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ABSTRACT

We ask how competition influences the prescribing practices of physicians. Law changes granting nurse practitioners (NPs) the ability to prescribe controlled substances without physician collaboration or oversight generate exogenous variation in competition. In response, we find that general practice physicians (GPs) significantly increase their prescribing of controlled substances such as opioids and controlled anti-anxiety medications. GPs also increase their co-prescribing of opioids and benzodiazepines, a practice that goes against prescribing guidelines. These effects are more pronounced in areas with more NPs per GP at baseline and are concentrated in physician specialties that compete most directly with NPs. Our findings are consistent with a simple model of physician behavior in which competition for patients leads physicians to move toward the preferences of marginal patients. These results demonstrate that more competition will not always lead to improvements in patient care and can instead lead to excessive service provision.

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I Introduction

Policy makers in the United States have long sought to increase competition in health care markets.[1] Yet, given imperfections in these markets, it is not clear that increased competition will always improve welfare (Gaynor et al., 2015). Increased competition could, for example, lead providers to exert their market power or increase demand inducement, thereby increasing the provision of costly or inappropriate care (McGuire, 2000).

Most empirical research into the effects of competition in health care has focused on large players, such as insurers and hospitals. There has been relatively little investigation of competition at the level of individual physicians, even though physicians ultimately make most decisions about patient care. This lack of research may be due in part to constraints on the availability of physician-level data and limited time-series variation in measures of concentration. Such constraints have made empirical analyses of the effects of competition on physician behavior difficult.

This paper asks how the prescribing practices of general practitioners (GPs) change following sharp increases in competition being experienced in many markets due to changes in state-level scope-of-practice laws granting nurse practitioners (NPs) the ability to independently prescribe controlled substances.[2] We analyze comprehensive data from IQVIA covering the prescriptions written by individual providers across the United States from 2006–2018 and find that GPs begin to prescribe more opioids and scheduled anti-anxiety medications (i.e., addictive, controlled substances) when they are subject to increased competition from NPs. GPs also increase their co-prescribing of opioids and benzodiazepines to the same patient on the same day, a behavior that the Centers for Disease Control and Prevention (CDC) prescribing guidelines indicate that clinicians should avoid "whenever

[1] For example, a joint commission of the Federal Trade Commission and the Department of Justice recommended increasing transparency in pricing and lowering barriers to entry into primary care for allied health professions to increase competition (FTC and DOJ, July 2004).

[2] We consider doctors in family, general, and internal medicine to be GPs; all our results are robust to including only physicians in family or general practice. An NP is a nurse who has obtained at least a master's degree in nursing and who has completed local licensure and national certification requirements. States have the authority to define what NPs are allowed to do and frequently update associated legislation, leading to wide variation in scope of practice for NPs both across states and within states over time. NPs are one type of advanced practice registered nurse (APRN); this broader category also includes certified nurse-midwifes, certified registered nurse anesthetists, and clinical nurse specialists.

possible" (CDC, 2016). We find no effects on the prescribing of unscheduled anti-anxiety medications and relatively small, positive effects on the prescribing of unscheduled antidepressants. While not directly affected by the law changes that we consider, antidepressants can lead to physical dependence and are often prescribed with benzodiazepines to control side effects (Bushnell et al., 2017). Taken together, these results are reminiscent of a "medical arms race" in that they suggest that more competition will not always lead to improvements in patient care and can instead lead to excessive service provision.

Three additional sets of results support the hypothesis that our findings are driven by increases in competition. First, observed increases in prescribing among physicians are higher in areas with a greater number of NPs per GP at baseline. That is, GPs respond more in areas in which they are subject to greater competition from NPs when NPs are allowed to prescribe independently. Second, changes in prescribing are concentrated among physicians practicing in the specialties that compete most directly with NPs rather than in specialties that face little competitive pressure from NPs. Finally, we rule out the possibility that our results could be driven by increases in physician workloads resulting from NPs leaving their joint practices by showing that the law changes do not affect the share of GPs practicing in clinics with NPs or the number of NPs per GP practice.

