. Still, even within specialty, if physicians trained at top schools always write prescriptions for a month's supply of high-dose opioids, whereas physicians trained at lower ranked schools always write prescriptions for a few low-dose pills, then differences in the number of prescriptions could emerge without this association having any bearing on the overall provision of opioids. However, even when looking within a given county over time, there is a significant relationship between the number of opioid prescriptions and deaths involving drugs: on average, a 10% increase in opioid prescriptions annually is associated with a 1.5% increase in deaths involving drugs each year (see Table 2.15). This relationship suggests that differences in prescribing patterns are not fully offset by differences in the number or strength of pills prescribed, and thus that it is meaningful to look at the number of prescriptions as an indicator of physician practice style.

A final limitation is that we only observe where each physician completed his or her initial medical training. Hence we cannot say how the rankings of institutions where physicians receive subsequent training are related to the propensity to prescribe opioids. However, the fact that physicians in specialties with significant further training in pain management have flatter relationships between opioid prescribing and initial medical school rank strongly suggests that the nature and type of further training is an important determinant of physician practice style. If physicians who receive their initial training at top medical schools are more likely to go on to residencies that offer better training in the use of pain medications, then this could be viewed as one of the mechanisms whereby initial medical school rank affects prescribing behavior.

2.7 Discussion and conclusions

This study offers several new facts about how doctor characteristics are related to their propensity to prescribe opioids. First, between 2006 and 2014, nearly half of all opioids prescribed by doctors were prescribed by GPs. This is true even though doctors in some specialties, like pain medicine, write many more prescriptions per practitioner. Thus, it will be important to understand and modify the prescribing behavior of GPs as well as those of doctors in certain key specialties like pain medicine if the opioid epidemic is to be successfully addressed.

Second, there is a striking inverse relationship between the rank of a physician's medical school and his/her propensity to prescribe opioids, especially among GPs. Previous research indicating that differences in practice style are largely set as early as the first year of medical practice (Epstein et al., 2016) suggests that the relationship between initial medical school rank and opioid prescribing behavior could reflect differences in training regarding the appropriate use of opioids across schools. An alternative hypothesis is that the estimated effect of medical school rank on the propensity to prescribe opioids reflects differences in either the types of patients seen by physicians who attend medical schools of higher and lower rank or the types of physicians who are selected into these schools.

While we cannot definitively rule out these alternatives, our ancillary results support the training hypothesis. In particular, the relationship between medical school rank and propensity to prescribe opioids persists even among specialists who attended different medical schools but practice in the exact same hospital or clinic—where patients can be assumed to be relatively homogenous in their need for opioids. Furthermore, the prescribing gradient is less pronounced in specialties in which physicians might be expected to receive specialized training in dealing with pain medications, such as pain medicine and anesthesiology. Finally, given the increasing competition to get into top ranked medical schools, the fact that the relationship between medical school rank and prescribing behavior has weakened over time (rather than strengthening) further suggests that the relationship

reflects the more rapid diffusion of best practices in top schools rather than the selection of certain types of physicians.

We cannot know how training regarding opioids has differed across medical schools over time, or even whether the differences in prescribing practices that we see reflect specific training about opioids. They might, for example, reflect more subtle differences in how doctors are taught to think about potential harms from medication, or periodic reviews of medications that patients are taking. Or they might reflect physician attitudes towards evidence-based medicine more generally.

A review of the curricula at all four medical schools in Massachusetts found that there was no standard in place to make sure that all students were taught safe and effective opioid-prescribing practices before graduation (Antman et al., 2016). Recognizing that more comprehensive training will be needed to improve prescriber practices, in March 2016 the White House asked medical schools to pledge to include the Center for Disease Control's new opioid-prescribing guidelines in their curriculum. Over 60 medical schools announced that they would update their curriculum by the fall of 2016, with 28% (43%) of ranked (unranked) US medical schools taking the pledge. If such training is effective in reducing opioid prescribing, then policy makers might consider offering stronger inducements for medical schools to incorporate these guidelines.

Taken together, our findings suggest that a doctor's initial training has a large impact on their attitudes towards opioid prescribing, especially for GPs who are less likely to receive subsequent training in pain management. Since variations in opioid prescribing have contributed to deaths due to the current opioid epidemic, training aimed at reducing prescribing rates among the most liberal prescribers—who disproportionately come from the lowest ranked medical schools—could possibly have large public health benefits. Education targeting the physicians responsible for the majority of opioid prescribing therefore likely has a role to play in addressing the opioid epidemic.

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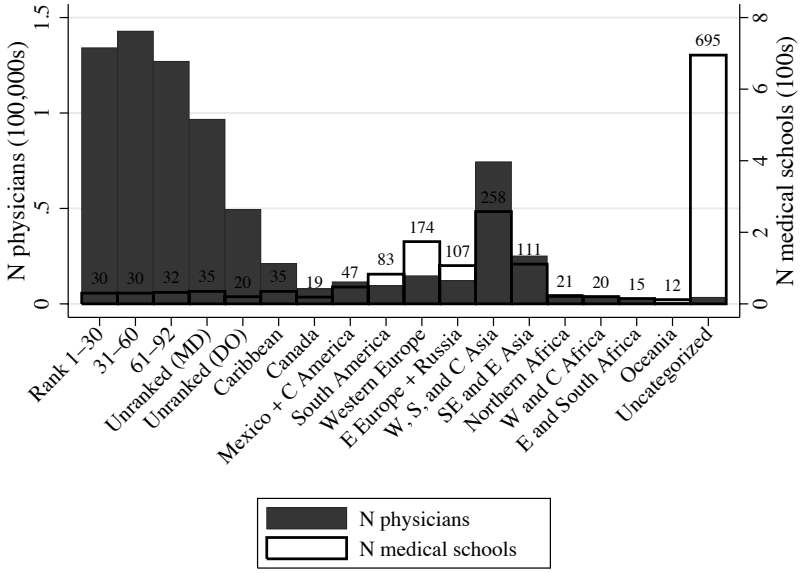
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Appendix

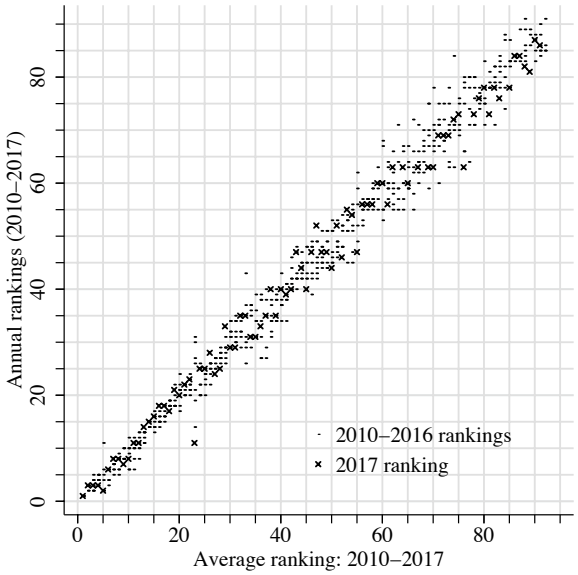
2.A Supplementary figures

Figure 2.5: Physicians and medical schools across rankings and world regions



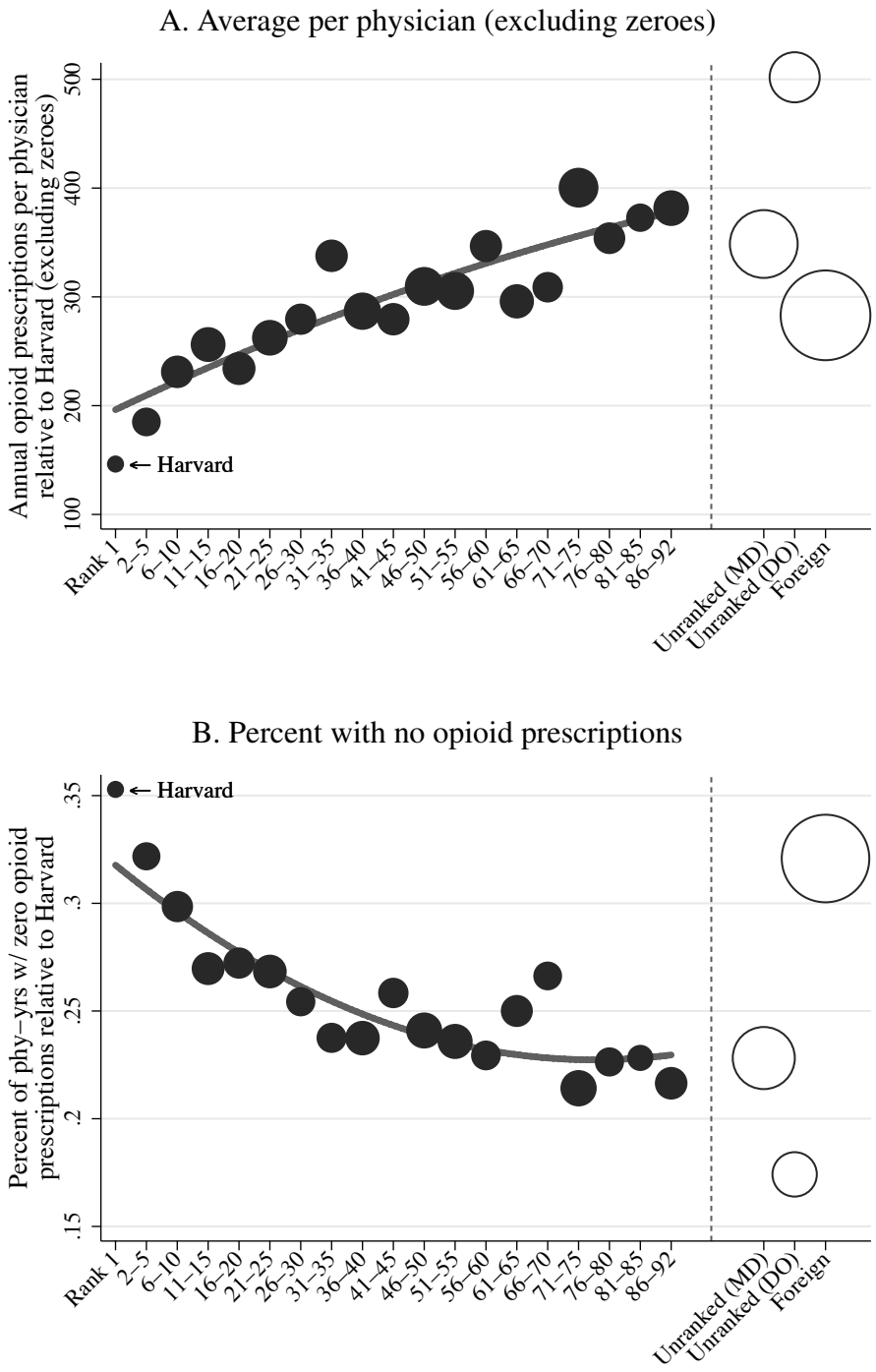
Notes: Rankings for the top 92 US schools are defined as in Section 2.2. US medical schools that are not ranked are divided by whether they grant the degree of DO or MD. Foreign medical schools are grouped according to the UN's classification of countries by world regions. For foreign medical schools with 10 or more opioid prescribers in our main sample, we googled the medical school and recorded the country of the school's primary campus. For foreign medical schools with fewer than 10 opioid prescribers in our main sample, we assign the medical school to the "Uncategorized" group.

Figure 2.6: Persistence across medical school rankings over time



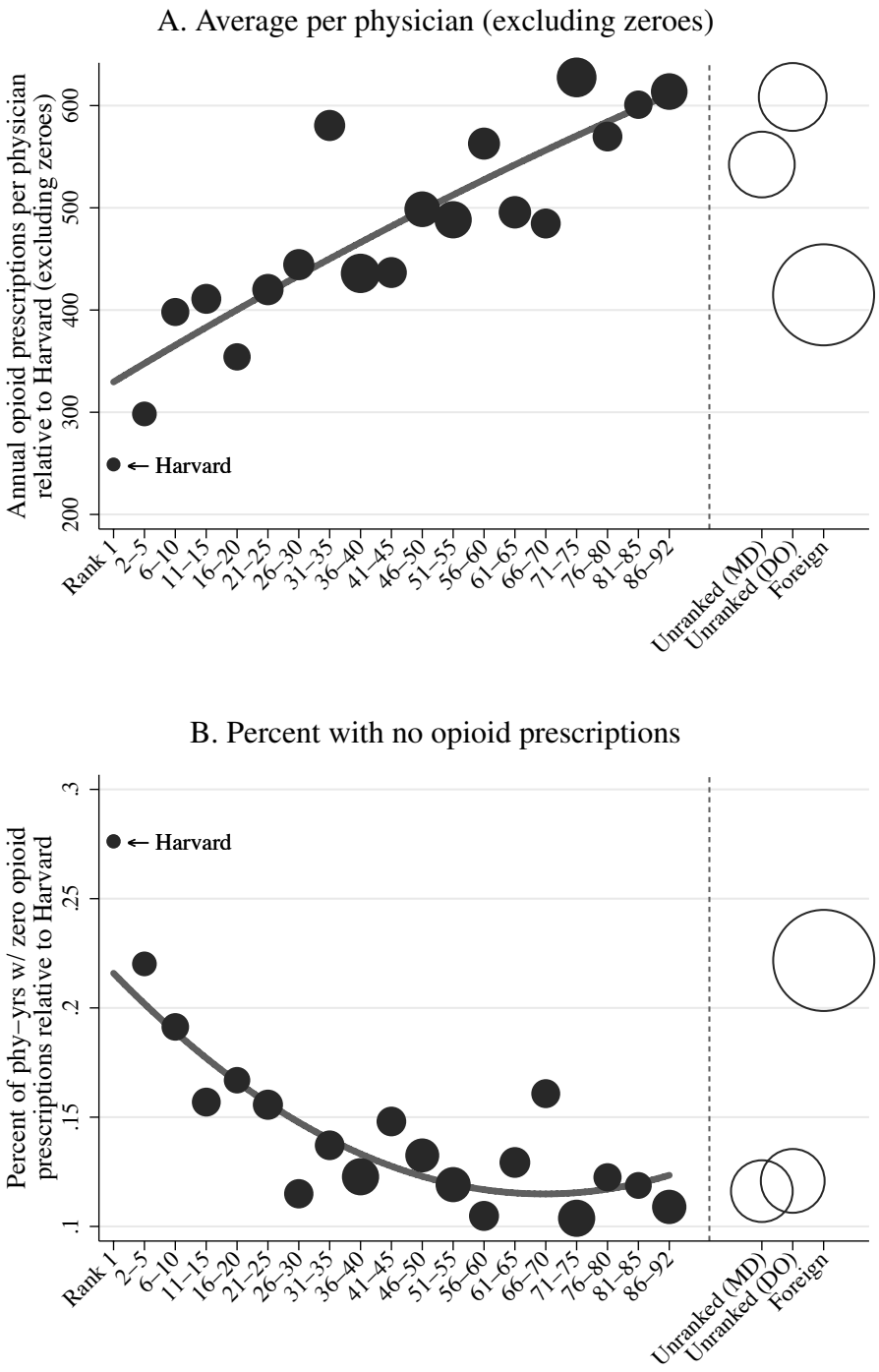
Notes: The above figure depicts how our composite ranking compares to annual rankings from 2010 to 2017. For each composite rank on the x-axis, there are up to eight observations denoting the corresponding medical school's rank in each year between 2010 and 2017. Annual rankings from 2010-2016 are denoted by a point; the most recent ratings (2017) are denoted by a cross.

Figure 2.7: Opioid prescriptions by medical school rank: all physicians



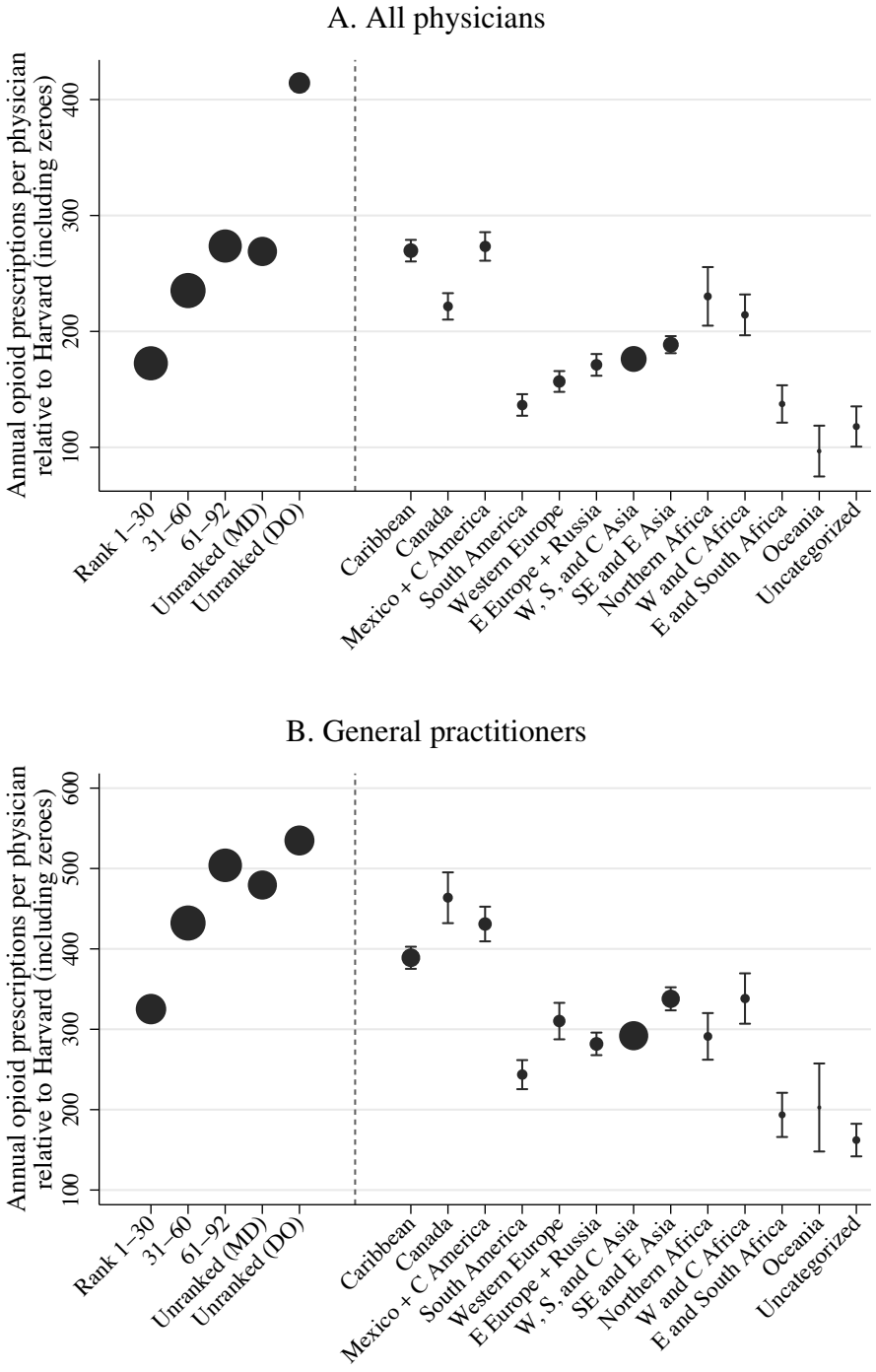
Notes: The above figures depict the average number of opioid prescriptions written yearly per physician conditional on writing at least one opioid prescription (Subfigure A) and the percent of physician-year observations with zero opioid prescriptions (Subfigure B) by medical school rank. All physicians are included; Figure 2.8 provides an analogous figure for GPs only. The size of the marker indicates the number of physician-year observations in a given bin. Refer to Table 2.8 for the underlying averages.

Figure 2.8: Opioid prescriptions by medical school rank: general practitioners



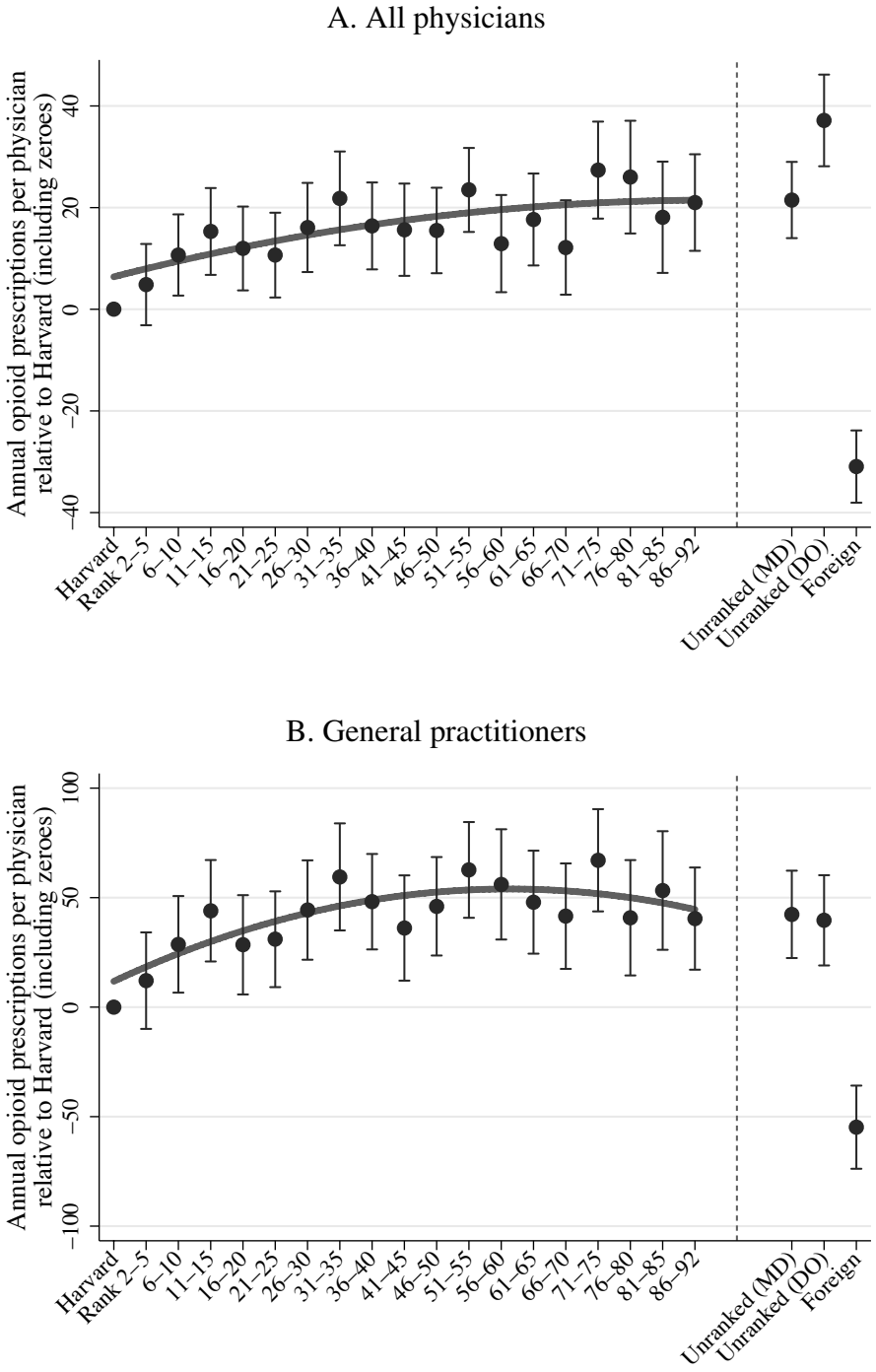
Notes: The above figures depict the average number of opioid prescriptions written yearly per physician conditional on writing at least one opioid prescription (Subfigure A) and the percent of physician-year observations with zero opioid prescriptions (Subfigure B) by medical school rank. Only GPs are included (physicians in general practice, family practice, and internal medicine); Figure 2.7 provides an analogous figure for all physicians. The size of the marker indicates the number of physician-year observations in a given bin. Refer to Table 2.9 for the underlying averages.

Figure 2.9: Opioid prescriptions by US rankings and regions of foreign schools



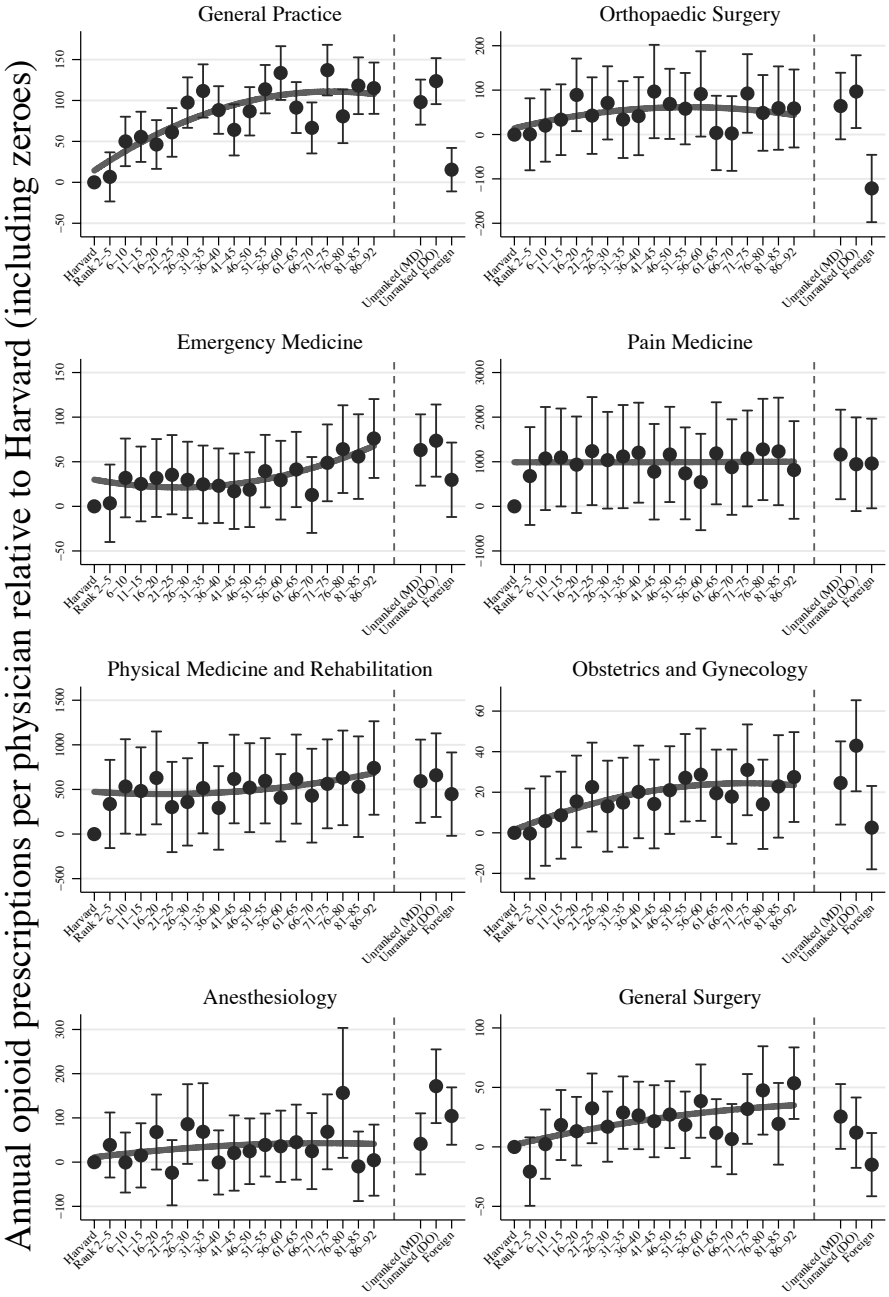
Notes: The above figures depict the average number of opioid prescriptions written yearly per physician by medical school rank for US-trained physicians and region of training for foreign-trained physicians. Subfigure A includes all physicians; Subfigure B only includes GPs (physicians in general practice, family practice, and internal medicine). Physician-years with zero opioid prescriptions are included. The size of the marker indicates the number of physician-year observations in a given bin; confidence intervals not displayed are covered by the marker. Refer to Tables 2.8 and 2.9 for the underlying averages for all physicians and GPs, respectively.

Figure 2.10: Opioids by rank controlling for specialty and practice address



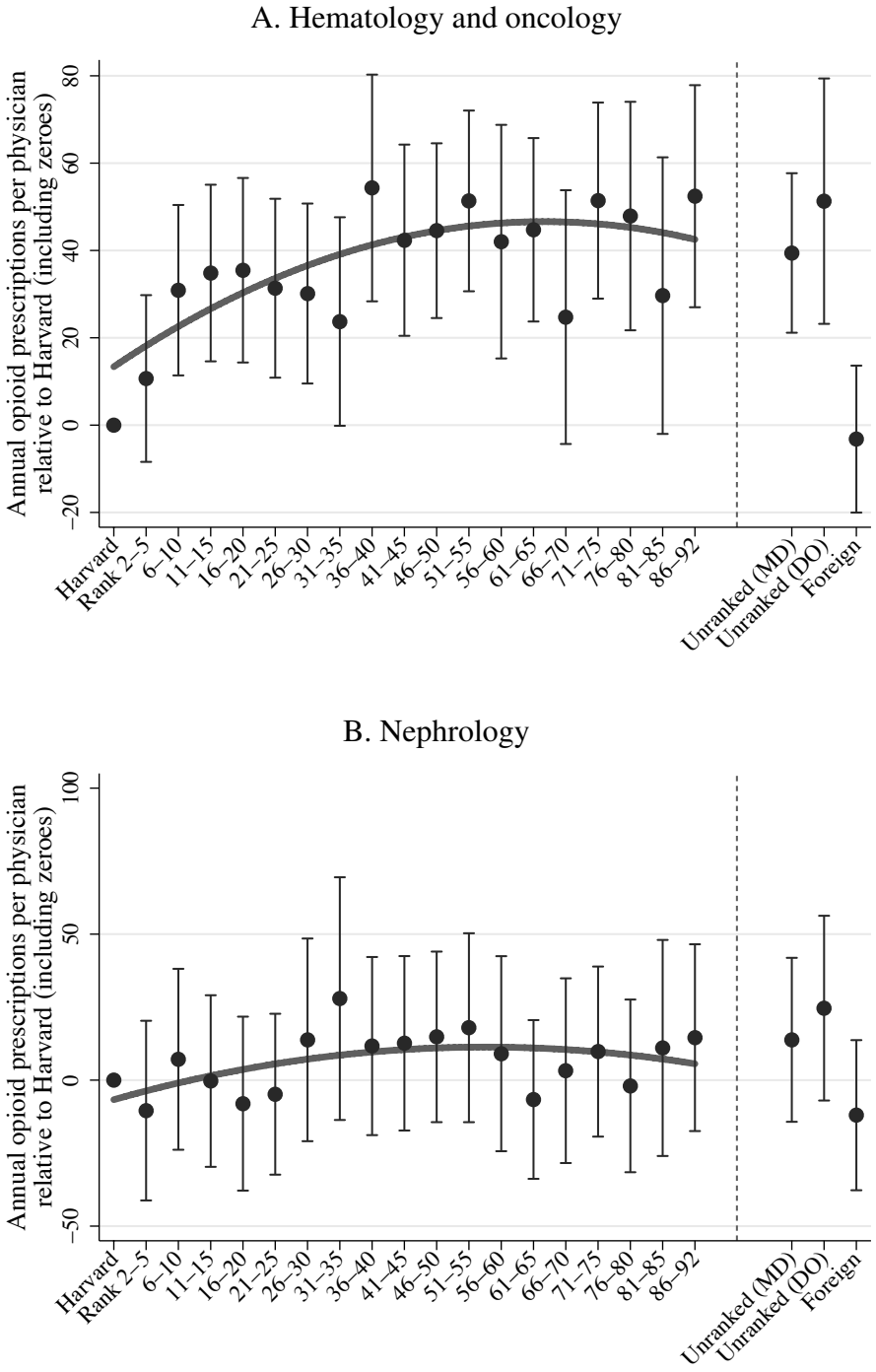
Notes: The above figures depict the coefficient estimates on indicators for medical school rank bins from regressions of opioid prescriptions at the physician-year level on medical school rank bin indicators with year, specialty, and practice address fixed effects (variants of Equation (2.1)). Subfigure A includes all physicians; Subfigure B only includes GPs (physicians in general practice, family practice, and internal medicine). Physician-years with zero opioid prescriptions are included. The bars denote 95% confidence intervals; standard errors are clustered by physician.

Figure 2.11: Opioid prescriptions by medical school rank across specialties



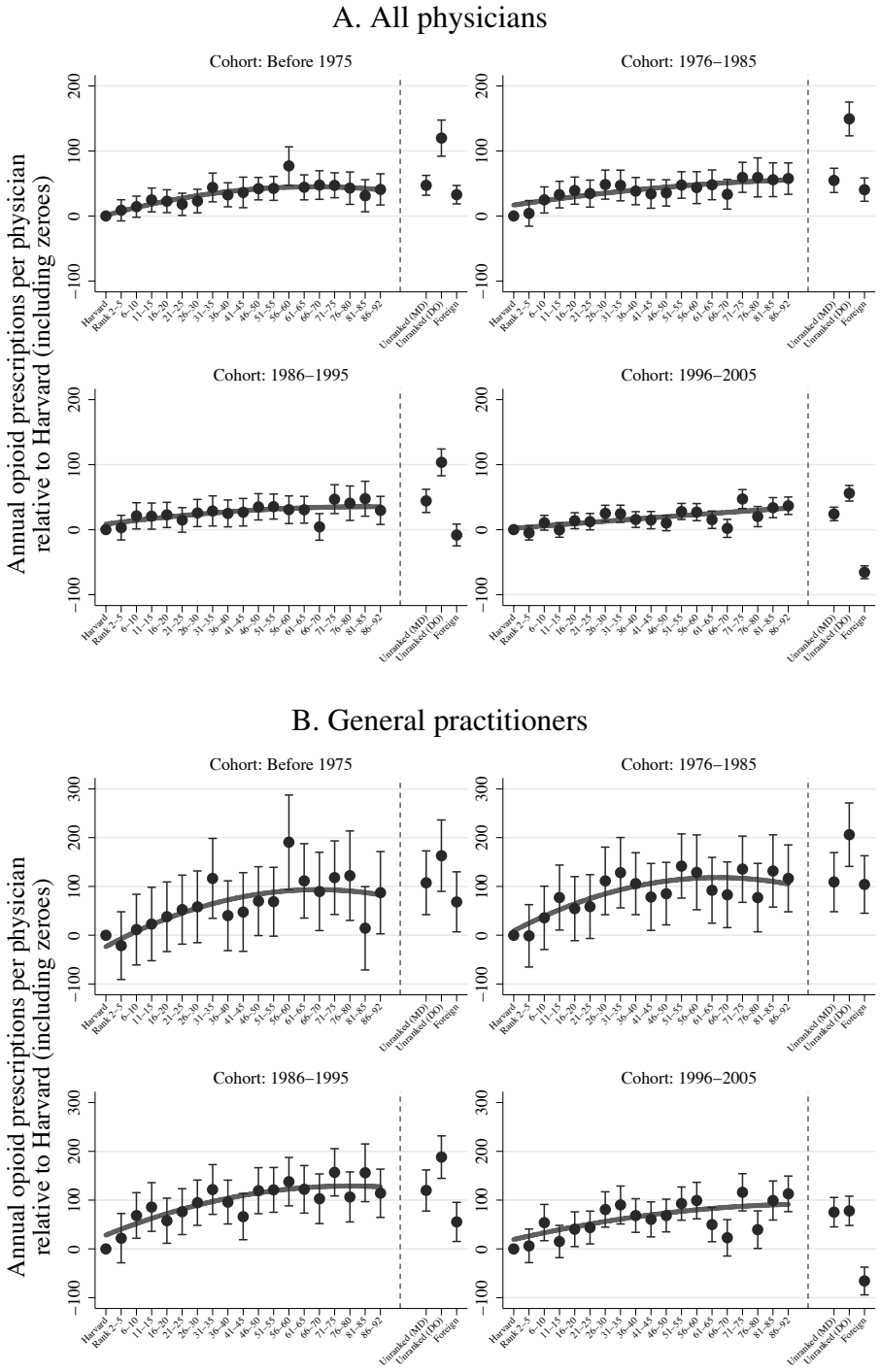
Notes: The above figures depict the coefficient estimates on indicators for medical school rank bins from regressions of opioid prescriptions at the physician-year level on medical school rank bin indicators with year and county fixed effects (variants of Equation (2.1)). The displayed specialties are the 8 specialties out of 57 specialties with the most opioid prescriptions collectively from 2006-2014 (Table 2.10). Physician-years with zero opioid prescriptions are included. The bars denote 95% confidence intervals; standard errors are clustered by physician.

Figure 2.12: Opioid prescriptions by medical school rank: oncology and nephrology



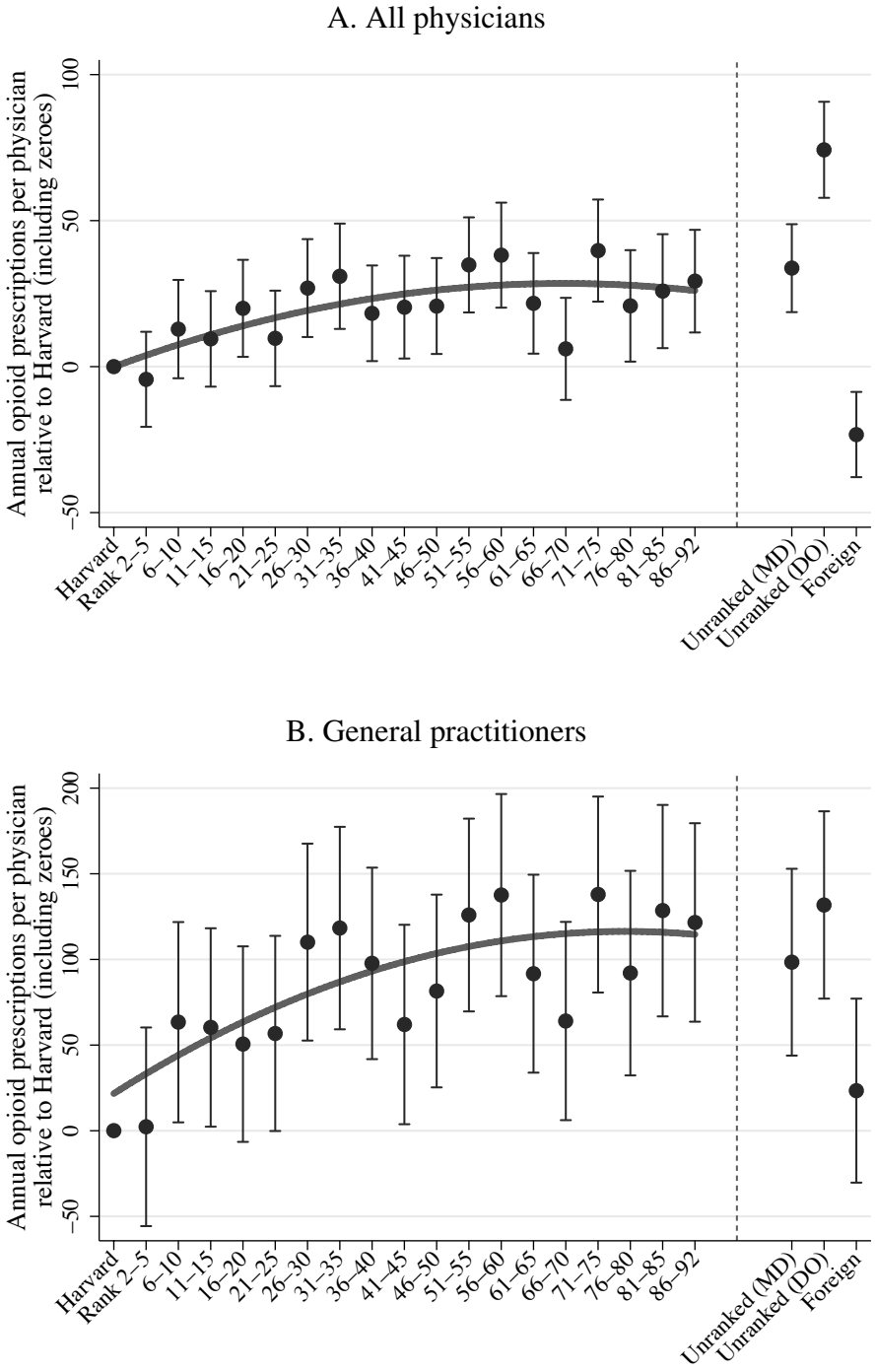
Notes: The above figures depict the coefficient estimates on indicators for medical school rank bins from regressions of opioid prescriptions at the physician-year level on medical school rank bin indicators with year and county fixed effects (variants of Equation (2.1)). Subfigure A includes physicians in hematology or oncology; Subfigure B includes physicians in nephrology. Physician-years with zero opioid prescriptions are included. The bars denote 95% confidence intervals; standard errors are clustered by physician.

Figure 2.13: Opioid prescriptions by medical school rank across graduation cohorts



Notes: The above figures depict the coefficient estimates on indicators for medical school rank bins from regressions of opioid prescriptions at the physician-year level on medical school rank bin indicators with year, specialty, and county fixed effects (Equation (2.1)). Subfigure A includes all physicians; Subfigure B only includes GPs (physicians in general practice, family practice, and internal medicine). Physician-years with zero opioid prescriptions are included. The bars denote 95% confidence intervals; standard errors are clustered by physician.

Figure 2.14: Opioids by medical school rank excluding university-affiliated zip codes



Notes: The above figures depict the coefficient estimates on indicators for medical school rank bins from regressions of opioid prescriptions at the physician-year level on medical school rank bin indicators with year, specialty, and county fixed effects (Equation (2.1)). Physicians whose practice address is in a zip code with a university-affiliated hospital are excluded. Physician-years with zero opioid prescriptions are included. The bars denote 95% confidence intervals; standard errors are clustered by physician.

2.B Supplementary tables

Table 2.5: Composite medical school rankings

1	HARVARD MEDICAL SCHOOL	47	WAKE FOREST SCHOOL OF MEDICINE
2	JOHNS HOPKINS UNIVERSITY SCHOOL OF MEDICINE	48	INDIANA UNIVERSITY SCHOOL OF MEDICINE
3	PERELMAN SCHOOL OF MEDICINE AT UPENN	49	TUFTS UNIVERSITY SCHOOL OF MEDICINE
4	UCSF SCHOOL OF MEDICINE	50	UNIVERSITY OF MIAMI MILLER SCHOOL OF MEDICINE
5	STANFORD UNIVERSITY SCHOOL OF MEDICINE	51	UNIVERSITY OF MASSACHUSETTS MEDICAL SCHOOL
6	WASH U IN ST LOUIS SCHOOL OF MEDICINE	52	UNIVERSITY OF UTAH SCHOOL OF MEDICINE
7	YALE UNIVERSITY SCHOOL OF MEDICINE	53	MEDICAL COLLEGE OF WISCONSIN
8	DUKE UNIVERSITY SCHOOL OF MEDICINE	54	TEMPLE UNIVERSITY SCHOOL OF MEDICINE
9	COLUMBIA U COLLEGE OF PHYSICIANS AND SURGEONS	55	UNIVERSITY OF ILLINOIS AT CHICAGO COLLEGE OF MEDICINE
10	UNIVERSITY OF WASHINGTON SCHOOL OF MEDICINE	56	UNIVERSITY OF TEXAS MEDICAL SCHOOL AT HOUSTON
11	UNIVERSITY OF MICHIGAN MEDICAL SCHOOL	57	SCHOOL OF MEDICINE AT STONY BROOK UNIVERSITY
12	UCHICAGO PRITZKER SCHOOL OF MEDICINE	58	UNIVERSITY OF VERMONT COLLEGE OF MEDICINE
13	DAVID GEFFEN SCHOOL OF MEDICINE AT UCLA	59	MEDICAL UNIVERSITY OF SOUTH CAROLINA
14	VANDERBILT UNIVERSITY SCHOOL OF MEDICINE	60	UT SCHOOL OF MEDICINE AT SAN ANTONIO
15	UNIVERSITY OF PITTSBURGH SCHOOL OF MEDICINE	61	SIDNEY KIMMEL MEDICAL COLLEGE AT THOMAS JEFFERSON U
16	UCSD SCHOOL OF MEDICINE	62	UNIVERSITY OF CONNECTICUT SCHOOL OF MEDICINE
17	WEILL CORNELL MEDICAL COLLEGE	63	UNIVERSITY AT BUFFALO SCHOOL OF MEDICINE
18	NORTHWESTERN UNIVERSITY	64	GEORGE WASHINGTON UNIVERSITY SCHOOL OF MEDICINE
19	ICHAN SCHOOL OF MEDICINE AT MOUNT SINAI	65	UNIVERSITY OF KENTUCKY COLLEGE OF MEDICINE
20	BAYLOR COLLEGE OF MEDICINE	66	UNIFORMED SERVICES F E HEBERT SCHOOL OF MEDICINE
21	UNC AT CHAPEL HILL SCHOOL OF MEDICINE	67	UNIVERSITY OF NEBRASKA COLLEGE OF MEDICINE
22	EMORY UNIVERSITY SCHOOL OF MEDICINE	68	RUSH MEDICAL COLLEGE OF RUSH UNIVERSITY
23	NEW YORK UNIVERSITY SCHOOL OF MEDICINE	69	ST LOUIS UNIVERSITY SCHOOL OF MEDICINE
24	UT SOUTHWESTERN MEDICAL SCHOOL	70	UNIVERSITY OF ARIZONA COLLEGE OF MEDICINE
25	CASE WESTERN UNIVERSITY SCHOOL OF MEDICINE	71	UNIVERSITY OF KANSAS SCHOOL OF MEDICINE
26	UNIVERSITY OF VIRGINIA SCHOOL OF MEDICINE	72	VIRGINIA COMMONWEALTH U SCHOOL OF MEDICINE
27	MAYO MEDICAL SCHOOL	73	WAYNE STATE UNIVERSITY SCHOOL OF MEDICINE
28	UNIVERSITY OF WISCONSIN SCHOOL OF MEDICINE	74	UNIVERSITY OF OKLAHOMA COLLEGE OF MEDICINE
29	UNIVERSITY OF IOWA	75	MEDICAL COLLEGE OF GEORGIA AT GEORGIA REGENTS U
30	UNIVERSITY OF ROCHESTER SCHOOL OF MEDICINE	76	U OF SOUTH FLORIDA HEALTH MORSANI COLLEGE OF MEDICINE
31	BOSTON UNIVERSITY SCHOOL OF MEDICINE	77	RUTGERS ROBERT WOOD JOHNSON MEDICAL SCHOOL
32	WARREN ALPERT MEDICAL SCHOOL OF BROWN	78	RUTGERS NEW JERSEY MEDICAL SCHOOL
33	UNIVERSITY OF ALABAMA SCHOOL OF MEDICINE	79	UNIVERSITY OF MISSOURI COLUMBIA SCHOOL OF MEDICINE
34	OREGON HEALTH & SCIENCE UNIVERSITY	80	UNIVERSITY OF LOUISVILLE SCHOOL OF MEDICINE
35	KECK SCHOOL OF MEDICINE OF THE USC	81	UNIVERSITY OF TENNESSEE COLLEGE OF MEDICINE
36	OHIO STATE UNIVERSITY COLLEGE OF MEDICINE	82	CREIGHTON UNIVERSITY SCHOOL OF MEDICINE
37	UNIVERSITY OF COLORADO SCHOOL OF MEDICINE	83	TEXAS A&M UNIVERSITY COLLEGE OF MEDICINE
38	GEISEL SCHOOL OF MEDICINE AT DARTMOUTH	84	UNIVERSITY OF HAWAII AT MANOA
39	UNIVERSITY OF MINNESOTA MEDICAL SCHOOL	85	UNIVERSITY OF NEW MEXICO SCHOOL OF MEDICINE
40	UNIVERSITY OF MARYLAND SCHOOL OF MEDICINE	86	UNIVERSITY OF ARKANSAS COLLEGE OF MEDICINE
41	ALBERT EINSTEIN COLLEGE OF MEDICINE OF YESHIVA U	87	TEXAS TECH UNIVERSITY SCHOOL OF MEDICINE
42	UNIVERSITY OF CINCINNATI COLLEGE OF MEDICINE	88	DREXEL UNIVERSITY COLLEGE OF MEDICINE
43	UC DAVIS SCHOOL OF MEDICINE	89	UNIVERSITY OF NEVADA SCHOOL OF MEDICINE
44	UC IRVINE COLLEGE OF MEDICINE	90	MICHIGAN STATE UNIVERSITY COLLEGE OF HUMAN MEDICINE
45	UNIVERSITY OF FLORIDA COLLEGE OF MEDICINE	91	WEST VIRGINIA UNIVERSITY SCHOOL OF MEDICINE
46	GEORGETOWN UNIVERSITY SCHOOL OF MEDICINE	92	UNIVERSITY OF SOUTH CAROLINA SCHOOL OF MEDICINE

Notes: The above table lists the composite rankings used for ranked US medical schools. Refer to Section 2.2 for a detailed overview of how these rankings are constructed.