The results on opioid prescribing are particularly important considering the ongoing opioid crisis in the United States. To shed additional light on how competition affects opioid prescribing, we conduct two additional analyses. First, focusing on patients who did not receive an opioid prescription in the past six months, we find that competition-induced increases in opioid prescribing are driven by new prescriptions to such "opioid-naïve" patients. Moreover, examining changes in average morphine milligram equivalents (MMEs) per prescription shows that competition leads GPs to write prescriptions with higher dosages, both for patients who are and are not opioid naïve. These results highlight the important role played by physicians in initiating opioid use and contribute to recent work documenting that the opioid crisis is driven in large part by supply-side factors.[3]

Our paper relates to four branches of literature. First, many studies examine the effects

[3] See Currie and Schwandt (2021) for a recent review of this large literature.

of competition among large players, such as insurers and hospitals.[4] Seminal work by Dafny (2010) and Dafny et al. (2012) documents high levels of concentration in markets for health insurance and finds that insurers charge higher premiums in more-concentrated insurance markets. However, Ho and Lee (2017) and Barrette et al. (2020) highlight that hospitals also have market power; thus, increased concentration in insurance markets could enable insurers to negotiate lower prices from hospitals, possibly increasing consumer welfare. Focusing on elderly heart attack patients, Kessler and McClellan (2000) find that while competition between hospitals can reduce both costs and mortality under certain market conditions, competition can also lead to a medical arms race in which more costly and unnecessary care is supplied.[5] We complement this work by showing that increased competition among individual providers can likewise have perverse effects, leading to increases in prescribing that are likely welfare reducing.

Second, this paper adds to a smaller literature examining the effects of competition among physicians and its impact on physician-induced demand. Given limited variation in concentration within markets over time, most investigations of competition at the physician level have been cross-sectional. For example, Dunn and Shapiro (2014, 2018) show that areas with higher concentrations of cardiac surgeons have higher prices and higher procedure use, and Scott et al. (2022) find that GPs practicing closer to other GPs provide more unnecessary imaging. An important exception is Gruber and Owings (1996), who show that reductions in the demand for obstetrical services due to declining fertility rates in the 1970s led to increases in the use of (presumably unnecessary) C-sections, which are more highly remunerated than vaginal deliveries.[6] We build on this literature by using comprehensive, individual-level panel

[4]Recent work on retail pharmacies by Janssen and Zhang (2023) shows that competitive pressures can help explain why independent pharmacies are more likely to dispense prescription opioids—both for legitimate and non-medical use—than chain pharmacies.

[5]Related work by Gowrisankaran and Town (2003) finds that the effect of competition for patients on hospital quality depends on the type of insurance held by patients. Other work on hospitals finds that measures that increase patient hospital choice in the United Kingdom reduce patient deaths and lengths of stay without increasing costs (Gaynor et al., 2013). Also in the U.K. setting, Bloom et al. (2015) find that decreases in competition due to hospital closures leads to reductions in management quality and increases in deaths among heart attack patients. A related literature at the intersection of health economics and industrial organization examines the impacts of hospital mergers on prices, quality, and patient outcomes. For example, Dafny (2009) shows that hospital mergers result in higher prices among rivals of merged firms; see Gowrisankaran et al. (2015) for more recent work on the impacts of hospital mergers on prices and Gaynor et al. (2015) for a recent overview of hospital merger effects.

[6]See McGuire (2000) for an overview of the literature on physician-induced demand. Early work by

data and a novel instrument for competition to examine how increased competition affects the prescribing practices of physicians.

Third, this paper relates to the large literature examining factors that drive physician decision-making. Studies have documented pronounced heterogeneity in the intensity of health care provision across locations (e.g., Fisher et al., 2003; Finkelstein et al., 2016) and individual providers (e.g., Parys, 2016; Currie et al., 2016; Currie and Zhang, forthcoming; Gowrisankaran et al., forthcoming). These findings have motivated work aimed at identifying factors that can explain such differences, including investigations into the roles played by financial incentives (Clemens and Gottlieb, 2014; Alexander and Schnell, 2019a), physician skill (Currie and MacLeod, 2017, 2020; Chan et al., 2022), and provider beliefs (Cutler et al., 2019). Particularly relevant for our study, recent work focusing on supply-side drivers of the opioid crisis has examined how opioid prescribing is affected by training (Schnell and Currie, 2018; Zhang, 2023), beliefs about risks (Doctor et al., 2018), pharmaceutical marketing (Alpert et al., 2022; Arteaga and Barone, 2022), and provider altruism (Schnell, 2017). We add to this literature by considering a novel driver of variation in physician behavior—exposure to competition—and show that the competitive landscape affects physicians' prescribing of controlled substances.[7]

Finally, our paper relates to a growing literature on the impacts of changes in scope-of-practice legislation for NPs on patient care. As outlined in a recent overview by Markowitz and McMichael (2020), much of this literature has focused on the impacts of expanded scope of practice on patient access and health using either aggregate or patient-level data.[8] For example, Traczynski and Udalova (2018) document that allowing NPs to both practice

Fuchs (1978) and Cromwell and Mitchell (1986) shows that rates of surgery are higher in locations with more surgeons, a finding that the authors attribute to demand inducement. However, follow-up work by Dranove and Wehner (1994) shows that similar findings also hold for obstetricians and childbirth, a service for which induced demand is likely minimal. These findings highlight the difficulties with designs that rely predominately on cross-sectional variation in provider supply. Another approach is to conduct a lab experiment as in Brosig-Koch et al. (2017).