Table 2.6: Summary statistics: prescription data

	By year									
	2006	2007	2008	2009	2010	2011	2012	2013	2014	*All*
Total opioids dispensed (100 million)	2.04	2.14	2.21	2.50	2.57	2.58	2.60	2.52	2.44	21.60
Panel A: All physicians										
N physicians	742,297	742,297	742,297	742,297	742,297	742,297	742,297	742,297	742,297	742,297
N physician-years	.	.	.	.	.	.	.	.		6,680,673
Opioids prescribed (100 million)	1.52	1.60	1.66	1.89	1.92	1.90	1.87	1.75	1.65	15.74
% of total dispensed	74.5	74.9	75.0	75.4	74.7	73.6	71.6	69.5	67.3	72.9
Average per physician-year	204.9	215.8	223.1	254.1	258.5	255.7	251.4	235.8	221.7	235.7
including zeroes	(1.2)	(1.3)	(1.4)	(1.6)	(1.6)	(1.7)	(1.6)	(1.6)	(1.5)	(1.4)
Average per physician-year	287.1	298.7	303.7	337.1	342.0	339.7	331.4	318.7	309.0	319.0
excluding zeroes	(1.7)	(1.8)	(1.8)	(2.0)	(2.1)	(2.1)	(2.1)	(2.1)	(2.1)	(1.8)
Zeroes (% physician-years)	28.6	27.7	26.5	24.6	24.4	24.7	24.2	26.0	28.3	26.1
Panel B: General practitioners										
N physicians	203,576	203,576	203,576	203,576	203,576	203,576	203,576	203,576	203,576	203,576
N physician-years	.	.	.	.	.	.	.	.		1,832,184
Opioids prescribed (100 million)	0.70	0.74	0.77	0.91	0.93	0.92	0.92	0.87	0.82	7.59
% of total dispensed	34.2	34.7	35.0	36.5	36.3	35.8	35.2	34.5	33.5	35.1
Average per physician-year	342.7	364.5	379.9	448.8	458.1	453.0	450.8	427.0	402.4	414.1
including zeroes	(2.8)	(3.0)	(3.1)	(3.5)	(3.6)	(3.5)	(3.5)	(3.3)	(3.2)	(2.9)
Average per physician-year	426.1	446.7	456.3	526.1	534.5	527.8	522.3	501.3	480.3	492.1
excluding zeroes	(3.3)	(3.5)	(3.6)	(3.9)	(4.0)	(4.0)	(3.9)	(3.8)	(3.7)	(3.3)
Zeroes (% physician-years)	19.6	18.4	16.7	14.7	14.3	14.2	13.7	14.8	16.2	15.8

Notes: Standard errors are displayed in parentheses and are clustered by physician. The top row displays the total number of opioids dispensed as reported in the QuintilesIMS data. The next two panels provide summary statistics for our cleaned sample of physicians (Panel A) and GPs (Panel B; physicians in general practice, family practice, and internal medicine). The prescription statistics are raw averages; that is, they do not control for physician specialty or county of practice.

Table 2.7: Summary statistics: county-level prescriptions and mortality

	By year									
	2006	2007	2008	2009	2010	2011	2012	2013	2014	*All*
N counties	3,140	3,140	3,140	3,140	3,140	3,140	3,140	3,140	3,140	3,140
N county-years	.	.	.	.	.	.	.	.	.	28,260
Unweighted averages										
Opioid prescriptions/ capita	0.53	0.55	0.56	0.65	0.65	0.65	0.67	0.66	0.64	0.62
Total deaths/100,000	1008.1	1004.8	1024.6	1002.3	1000.0	1015.6	1024.8	1040.0	1050.9	1019.0
Deaths involving drugs/100,000	12.9	13.7	14.0	14.4	14.7	16.0	15.8	16.7	17.4	15.1
Population-weighted averages										
Opioid prescriptions/ capita	0.64	0.67	0.69	0.77	0.79	0.79	0.79	0.76	0.73	0.74
Total deaths/100,000	813.3	804.8	813.1	794.6	797.9	806.9	809.6	820.7	823.6	809.5
Deaths involving drugs/100,000	14.9	15.2	15.1	15.1	15.5	16.7	16.6	17.5	18.6	16.2

Notes: "Deaths involving drugs" include poisonings from drugs resulting in death as well as deaths in which drug dependence was indicated on the death certificate.

Table 2.8: Opioid prescriptions by detailed medical school rank

		Opioid prescriptions					
			Including zeroes		Excluding zeroes		
	Unique physicians	Total (in millions)	Average per phy-yr	95% CI of average	Average per phy-yr	95% CI of average	Zeroes (% phys-yrs)
A. US trained							
Ranked							
1 (Harvard)	5,762	4.9	94.7	(88, 102)	146.4	(136, 157)	35.3
2-5	17,155	19.4	125.5	(120, 131)	185.1	(178, 192)	32.2
6-10	21,602	31.5	162.2	(156, 168)	231.2	(223, 239)	29.8
11-15	24,031	40.4	187.0	(181, 193)	256.1	(248, 264)	27.0
16-20	21,589	33.1	170.4	(164, 177)	234.1	(226, 242)	27.2
21-25	25,246	43.6	191.9	(186, 198)	262.3	(254, 270)	26.8
26-30	18,734	35.1	208.4	(202, 215)	279.5	(271, 288)	25.4
31-35	19,919	46.2	257.5	(249, 266)	337.8	(327, 349)	23.8
36-40	26,607	52.4	218.8	(213, 225)	286.9	(279, 295)	23.7
41-45	20,308	37.9	207.3	(199, 215)	279.5	(269, 290)	25.8
46-50	29,076	61.5	235.1	(229, 241)	309.7	(302, 318)	24.1
51-55	27,519	57.8	233.5	(227, 240)	305.6	(298, 313)	23.6
56-60	19,393	46.6	267.1	(259, 276)	346.6	(336, 357)	22.9
61-65	22,628	45.2	222.0	(214, 229)	296.0	(286, 306)	25.0
66-70	18,054	36.8	226.7	(219, 234)	309.0	(299, 319)	26.6
71-75	29,563	83.7	314.7	(307, 323)	400.4	(391, 410)	21.4
76-80	18,561	45.7	273.8	(263, 285)	354.0	(340, 368)	22.6
81-85	14,668	38.0	287.7	(277, 298)	372.8	(360, 386)	22.8
86-92	23,533	63.3	299.0	(291, 307)	381.6	(371, 392)	21.6
Unranked							
US (MD)	96,644	234.0	269.0	(265, 273)	348.6	(343, 354)	22.8
US (DO)	49,376	184.1	414.3	(407, 422)	501.7	(493, 510)	17.4
US total	549,968	1241.5	250.8	(249, 252)	330.2	(328, 332)	24.0
B. Foreign trained							
Caribbean	21,154	51.3	269.7	(260, 279)	363.7	(352, 376)	25.9
Canada	7,931	15.8	221.6	(210, 233)	324.7	(309, 341)	31.8
Mexico + C America	11,502	28.3	273.3	(261, 286)	357.4	(342, 373)	23.5
South America	9,501	11.7	136.6	(127, 146)	214.3	(200, 228)	36.3
Western Europe	14,673	20.7	156.8	(148, 166)	242.2	(229, 256)	35.2
E Europe + Russia	12,185	18.8	171.1	(162, 180)	256.4	(243, 270)	33.2
W, S, and C Asia	74,392	118.0	176.2	(172, 180)	257.8	(252, 264)	31.7
SE and E Asia	25,053	42.5	188.6	(181, 196)	291.1	(280, 302)	35.2
Northern Africa	4,843	10.0	230.2	(205, 255)	344.1	(307, 381)	33.1
W and C Africa	4,177	8.1	214.3	(197, 232)	313.7	(289, 339)	31.7
E and South Africa	2,671	3.3	137.4	(121, 154)	215.0	(191, 239)	36.1
Oceania	863	0.8	96.8	(75, 119)	178.0	(139, 217)	45.6
Uncategorized	3,384	3.6	118.0	(101, 135)	233.0	(200, 266)	49.4
Foreign total	192,329	332.8	192.3	(190, 195)	283.1	(279, 287)	32.1
Total	742,297	1574.3	235.7	(234, 237)	319.0	(317, 321)	26.1

Notes: The prescription statistics are raw averages; that is, they do not control for specialty or county of practice. Standard errors are clustered by physician.

Table 2.9: Opioid prescriptions by detailed medical school rank: GPs

		Opioid prescriptions					
			Including zeroes		Excluding zeroes		
	Unique physicians	Total (in millions)	Average per phy-yr	95% CI of average	Average per phy-yr	95% CI of average	Zeroes (% phys-yrs)
A. US trained							
Ranked							
1 (Harvard)	947	1.5	180.2	(153, 207)	248.9	(214, 284)	27.6
2-5	3,175	6.6	232.7	(217, 248)	298.4	(279, 317)	22.0
6-10	4,029	11.7	321.9	(306, 338)	398.1	(379, 417)	19.1
11-15	4,447	13.9	346.4	(330, 363)	410.8	(392, 430)	15.7
16-20	3,693	9.8	295.1	(280, 310)	354.2	(337, 372)	16.7
21-25	4,890	15.6	354.6	(339, 370)	420.0	(403, 437)	15.6
26-30	4,610	16.3	393.3	(377, 410)	444.4	(427, 462)	11.5
31-35	4,718	21.3	500.9	(478, 524)	580.5	(555, 606)	13.7
36-40	7,625	26.2	382.4	(370, 394)	435.8	(423, 449)	12.3
41-45	4,719	15.8	372.0	(354, 390)	436.7	(417, 457)	14.8
46-50	6,295	24.5	432.5	(418, 447)	498.6	(482, 515)	13.3
51-55	6,762	26.2	430.2	(415, 445)	488.3	(472, 505)	11.9
56-60	4,839	21.9	503.8	(483, 525)	562.8	(540, 585)	10.5
61-65	5,107	19.8	431.6	(413, 451)	495.7	(475, 517)	12.9
66-70	4,463	16.3	406.7	(390, 424)	484.7	(466, 503)	16.1
71-75	7,645	38.7	562.5	(546, 579)	627.6	(610, 645)	10.4
76-80	4,228	19.0	499.9	(477, 523)	569.7	(545, 595)	12.3
81-85	3,801	18.1	529.5	(505, 554)	600.9	(575, 627)	11.9
86-92	6,452	31.8	546.9	(528, 566)	613.7	(593, 635)	10.9
Unranked							
US (MD)	23,363	100.8	479.4	(470, 488)	542.4	(533, 552)	11.6
US (DO)	25,020	120.5	534.9	(525, 545)	608.5	(597, 620)	12.1
US total	140,828	576.4	454.8	(451, 458)	522.9	(519, 527)	13.0
B. Foreign trained							
Caribbean	8,904	31.2	388.9	(375, 403)	466.1	(450, 482)	16.5
Canada	2,064	8.6	463.6	(432, 495)	579.8	(543, 617)	20.0
Mexico + C America	4,203	16.3	431.0	(409, 453)	509.9	(485, 534)	15.5
South America	2,325	5.1	243.6	(226, 262)	327.5	(305, 350)	25.6
Western Europe	3,501	9.8	310.2	(287, 333)	396.4	(368, 424)	21.8
E Europe + Russia	4,451	11.3	281.8	(268, 296)	353.7	(337, 370)	20.3
W, S, and C Asia	23,502	61.8	292.1	(284, 300)	384.4	(375, 394)	24.0
SE and E Asia	8,472	25.8	337.9	(324, 352)	434.2	(417, 452)	22.2
Northern Africa	1,477	3.9	291.1	(262, 320)	393.6	(357, 431)	26.0
W and C Africa	1,759	5.4	338.2	(307, 370)	454.0	(414, 494)	25.5
E and South Africa	810	1.4	193.5	(166, 221)	278.1	(241, 315)	30.4
Oceania	138	0.3	202.7	(148, 257)	305.1	(232, 379)	33.6
Uncategorized	1,142	1.7	162.1	(142, 182)	272.9	(242, 304)	40.6
Foreign total	62,748	182.3	322.9	(318, 328)	414.9	(409, 421)	22.2
Total	203,576	758.8	414.1	(411, 417)	492.1	(489, 495)	15.8

Notes: Only GPs are included (physicians in general practice, family practice, and internal medicine). The prescription statistics are raw averages; that is, they do not control for specialty or county of practice. Standard errors are clustered by physician.

Table 2.10: Opioid prescriptions by physician specialty

		Opioid prescriptions					
			Including zeroes		Excluding zeroes		
	Unique physicians	Total (in millions)	Average per phys-yr	95% CI of average	Average per phys-yr	95% CI of average	Zeroes (% phys-yrs)
General Practice	203,576	758.8	414.1	(411, 417)	492.1	(489, 495)	15.8
Orthopaedic Surgery	24,385	147.2	670.5	(661, 681)	750.6	(740, 761)	10.7
Emergency Medicine	33,375	116.5	388.0	(384, 392)	429.7	(425, 434)	9.7
Pain Medicine	3,783	69.5	2040.2	(1947,2133)	2454.7	(2349,2560)	16.9
Physical Med & Rehab	8,218	62.2	841.2	(805, 877)	1028.0	(985,1071)	18.2
Obstetrics & Gynecology	39,794	51.0	142.4	(140, 144)	166.1	(164, 168)	14.2
Anesthesiology	32,585	50.6	172.5	(162, 183)	460.6	(433, 488)	62.6
General Surgery	29,965	49.1	182.2	(179, 185)	224.9	(222, 228)	19.0
Neurology	14,092	30.9	243.3	(230, 256)	321.6	(305, 338)	24.3
Rheumatology	4,949	29.6	664.4	(636, 693)	775.4	(744, 807)	14.3
Hematology & Oncology	19,156	28.7	166.2	(163, 170)	196.7	(193, 201)	15.5
Neurological Surgery	5,540	19.5	391.2	(372, 410)	470.4	(448, 493)	16.8
Urology	10,099	17.6	193.8	(190, 198)	219.9	(216, 224)	11.9
Otolaryngology	9,588	17.3	200.7	(196, 205)	226.9	(222, 231)	11.5
Plastic Surgery	7,914	15.0	210.3	(205, 216)	237.9	(232, 244)	11.6
Sports Medicine	2,593	11.6	496.4	(474, 518)	552.9	(530, 576)	10.2
General other	6,593	10.9	183.2	(175, 191)	218.3	(209, 228)	16.1
Geriatrics	4,518	8.6	212.3	(198, 226)	275.2	(258, 293)	22.9
Cardiovascular Disease	23,274	8.2	39.4	(38, 41)	51.0	(49, 53)	22.8
Pediatrics	50,584	7.5	16.6	(16, 17)	24.5	(24, 26)	32.5

Notes: The displayed specialties are the 20 specialties out of 57 specialties with the most opioid prescriptions collectively from 2006-2014. "General Practice" includes physicians in general practice, family practice, and internal medicine. The prescription statistics are raw averages; that is, they do not control for county of practice. Standard errors are clustered by physician.

Table 2.11: Opioids by rank controlling for specialty and practice county

	Annual opioid prescriptions					
	Including zeroes		Excluding zeroes		I[zero]	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
A. By medical school rank						
1 (Harvard)	0	-	0	-	0	-
2-5	1.91	(4.27)	0.33	(5.99)	-0.02***	(0.00)
6-10	16.30***	(4.42)	16.93***	(6.17)	-0.03***	(0.00)
11-15	17.00***	(4.57)	14.52**	(6.28)	-0.05***	(0.00)
16-20	23.00***	(4.54)	21.86***	(6.24)	-0.05***	(0.00)
21-25	18.49***	(4.50)	17.29***	(6.17)	-0.05***	(0.00)
26-30	30.99***	(4.84)	29.96***	(6.58)	-0.05***	(0.00)
31-35	34.27***	(5.27)	31.98***	(7.04)	-0.06***	(0.00)
36-40	25.37***	(4.69)	23.38***	(6.36)	-0.06***	(0.00)
41-45	25.95***	(5.06)	22.82***	(6.86)	-0.06***	(0.00)
46-50	27.99***	(4.54)	25.86***	(6.15)	-0.06***	(0.00)
51-55	37.16***	(4.54)	36.59***	(6.14)	-0.06***	(0.00)
56-60	38.65***	(5.26)	33.11***	(6.97)	-0.07***	(0.00)
61-65	31.48***	(4.95)	29.34***	(6.71)	-0.06***	(0.00)
66-70	17.83***	(4.99)	21.51***	(6.77)	-0.03***	(0.00)
71-75	49.85***	(5.15)	44.37***	(6.81)	-0.07***	(0.00)
76-80	38.96***	(6.34)	35.70***	(8.29)	-0.07***	(0.00)
81-85	36.86***	(5.99)	35.10***	(7.83)	-0.07***	(0.00)
86-92	41.75***	(5.25)	34.50***	(6.95)	-0.07***	(0.00)
Unranked US (MD)	39.89***	(4.03)	35.69***	(5.58)	-0.07***	(0.00)
Unranked US (DO)	85.63***	(4.95)	85.53***	(6.46)	-0.06***	(0.00)
Foreign	-14.07***	(3.79)	-4.55	(5.36)	0.02***	(0.00)
B. By regions of training						
Rank 1-30	0	-	0	-	0	-
31-60	14.10***	(1.73)	12.53***	(2.23)	-0.02***	(0.00)
61-92	19.67***	(2.00)	17.59***	(2.55)	-0.02***	(0.00)
Unranked US (MD)	22.49***	(2.21)	19.18***	(2.81)	-0.03***	(0.00)
Unranked US (DO)	67.99***	(3.61)	68.79***	(4.28)	-0.02***	(0.00)
Caribbean	5.88	(4.60)	14.96**	(5.92)	0.01***	(0.00)
Canada	-4.69	(5.36)	14.60**	(7.31)	0.07***	(0.00)
Mexico + C America	29.99***	(5.90)	40.17***	(7.40)	-0.01***	(0.00)
South America	-46.63***	(4.66)	-40.44***	(6.77)	0.08***	(0.00)
Western Europe	-13.49***	(4.42)	-2.33	(6.45)	0.07***	(0.00)
E Europe + Russia	-44.53***	(4.67)	-42.60***	(6.57)	0.05***	(0.00)
W, S, and C Asia	-47.78***	(2.40)	-40.53***	(3.30)	0.06***	(0.00)
SE and E Asia	-40.19***	(3.71)	-29.63***	(5.36)	0.07***	(0.00)
Northern Africa	-19.20	(11.81)	1.39	(16.90)	0.06***	(0.00)
W and C Africa	-38.97***	(8.47)	-19.44*	(11.70)	0.08***	(0.00)
E and South Africa	-57.82***	(7.61)	-55.52***	(10.77)	0.07***	(0.01)
Oceania	-58.35***	(10.37)	-56.02***	(16.23)	0.14***	(0.01)
Uncategorized	-89.76***	(8.59)	-70.70***	(15.59)	0.20***	(0.01)

Notes: The prescription statistics control for specialty and county of practice and are relative to either Harvard (Panel A) or the top 30 schools (Panel B). Standard errors are clustered by physician.

Table 2.12: Opioids by rank controlling for specialty and practice county: GPs

	Annual opioid prescriptions					
	Including zeroes		Excluding zeroes		I[zero]	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
A. By medical school rank						
1 (Harvard)	0	-	0	-	0	-
2-5	6.64	(15.31)	5.42	(19.72)	-0.03***	(0.01)
6-10	49.94***	(15.40)	50.82***	(19.72)	-0.05***	(0.01)
11-15	55.59***	(15.65)	47.53**	(19.83)	-0.08***	(0.01)
16-20	46.20***	(15.20)	39.53**	(19.35)	-0.08***	(0.01)
21-25	60.95***	(15.16)	51.25***	(19.30)	-0.08***	(0.01)
26-30	97.40***	(15.73)	87.96***	(19.73)	-0.10***	(0.01)
31-35	111.66***	(16.59)	103.54***	(20.69)	-0.09***	(0.01)
36-40	88.33***	(14.85)	78.90***	(18.92)	-0.10***	(0.01)
41-45	64.06***	(15.93)	52.70***	(20.09)	-0.08***	(0.01)
46-50	86.77***	(15.08)	77.79***	(19.12)	-0.10***	(0.01)
51-55	113.82***	(15.07)	105.32***	(19.09)	-0.10***	(0.01)
56-60	133.52***	(16.74)	116.44***	(20.65)	-0.11***	(0.01)
61-65	91.34***	(15.87)	77.10***	(19.91)	-0.10***	(0.01)
66-70	66.45***	(15.89)	73.15***	(20.02)	-0.06***	(0.01)
71-75	137.10***	(15.77)	119.81***	(19.70)	-0.11***	(0.01)
76-80	80.64***	(16.72)	64.85***	(20.68)	-0.09***	(0.01)
81-85	118.01***	(17.67)	106.02***	(21.62)	-0.10***	(0.01)
86-92	115.03***	(16.00)	92.48***	(20.01)	-0.11***	(0.01)
Unranked US (MD)	98.00***	(14.05)	79.71***	(18.16)	-0.11***	(0.01)
Unranked US (DO)	123.64***	(14.33)	120.13***	(18.41)	-0.09***	(0.01)
Foreign	15.47	(13.55)	31.14*	(17.73)	-0.02	(0.01)
B. By regions of training						
Rank 1-30	0	-	0	-	0	-
31-60	46.39***	(4.56)	41.19***	(5.12)	-0.03***	(0.00)
61-92	51.28***	(4.95)	42.97***	(5.54)	-0.03***	(0.00)
Unranked US (MD)	44.58***	(5.44)	31.37***	(6.07)	-0.04***	(0.00)
Unranked US (DO)	71.10***	(6.06)	72.58***	(6.72)	-0.02***	(0.00)
Caribbean	15.01*	(7.73)	23.55***	(8.80)	0.00	(0.00)
Canada	35.91**	(15.25)	71.68***	(17.81)	0.05***	(0.01)
Mexico + C America	69.48***	(11.24)	83.89***	(12.67)	-0.01**	(0.00)
South America	-93.09***	(9.67)	-79.11***	(11.85)	0.08***	(0.01)
Western Europe	2.84	(11.12)	22.31*	(13.52)	0.04***	(0.01)
E Europe + Russia	-37.95***	(7.72)	-26.09***	(9.00)	0.03***	(0.00)
W, S, and C Asia	-74.50***	(5.00)	-54.32***	(5.99)	0.07***	(0.00)
SE and E Asia	-27.10***	(7.73)	-7.07	(9.32)	0.05***	(0.00)
Northern Africa	-74.43***	(14.87)	-49.87***	(18.71)	0.09***	(0.01)
W and C Africa	-48.76***	(15.84)	-12.53	(19.83)	0.09***	(0.01)
E and South Africa	-139.10***	(14.63)	-131.26***	(19.23)	0.13***	(0.01)
Oceania	-132.62***	(28.13)	-112.65***	(36.33)	0.16***	(0.03)
Uncategorized	-156.49***	(10.95)	-118.82***	(15.58)	0.23***	(0.01)

Notes: Only GPs are included (physicians in general practice, family practice, and internal medicine). The prescription statistics control for specialty and county of practice and are relative to either Harvard (Panel A) or the top 30 schools (Panel B). Standard errors are clustered by physician.

Table 2.13: Opioids by medical school rank across cohorts: pain specialists

	Annual opioid prescriptions (including zeroes)				
	(1)	(2)	(3)	(4)	(5)
Graduation cohort:	All	$\leq$ 1975	1976-1985	1986-1995	1996-2005
Medical rank	-2.825	-40.905	-4.020	16.392	7.412
	(9.272)	(69.125)	(32.154)	(21.533)	(11.196)
(Medical rank)^2	0.031	0.093	0.080	-0.175	-0.001
	(0.101)	(0.878)	(0.358)	(0.231)	(0.113)
Constant	1355.253***	3964.478***	2343.257***	1575.692***	-71.116
	(199.171)	(1079.542)	(650.081)	(431.728)	(266.479)
N (physician-years)	15,318	882	2,790	5,094	6,552
R^2	0.353	0.657	0.613	0.538	0.425

Notes: The above table presents output from regressions of opioid prescriptions at the physician-year level on a quadratic in medical school rank with year, specialty, and county fixed effects (Equation (2.2)) estimated separately across different graduation cohorts. Standard errors are clustered by physician. Only physicians specializing in pain medicine are included.

Table 2.14: Opioids by medical school rank excluding university-affiliated zip codes

	Annual opioid prescriptions (including zeroes)			
	All physicians		General practitioners	
	(1)	(2)	(3)	(4)
Medical rank	0.635***	0.814***	2.418***	2.325***
	(0.109)	(0.168)	(0.292)	(0.415)
(Medical rank)^2	-0.003***	-0.006***	-0.018***	-0.018***
	(0.001)	(0.002)	(0.003)	(0.004)
Constant	111.570***	93.507**	354.644***	391.920***
	(31.767)	(36.805)	(6.264)	(9.011)
Excl. uni. zips	No	Yes	No	Yes
N (physician-years)	3,635,532	1,922,193	832,005	539,064
R^2	0.194	0.209	0.178	0.186

Notes: The above table presents output from regressions of opioid prescriptions at the physician-year level on a quadratic in medical school rank with year, specialty, and county fixed effects (Equation (2.2)). Columns (1)-(2) include all physicians; Columns (3)-(4) only include GPs (physicians in general practice, family practice, and internal medicine). Columns (2) and (4) exclude physicians whose practice address is in a zip code with a university-affiliated hospital. Standard errors are clustered by physician.

Table 2.15: Opioid prescriptions and deaths involving drugs

	ln(Deaths involving drugs per capita)	
	(1)	(2)
ln(Opioid prescriptions per capita)	0.286***	0.150***
	(0.026)	(0.040)
County FEs	No	Yes
N (county-years)	22,801	22,801
R^2	0.118	0.706

Notes: The above table presents output from regressions of log deaths involving drugs per capita at the county-year year on log opioid prescriptions per capita at the county-year level. All specifications include year fixed effects. Standard errors are clustered by county. We define "deaths involving drugs" as both poisonings from drugs resulting in death as well as deaths in which drug dependence was indicated on the death certificate.

Chapter 3

Physician Payments and Access to Care: Evidence from Medicaid*

3.1 Introduction

Despite being covered by the nation's largest insurer, Medicaid beneficiaries often have a hard time finding available health care providers. Many doctors either do not accept Medicaid or are not currently accepting new Medicaid patients: in 2009, office-based physicians were 35% less likely to accept new patients covered by Medicaid than by private insurance (MACPAC, 2011). Whether this preference for the privately insured is driven by differences in reimbursement generosity—rather than Medicaid payment delays, complex program requirements, and concerns about managing the care of difficult patients—remains an open question (Long, 2013; Rosenbaum, 2014). Will increasing Medicaid payments to primary care physicians improve access and health among beneficiaries?

In this paper, we exploit exogenous variation in the generosity of Medicaid reimbursement rates for primary care providers to estimate the effect of physician reimbursement on access and health outcomes. Most of the variation in physician payments comes from a

*This chapter is joint work with Diane Alexander. Materials from this chapter were presented at the 2017 CSWEP CeMENT workshop, the 2017 Society of Labor Economists Meeting, the 2017 Midwest Health Economics Conference, the 2017 Barcelona GSE Summer Forum, the 2017 International Health Economics Association Congress, and the 2018 NBER Program on Children meeting. We thank Marguerite Burns, Janet Currie, Pinar Karaca-Mandic, Anthony Keats, Ilyana Kuziemko, Nicole Maestas, and Melissa McInerney for helpful comments. Generous financial support from the Griswold Center for Economic Policy Studies and the Center for Health and Wellbeing at Princeton University is gratefully acknowledged.

federal mandate that states increase Medicaid payments for primary care services to Medicare levels in 2013 and 2014.[1] As Medicaid is administered at the state level, physician payments varied geographically by large margins before the mandate went into effect. A few states already had very generous Medicaid payments relative to Medicare, and thus were unaffected. In other states, however, the payments to doctors for primary care services more than doubled. Before the primary care rate increase, Medicaid programs paid doctors just 66 percent of Medicare payments for the same services on average across states (Zuckerman and Goin, 2012). The rate increase was designated in Section 1202 of the Affordable Care Act (ACA), was federally funded, and was intended to ease the absorption of new Medicaid enrollees entering through the ACA's Medicaid expansion by encouraging primary care physicians to participate in Medicaid (Blumenthal and Collins, 2014).

We find that increased physician reimbursement for new Medicaid patients is associated with statistically and economically significant improvements in access to primary care, using a new database of state-level Medicaid reimbursement rates for primary care services from 2009 to 2015, combined with access measures from the National Health Interview Survey (NHIS). A $10 increase in Medicaid payments to primary care doctors is associated with a 26 percent decrease in parents reporting having trouble finding a doctor for their Medicaid-covered children, and decreases in reports of doctors telling adult Medicaid beneficiaries that they are not accepting new patients or their insurance of 14 and 11 percent, respectively. Having an easier time finding a doctor also translates into seeing doctors more often; a $10 increase in Medicaid payments is associated with an 1.5 percent increase in the probability that Medicaid beneficiaries visited a doctor in the past two weeks.

[1]The primary care services covered by the fee boost include evaluation and management services and vaccine administration provided by physicians in family medicine, general internal medicine, and pediatric medicine.

Increased physician reimbursement under Medicaid is further associated with improvements in self-reported health and school attendance among the program's beneficiaries. We find modest improvements in self-reported health across all Medicaid beneficiaries, as well as dramatic improvements in school attendance among children, which come primarily from the far right tail of the absence distribution. Using a combination of self-reported data from the NHIS and educational attainment data from the National Assessment of Educational Progress (NAEP), we find that a $10 increase in Medicaid payments is associated with a decrease in chronic absenteeism of 2 to 8 percent, with the largest reductions coming from absences due to illness and injury. Finally, there is no evidence that the benefits of increasing Medicaid payment rates are offset by negative spillovers for the privately insured.

Of course, the changes in Medicaid payments stemming from the primary care fee boost did not occur in isolation. The US health care system in general, and Medicaid in particular, experienced many changes between 2009 and 2015. Following the 2012 decision by the Supreme Court, in 2014, 27 states and the District of Columbia expanded their Medicaid programs to include coverage for low-income adults without children. While the timing is similar, we do not believe that our results are confounded by the 2014 Medicaid expansion for three reasons. First, we find the strongest effects of the primary care rate increase on access and health among children, whose eligibility was essentially unaffected by the Medicaid expansions. Second, we find similar effects in states that did and did not expand their Medicaid programs under the ACA. Finally, we find a similar relationship between payments and access using variation in Medicaid payments from before the 2014 Medicaid expansion.

While there is a large empirical literature studying the effect of Medicaid coverage itself on the use of medical services and health outcomes (Currie et al., 1995; Currie and Gruber, 1996b,a; Finkelstein et al., 2012; Baicker et al., 2013; Buchmueller et al., 2014; Alexander and Currie, 2017), there is less work examining how Medicaid program generosity affects

access to treatment. Recent work studying the impact of reimbursement levels on physician participation in Medicaid has been hampered by two important data limitations (Shen and Zuckerman, 2005; Atherly and Mortensen, 2014; Chen, 2014; Callison and Nguyen, 2017).[2] First, most states have not made large changes to their Medicaid reimbursement rates for primary care in the last decade. Without significant and plausibly exogenous variation in payment rates within a state over time, researchers must rely on cross-sectional evidence that is likely to suffer from omitted variable bias, or small changes in just a few states. Second, the rise of Medicaid Managed Care that began in the early 1990s has made it difficult to know how much doctors are actually reimbursed through Medicaid.

Despite the fact that 60 percent of Medicaid beneficiaries were enrolled in comprehensive risk-based managed care plans in 2014, states have little knowledge about how or how much MCOs pay their doctors. Under fee-for-service, state Medicaid programs pay doctors a fixed amount for each service provided to beneficiaries. Although time consuming, these reimbursement rates are theoretically available by contacting each state (though prior work almost exclusively uses infrequently published secondary sources, such as the Urban Institute's Medicaid to Medicare fee index or the American Academy of Pediatrics Medicaid Reimbursement Reports). Conversely, under managed care states typically pay managed care organizations (MCOs) a fixed amount per beneficiary to provide all covered services, and the MCO pays providers for the services.[3]

We address both of these problems simultaneously by exploiting a federally mandated change to both Medicaid fee-for-service and managed care reimbursement rates for primary

[2]Using a cross-sectional Medicaid payment variation from 1975, Long et al. (1986) find that low physician reimbursement levels do not impede access to ambulatory care. Using a similar strategy for 1987, Cohen and Cunningham (1995) demonstrate that higher Medicaid fees are associated with both primary care doctors accepting more Medicaid patients and a greater likelihood of children having a doctor's office as a usual source of care. Baker and Royalty (2000) look at changes in Medicaid-to-private fee ratios between 1986 and 1990, and find that increases in this ratio are associated with increases in the percent poor of patients seen by office based physicians and decreases in the percent poor of patients seen by public physicians. As there have been important structural changes to both Medicaid and the US healthcare system over the past two decades, these findings from the 1970s and 1980s may no longer hold.

[3]Comprehensive risk-based managed care is the dominant model in Medicaid managed care, whereby states shift the financial risk for serving their Medicaid beneficiaries to the managed care organizations (Paradise, 2014).

care doctors. As Medicaid generosity varies considerably across states, increasing payments to Medicare levels had large and heterogeneous impacts across states. Furthermore, since state Medicaid payments were required to achieve parity with Medicare for both their fee-for-service and managed care programs, we know exactly how much doctors were reimbursed under Medicaid in 2013 and 2014. To estimate payments in the pre-period, we combine quarterly state-level fee-for-service rates collected directly from each state's Medicaid office with state-level Medicaid managed care to fee-for-service reimbursement ratios for primary care services and data on the fraction enrolled in each system in each state. We are thus able to examine the effects of changing physician payments on the entire Medicaid system, rather than just the rapidly shrinking fee-for-service portion.

To our knowledge, we are the first comprehensive study of the effects of the Medicaid primary care rate increase on access and health outcomes. Early work on the program has been hampered by lags in data availability. The only study of the fee boost of which we are aware is an early audit study, which finds that the payment increase was associated with large increases in appointment availability for Medicaid patients (Polsky et al., 2015). The research team behind Polsky et al. (2015) called doctors' offices in ten states over two time periods—11/2012-3/2013 and 5/2014-7/2014—and measured changes in appointment availability between the two periods.[4] In contrast, we use a large dataset that covers every state from 2009 to 2015, continuous variation in the magnitude of the fee boost across states (incorporating both fee-for-service and managed care payment rates), and look at both access and health outcomes measures.

The rest of the paper proceeds as follows. We provide an overview of our data in Section 3.2. In Section 3.3, we introduce our empirical strategy. Results are presented in Section 3.4. Section 3.5 provides a variety of robustness checks. Section 3.6 provides a discussion and concludes.

[4]Polsky et al. (2017) update the paper with a second follow up in 2016, though the fee boost expired in 8 out of 10 states studied in 2014.

3.2 Data

We use three main data sources to document how changing reimbursement rates for physicians affect access to health care services and the health of Medicaid beneficiaries. To measure physician reimbursement, we construct a new dataset containing Medicaid fees for evaluation and management services for all states from 2009 to 2015. To measure access and health outcomes, we use the National Health Interview Survey (NHIS)—a large survey conducted each year to track the illnesses and disabilities in the US. Finally, to corroborate the NHIS outcomes related to schooling, we use data on school absences and test scores from the National Center for Education Statistics. These datasets are supplemented with information from the Health Resources and Services Administration's Area Resource Files (ARF) to control for spatial differences in health care resources.

3.2.1 Medicaid reimbursement rates

Our primary explanatory variable is the amount Medicaid pays doctors for new patient evaluation and management services across states and over time. Under fee-for-service, there are five Medicaid reimbursement rates for these services, each corresponding to a specific length and complexity of the visit. We obtained historical fee-for-service payment data for these five codes by contacting the Medicaid offices of all 50 states and the District of Columbia.[5] Our main results use reimbursement rates associated with a visit of mid-level complexity and severity (CPT 99203). According to CMS Medicare utilization statistics for Part B, CPT 99203 is by far the most billed new patient evaluation and management code from 2009 to 2015; unfortunately, analogous reports are not published for Medicaid.

The amount doctors are paid under fee-for-service Medicaid does not tell the full story, however, as around half of Medicaid beneficiaries were enrolled in comprehensive risk-basked managed care over our time period. We take Medicaid managed care into ac-

[5]Our payment data series is complete with the exception of Tennessee and South Dakota. Refer to Appendix 3.A.2 for details on how payment rates are imputed for these two states.

count by creating an expected Medicaid payment measure that combines the state-level fee-for-service data with state-level managed care to fee-for-service payment ratios and state-level managed care enrollment. To construct our main payment measure, we first create an expected payment for Medicaid managed care that scales the fee-for-service rates by the managed care to fee-for-service payment ratio for primary care services. These payment ratios come from a Government Accountability Office (GAO) report documenting the difference between managed care and fee-for-service payments under Medicaid at the state level in 2010 (Yocom, 2014).[6] Using data from the Centers for Medicare and Medicaid Services (CMS) on the percent of Medicaid beneficiaries enrolled in managed care annually in each state (see Figure 3.7), we then define the overall expected payment from Medicaid as the enrollment-weighted average of the fee-for-service payment and the expected managed care payment.[7]

Both the initial geographical variation in Medicaid payment rates and the changes over our sample period are substantial. Figure 3.1 shows the variation in our constructed measure of Medicaid primary care fees across the US at the start of our period (2009) and in the first year of the primary care rate increase (2013). In the first quarter of 2009, the expected Medicaid payment for treating a new patient (CPT 99203) varied from $37 to $160. The bottom dropped out of the payment distribution when the fee boost went into effect in 2013, with the least generous state paying $101 and the most generous state paying

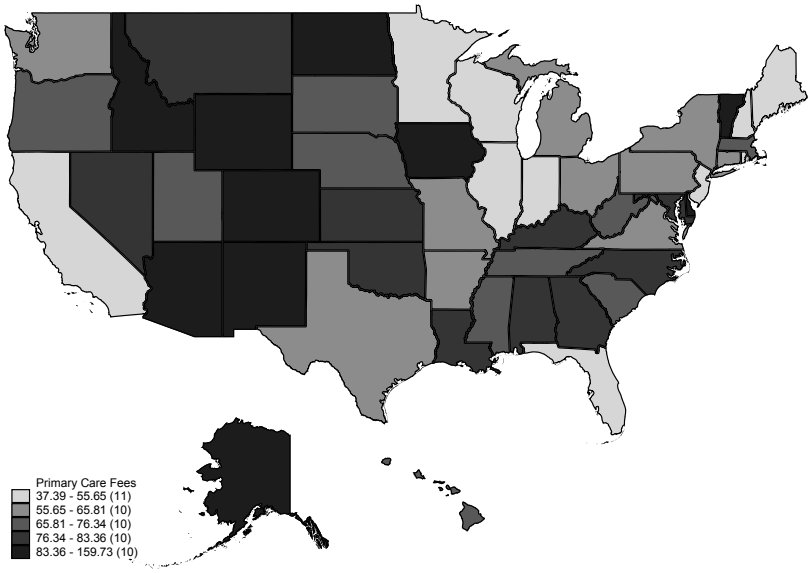
[6]The GAO data only gives a Medicaid managed care to fee-for-service ratio for 20 states (see Table 3.7). We use the reported ratio for the states in the report and the median ratio (5% more for managed care) for the missing states. Our results are robust to a range of assumptions about the Medicaid managed care to fee-for-service ratios for the remaining states, such as using only the states in the GAO report, and imputing missing states using the mean.

[7]That is, letting R_{sy}^{FFS} denote the Medicaid fee-for-service reimbursement rate in state s in year y, $\left(\frac{R^{MC}}{R^{FFS}}\right)_{s,2010}$ the managed care to fee-for-service payment ratio in state s in 2010, and $\%B_{sy}^{MC}$ the fraction of Medicaid beneficiaries enrolled in a managed care plan in state s in year y, the overall expected Medicaid reimbursement for evaluation and management services in each state-year before the fee increase is approximated by

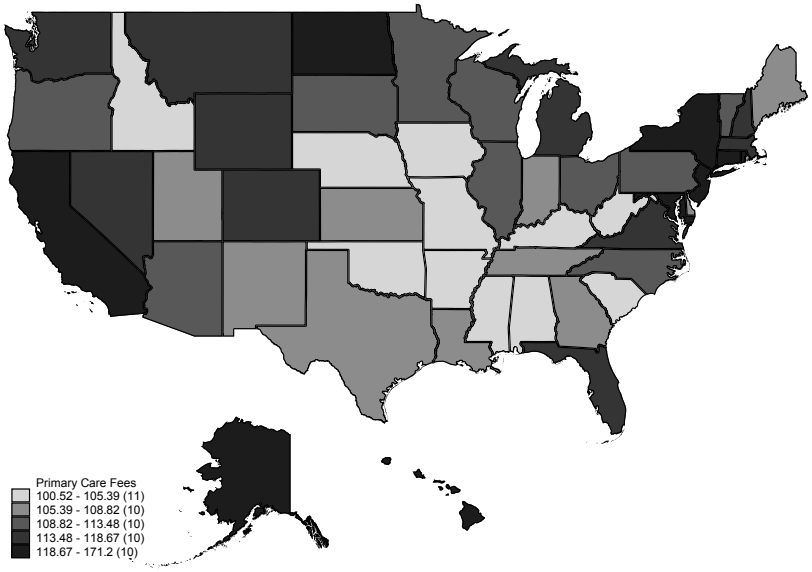
$$\tilde{R_{sy}} = (1 - \%B_{sy}^{MC}) \cdot R_{sy}^{FFS} + \%B_{sy}^{MC} \cdot R_{sy}^{FFS} \cdot \left(\frac{R^{MC}}{R^{FFS}}\right)_{s,2010}$$

Figure 3.1: Maps of state-level Medicaid fees for new patient primary care services

2009



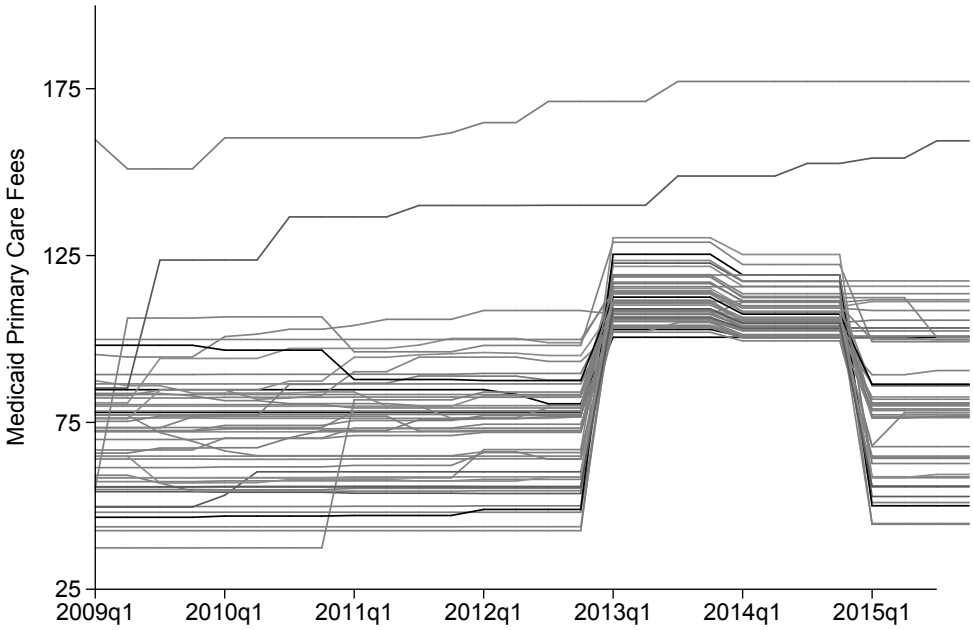
2013



Notes: The above maps depict yearly averages of Medicaid payments for each state in 2009 and 2013. The fees used are weighted averages of Medicaid fee-for-service and managed care payments for new patient management and evaluation services, where the weights are the fraction of beneficiaries enrolled in each type of plan at the state-year level.

doctors just over $170. In fact, after the fee boost, all states' fees were within the range of the top quintile of states in the previous quarter. While there were some changes in Medicaid payment rates prior to 2013 (see Figure 3.2), most of our variation comes from the primary care rate increase mandated by the ACA.

Figure 3.2: State-level Medicaid fees for new patient primary care services over time



Notes: The above figure depicts quarterly averages of Medicaid payments for each state from 2009 to 2016. The fees used are weighted averages of Medicaid fee-for-service and managed care payments for new patient management and evaluation services, where the weights are the fraction of beneficiaries enrolled in each type of plan at the state-year level. The top two lines are Alaska (1) and North Dakota (2); the bottom two lines in 2009 are New Hampshire (50) and Minnesota (51).

While the federally mandated rate increase in 2013 and 2014 provides exogenous variation in reimbursement rates for the later half of our time period, we also include changes to Medicaid payments made between 2009 and 2012. These earlier changes in Medicaid reimbursement rates are driven by local legislators making state budget decisions that are unlikely to be related to specific concerns over new patient evaluation and management. In particular, the we believe the precise timing of adoption is plausibly exogenous, as it comes from the idiosyncratic nature of legislative cycles. As a practical matter, however, only a handful of states made meaningful changes to their reimbursement rates between

2009 and 2012, and these fee changes are dwarfed in both number and magnitude by those from the primary care fee boost. Across states, the average change in payments from 2009 to 2012 was $4.27, and 25 states made no changes to their primary care fee schedules. The stickiness of physician payments under Medicaid highlights the difficulty of estimating how doctors respond to changing Medicaid payments; while we did not systematically collect data on payment rates before 2009, the effective dates on the payment information supplied by some states suggest that no changes had been made to their primary care physician payments since well before our time period, and in one case since 1980.

When the primary care rate increase was initially passed, it was unclear whether the federal funding for the higher rates would extend beyond 2014. In the end, the funding for the higher rates was not extended and many states chose to return to their previous payment levels in 2015 (see Figures 3.2 and 3.8). While this provides another large change in state-level payment rates, states may have made this decision based on their experiences during the primary care rate increase. Thus, in our main analysis we do not use the variation in payments coming from the fee boost turning off in 2015. Instead, we examine the effects of this reverse experiment on health and outcome measures separately and note the potential endogeneity concerns.