[7]Our findings that competition increases both the number of prescriptions for opioid-naïve patients and the strength of prescriptions for naïve and non-naïve patients suggests that competitive landscapes are important components of both the addiction and availability channels of place-based factors identified by Finkelstein et al. (2022).

[8]Recent work by Chan and Chen (2022) documents wide variation in productivity among both physicians and NPs by leveraging random assignment of patients to providers in the emergency department. Our paper complements this work by showing that competition between these two classes of professionals can alter physician practice styles.

and prescribe independently leads to increases in utilization of primary care services, while Alexander and Schnell (2019b) show that allowing NPs to independently prescribe unscheduled drugs (including most antidepressants) leads to improvements in mental health. In a law review article, McMichael (2020) argues that similar laws allowing NPs to prescribe opioids reduced opioid prescribing among physicians over the period 2011–2018. However, opioid prescribing was steeply declining over this period, suggesting that this result could be driven by pre-trends, an issue we discuss further below. We build on this work by examining the impacts of changes in scope-of-practice legislation on the prescribing practices of individual providers over a 13-year period, which allows for a careful consideration of pre-trends, and show that these laws affect the behavior of both NPs and physicians by changing the competitive landscape.

The rest of the paper proceeds as follows. Section II provides a theoretical framework that highlights how increased competition can lead physicians to increase unnecessary, and potentially harmful, service provision. Section III provides an overview of the data, and Section IV discusses our methods. Results are presented in Section V, and Section VI gives a discussion and concludes.

II Theoretical framework

This section offers a theoretical framework that outlines how competition can influence the intensity of services provided by physicians. The framework highlights the idea that the effects of competition will depend on the type of service being rendered.

In particular, the model predicts that increased competition should put *downward pressure* on the provision of services like C-sections that physicians might like to do more of (e.g., because they are time efficient and highly remunerated) but marginal patients may not want (e.g., because they are unnecessary and cause complications). In contrast, increased competition should put *upward pressure* on the provision of services like prescription opioids that some marginal patients want (e.g., because of addiction, resale value, or the possibility of immediate pain relief) but physicians may not want to provide more of (because their utility of prescribing to marginal patients is negative).[9] In both cases, physician behavior shifts toward the preferences of the marginal patient when competition increases. Whether increased competition leads to more or less service provision therefore depends on whether physicians are over- or underproviding care from the perspective of the marginal patient at baseline.

Let x denote the intensity of service provision. This x can either be thought of as an extensive margin measure of the share of patients receiving a given service (e.g., the share of patients receiving an opioid prescription) or an intensive margin measure that further captures the intensity of treatment conditional on its provision (e.g., average daily MME per opioid prescription).[10] For a given intensity of service provision, the physician sees $N(x)$ patients and receives utility $u(x)$ per patient. $N(x)$ captures patient preferences and will be increasing (decreasing) in x if patients find additional x beneficial (harmful). Analogously, $u(x)$ captures the physician's preferences and financial incentives regarding treatment for a given patient and will be increasing (decreasing) in x if physicians believe additional x to be beneficial (harmful) to their own utility.[11] For simplicity, we assume that $N_{xx} = u_{xx} = 0$.

The physician chooses her optimal level of service intensity to maximize her total utility. The physician's problem can therefore be written as:

$$\max_x \quad N(x) \cdot u(x).$$

[9]Note that this does not imply that physicians are necessarily altruistic and trying to protect patients from the dangers of addictive medications. As outlined in Schnell (2017), a physician's optimal prescription decision can be modeled as a threshold rule in which the provider chooses a level of patient pain above (below) which they do (do not) prescribe. This threshold is set such that the physician's marginal utility of prescribing to the threshold patient is zero; if a provider cares both about their impact on patient health and their revenue, this is the point at which the harm caused by the medication just offsets the monetary reimbursement that the provider receives per office visit. In this context, the provider (1) harms their threshold patient from a medical perspective (i.e., they overprescribe) but (2) does not want to prescribe more at the margin (i.e., they do not want to reduce their threshold). Nevertheless, some marginal patients—for example, those with low pain but high tastes for opioids—will want additional prescriptions.

[10]If all patients are identical, x as an extensive margin measure represents the fraction of these identical patients who receive a given service. If patients differ and are ordered by their appropriateness for the treatment, then a higher value of x indicates that additional patients for whom the treatment is less appropriate receive the service in question.