Although the federal government mandated that states increase their Medicaid payments to primary care providers starting on January 1st, 2013, many states experienced implementation delays. We do not incorporate state-level variation in the implementation of the primary care rate increase into our Medicaid payment variable; that is, we use the payment rates reported by the state as effective in each month and year. States with implementation delays were required to retroactively pay doctors the difference between the amount paid and the enhanced Medicaid rate for dates of service starting January 1, 2013. We therefore believe that even if a state had a delayed implementation, the behavior of physicians, who are largely not credit constrained, should respond at the start of the fee increase rather than when the higher payments were actually released.

Finally, we can only expect physician behavior to respond to increased payment rates if doctors are aware of changes in reimbursement. While we cannot formally assess how much physicians know about reimbursements under Medicaid, we note that the federally mandated primary care rate increase was covered widely by news outlets. For example, *The Washington Post* published an article on December 21, 2012—before the fee increase went into effect—titled "Obamacare is about to give Medicaid docs a 73 percent raise." As payments more than doubled for primary care physicians in some states, we find it reasonable that physicians would take notice of the change, and thus there is scope for physician behavior to respond.

3.2.2 National Health Interview Survey

The National Health Interview Survey is the largest in-person household health survey in the US, and is designed to measure the amount, distribution, and effects of illness and disability in the United States, and the services rendered for or because of such conditions. Importantly, the sample size is large enough for the survey to be representative at the state level, and information on insurance coverage and type of insurer are collected.

The outcome variables we draw from the NHIS can be divided into two broad categories: (1) access to and use of health care services and (2) health outcomes. We use outcomes from three NHIS components: family, sample child, and sample adult. The family component collects demographic information and answers to basic questions (e.g., health status) for all members in the family. The sample child and sample adult components each sample one child and one adult in the family, respectively, and ask a longer list of more detailed questions (e.g., days of school or work missed in the past year). Sample sizes are thus more limited when working with questions only asked to the sample child or sample adult relative to the full family sample (see Table 3.1).

Table 3.1: Summary statistics: outcome measures

		Medicaid	Private
Full Sample	Office visit in past 2 weeks	0.196	0.174
	N	95,736	337,717
	Fair or poor health	0.174	0.061
	N	95,786	338,114
	Excellent or very good health	0.566	0.728
	N	95,786	338,114
Child Subsample	Trouble finding a doctor	0.021	0.008
	N	16,786	24,454
	No usual place of care	0.028	0.020
	N	21,249	34,261
	14+ school days missed	0.054	0.028
	N	14,630	27,909
Adult Subsample	Don't accept new patient	0.055	0.016
	N	14,806	80,409
	Don't accept insurance	0.075	0.022
	N	14,805	80,399
	Work days missed	4.927	3.731
	N	6,295	77,571

Notes: The reported statistics are weighted using the sample weights provided in the NHIS. The exact survey questions used are outlined in Appendix 3.A.1. Fewer children report days of missed school relative to other child outcomes since a child must be at least five years old to be asked this question. Similarly, only adults with employment histories are asked how many days of work they missed in the past year.

To measure access to health care services, we consider whether respondents had a doctors' office visit in the past two weeks, and whether respondents report difficulty with doctors either not accepting new patients or not accepting their insurance.[8] For children, we further consider indicators denoting whether parents report having difficulty finding a doctor to see their child and whether their child has a usual place of care. As seen in Table 3.1, Medicaid beneficiaries have a similar likelihood of visiting a doctor in the past two weeks to the privately insured. However, those covered by Medicaid are much more likely to report difficulties finding doctors.

[8]The exact survey questions used are outlined in Appendix 3.A.1. All questions are asked over our full sample period except those asking whether children and adults had trouble finding a doctor, which started in 2011.

To measure health outcomes, we focus on summary measures that are applicable to the entire health distribution. First, we consider indicators denoting whether people rate their health as excellent/very good or fair/poor. While self-reported, this measure represents a summary of a person's view of their own health status, and how it affects their day to day life. For a more objective measure, we further consider the number of school and work days respondents report having missed in the past year.

Baseline differences in health status between those covered by Medicaid and private insurers are large. Survey respondents covered by Medicaid are almost three times more likely to report being in fair or poor health than the privately insured (Table 3.1). Medicaid beneficiaries also report missing many more days of school and work per year than the privately insured. Assuming a 180 day school year, Table 3.1 suggests that children on Medicaid have an absentee rate of 6.7 percent. Privately insured children, on the other hand, report a much lower absentee rate of 4.1 percent, which is more in line with previous research on school attendance (Fowler et al., 1992; Currie et al., 2009). Given that school absences have been shown to limit human capital attainment, these differences in absenteeism may translate into meaningful differences in later life outcomes (Grossman and Kaestner, 1997; Currie et al., 2009). Furthermore, as most school absences are attributable to either respiratory infections or gastroenteritis, illnesses that are most commonly treated in a primary care setting, school absenteeism may be particularly responsive to increased access to primary care (Gilliland et al., 2001).

The NHIS contains many different outcome variables that represent different facets of a person's health, as well as their interactions with the health care system. First and foremost, we expect higher Medicaid payments to doctors to influence Medicaid beneficiaries' access to treatment. When considering the health effects of increases in primary care, however, selecting outcomes becomes more difficult for two reasons. First, as primary care is often preventive, health improvements which may follow an increase in access will likely be slow to appear. Second, even in a large survey, the occurrence of rare conditions and events such

as the use of hospitals and emergency rooms is fairly sparse. Because of these limitations, we use summary measures which are relevant to the entire population, and could reasonably be quickly influenced by changes in the availability of primary care.

Our main sample contains the population for which changes in Medicaid payments to doctors are directly relevant: Medicaid beneficiaries. The sample size is large, with approximately 96,000 Medicaid beneficiaries in the full survey over our sample period, and between 15,000 and 17,000 Medicaid beneficiaries in the child and adult sub-samples, respectively. The sample size varies somewhat depending on the number of years a question was asked (see Table 3.6 for a list of outcomes and the years they are available). We also look at the privately insured population for comparison, to examine whether the effects of changes in Medicaid reimbursement rates spill over into the care of other groups. If primary care doctors are capacity constrained and therefore unable to increase the number of patients they see, incentivizing doctors to see more Medicaid patients could lead to reductions in access for the privately insured.

To control for differences in the availability of medical resources and population demographics across states and over time, we include both individual demographic controls from the NHIS and county-level characteristics from the ARF. Table 3.2 reports summary statistics for included individual and county-level controls by insurer. Relative to the privately insured, Medicaid beneficiaries have lower income and education levels, live in larger families, are less likely to be married, and are more likely to be black and Hispanic. Furthermore, respondents covered by Medicaid live in poorer, more densely populated areas with fewer health care providers per capita.

Table 3.2: Summary statistics: individual and county controls

	All	Medicaid	Private
Avg. Medicaid new patient fee	80.1	81.7	80.0
Individual level controls			
Pct male	48.9	43.9	48.9
Pct US citizen	92.7	93.6	95.9
Average age	37.3	24.2	38.4
Pct black	13.2	25.2	9.7
Pct Hispanic	16.7	29.6	10.1
Welfare	12.7	48.3	3.5
Married	58.2	40.0	66.6
Live with partner	5.5	4.9	4.5
Pct family w/ no children	47.9	22.9	50.3
Pct family w/ 1 child	17.6	19.3	17.9
Pct family w/ 2 children	19.1	24.3	19.7
Pct family w/ 3 children	9.9	18.5	8.6
Pct family w/ 4 children	3.6	9	2.5
Pct family w/ 5+ children	1.9	5.9	1.0
Pct homeowner	33.4	64.5	22.3
Pct income:poverty line: <1	13.8	47.5	3.6
Pct income:poverty line: 1-1.99	16.6	28.5	9.7
Pct income:poverty line: 2-3.99	25.0	10.9	28.6
Pct income:poverty line: 4+	29.9	2.5	43.6
Educ: < high school	13.5	30.7	5.8
Educ: high school/GED	25.5	30.7	21.8
Educ: some college	19.0	17.9	19.4
Educ: assoc. degree	10.7	7.9	12.0
Educ: bachelor's degree	18.1	4.9	24.6
Educ: master/prof/phd	9.7	1.3	13.9
County level controls			
Population	1,126,919	1,284,943	1,050,948
Population density	2,010	3,087	1,834
Median income	53,749	50,031	55,408
Unemployment rate (16+)	8.3	8.7	8.1
Medicaid eligibles	286,546	362,920	255,757
Pediatricians	234	265	222
Primary care doctors	876	969	838
Nurse practitioners	401	447	386
Hospital beds	3,254	3,750	3,037
Expansion state (2014)	9.3	11.8	9.6
Observations	603,074	96,128	338,174

Notes: Averages are weighted using the sample weights provided in the NHIS. County-level controls come from the HRSA's Area Resource Files. Missing categories for these variables are additionally included in all regressions.

While much of the NHIS data is publicly available, geographic identifiers for levels of disaggregation smaller than Census regions are restricted. In order to link our outcome measures to state-level variation in Medicaid reimbursement rates and county-level health resources, we applied for access to confidential state and county identifiers. Our analyses using the NHIS data are therefore conducted in a Census Research Data Center.

3.2.3 National Assessment of Educational Progress

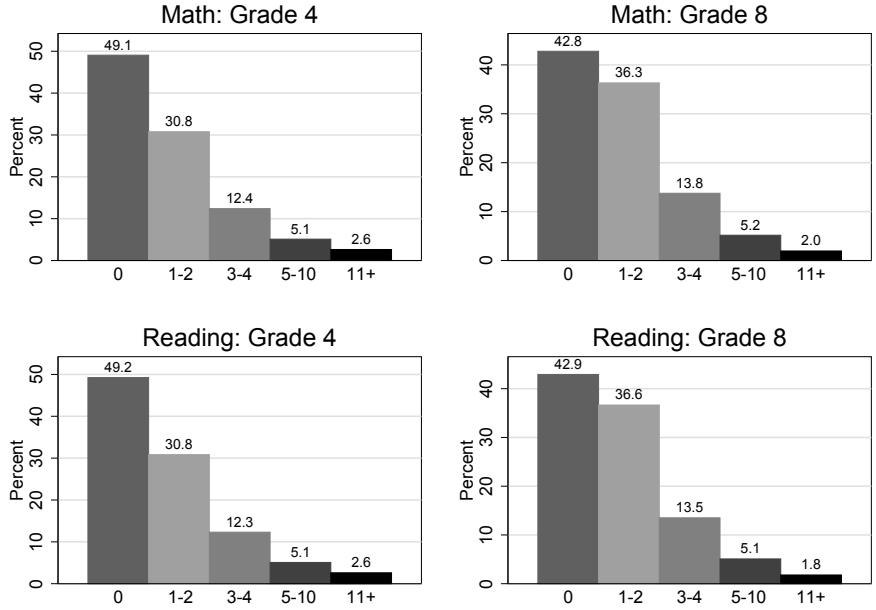
Childhood health investments impact educational attainment, which in turn affects productivity in adulthood. Therefore, an important question is the extent to which improving access to health care is associated with better educational outcomes for low-income children. While the NHIS does consider school attendance, the question is only asked in the child subsample, which has a relatively small sample size. We therefore supplement this information with data from the National Assessment of Educational Progress (NAEP). NAEP data is provided through the National Center for Education Statistics, a federal institution that collects information on reading and mathematics assessments in grades 4 and 8 every other year in all states. While not all schools are tested in each wave, the schools and students participating in NAEP assessments are selected to be representative of all schools nationally and of public schools at the state/jurisdiction and district levels.

Importantly for our work, the NAEP reports not just test scores, but also information on fraction of children reporting different numbers of absences in the month preceding the test: 0 days, 1-2 days, 3-4 days, 5-10 days, and 11 or more. We are therefore able to consider effect of increasing physician reimbursement on the overall distribution of reported school absences. We focus much of our attention on the fraction of chronically absent children, which at the monthly level is most often defined as missing three or more days of school (KewalRamani et al. (2007); Ginsburg et al. (2014); Schanzenbach et al. (2016)). We focus primarily on school absences, rather than test scores, as they are most proximate outcome to

primary care. In particular, as previously discussed, school absences for younger children are often caused by primary care treatable conditions.

The NAEP data is available at the state level for grades 4 and 8 in 2009, 2011, and 2013. The information on absences is collected before both math and reading assessments. Figure 3.3 shows the distribution of absences reported on math and reading test scores in grades 4 and 8 over our sample period. The fraction of children in each bin is nearly identical for math and reading tests within the same grade.[9] There are large differences by grade, however, with a much larger fraction of students reporting zero absences in the past month in grade 4 than in grade 8.

Figure 3.3: Distribution of school absences by grade and subject



Notes: The above figures display the average percent of students who had missed 0, 1-2, 3-4, 5-10, or 11+ days in the month preceding their state assessment tests from 2009 to 2013. Data comes from the National Assessment of Educational Progress.

As was seen in the NHIS data, there are large differences in the number of school absences by socioeconomic status.[10] While we do not observe whether children are covered

[9]Discrepancies can be attributed to testing that takes place over multiple days.

[10]When comparing the absence measures between the NHIS and the NAEP, it is important to note that the NHIS asks for the number of absences over the past year, while the NAEP asks about the past month.

by Medicaid in the NAEP data, we can isolate children that are eligible to receive free lunch and those that are not; like Medicaid, free school lunch is a means-tested program. In 4th grade, 53 percent of children ineligible for free lunch missed zero days in the past month, whereas just 44 percent of free-lunch-eligible reported missing no school. The discrepancy in school absences between free-lunch-eligible and ineligible children is similar in 8th grade, though fewer children report zero absences in both groups. The full distribution of absences broken down by free lunch eligibility are shown in Figure 3.9.

In all grades and subjects, average test scores are monotonically decreasing in the number of school days missed in the past month (Figure 3.10). Given the negative correlation between absences and test scores, it is also conceivable that test scores could also be affected by any changes in access to primary care. Thus, we also look at the effect of primary care reimbursement to physicians on test scores, using the composite scores for the math and reading assessments.

3.3 Empirical strategy

The summary statistics in Table 3.1 demonstrate that those covered by Medicaid tend to have worse access to health care services and worse health outcomes than the privately insured. In order to investigate the relationship between these variables and physician payment levels, we estimate the effect of changes in physician reimbursement on both health care utilization and health outcomes:

$$Outcome_{icst} = \beta_0 + \beta_1 Fee_{st} + \gamma X_i + \delta Z_{ct} + \lambda_s + \lambda_t + \epsilon_{icst} \tag{3.1}$$

where $Outcome_{icst}$ denotes a utilization or health outcome for individual i living in county c in state s in quarter t; Fee_{st} is the relevant Medicaid fee in state s in quarter t; X_i and Z_{ct} are vectors of individual and county characteristics, respectively (listed in Table 3.2); and λ_s and λ_t are state and quarter-year fixed effects, respectively. Since we include state and

quarter-year fixed effects, the identification for our main coefficient of interest, β_1, comes from changes in reimbursement rates within states over time. For the outcomes covering a retrospective time period of 12 months, the fee variable used is the average of the Medicaid fees over the past four quarters. For all other NHIS outcomes, we use the average fee in the quarter of the interview. All regressions use the sampling weights provided by the NHIS, and standard errors are clustered at the state level.

When looking at the effect of Medicaid payments on the distribution of school absences or test scores, we use a similar regression specification but at the state-year level:

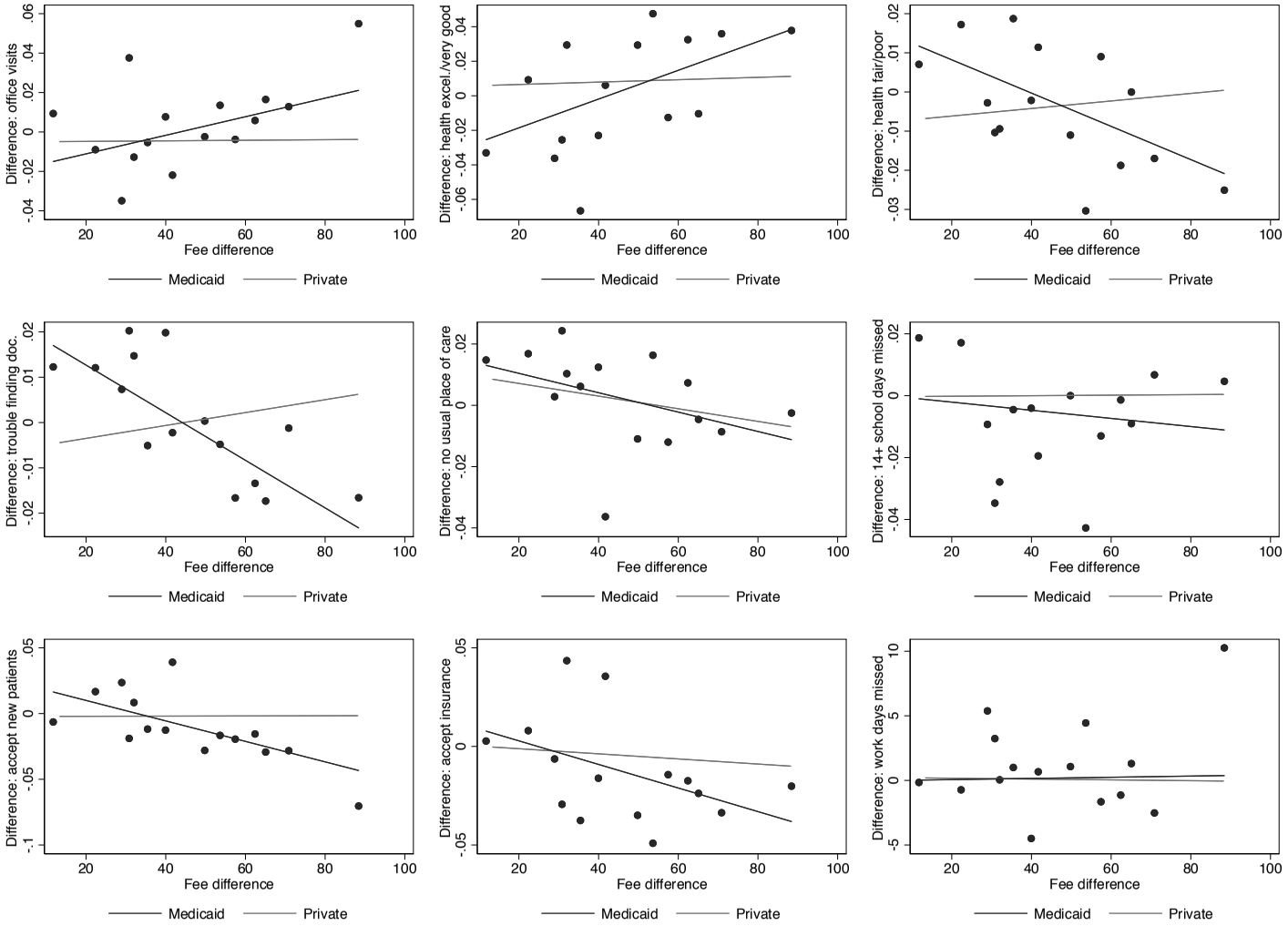
$$Outcome_{st} = \beta_0 + \beta_1 Fee_{st} + \lambda_s + \lambda_t + \epsilon_{st} \tag{3.2}$$

where $Outcome_{st}$ denotes an average schooling outcome in state s in year t; Fee_{st} is the expected Medicaid reimbursement in the first quarter of year t; and λ_s and λ_t are state and year fixed effects, respectively. As all state assessments take place from January through March, we attach average Medicaid payment rates over the first quarter to each calendar year of test scores. Standard errors are again clustered at the state level.

3.4 Results

Higher Medicaid payments are associated with improvements in access and health measures among Medicaid beneficiaries. Figure 3.4 shows strong associations in the raw data between increases in state-level Medicaid primary care rates and improvements in access and health outcomes among Medicaid beneficiaries from before the rate increase (2011-2012) to after the rate increase (2013-2014). Table 3.3 presents these results in regression form, where the three panels of Table 3.3 show the impact of a $10 increase in Medicaid reimbursement levels on the full NHIS sample, the child subsample, and the adult subsample, respectively. The first three columns of each panel show the effects of changes

Figure 3.4: Before-after differences by size of fee increase



Notes: The above figures plot the average change in each outcome at the state level between 2011-2012 (before) and 2013-2014 (after).

in Medicaid fees on survey respondents covered by Medicaid, while the last three columns show the effects of changes in Medicaid payments on respondents with private insurance.

Table 3.3: Effects of physician reimbursement on access and health

Full Sample	Medicaid			Private		
	(1) Office Visits	(2) P/F Health	(3) Ex/VG Health	(4) Office Visits	(5) P/F Health	(6) Ex/VG Health
Medicaid fees, in $10	0.0029*	-0.0030*	0.0058**	-0.0008	0.0002	0.0018
	(0.0017)	(0.0017)	(0.0023)	(0.0010)	(0.0006)	(0.0017)
Observations	96,017	96,067	96,067	337,506	337,903	337,903
R^2	0.071	00.296	0.232	0.036	0.079	0.138
Mean dep. var.	0.196	0.174	0.566	0.174	0.061	0.729
Child Subsample	Medicaid			Private		
	(1) Trouble finding doctor	(2) No usual place of care	(3) Days missed school	(4) Trouble finding doctor	(5) No usual place of care	(6) Days missed school
Medicaid fees, in $10	-0.0055***	-0.0037**	-2.5195**	0.0012*	0.0002	0.8868
	(0.0015)	(0.0018)	(1.0416)	(0.0007)	(0.0010)	(0.7016)
Observations	16,810	21,290	13,575	26,443	34,246	25,314
R^2	0.016	0.022	0.027	0.007	0.029	0.016
Mean dep. var.	0.021	0.031	12.023	0.008	0.021	7.347
Adult Subsample	Medicaid			Private		
	(1) Don't accept new patient	(2) Don't accept insurance	(3) Days missed	(4) Don't accept new patient	(5) Don't accept insurance	(6) Days missed
Medicaid fees, in $10	-0.0078***	-0.0082***	-0.1778	0.0005	-0.0007	0.1037
	(0.0015)	(0.0030)	(0.3674)	(0.0006)	(0.0007)	(0.1129)
Observations	14,855	14,854	6,321	80,351	80,341	77,548
R^2	0.037	0.040	0.075	0.006	0.009	0.009
Mean dep. var.	0.055	0.075	4.929	0.016	0.022	3.730

Notes: Observations are at the individual level; standard errors are clustered by state. All regressions include state and quarter-year fixed effects, and all individual and county-level controls listed in Table 3.2 are included (age enters the regressions in 5-year bins). Regressions are weighted using the sample weights provided in the NHIS.

Primary care payment increases are associated with improved access measures for both adults and children. Parents of children covered by Medicaid (Panel 2 of Table 3.3) report decreases in the difficulty of finding a doctor for their child and are less likely to report having no usual place of care for their child—a $10 increase is associated with a 0.55 and 0.37 percentage point decrease, respectively (reflecting a 26 and 12 percent decrease relative to the mean). Among adults on Medicaid (Panel 3 of Table 3.3), a $10 increase in payments is associated with both a 0.55 percentage point reduction in the probability of being turned away as a new patient and a 0.37 percentage point reduction in the probability of being told that one's insurance is not accepted (decreases of 14 and 11 percent of the mean, respectively). Finally, people also report using health care services more when Medicaid payments increase. In the full sample (Panel 1 of Table 3.3), a $10 increase in physician reimbursement is associated with a 0.29 percentage point (1.5 percent) increase in the probability that respondents covered by Medicaid went to a doctor's office in the past two weeks.

Increased payments to physicians are associated with improved access measures for both adults and children. Parents of children covered by Medicaid (Panel 2 of Table 3.3) report decreases in the difficulty of finding a doctor for their child and are less likely to report having no usual place of care for their child—a $10 increase is associated with a 0.55 and 0.37 percentage point decrease, respectively (reflecting a 26 and 12 percent decrease relative to the mean). Among adults on Medicaid (Panel 3 of Table 3.3), a $10 increase in payments is associated with both a 0.55 percentage point reduction in the probability of being turned away as a new patient and a 0.37 percentage point reduction in the probability of being told that one's insurance is not accepted (decreases of 14 and 11 percent of the mean, respectively). Finally, people also report using health care services more when Medicaid payments increase. In the full sample (Panel 1 of Table 3.3), a $10 increase in physician reimbursement is associated with a 0.29 percentage point (1.5 percent) increase

in the probability that respondents covered by Medicaid went to a doctor's office in the past two weeks.