[11]For our purposes it is not necessary to specify a precise functional form for $u(x)$, but it is typically presumed that a physician derives utility both from the impact their service provision has on patient health and from their revenue (McGuire, 2000).

Taking the derivative with respect to x and setting it equal to zero yields the following first-order condition:

$$N_x \cdot u(x^*) + N(x^*) \cdot u_x = 0$$
$$\Rightarrow \frac{N_x}{N(x^*)} = -\frac{u_x}{u(x^*)}. \tag{1}$$

This first-order condition shows that the physician decides on the intensity of service provision by balancing the elasticities with respect to service intensity of the number of patients that she attracts and the utility that she receives per patient.

There are four cases to consider. If both patients and physicians benefit from additional service intensity (i.e., if $N_x > 0$ and $u_x > 0$), then there is no trade-off between per patient utility and the number of patients seen, and the physician sets x^* at the highest possible level. Analogously, the physician sets x^* at the lowest possible level if both patients and physicians are harmed by additional service delivery (i.e., if $N_x < 0$ and $u_x < 0$). The interesting cases occur when the incentives of patients and physicians are misaligned. This will occur whenever: (1) physicians receive higher per-patient utility by increasing service intensity, but additional service intensity loses them patients (i.e., if $N_x < 0$ and $u_x > 0$), or (2) patients desire additional service intensity that physicians do not want to provide for a given patient (i.e., if $N_x > 0$ and $u_x < 0$).

We ask how competition affects the optimal intensity of service provision chosen by the physician. As the market becomes more competitive, each patient's decision about which provider to see becomes more sensitive to the level of service intensity because the patient has greater outside options. In turn, N becomes more sensitive to the intensity of service provision, and thus $\mid N_x \mid$ is increasing in competition. Since an increase in $\mid N_x \mid$ increases the magnitude of the left-hand side of equation (1), either $N(x^*)$ must increase or $u(x^*)$ must decrease for the first-order condition to stay in balance. That is, when there is a tension between the preferences of patients and physicians, competition leads the physician to sacrifice per-patient utility to try to maintain the number of patients.

Suppose first that $N_x < 0$ and $u_x > 0$. In this case, an increase in competition leads to a reduction in x^*. That is, for services that marginal patients do not want (e.g., because the costs outweigh the potential benefits), but that physicians would like to do more of (e.g., because they are highly remunerated), increased competition should reduce the intensity of service provision. Consistent with this logic, Markowitz et al. (2017) find that C-section rates decrease when scope-of-practice laws for certified nurse-midwives are relaxed, thereby increasing competition facing obstetricians.

Now suppose that $N_x > 0$ and $u_x < 0$. In this case, an increase in competition should instead lead to an increase in x^*. That is, for services that providers do not want to provide more of (e.g., because they are harming marginal patients), but that some marginal patients want (e.g., because of desired pain relief, addiction, or non-health benefits like resale value), increased competition should increase the intensity of service provision. As long as some patients want medications that they are not currently prescribed (or larger prescriptions than they are currently prescribed)—as the presence of secondary markets for many addictive and abusable medications suggests is the case—this logic will likely govern the impacts of competition on the intensity of services like opioid and benzodiazepine prescribing.

Of course, alternative models of physician behavior can also be used to micro-found our finding that increased competition leads to increases in the prescribing of certain medications. For example, as shown in Appendix C, a model of demand inducement can likewise deliver this result (Gruber and Owings, 1996; McGuire, 2000). In a demand-inducement framework, the effect operates through an income effect: When competition increases, physicians lose patients, thereby reducing their income. Given diminishing marginal utility of income, physician utility is more responsive to changes in income at lower levels of income, and thus inducing demand—which is assumed to have a constant marginal cost—is now more appealing. This mechanism will lead to an increase in the intensity of service provision, like unnecessary opioid and benzodiazepine prescribing, that physicians might find more profitable than alternative treatment options.[12] Perverse effects of competition on physician behavior are therefore consistent with a range of theoretical underpinnings.

[12] Although physicians do not directly increase their profits by prescribing opioids as they would, for example, by performing C-sections instead of vaginal deliveries, prescribing opioids takes little time and may make patients more likely to return, leading to more billing for office visits.

III Data

We use two main data sources to examine how changes in competition affect the prescribing practices of physicians. As outlined below, provider-level information on prescriptions come from the IQVIA LRx database, and information on state-level changes in scope-of-practice legislation for NPs come from Markowitz and McMichael (2020). These data are supplemented with population counts at the county-year level from the five-year American Community Survey (ACS) to construct measures of prescriptions and providers per capita.[13] We also use information on drug-related mortality at the county-year level from the National Vital Statistics System (NVSS) to examine whether competition-induced changes in prescribing affect fatal drug overdoses.

III.A Prescription data

The prescription data come from IQVIA, a public company specializing in pharmaceutical market intelligence. These data include detailed information on most opioid, anti-anxiety, and antidepressant prescriptions written in the United States from 2006–2018.[14] These data also include information on each provider from the American Medical Association (AMA).

Four features of these data are important for our analyses. First, the data have both a provider and an (anonymized) patient identifier. These identifiers allow us to track the prescriptions from a given provider and for a given patient over time. They also allow us to measure instances of co-prescribing and to identify patients who are starting new medications ("naïve" patients). Second, the data have prescription-specific information on each patient's zip code. As outlined in Appendix B, we use this information to construct a provider-year–level panel of practice locations over our sample period.[15] Third, the data

[13] The data for 2008–2018 are available here: https://www.socialexplorer.com/explore-tables. We use a linear extrapolation to impute population for 2006 and 2007.

[14] IQVIA directly surveys most retail pharmacies, long-term care homes, and mail-order drug suppliers and then uses a patented projection method to impute any remaining prescriptions to match industry totals. While IQVIA therefore tracks most retail prescribing in the United States, the LRx data contain the subset of these prescriptions that are written for patients who can be tracked over time. We estimate that the LRx data cover over 75 percent of U.S. retail prescriptions over our sample period for the drug classes that we use, with nearly 90 percent coverage by 2018. The IQVIA data are available for purchase to qualified researchers; for further information, contact Allen.Campbell@iqvia.com.

[15] The data from IQVIA include snapshots of provider locations in 2014 and 2018, whereas we aim to know

have detailed information on the prescription being dispensed, including the National Drug Code (NDC) of the product, the strength of the medication, and the number of pills at the prescription level. We use the Food and Drug Administration's (FDA's) NDC data to determine which products are controlled substances.[16] Information on the size and strength of prescriptions is used to examine intensive margin measures such as average daily MME per opioid prescription. Finally, these data have information on each provider's specialty. This information allows us to examine heterogeneity in the effects of competition across physician types that are differentially exposed to competition from NPs.

We consider the prescribing and co-prescribing of four types of medication throughout the paper. First, we expect the changes in competition that we consider to have the largest impacts on the prescribing of controlled substances. Hence, we focus on the prescribing of opioids and scheduled anti-anxiety medications like benzodiazepines. These medications are regulated under the Controlled Substances Act because they are generally addictive and carry a risk of fatal overdose. Moreover, the CDC recommends that clinicians avoid prescribing benzodiazepines concurrently with opioids "whenever possible" due to a heightened risk of respiratory failure (CDC, 2016). We therefore also consider instances in which the same patient receives both an opioid prescription and a benzodiazepine prescription from the same provider on the same day ("co-prescribing").

In addition to controlled substances, we consider the prescribing of two types of unscheduled medications available in our data: non-controlled anti-anxiety medications and antidepressants.[17] The prescribing of non-controlled anti-anxiety medications is expected to

provider locations in each year from 2006 to 2018. As outlined in Appendix B, we use information on the zip codes of patients who fill the prescriptions written by each provider in each year to assign providers to their likely county of practice annually. This location-assignment algorithm identifies the same county (state) in 2018 as IQVIA for 66.6 (89.7) percent of providers and 76.4 (94.8) percent of prescriptions; statistics are slightly lower when comparing our inferred locations to those in IQVIA's 2014 snapshot. We further compare our constructed location panel to locations provided in the AMA Masterfile, the National Plan and Provider Enumeration System, and the Centers for Medicaid and Medicare Services' "Physician Compare" database in Appendix B. These comparisons highlight a number of problems with these alternative data sources—including outdated location information and poor provider coverage—that motivate our use of a data-driven location assignment algorithm.

[16] The FDA's NDC data is available through the NBER at https://data.nber.org/data/national-drug-code-data-ndc.html.

[17] All antidepressant medications except for chlordiazepoxide products are unscheduled. As chlordiazepoxide products account for less than 0.5 percent of all antidepressant prescriptions, we exclude them from the list of antidepressants and consider only the prescribing of non-controlled antidepressants.

either decrease (if controlled anti-anxiety medications replace non-controlled medications) or to remain the same. It is less clear what would be expected to happen to antidepressant medications. While these medications are not controlled substances, patients can develop a physical dependence on them (Gabriel and Sharma, 2017). Moreover, patients who are prescribed antidepressants are frequently co-prescribed benzodiazepines to deal with the side effects (Bushnell et al., 2017), in which case antidepressants and controlled anti-anxiety medications might be considered complements. Hence, the prescribing of antidepressants could either remain the same or increase.