In addition to improved access, increases in Medicaid reimbursement rates are associated with improvements in self-reported health among the program's beneficiaries. As shown in the top panel of Table 3.3, a $10 increase in physician reimbursement is associated with a 0.3 percentage point (1.7 percent) decrease in the probability of reporting fair or poor health and a 0.58 percentage point (1 percent) increase in the probability of reporting very good or excellent health.

To get a sense of what these magnitudes imply for the experience of a typical state under the primary care rate increase, we consider the implied changes associated with an increase in payments of $40—the average increase in payments across states from the third quarter of 2012 to the first quarter of 2013.[11] Multiplying the point estimates in Table 3.3 by four, we see that an increase of $40 in physician reimbursement is associated with a 6 percent increase in the probability of Medicaid beneficiaries having visited a doctor's office in the past two weeks, a 6.8 percent decrease in the probability of being in fair or poor health, and an increase of 4 percent in the probability of being in very good or excellent health. Applying the same calculations to the access measures additionally suggest that the primary care rate increase eliminated parents having trouble finding doctors for their Medicaid-covered children in the average state, and approximately halved these difficulties for adult beneficiaries.

While we find strong evidence that increased physician reimbursement under Medicaid is associated with improved access and health among Medicaid beneficiaries, there is little evidence of spillovers on the privately insured. The last three columns of Table 3.3 present the analogous estimates for privately insured respondents, who may be indirectly affected by Medicaid patients becoming relatively more attractive to doctors. However, this does not appear to be the case, at least on a large scale. There is no change in access measures

[11] The average change in payments between the last quarter of 2012 and the first quarter of 2013 is $39; the median is $36.

or health outcomes among the privately insured when Medicaid payments to primary care doctors increase, with the exception of parents reporting slightly more trouble finding a doctor for their children (an increase of 0.12 percentage points, significant at the ten percent level). Not only are the coefficients nearly all statistically insignificant despite much larger sample sizes, but the point estimates are also generally very small.

Finally, the improvements in access for Medicaid beneficiaries translate into improved school attendance for children. Column 3 of the second panel of Table 3.3 shows that a $10 increase in physician reimbursement is associated with a statistically significant decrease in the probability of being chronically absent of 0.4 percentage points for children covered by Medicaid (a decrease of 8 percent of the mean). However, there is no corresponding decrease in the number of days missed of work for adults. These differential findings for adults and children may reflect differences in the immediate consequences of missing work versus school, as well as differences in the characteristics of the adult and child Medicaid populations.

Table 3.4 shows that the association between Medicaid fees and school attendance that we documented in the NHIS is also present in a completely different dataset: educational achievement data from the NAEP. While the NAEP data does not allow us to look separately at children that are covered by Medicaid, we can narrow the sample to children who are eligible for free lunch. While the requirements are not identical, both free school lunch and Medicaid are means-tested programs and likely have substantial overlap. For low-income children in the 4th grade, an increase in Medicaid primary care physician payments of $10 is associated with 0.4 to 0.5 percentage point fewer chronically absent children (measured as three or more days missed in the past month; see columns 1 and 2 in Panel 1 of Table 3.4). Columns 1 and 2 in Panel 2 of Table 3.4 show that no such pattern is present for children who are not eligible for free lunch (and who are thus unlikely to be covered by Medicaid). Columns 3 and 4 in Table 3.4 show the effects of increased payments to primary care physicians on the fraction of children with zero absences in the past month. Consistent with

Table 3.4: Effects of physician reimbursement on school absences: grade 4

Free lunch eligible	3+ days missed		0 days missed	
	(1) Math	(2) Reading	(3) Math	(4) Reading
Medicaid fees, in $10	-0.493***	-0.447***	0.462***	0.429***
	(0.133)	(0.145)	(0.142)	(0.148)
Observations	150	150	150	150
R^2	0.790	0.805	0.867	0.866
Mean dep. var.	24.627	24.387	44.000	44.207
Free lunch ineligible	3+ days missed		0 days missed	
	(1) Math	(2) Reading	(3) Math	(4) Reading
Medicaid fees, in $10	-0.197	-0.113	0.431*	0.286
	(0.171)	(0.144)	(0.229)	(0.193)
Observations	150	150	150	150
R^2	0.728	0.724	0.772	0.784
Mean dep. var.	16.713	16.473	52.967	53.133

Notes: Observations are at the state-year level; standard errors clustered by state. All regressions include state and year fixed effects. Data is from 2009, 2011, and 2013. Refer to Table 3.10 for an analogous figure for grade 8.

the results in columns 1 and 2, we find that increased physician payments are assoicated with increases in the probability of no absenteeism for low-income children in grade 4. Similar patterns are present for students in grade 8, though the point estimates are less precise (see Table 3.10). The larger effects in 4th grade relative to 8th grade may reflect the fact that absences for younger children are more closely tied to health status, whereas absences for older children are more likely to be for non-health-care related reasons, such as truancy.

Results from both the NHIS and NAEP data suggest that improvements in school attendance associated with increased access to primary care come at least partly from children at the high end of the absence distribution: those missing 3+ days of school per month or two weeks or more per year. Chronic absenteeism is known to be a problem in

low income populations, and our results suggest that lack of adequate primary care is an important contributing factor (Chang and Romero, 2008).

While increasing physician reimbursement is strongly associated with reductions in school absenteeism, we find little immediate effect on test scores (see Tables 3.11 and 3.12). In 4th grade, where we found the strongest improvements in attendance, there is no evidence that Medicaid fees are related to math or reading test scores. In 8th grade, there is some suggestive evidence that higher Medicaid fees are associated with slight improvements in test scores for math. It is possible that 8th grade math is particularly sensitive to either attendance or health, and that missing fewer days during this period or being healthier and better able to concentrate could help test scores.[12] However, the point estimates are very small and the pattern is not consistent across tests and grades, suggesting that there is little evidence of immediate improvements on test scores due to better health care access.

The Fee Increase and Duration Expectations

One potential drawback to using physician payments as a policy instrument to influence physician behavior is the possibility that providers may not respond to a change in payments whose duration they view as uncertain. Physician-patient relationships tend to last for many years, so if providers expect payment increases to be temporary they may hesitate to take on new patients; uncertainty over the duration of payment increases could erode such a policy's effectiveness.[13] For example, uncertainty over duration could cause the primary care rate increase to have a smaller effect on the behavior of a forward-looking doctor who expects the fee increase to last two years than on the behavior of a physician who

[12]Currie and Gruber (2001) find that success in math is more dependent on what happens in school than success in reading, which is consistent with only finding effects on math scores.

[13]Data from the Medicare Current Beneficiary Survey suggests that a third of Medicare beneficiaries have been seeing their usual doctors for over 10 years, and half of beneficiaries have been with their primary doctor for over 5 years (Donahue et al., 2005). Similar patterns were found in a survey conducted in non-metropolitan counties of eight southern US states, where over half of respondents reported being with their primary physician for more than 5 years (Parchman and Burge, 2004).

expects the higher rate to persist indefinitely. Given that the duration of the fee increase was unknown when it was enacted, we can directly examine the extent to which heterogeneity in beliefs about the expected duration of increased payments—proxied by assuming perfect foresight—impacted the policy's effectiveness.

Perhaps surprisingly, we find little evidence that the effect of the Medicaid fee increase differed across states that did and did not extend the increased payments. In Table 3.9, we interact Medicaid payments with an indicator for whether states extended the higher payments into 2015. For the access measures, there is no difference in responses to payment changes between doctors living in states that did and did not extend the fee boost beyond 2014. The fact that improvements in access were not greater in states that ultimately extended the higher payments seems to indicate that physicians place little weight on their expectations of the duration of a fee increase—perhaps because it is difficult to forecast political outcomes such as whether the fee boost would be maintained in 2015. In the case of the primary care fee increase, it was not announced until late 2014 that the increased payments would not receive federal funding in 2015, and the states that chose to extend the increased payments show diversity in geography, demographics, and political affiliations (see Figure 3.8). There is also no significant difference between extension and non-extension states for self reported health (though we do find that days of work and school missed both show evidence of a larger effect in states that ultimately extended the payments).

3.5 Robustness

3.5.1 The fee increase and the 2014 Medicaid expansion

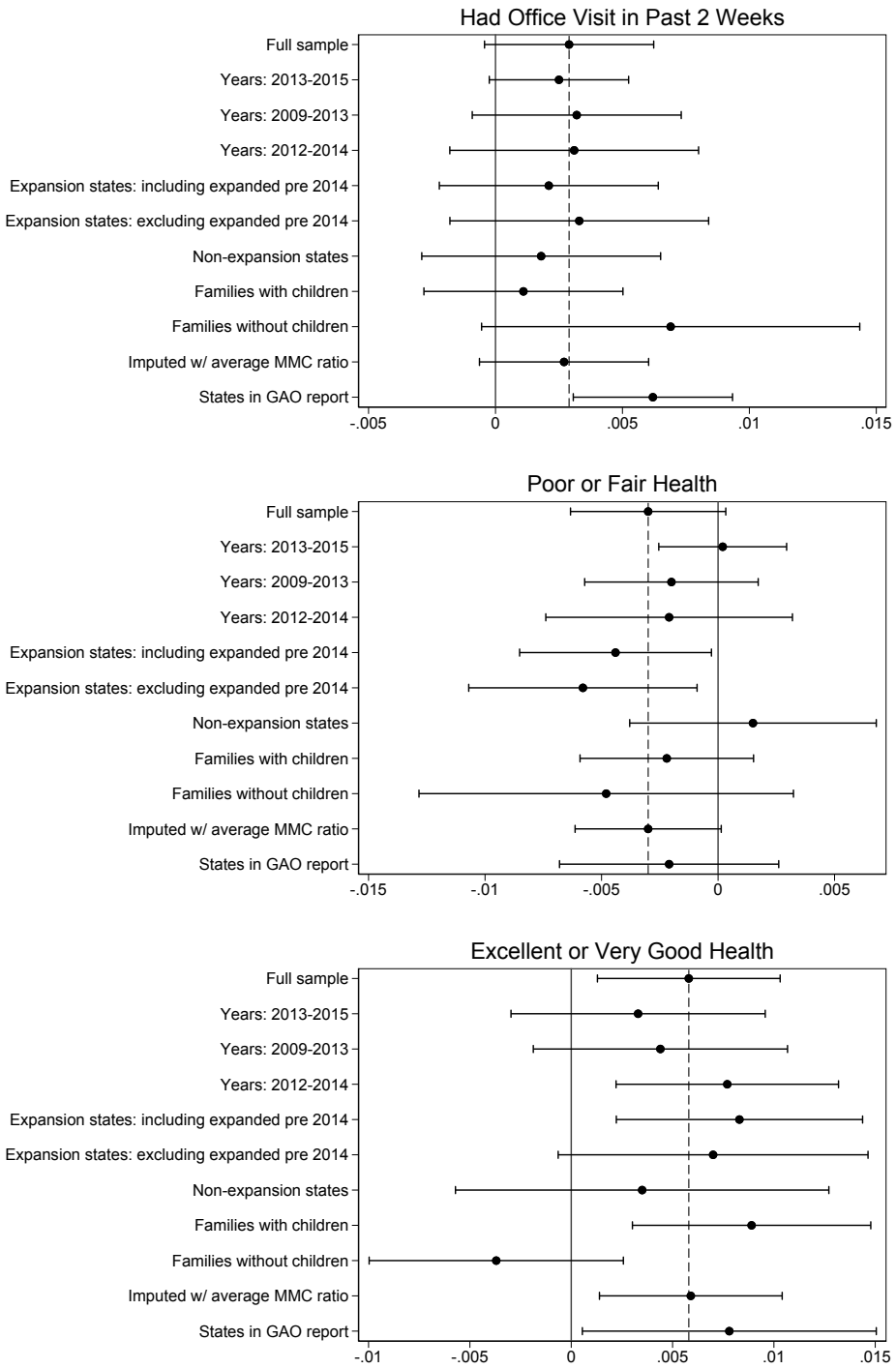
Many aspects of the US health care system were in flux as the ACA began to go into effect, which covers most of the time period we study. Most relevant for this paper, Medicaid was expanded in 2014, making low-income, childless adults eligible for the first time in

many states. The 2014 Medicaid expansion complicates our analysis of the primary care rate increase for two reasons. First, the timing is similar, and thus we need to show that our results are not confounded by the Medicaid expansion. Second, the Medicaid expansion resulted in large changes in the composition of Medicaid beneficiaries in some states. From a policy perspective, it would be useful to know whether the improvements in access and health that we observe differ between the newly eligible or traditionally eligible Medicaid populations.

Timing of Medicaid expansion Perhaps the best evidence that our results reflect the effects of changing payments and are not confounded by the Medicaid expansion is that many of our strongest results are for child outcomes, and children were relatively unaffected by the 2014 expansions. However, we can also look directly at the timing by comparing the effect of changing Medicaid rates on access and health across different time periods. In particular, we estimate our main specification excluding the overlap with the Medicaid expansion (2009-2013), isolating the variation from the ACA rate increase (2012-2014), and using the variation from the reverse experiment as the rate increase was phased out in some states (2013-2015). Figures 3.5 and 3.6 compare the point estimates from our main specification with those using different time periods for the full sample and the adult subsample, respectively (analogous results for children can be found in Figure 3.11). The point estimates across the different time periods are remarkably consistent with our main results.

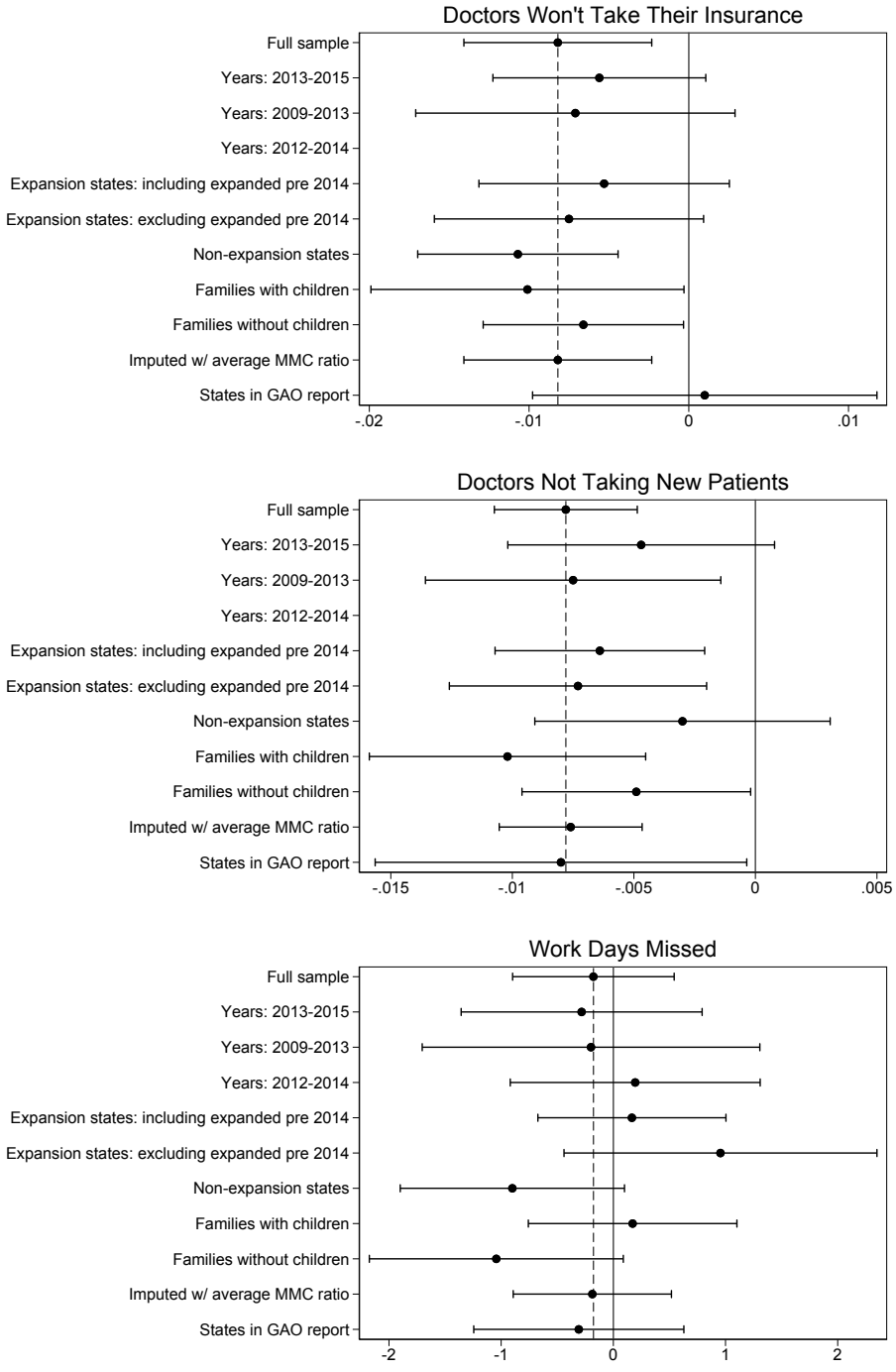
We also look at the timing directly in event time. As the primary care fee increase turned on for all states simultaneously, there is no control group in 2013 and 2014. However, we expect the effects generally to be larger among states that saw a bigger payment increase than in states that saw a smaller payment increase. Thus, we divide states into more and less affected groups at the median by the size of the fee increase experienced from 2012 to 2013. Figure 3.12 plots the difference in the quarter dummy coefficients for these two

Figure 3.5: Heterogeneous effects of physician reimbursement



Notes: Each dot in the above figures depicts the estimated effect on a $10 increase in physician reimbursement under Medicaid for the subsample or alternative specification listed on the y-axis. Each coefficient comes from a separate regression. 95% confidence intervals for each coefficient are also reported. The dashed vertical lines show the coefficients in the full sample (as reported in Table 3.3).

Figure 3.6: Heterogeneous effects of physician reimbursement: adult subsample



Notes: Each dot in the above figures depicts the estimated effect on a $10 increase in physician reimbursement under Medicaid for the subsample or alternative specification listed on the y-axis. Each coefficient comes from a separate regression. 95% confidence intervals for each coefficient are also reported. The dashed vertical lines show the coefficients in the full sample (as reported in Table 3.3).

groups from a specification which does not include the fee variable, but is otherwise the same as equation 3.1. As payments vary at the state level, splitting the sample sharply reduces our identifying variation, and we lack the power to statistically differentiate the quarter dummy estimates in high fee increase states from low fee increase states. Still, Figure 3.12 shows suggestive evidence that the trends in outcomes were similar between these groups before 2013, and diverged after the fee increase was introduced in 2013.

Changing composition of Medicaid beneficiaries In order to examine whether changes in physician payments have heterogeneous impacts across new and previously eligible Medicaid beneficiaries, we cut the sample in several ways. For a coarse perspective on the Medicaid expansion, we look separately at states that did and did not expand Medicaid—though as mentioned above, this strategy reduces our identifying variation. In addition, we look separately at adults with and without children, as childless adults experienced the largest increases in Medicaid eligibility under the ACA.

Figures 3.5 and 3.6 compare the point estimates from our main results with those from running the same specification on these different subsamples. Again, the first order result is that the point estimates are broadly consistent across subsamples, and the estimates are not statistically different from the full sample point estimates or each other. If anything, it appears that the newly Medicaid eligible—as proxied by childless adults—experience the largest increases in office visits and the largest decreases in reports of fair or poor health. This may reflect the fact that many adults who became newly eligible for health insurance under the Medicaid expansion transitioned from an uninsured state, and therefore had both built up a stock of poor health and had postponed seeing doctors. The point estimates for expansion states also tend to be slightly larger than for states that did not expand Medicaid, though the differences are not statistically significant. Finally, the estimates for children are also similar across states that did and did not expand Medicaid, which is reassuring,

as poor children did not experience a compositional change after the Medicaid expansions (Figure 3.11).

3.5.2 Robustness of the fee variable

While our data represents the most comprehensive set of Medicaid primary care payment data of which we are aware, they are not perfect. The main weakness of our payment data comes from Medicaid managed care. We believe this paper represents a step forward with respect to the literature by incorporating managed care payment rates and utilizing them in the analysis. However, as discussed previously, we do not observe the exact payments made to doctors by Medicaid managed care organizations. Instead, we use state-level Medicaid fee-for-service to managed care payment ratios for primary care services in 2010 published in a GAO report (Yocom, 2014) to back out the managed care payment levels. Unfortunately, these fee-for-service to managed care payment ratios are only available for 20 states. In our main analysis, we use use the median payment ratio to impute Medicaid manage care payments for states which do not appear in the report.

In Table 3.13, we explore the sensitivity or our estimates to measurement error around Medicaid managed care payment levels by reestimating our main results using the mean instead of the median to impute the share in Medicaid managed care. In Table 3.14, we reestimate our main results using the subsample of states for whom we know the exact Medicaid managed care share from Yocom (2014). As can be seen in Tables 3.13 and 3.14, our results are robust to different ways of treating Medicaid managed care. Narrowing the sample to just the states listed in the GAO report decreases the power of our fee variable; nevertheless, the estimated coefficients are similar in magnitude to our main result. Using the average payment ratio rather than the median to impute managed care payment rates has very little effect on the magnitude or precision of our estimated coefficients. The point estimates for these alternative payment variables are also plotted in Figures 3.5, 3.6, and 3.11 for easy comparison to our preferred estimates.

3.5.3 Alternative empirical specification: difference-in-difference

In our preferred empirical specification, we run all regressions separately on Medicaid beneficiaries and those covered by private insurers. We look separately at these two groups, rather than using the privately insured as a control group, as changes in the treatment of Medicaid beneficiaries could spill over into the treatment of those covered by other insurers. If the increase in reimbursement rates for treating Medicaid beneficiaries caused doctors to spend more time with their Medicaid population and less time with other patients, a difference-in-difference strategy would both miss this negative spillover and potentially over-estimate the magnitude of the effects of the payment change on outcomes for Medicaid beneficiaries. In fact, we find some evidence of this in Table 3.3, as parents of children with private insurance report having a slightly harder time finding doctors when Medicaid payments increase. However, as this strategy has been used by other papers in the existing literature on the Medicaid payment changes (Shen and Zuckerman, 2005; Atherly and Mortensen, 2014; Callison and Nguyen, 2017), we show difference-in-difference estimates for comparison.