Table 1 provides an overview of the number of unique providers (column (1)) and the total number of prescriptions across drug types (columns (2)–(6)) observed in our data. These statistics are provided over the entire sample period (panel (a)) and separately for the first and last year of the sample (panels (b) and (c), respectively). The over 1.5 million unique prescribers observed in the data wrote 2.06 billion opioid prescriptions, 925 million anti-anxiety prescriptions (both controlled and non-controlled), and 2.36 billion antidepressant prescriptions from 2006–2018. Over 80 percent of the anti-anxiety prescriptions were written for controlled drugs such as benzodiazepines, and over 100 million benzodiazepine prescriptions were co-prescribed with an opioid prescription. Prescriptions for anti-anxiety medications and antidepressant medications increased substantially from 2006 to 2018; in contrast, prescriptions for opioids increased nationally from 2006 to around 2010 and have since been trending downward.

Columns (2)–(6) of Table 1 report the shares of each prescription type written by physicians in different specialties and by NPs. Across all drug types considered, GPs account for the most prescriptions of any specialty. This is both because there are many GPs and because they often rank near the top in terms of prescriptions per provider across specialties. Despite being unable to prescribe independently in many state-years over our sample period, NPs also accounted for a large share of total prescriptions. As shown in panels (a) and (c), respectively, NPs accounted for the third highest share of opioid prescriptions from 2006–2018 (behind GPs and orthopedic surgeons) and the second highest share in 2018 (behind only GPs). NPs also accounted for the third highest share of controlled anti-anxiety prescriptions, non-controlled anti-anxiety prescriptions, and antidepressant prescriptions over our sample period (behind GPs and psychiatrists/neurologists for all three categories). This prominence is due in large part to the high number of NPs: as shown in column (1), the number of NPs observed prescribing these drug classes nearly quadrupled from 2006 to 2018, making them the second largest provider category (behind only GPs) by the end of the sample period.

III.B Scope-of-practice legislation

In Section IV, we exploit changes in scope-of-practice legislation regulating whether NPs can independently prescribe controlled substances as an instrument for the competition faced by GPs. These law changes come from Markowitz and McMichael (2020) and capture whether NPs could prescribe controlled substances without the supervision or collaboration of a physician in each year of the sample. This legal change often removes the final barrier to NPs practicing fully without any required physician oversight.

As shown in Figure 1, 18 states allowed NPs to prescribe controlled substances independently as of 2005. Over our study period (2006–2018), 18 states relaxed their scope-of-practice restrictions and granted NPs the ability to prescribe these medications independently. The geographic distribution of these states is diverse, with two states in the West, seven in the South, five in the Midwest, and four in the Northeast granting independent prescriptive authority for controlled substances over the period.

Table 2 provides an overview of prescribing patterns among GPs (panel (a)) and NPs (panel (b)) in the 33 states in which the relevant scope-of-practice laws did not change (columns (1)–(3)) and the 18 states in which the laws did change (columns (4)–(6)) over the sample period. For prescriptions of each type written by either GPs or NPs in each group of states, we consider the number of prescriptions per 1,000 people, the number of prescribing providers per 1,000 people, and the average number of prescriptions per prescribing provider at the county-year level. As in Table 1, we provide statistics over the entire sample period (columns (1) and (4)) and separately for the first and last year of the sample (columns (2) and (5) and columns (3) and (6), respectively).

The number of prescriptions per 1,000 people written by GPs and NPs were generally higher in control states than in treatment states over our sample period. This is true even for most drug types in 2018, the point by which NPs were allowed to independently prescribe controlled substances in all 18 treatment states. We observe NPs prescribing in control states because (1) 18 of these states granted NPs independent prescriptive authority before our sample period and (2) NPs were allowed to prescribe controlled substances either in collaboration with or under the supervision of a physician in the 15 other control states over our sample period. Looking to the number of prescribing providers per capita, we see that the concentration of prescribing GPs is generally higher in treatment states whereas the concentration of prescribing NPs is relatively similar in treatment and control states. The average number of prescriptions per prescribing provider is also higher in control states. These observations suggest that simple cross-state comparisons between treatment and control states could be misleading.

An important question is whether changes in scope-of-practice legislation granting NPs the ability to prescribe controlled substances independently are correlated with other changes that might also influence prescribing patterns. To examine whether our identifying variation is orthogonal to changes in local socio-demographics such as the age, racial, and educational structure, we estimate balancing regressions that use these candidate controls as dependent variables (Pei et al., 2019).[18] Reassuringly, as shown in Figure A1, there is no evidence that changes in scope-of-practice legislation are correlated with changes in local socio-demographics.