In particular, we estimate the following regression:

$$\begin{aligned} Outcome_{icst} &= \beta_0 + \beta_1 Fee_{st} + \beta_2 Medicaid_{icst} + \beta_3 Fee_{st} * Medicaid_{icst} \\ &\quad + \gamma X_i + \delta Z_{ct} + \lambda_s + \lambda_t + \epsilon_{icst} \end{aligned} \tag{3.3}$$

where $Medicaid_{icst}$ is an indicator for Medicaid beneficiaries, and $Fee_{st} * Medicaid_{icst}$ is an interaction between the Medicaid indicator and the state-year payment variable. All individual and county level controls, as well as state and quarter-year fixed effects included in equation 3.1 are also included. The sample used here is the combination of the Medicaid and privately insured samples used in our main results. Table 3.5 shows that the pattern of results in the difference-in-difference specification is similar to those found for Medicaid beneficiaries in Table 3.3. The similarity is not surprising, given the minimal evidence of spillovers on the privately insured. The main difference between the two specifications

Table 3.5: Effects of physician reimbursement: difference-in-difference specification

Full Sample	Medicaid + Private		
	(1) Office Visits	(2) P/F Health	(3) E/VG Health
Medicaid fees, in $10	0.0001	0.0007	0.0019
	(0.0009)	(0.0006)	(0.0015)
Medicaid	0.0800***	0.0793***	-0.0878***
	(0.0097)	(0.0065)	(0.0113)
Medicaid fees * Medicaid	-0.001	-0.0027***	0.0035***
	(0.0008)	(0.0006)	(0.0012)
Observations	596,508	597,078	597,078
R^2	0.046	0.129	0.172
Mean dep. var.	0.168	0.101	0.66
Child Subsample	Medicaid + Private		
	(1) Trouble Finding Doc	(2) No Usual Care	(3) 14+ School Days Missed
Medicaid fees, in $10	-0.0006	-0.0010	-0.0009
	(0.0006)	(0.0010)	(0.0006)
Medicaid	0.0102*	-0.0496***	0.0325***
	(0.0054)	(0.0084)	(0.0078)
Medicaid fees * Medicaid	-0.0012**	-0.0001	-0.0021**
	(0.0006)	(0.0007)	(0.0008)
Observations	52,061	67,474	52,493
R^2	0.008	0.061	0.017
Mean dep. var.	0.015	0.043	0.035
Adult Subsample	Medicaid + Private		
	(1) Don't accept new patient	(2) Don't accept insurance	(3) Days missed
Medicaid fees, in $10	0.0007	-0.0005	-0.0451
	(0.0007)	(0.0007)	(0.0703)
Medicaid	0.0497***	0.0761***	1.8789*
	(0.0119)	(0.0112)	(0.9693)
Medicaid fees * Medicaid,	-0.0037***	-0.0046***	-0.1021
	(0.0011)	(0.0011)	(0.1021)
Observations	137,174	137,125	112,835
R^2	0.015	0.016	0.008
Mean dep. var.	0.024	0.030	3.710

Notes: Observations are at the individual level; standard errors are clustered by state. All regressions include state and quarter-year fixed effects, and all individual and county-level controls listed in Table 3.2 are included (age enters the regressions in 5-year bins). Regressions are weighted using the sample weights provided in the NHIS.

is the magnitude of some coefficients. However, when viewed as a percentage of the combined population mean, the magnitudes are fairly similar.

3.6 Conclusion

The intention of the Medicaid primary care rate increase was to increase access to primary care services for disadvantaged populations in the US. Without ongoing access to primary care services, existing chronic conditions go untreated and essential preventive services are not provided. In addition to the direct welfare losses that result from inadequate care, conditions that are left untreated at the primary care level often lead to expensive yet preventable emergency situations, adding to the rapid growth in health care spending (Alexander et al., 2017). Our results suggest that the ACA's strategy of increasing primary care reimbursement rates was successful in both expanding access to care and improving health outcomes among the Medicaid population. Conversely, evidence from the rate increase expiring in 2015 suggests that cutting Medicaid payments to providers can make it significantly harder for low income Americans to find doctors willing to treat them.

An outstanding question that is beyond the scope of this paper is how doctors absorb new patients when reimbursement rates increase. As we do not find a clear pattern of negative effects of the fee boost on the privately insured, it does not appear that physicians respond by substituting away from the non-Medicaid population, at least on the extensive margin. How then are physicians able to see more patients? Neprash (2017) finds preliminary evidence that physicians already participating in Medicaid respond to higher payments by increasing both the total number of appointments and the number of unique patients. One way physicians could see more patients is by decreasing appointment length, which could result in negative health consequences if providers are rushed and diagnoses are missed. To the extent that this response would be reflected in the outcome measures used in this paper, however, our results do not support this mechanism: we find no evidence

that higher payments for Medicaid are associated with worse outcomes for the privately insured. On the other hand, it is also possible that doctors were previously treating their privately insured patients too intensely, in which case outcomes of the privately insured could be unaffected by reallocating time to Medicaid beneficiaries.

While we cannot look at physician labor supply directly in our data, we can divide counties by those with and without shortages of primary care providers as defined by by the Health Resources and Services Administration. If increasing labor supply was the main margin of response, we would expect the higher fees to have no impact in areas with primary care provider shortages—where providers presumably have little scope to take on more patients. However, we find no evidence of differing effects between counties that are and are not designed as primary care shortage areas (see Table 3.15). There are many ways physicians could treat more patients: practices could be expanded by increasing the hours of non-physician providers, decreasing appointment length, having doctors work longer hours, or taking fewer breaks. While identifying the exact mechanisms through which physicians respond to increased payments is important, our results show that increasing the generosity of Medicaid payments to physicians can improve access to care and health of low-income populations.

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Appendix

3.A Data appendix

3.A.1 Outcomes

Table 3.6: Overview of data sources used for outcome measures

		Medicaid	Private
Full Sample	Office visit in past 2 weeks	0.196	0.174
	N	95,736	337,717
	Fair or poor health	0.174	0.061
	N	95,786	338,114
	Excellent or very good health	0.566	0.728
	N	95,786	338,114
Child Subsample	Trouble finding a doctor	0.021	0.008
	N	16,786	24,454
	No usual place of care	0.028	0.020
	N	21,249	34,261
	14+ school days missed	0.054	0.028
	N	14,630	27,909
Adult Subsample	Don't accept new patient	0.055	0.016
	N	14,806	80,409
	Don't accept insurance	0.075	0.022
	N	14,805	80,399
	Work days missed	4.927	3.731
	N	6,295	77,571

National Health Interview Survey questions

Full Sample

- During the last two weeks, did {person} see a doctor or other health care professional at a doctor's office, a clinic, an emergency room, or some other place? (Do not include times during an overnight hospital stay.) [available 2009-2015]

- Would you say {person's} health in general is excellent, very good, good, fair, or poor? [available 2009-2015]

Child Subsample

- During the past 12 months, did you have any trouble finding a general doctor or provider who would see {sample child} [available 2011-2015]
- Is there a place that {sample child} usually goes when {he/she} is sick or you need advice about {his/her} health? [available 2009-2015]
- During the past 12 months, that is, since {12-month ref. date}, about how many days did {sample child} miss school because of illness or injury? [available 2009-2015]

Adult Subsample

- During the past 12 months, were you told by a doctor's office or clinic that they would not accept {sample adult} as a new patient? [available 2011-2015]
- During the past 12 months, were you told by a doctor's office or clinic that they would not accept {sample adult}'s health care coverage? [available 2011-2015]
- During the past 12 months, about how many days did {sample adult} miss work? [available 2009-2015]

3.A.2 Medicaid fees

Table 3.7: Medicaid enrollment and managed care to fee-for-service payment ratios

State	MC to FFS ratio	Enrollees (millions)	Percent in MC
New Mexico	-6	0.5	73
California	-10	7.3	55
State A	0	-	-
Connecticut	1	0.5	70
Indiana	2	1	68
Arizona	1	1.3	91
Wisconsin	1	1.1	60
New York	4	4.7	67
Georgia	4	1.5	62
Florida	6	2.9	38
Washington	3	1.1	58
Michigan	11	1.8	66
South Carolina	7	0.8	49
Ohio	6	2.1	74
Virginia	7	0.9	59
Pennsylvania	11	2	54
State B	15	-	-
Texas	25	3.8	44
New Jersey	59	1	77
Rhode Island	132	0.2	67

Notes: Data on payment ratios comes from Yocom (2014). Data on Medicaid enrollment comes from CMS.

The fee-for-service fee data used in this project has two components. The augmented primary care fee-for-service rates under the ACA rate increase in 2013 and 2014, and the standard fee-for-service rates applicable between 2009 and 2012. We get both components from each state's Medicaid office. While theoretically we could back out rates for 2013 and 2014 for each state using Medicare rates, due to geographic adjustment factors and state specific idiosyncrasies, we prefer to take both components directly from state Medicaid offices. For 44 states and the District of Columbia, we have no missing data. For the remaining six states, we use the following procedures to impute missing rate information:

- For California and Hawaii, we have the ACA rate information for both years, but we only have standard rates for 2009 and a date in or after 2012. However, in these

states the rates did not change between our two data points for regular Medicaid rates. Therefore, we feel confident in the assumption that the standard Medicaid rates were constant across the 2009 to 2012 period.

- New Mexico and Utah, we have the ACA rate information for both years, and most of the standard rate information, but are missing a few months of the standard rates (see Table 3.8 below for which months are missing). For these states, we impute the missing months based on the closest month with rate information available.

- For South Dakota, we have the ACA rate information for both years, but only have the 2015 standard Medicaid rates, as rates are not archived. To impute standard rates from 2009 to 2012, we apply the average change in reimbursement rates for neighboring states (MT, ND, MN, IA, NE, WY) over the period. Our results are not sensitive to dropping South Dakota from the analysis.

- For Tennessee, we have no micro-data on reimbursement rates, because the state only uses Medicaid Managed Care. However, we do know that average fees to physicians increased by 44% between 2012 and 2013, when the fee boost went into effect. We impute reimbursement rates for Tennessee by averaging the 2013 and 2014 ACA Medicaid reimbursement rates for neighboring states (MO, KY, VA, NC, GA, AL, MS, AR) and then go backwards from 2013 to 2012 using the fact that fees increased by 44% from 2012 to 2013. We then calculate the average rate of increase for physician fees in the neighboring states from 2009-2012, and apply this rate of change to Tennessee over the same time period.

Table 3.8: Overview of Medicaid rate data

	2009	2010	2011	2012	2013	2013 ACA	2014	2014 ACA	2015	Notes
AL	✓	✓	✓	✓	✓	✓	✓	✓	✓	
AK	✓	✓	✓	✓	✓	✓	✓	✓	✓	
AZ	✓	✓	✓	✓	✓	✓	✓	✓	✓	
AR	✓	✓	✓	✓	✓	✓	✓	✓	✓	
CA	✓	-	-	-	-	✓	-	✓	✓	Rates same in 2009 and 2015
CO	✓	✓	✓	✓	✓	✓	✓	✓	✓	
CT	✓	✓	✓	✓	✓	✓	✓	✓	✓	
DE	✓	✓	✓	✓	✓	✓	✓	✓	✓	
DC	✓	✓	✓	✓	✓	✓	✓	✓	✓	
FL	✓	✓	✓	✓	✓	✓	✓	✓	✓	
GA	✓	✓	✓	✓	✓	✓	✓	✓	✓	
HI	✓	-	-	-	✓	✓	-	✓	✓	Rates same in 2009 and standard 2013
ID	✓	✓	✓	✓	✓	✓	✓	✓	✓	
IL	✓	✓	✓	✓	✓	✓	✓	✓	✓	
IN	✓	✓	✓	✓	✓	✓	✓	✓	✓	
IA	✓	✓	✓	✓	✓	✓	✓	✓	✓	
KS	✓	✓	✓	✓	✓	✓	✓	✓	✓	
KY	✓	✓	✓	✓	✓	✓	✓	✓	✓	
LA	✓	✓	✓	✓	✓	✓	✓	✓	✓	
ME	✓	✓	✓	✓	✓	✓	✓	✓	✓	
MD	✓	✓	✓	✓	✓	✓	✓	✓	✓	
MA	✓	✓	✓	✓	✓	✓	✓	✓	✓	
MI	✓	✓	✓	✓	✓	✓	✓	✓	✓	
MN	✓	✓	✓	✓	✓	✓	✓	✓	✓	
MS	✓	✓	✓	✓	✓	✓	✓	✓	✓	
MO	✓	✓	✓	✓	✓	✓	✓	✓	✓	
MT	✓	✓	✓	✓	✓	✓	✓	✓	✓	
NE	✓	✓	✓	✓	✓	✓	✓	✓	✓	
NV	✓	✓	✓	✓	✓	✓	✓	✓	✓	
NH	✓	✓	✓	✓	✓	✓	✓	✓	✓	
NJ	✓	✓	✓	✓	✓	✓	✓	✓	✓	
NM	✓	✓	✓	✓	✓	✓	✓	✓	✓	Missing 1/09 - 11/09
NY	✓	✓	✓	✓	✓	✓	✓	✓	✓	
NC	✓	✓	✓	✓	✓	✓	✓	✓	✓	
ND	✓	✓	✓	✓	✓	✓	✓	✓	✓	
OH	✓	✓	✓	✓	✓	✓	✓	✓	✓	
OK	✓	✓	✓	✓	✓	✓	✓	✓	✓	
OR	✓	✓	✓	✓	✓	✓	✓	✓	✓	
PA	✓	✓	✓	✓	✓	✓	✓	✓	✓	
RI	✓	✓	✓	✓	✓	✓	✓	✓	✓	
SC	✓	✓	✓	✓	✓	✓	✓	✓	✓	
SD	-	-	-	-	-	✓	✓	✓	✓	Do not archive rates
TN	-	-	-	-	-	-	-	-	-	All MMC; have Δ from 2012-2013
TX	✓	✓	✓	✓	✓	✓	✓	✓	✓	
UT	✓	✓	✓	✓	✓	✓	✓	✓	✓	Missing 1/09 - 5/09, 7/12 - 12/12
VT	✓	✓	✓	✓	✓	✓	✓	✓	✓	
VA	✓	✓	✓	✓	✓	✓	✓	✓	✓	
WA	✓	✓	✓	✓	✓	✓	✓	✓	✓	
WV	✓	✓	✓	✓	✓	✓	✓	✓	✓	
WI	✓	✓	✓	✓	✓	✓	✓	✓	✓	
WY	✓	✓	✓	✓	✓	✓	✓	✓	✓	

3.B Results by duration expectations

Doctors living in different states may have different expectations about the duration of the payment increase, which may in turn may influence their responses to the fee bump. We therefore consider an additional specification where we allow the impact of changing Medicaid fees to differentially influence outcomes in states where doctors might believe that the fee boost would be extended: states that actually extended the fee boost. That is, we estimate the effect of physician payments interacted with state type on our outcome measures:

$$\begin{aligned} Outcome_{icst} &= \beta_0 + \beta_1 Fee_{st} + \beta_2 Extended\ Fee\ Boost_s \\ &\quad + \beta_3 Fee_{st} * Extended\ Fee\ Boost_s \\ &\quad + \gamma X_i + \delta Z_{ct} + \lambda_s + \lambda_t + \epsilon_{icst} \end{aligned} \tag{3.4}$$

where $Extended\ Fee\ Boost_s$ is an indicator denoting states that extended the fee boost in 2015 (displayed in Figure 3.8), and all other variables are defined as in Equation (3.1). Here, the parameters of interest are β_1, the main effect of physician payments, and β_3, the differential effect of physician payments in states where doctors may reasonably have expected the fee boost to be extended. If the fee increase only influences physician behavior in states where doctors predict the fee increase to be permanent, then β_1 would be zero and β_3 would be significant. If, however, doctors are unable to predict the duration of the payment increase, we would expect β_3 to be zero.

Results for this specification are provided in Table 3.9.

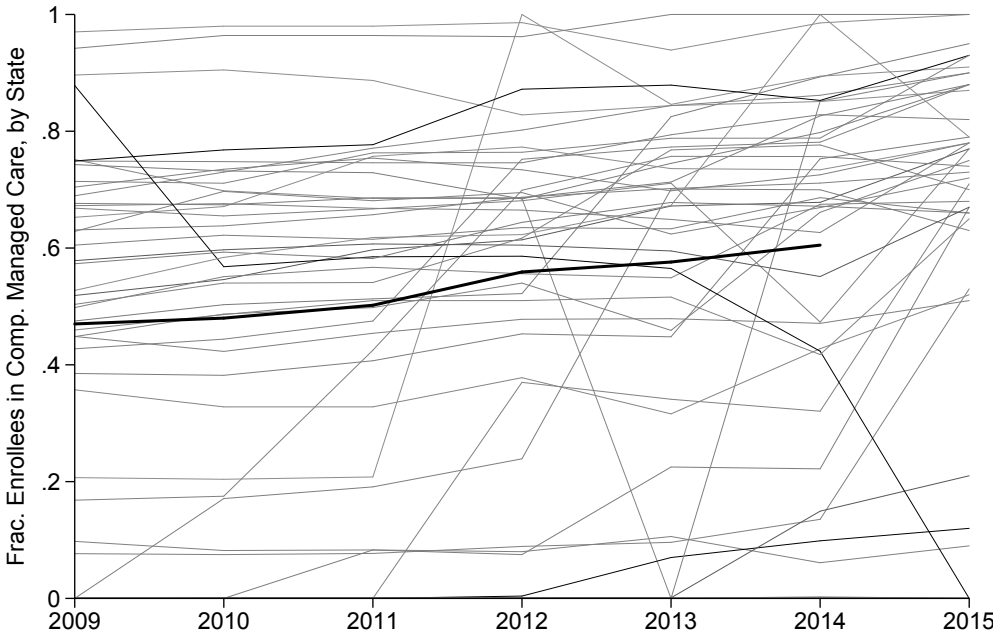
Table 3.9: Effects of physician reimbursement by duration expectations

Full Sample	Medicaid			Private		
	(1) Office Visits	(2) P/F Health	(3) Ex/VG Health	(4) Office Visits	(5) P/F Health	(6) Ex/VG Health
Medicaid fees, in $10	0.0027	-0.0027	0.0059**	-0.0007	0.0002	0.0019
	(0.0017)	(0.0017)	(0.0023)	(0.0010)	(0.0006)	(0.0017)
Extended Payments	-0.0264	-0.0244	-0.0384	-0.0221	0.0272***	-0.0496**
	(0.0183)	(0.0395)	(0.0301)	(0.0073)	(0.0046)	(0.0134)
Fees * Extended	-0.0018	0.0028	0.0007	0.0019**	-0.0002	0.0010
	(0.0020)	(0.0023)	(0.0033)	(0.0008)	(0.0005)	(0.0014)
Observations	96,017	96,067	96,067	337,506	337,903	337,903
R^2	0.071	00.296	0.232	0.036	0.079	0.138
Mean dep. var.	0.196	0.174	0.566	0.174	0.061	0.729
Child Subsample	Medicaid			Private		
	(1) Trouble finding doctor	(2) No usual place of care	(3) 14+ school days missed	(4) Trouble finding doctor	(5) No usual place of care	(6) 14+ school days missed
Medicaid fees, in $10	-0.006***	-0.0035*	-0.005**	0.0012*	0.0002	-0.0011
	(0.0015)	(0.0018)	(0.0019)	(0.0007)	(0.0010)	(0.0013)
Extended Payments	0.0344	-0.0193	-0.0053	-0.025***	0.0667***	0.0093
	(0.0206)	(0.0326)	(0.0438)	(0.0080)	(0.0236)	(0.0394)
Fees * Extended	0.0002	0.0016	-0.0027	-0.0002	-0.0001	-0.0020
	(0.0011)	(0.0017)	(0.0023)	(0.0004)	(0.0012)	(0.0022)
Observations	16,810	21,290	14,630	26,443	34,246	27,909
R^2	0.016	0.022	0.028	0.007	0.029	0.016
Mean dep. var.	0.021	0.031	0.054	0.008	0.021	0.028
Adult Subsample	Medicaid			Private		
	(1) Don't accept new patient	(2) Don't accept insurance	(3) Days missed	(4) Don't accept new patient	(5) Don't accept insurance	(6) Days missed
Medicaid fees, in $10	-0.008***	-0.008***	-0.2976	0.0005	-0.0006	0.1275
	(0.0014)	(0.0030)	(0.3658)	(0.0006)	(0.0007)	(0.1129)
Extended Payments	0.0594**	0.0347	9.7533***	0.001	-0.0088	-1.6091*
	(0.0249)	(0.0365)	(3.2685)	(0.0133)	(0.0148)	(0.8514)
Fees * Extended	-0.0021	0.001	-0.7765**	-0.0003	0.0006	0.1857*
	(0.0025)	(0.0038)	(0.2956)	(0.0008)	(0.0008)	(0.0958)
Observations	14,855	14,854	6,321	80,351	80,341	77,548
R^2	0.037	0.040	0.075	0.006	0.009	0.009
Mean dep. var.	0.055	0.075	4.929	0.016	0.022	3.730

Notes: Observations are at the individual level; standard errors are clustered by state. All regressions include state and quarter-year fixed effects and controls.

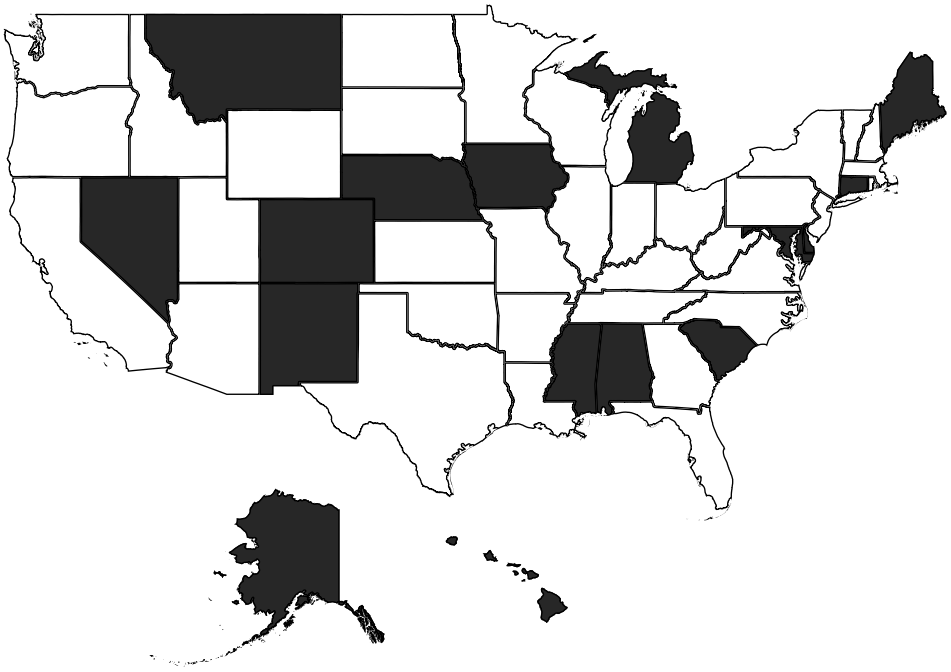
3.C Supplementary tables and figures

Figure 3.7: State-level Medicaid Managed Care penetration over time



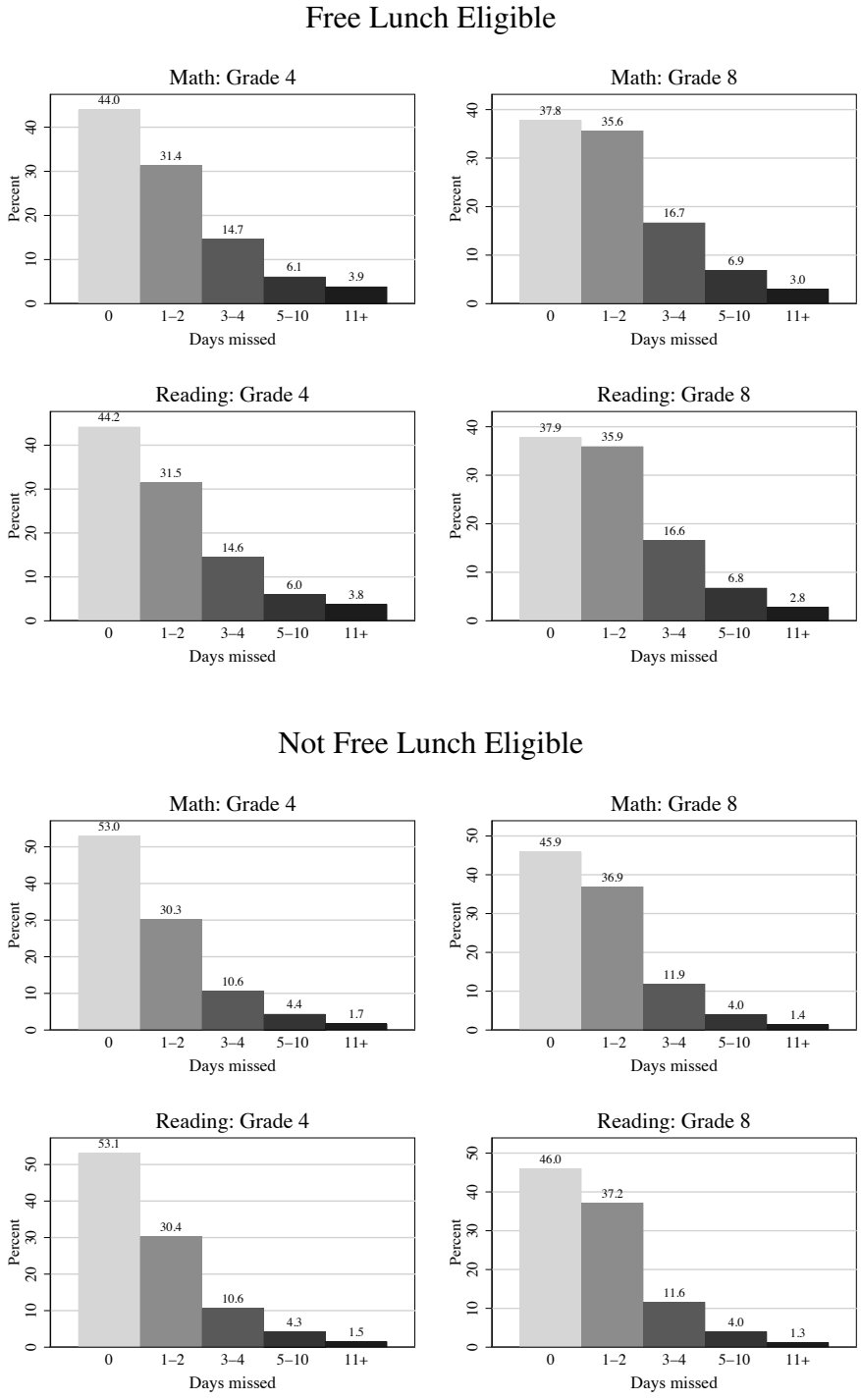
Notes: The above figure depicts the fraction of Medicaid beneficiaries enrolled in comprehensive risk-based managed care in each state from 2009 to 2015. The black line depicts the national average. Data for 2009 through 2014 come from CMS; data for 2015 comes from the Henry J. Kaiser Family Foundation. In 2014, 11 states had less than one percent of their Medicaid beneficiaries enrolled in these plans: Alabama, Alaska, Arkansas, Connecticut, Idaho, Maine, Montana, North Carolina, Oklahoma, South Dakota, and Wyoming. In the same year, nine states had more than 85 percent of their Medicaid beneficiaries enrolled in managed care plans: Arizona, Delaware, Hawaii, Kansas, Kentucky, New Hampshire, New Jersey, Tennessee, and Washington.