III.C Mortality data

Data on drug-related mortality come from the NVSS. The NVSS data that we use cover 2006–2018 and contain information on the date, location, and cause for all deaths in the United States. We follow previous work and define fatal drug overdoses as deaths with International Classification of Disease Version 10 (ICD-10) underlying cause of death codes X40–44, X60–X64, X85, and Y10–Y14. Multiple cause of death codes are used to identify fatal drug overdoses that involved any opioid (T40.0–T40.4 and T40.6) and prescription opioids (T40.2 and T40.3). As with the prescription data, we combine mortality at the county-year level with population data from the ACS to measure fatal drug overdoses per capita.

[18] In particular, we estimate analogues of equation (3) introduced in Section IV.

IV Methods

To examine the effects of competition on the prescribing practices of physicians, we leverage changes in scope-of-practice legislation granting NPs the ability to prescribe controlled substances independently as an instrument for competition.

In what follows, we focus on a balanced panel of law changes. In particular, we consider law changes for which at least three years of prescription data are available before and after the event. This restriction ensures that a consistent sample of states is used to identify the event-time coefficients of interest and that all treatment states contribute the same number of post-treatment years to the primary regression results. Since the outcome data cover the period 2006–2018, this restriction leads us to consider the 11 law changes that took place between 2009 and 2015. As discussed below, the results are robust to including the full set of 18 law changes that took place between 2006 and 2018 (i.e., to not using a balanced panel) and to either including or excluding states with law changes between 2006–2008 and 2016–2018 from the set of control states.

Let Rx^{p}_{cst} denote a prescription outcome for providers of type p in county c of state s in year t. We consider county-year prescription outcomes among all providers and by NPs and GPs separately (i.e., $p \in \{all, \mathrm{NPs}, \mathrm{GPs}\}$). Letting t^*_s denote the year of the law change in state s, we begin by estimating event-study specifications of the form:

$$\begin{aligned} Rx^{p}_{cst} \;=\; & \sum_{n\in\{(-4)+,-3,\ldots,3,4+\}} \alpha_n \cdot B_s \cdot 1\left\{t^*_s + n = t\right\} \\ & + \delta \cdot X_{ct} + \gamma_c + \gamma_t + \gamma_c \cdot t + \epsilon_{cst}, \end{aligned} \tag{2}$$

where $1\left\{t^*_s + n = t\right\}$ is an indicator denoting whether year t for state s is n years from the law change; B_s is an indicator denoting whether state s is part of the balanced panel; X_{ct} are the time-varying, county-level controls listed in Figure A1; γ_c and γ_t are county and year fixed effects, respectively; and $\gamma_c \cdot t$ are county-specific linear time trends.[19] The year

[19] While unit-specific time trends help account for differential pre-trends across locations, they overcontrol for time-varying treatment effects (Neumark et al., 2014; Goodman-Bacon, 2021). As discussed further below, our main results are robust to including county-specific time trends that are predicted using only pre-period data, to excluding time trends, and to including state-specific rather than county-specific linear time trends.

before the law change ($n = -1$) is the omitted category, and standard errors are clustered by state. Because of the balanced panel restriction, the coefficients $[\alpha_{-3}, \alpha_3]$ are identified by a consistent sample of states.

To summarize the effects in the years following the law changes, we estimate specifications that pool the post-period coefficients:

$$\begin{aligned} Rx_{cst}^{p} &= \beta_1 \cdot B_s \cdot 1\{t - t_s^* \in [0,3]\} + \beta_2 \cdot B_s \cdot 1\{t - t_s^* \geq 4\} \\ &\quad + \delta \cdot X_{ct} + \gamma_c + \gamma_t + \gamma_c \cdot t + \epsilon_{cst}, \end{aligned} \tag{3}$$

where $1\{t - t_s^* \in [0,3]\}$ is an indicator denoting the year of and the three years following the law change in state s (balanced post period), $1\{t - t_s^* \geq 4\}$ is an indicator denoting years that are at least four years after the law change in state s, and all other variables are defined as in equation (2). Standard errors are again clustered by state. The coefficient of interest is β_1, which measures the average county-level change in a given prescription outcome in the three years following a change in state-level scope-of-practice laws granting NPs the ability to prescribe independently. Because of the balanced panel restriction, all treatment states used to identify β_1 are observed for the entirety of this three-year post-period.

As noted in Section III.A, the primary outcomes of interest are the number of prescriptions per 1,000 people for opioids, controlled anti-anxiety medications, and co-prescriptions of opioids and benzodiazepines by provider type at the county-year level. We also consider analogous measures for unscheduled anti-anxiety medications and antidepressants to examine effects on non-controlled substances.