Figure 3.8: States extending Medicaid primary care rate increase past 2014



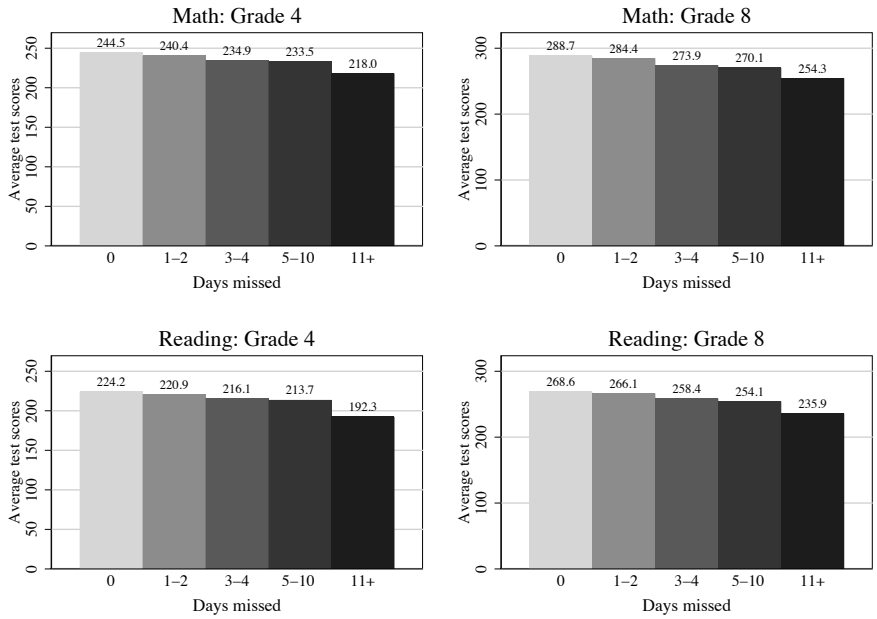
Notes: The above map depicts whether states chose to maintain the primary care rate increase after the federally funded and mandated period ended: shaded states extended higher Medicaid payment rates into 2015.

Figure 3.9: Distribution of school absences by free lunch eligibility



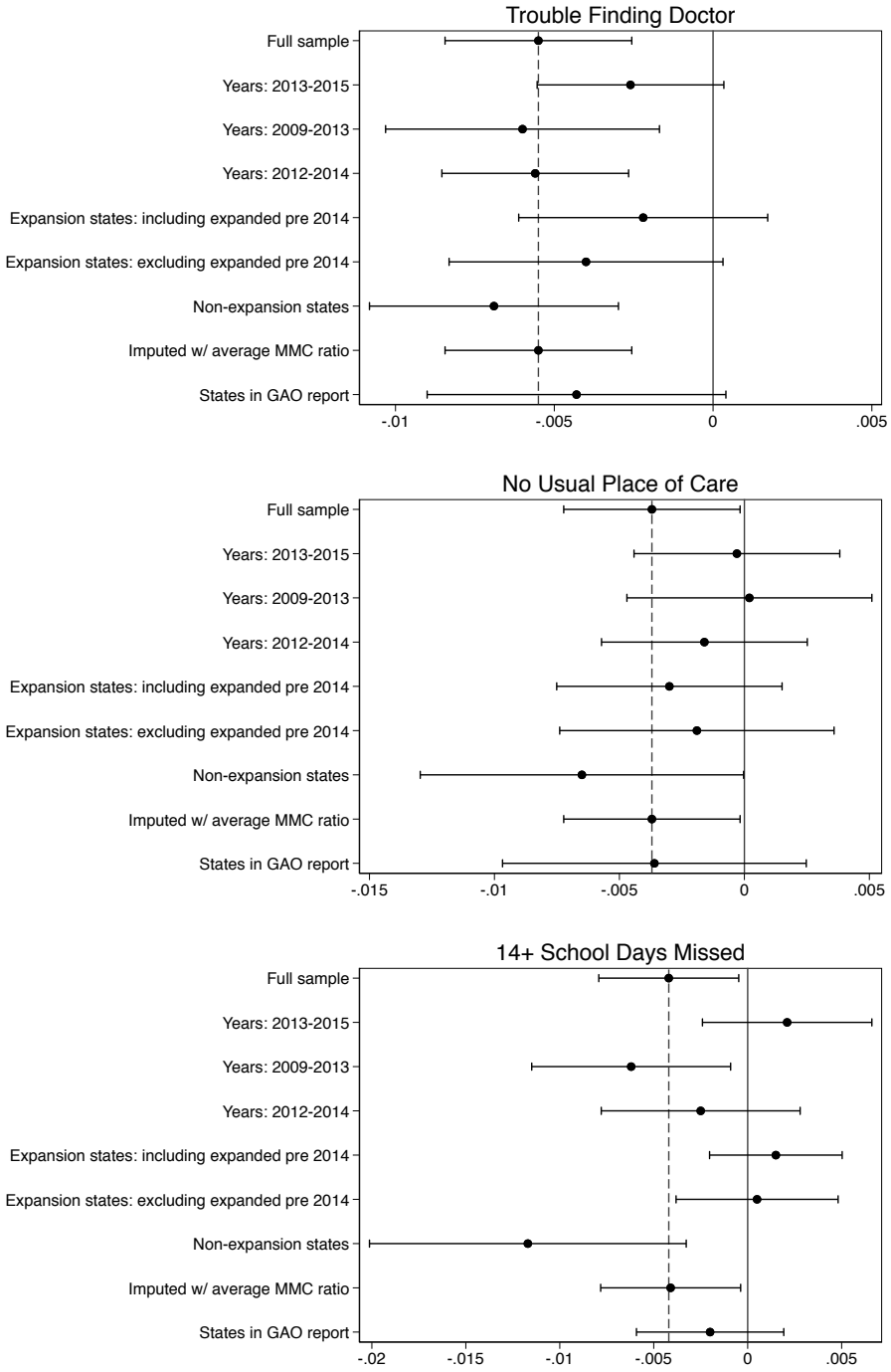
Notes: The above figures display the average percent of students who had missed 0, 1-2, 3-4, 5-10, or 11+ days in the month preceding their state assessment tests from 2009 to 2013. Data comes from the National Assessment of Educational Progress.

Figure 3.10: Average test scores by school absences



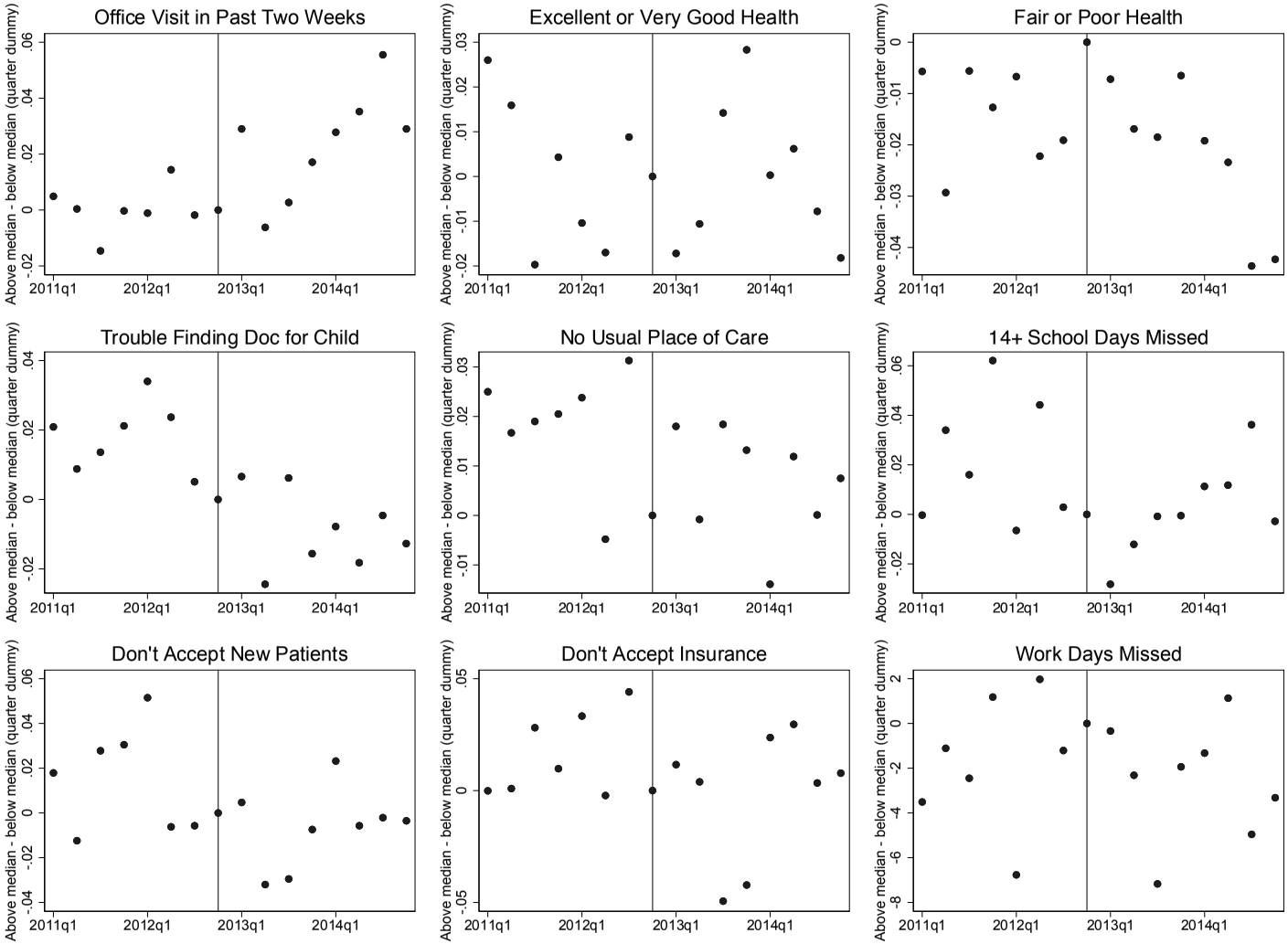
Notes: The above figures display the average test scores of students who had missed 0, 1-2, 3-4, 5-10, or 11+ days in the month preceding their state assessment tests from 2009 to 2013. Data comes from the National Assessment of Educational Progress.

Figure 3.11: Heterogeneous effects of physician reimbursement: child subsample



Notes: Each dot in the above figures depicts the estimated effect on a $10 increase in physician reimbursement under Medicaid for the subsample or alternative specification listed on the y-axis. Each coefficient comes from a separate regression. 95% confidence intervals for each coefficient are also reported. The dashed vertical lines show the coefficients in the full sample (as reported in Table 3.3).

Figure 3.12: Event time figures by size of fee increase



Notes: The above figures plot the difference between the coefficients on quarter-year dummies for states above and below the median fee increase from 2012-2013. The empirical specification is the same as in equation 1, except without the fee variable.

Table 3.10: Effects of physician reimbursement on school absences: grade 8

Free lunch eligible	3+ days missed		0 days missed	
	(1) Math	(2) Reading	(3) Math	(4) Reading
Medicaid fees, in $10	-0.208	-0.449**	0.484**	0.343
	(0.164)	(0.196)	(0.195)	(0.265)
Observations	150	150	150	150
R^2	0.827	0.825	0.866	0.856
Mean dep. var.	26.660	26.253	37.760	37.880
Free lunch ineligible	3+ days missed		0 days missed	
	(1) Math	(2) Reading	(3) Math	(4) Reading
Medicaid fees, in $10	-0.271	-0.138	0.200	0.268
	(0.165)	(0.115)	(0.207)	(0.184)
Observations	143	145	150	150
R^2	0.808	0.793	0.835	0.861
Mean dep. var.	17.336	16.890	45.887	46.027

Notes: Observations are at the state-year level; standard errors clustered by state. All regressions include state and year fixed effects. Data is from 2009, 2011, and 2013.

Table 3.11: Effects of physician reimbursement on test scores: grade 4

Math	(1) 0 days missed	(2) 1-2 days missed	(3) 3-4 days missed	(4) 5-10 days missed	(5) 11+ days missed
Medicaid fees, in $10	-0.128	-0.261	-0.233	0.163	0.468
	(0.138)	(0.172)	(0.175)	(0.274)	(0.443)
Observations	150	150	150	150	133
R^2	0.950	0.948	0.903	0.888	0.783
Mean dep. var.	244.547	240.395	234.898	233.547	218.007
Reading	(1) 0 days missed	(2) 1-2 days missed	(3) 3-4 days missed	(4) 5-10 days missed	(5) 11+ days missed
Medicaid fees, in $10	0.002	0.057	0.062	-0.480	0.152
	(0.129)	(0.145)	(0.277)	(0.453)	(0.795)
Observations	150	150	150	150	131
R^2	0.962	0.949	0.902	0.865	0.723
Mean dep. var.	224.185	220.928	216.108	213.696	192.338

Notes: Observations are at the state-year level; standard errors clustered by state. All regressions include state and year fixed effects. Data is from 2009, 2011, and 2013.

Table 3.12: Effects of physician reimbursement on test scores: grade 8

Math	(1) 0 days missed	(2) 1-2 days missed	(3) 3-4 days missed	(4) 5-10 days missed	(5) 11+ days missed
Medicaid fees, in $10	0.411**	0.298*	0.477**	-0.036	-0.610
	(0.176)	(0.164)	(0.224)	(0.310)	(1.334)
Observations	150	150	150	150	64
R^2	0.968	0.966	0.939	0.862	0.790
Mean dep. var.	288.665	284.352	273.929	270.138	254.282
Reading	(1) 0 days missed	(2) 1-2 days missed	(3) 3-4 days missed	(4) 5-10 days missed	(5) 11+ days missed
Medicaid fees, in $10	0.195	-0.047	0.182	-0.363	1.478
	(0.168)	(0.134)	(0.226)	(0.456)	(0.890)
Observations	150	150	150	150	55
R^2	0.959	0.961	0.917	0.811	0.751
Mean dep. var.	268.644	266.059	258.375	254.061	235.907

Notes: Observations are at the state-year level; standard errors clustered by state. All regressions include state and year fixed effects. Data is from 2009, 2011, and 2013.

Table 3.13: Effects of physician reimbursement: imputing with mean fee ratio

Full Sample	Medicaid			Private		
	(1) Office Visits	(2) P/F Health	(3) Ex/VG Health	(4) Office Visits	(5) P/F Health	(6) Ex/VG Health
Medicaid fees, in $10	0.0027	-0.0030*	0.0059**	-0.0008	0.0002	0.0017
	(0.0017)	(0.0016)	(0.0023)	(0.0010)	(0.0006)	(0.0017)
Observations	96,017	96,067	96,067	337,506	337,903	337,903
R^2	0.071	0.296	0.232	0.036	0.079	0.138
Mean dep. var.	0.196	0.174	0.566	0.174	0.061	0.729
Child Subsample	Medicaid			Private		
	(1) Trouble finding doctor	(2) No usual place of care	(3) 14+ school days missed	(4) Trouble finding doctor	(5) No usual place of care	(6) 14+ school days missed
Medicaid fees, in $10	-0.0055***	-0.0037**	-0.0041**	0.0012*	0.0002	0.0009
	(0.0015)	(0.0018)	(0.0019)	(0.0007)	(0.0010)	(0.0013)
Observations	16,810	21,290	14,630	26,443	34,246	27,909
R^2	0.016	0.022	0.027	0.007	0.029	0.015
Mean dep. var.	0.021	0.031	0.054	0.008	0.021	0.028
Adult Subsample	Medicaid			Private		
	(1) Don't accept new patient	(2) Don't accept insurance	(3) Days missed	(4) Don't accept new patient	(5) Don't accept insurance	(6) Days missed
Medicaid fees, in $10	-0.0076***	-0.0082***	-0.1872	0.0005	-0.0007	0.1040
	(0.0015)	(0.0030)	(0.3598)	(0.0006)	(0.0006)	(0.1117)
Observations	14,855	14,854	6,321	80,351	80,341	77,548
R^2	0.037	0.040	0.075	0.006	0.009	0.009
Mean dep. var.	0.055	0.075	4.929	0.016	0.022	3.730

Notes: Observations are at the individual level; standard errors are clustered by state. All regressions include state and quarter-year fixed effects, and all individual and county-level controls listed in Table 3.2 are included (age enters the regressions in 5-year bins). Regressions are weighted using the sample weights provided in the NHIS.

Table 3.14: Effects of physician reimbursement: states in GAO report

Full Sample	Medicaid			Private		
	(1) Office Visits	(2) P/F Health	(3) Ex/VG Health	(4) Office Visits	(5) P/F Health	(6) Ex/VG Health
Medicaid fees, in $10	0.0062**	-0.0021	0.0078**	-0.0024	-0.0000	0.0003
	(0.0016)	(0.0024)	(0.0037)	(0.0016)	(0.0009)	(0.0024)
Observations	61,245	61,282	61,282	193,285	193,545	193,545
R^2	0.070	0.282	0.223	0.036	0.075	0.132
Mean dep. var.	0.192	0.172	0.566	0.173	0.060	0.729
Child Subsample	Medicaid			Private		
	(1) Trouble finding doctor	(2) No usual place of care	(3) 14+ school days missed	(4) Trouble finding doctor	(5) No usual place of care	(6) 14+ school days missed
Medicaid fees, in $10	-0.0043*	-0.0036	-0.002	0.0009	0.0008	-0.0008
	(0.0024)	(0.0031)	(0.002)	(0.0013)	(0.0022)	(0.0016)
Observations	10,109	13,221	9,224	14,544	19,657	16,164
R^2	0.022	0.021	0.032	0.009	0.029	0.019
Mean dep. var.	0.021	0.031	0.051	0.009	0.022	0.027
Adult Subsample	Medicaid			Private		
	(1) Don't accept new patient	(2) Don't accept insurance	(3) Days missed	(4) Don't accept new patient	(5) Don't accept insurance	(6) Days missed
Medicaid fees, in $10	-0.0080*	0.001	-0.3079	0.0005	0.001	0.0310
	(0.0039)	(0.0055)	(0.4778)	(0.0011)	0.0011)	(0.1655)
Observations	8,597	8,595	3,839	41,499	41,491	42,137
R^2	0.051	0.046	0.194	0.007	0.010	0.010
Mean dep. var.	0.057	0.070	5.123	0.014	0.021	3.626

Notes: Observations are at the individual level; standard errors are clustered by state. All regressions include state and quarter-year fixed effects, and all individual and county-level controls listed in Table 3.2 are included (age enters the regressions in 5-year bins). Regressions are weighted using the sample weights provided in the NHIS.

Table 3.15: Effects of physician reimbursement: primary care shortage areas

Full Sample	Medicaid			Private		
	(1) Office Visits	(2) P/F Health	(3) Ex/VG Health	(4) Office Visits	(5) P/F Health	(6) Ex/VG Health
Medicaid fees, in $10	0.0025	-0.0028	0.0055**	-0.0006	0.0007	0.0014
	(0.0017)	(0.0017)	(0.0027)	(0.0010)	(0.0006)	(0.0018)
PC shortage	-0.0058	0.015	-0.0248	0.0029	0.0086***	-0.0111*
	(0.0127)	(0.0113)	(0.0183)	(0.0045)	(0.0029)	(0.0063)
Fees * Shortage	0.0008	-0.0007	0.0012	-0.0005	-0.0009**	0.0008
	(0.0017)	(0.0014)	(0.0022)	(0.0006)	(0.0004)	(0.0008)
Observations	96,017	96,067	96,067	337,506	337,903	337,903
R^2	0.071	00.296	0.232	0.036	0.079	0.138
Mean dep. var.	0.196	0.174	0.566	0.174	0.061	0.729
Child Subsample	Medicaid			Private		
	(1) Trouble finding doctor	(2) No usual place of care	(3) 14+ school days missed	(4) Trouble finding doctor	(5) No usual place of care	(6) 14+ school days missed
Medicaid fees, in $10	-0.006***	-0.0037*	-0.0042	0.0011	0.0003	-0.0010
	(0.0017)	(0.0020)	(0.0022)	(0.0008)	(0.0012)	(0.0013)
PC shortage	-0.0078	-0.0001	-0.0014	0.0012	0.0021	-0.0038
	(0.0140)	(0.0114)	(0.0201)	(0.0052)	(0.0059)	(0.0089)
Fees * Shortage	0.0006	0.0000	0.0000	0.0002	-0.0002	0.0003
	(0.0015)	(0.0012)	(0.0022)	(0.0006)	(0.0007)	(0.0011)
Observations	16,810	21,290	14,630	26,443	34,246	27,909
R^2	0.016	0.022	0.028	0.007	0.029	0.016
Mean dep. var.	0.021	0.031	0.054	0.008	0.021	0.028
Adult Subsample	Medicaid			Private		
	(1) Don't accept new patient	(2) Don't accept insurance	(3) Days missed	(4) Don't accept new patient	(5) Don't accept insurance	(6) Days missed
Medicaid fees, in $10	-0.008***	-0.0071**	-0.2885	0.0004	-0.0005	0.1703
	(0.0017)	(0.0030)	(0.3118)	(0.0007)	(0.0008)	(0.1248)
PC shortage	-0.0225*	-0.0018	-2.184	-0.0032	0.0046	0.8044
	(0.0129)	(0.0164)	(2.7856)	(0.0052)	(0.0075)	(0.7220)
Fees * Shortage	0.0008	-0.0019	0.2566	0.0003	-0.0003	-0.1255
	(0.0013)	(0.0016)	(0.3115)	(0.0006)	(0.0008)	(0.0844)
Observations	14,855	14,854	6,321	80,351	80,341	77,548
R^2	0.037	0.040	0.075	0.006	0.009	0.009
Mean dep. var.	0.055	0.075	4.929	0.016	0.022	3.730

Notes: Observations are at the individual level; standard errors are clustered by state. All regressions include state and quarter-year fixed effects and controls.