Any increases in these measures could come either from additional providers starting to prescribe a certain drug type (extensive margin adjustments) or from existing prescribers increasing their prescription levels (intensive margin adjustments). To shed light on mechanisms, we examine two additional sets of outcomes. First, to examine extensive margin adjustments, we consider effects on the number of providers of a given type (i.e., all, NPs, or GPs) who are observed prescribing a medication of a given type (e.g., opioids) per 1,000 people at the county-year level. However, since very small increases in prescribing—for example, a provider moving from zero to one prescription of a given type per year—is unlikely to be relevant for population health and might reflect measurement error in the data, we also consider a measure of "frequent" prescribing. In particular, we consider providers to be frequent prescribers if they both (1) write a given type of prescription in each month (or year for co-prescribing of opioids and benzodiazepines) and (2) are above the 25th percentile (measured across all years) among all GPs who satisfy criterion (1).[20] The goal of this measure is to capture the number of providers for whom a given type of prescribing has become a relevant part of their clinical practice. Second, to examine intensive margin adjustments, we consider effects on the average number of prescriptions of a given type written by prescribing providers of a given type at the county-year level.

To probe how competition affects opioid prescribing in particular, we conduct three additional sets of analyses. First, a distinction is often made in the literature between opioid-naïve and non–opioid-naïve patients. If physicians respond to increased competition by writing opioid prescriptions for naïve patients, then competition could have important implications for the initiation of opioid use and future opioid abuse. To examine effects by patient type, we divide prescriptions based on whether they were written for a patient who had an opioid prescription from any provider in the past six months ("non-opioid naïve") or not ("opioid naïve").

Second, since larger opioid prescriptions carry additional risk of physical dependence and misuse (CDC, 2016), we examine effects on the average days supplied and the average daily MME per prescription. We also consider the number of opioid prescriptions with greater than 120 MME daily per 1,000 people given work documenting that prescriptions of this size are strongly correlated with adverse patient outcomes (Sullivan et al., 2010; Bohnert et al., 2011).[21] Finally, to ask how any increases in opioid prescribing affect drug mortality, we estimate analogues of equation (3) that measure how granting NPs the ability to prescribe controlled substances independently affects the number of fatal drug overdoses per million people involving any drug, any opioid, and prescription opioids at the county-year level.

We conduct three additional analyses to verify that the identified changes in prescribing

[20] We only require providers to co-prescribe opioids and benzodiazepines at least once in a given year (rather than monthly) since co-prescribing is a relatively rare outcome. As discussed in Section V, our results are robust to alternative definitions of "frequent" prescribers.

[21] Prescriptions with more than 120 MME daily have been commonly used in the literature as a measure of risky prescription opioid use (e.g., Finkelstein et al., 2022).

practices among physicians are driven by changes in competition. First, and most directly, we ask whether the effects are more pronounced in areas in which GPs face greater competition from NPs. In particular, counties are divided into two groups based on whether they had an above- or below-median number of NPs per GP among treatment states at the start of the sample period. We then estimate an augmented version of equation (3) that includes an interaction between the treatment indicator and an indicator denoting whether the county had an above-median number of NPs per GP in 2006. Allowing NPs to independently prescribe controlled substances should have greater effects on the prescribing behaviors of GPs practicing in areas with a greater concentration of NPs at baseline.

Second, we ask whether the estimated effects differ across physicians in different specialties. Since approximately 90 percent of NPs are certified in primary care, NPs are likely to compete most directly with GPs (AANP, 2022). However, NPs also practice in a range of specialties, with nearly 8 percent certified in acute care medicine, 5 percent certified in psychiatry/mental health, and 3 percent certified in women's health. We therefore consider the effects of allowing NPs to independently prescribe controlled substances on the prescribing behaviors of physicians in emergency medicine, psychiatry and neurology, and obstetrics and gynecology. We also consider the effects of the law changes on prescribing practices among two types of surgeons: orthopedic surgeons and general surgeons. While NPs do not provide surgeries, NPs with independent prescriptive authority can offer services such as pain management that are alternatives to some orthopedic surgeries (Blom et al., 2021), thereby competing indirectly with orthopedic surgeons. On the other hand, independent prescriptive authority for NPs should not substantively change the competitive landscape for general surgeons. Constructing the primary outcomes for physicians in these five additional specialties, we then estimate equation (3) separately for these physician types. Allowing NPs to independently prescribe controlled substances should have greater effects on the prescribing behaviors of physicians practicing in specialties that compete more directly with NPs.

Finally, we ask whether our results can be explained by changes in physician workloads rather than changes in competition induced by the law changes. NPs who were practicing in collaboration with or under the supervision of a physician might leave the physician's office to practice elsewhere (e.g., open their own practice) when they can prescribe controlled substances independently. In this case, increases in prescribing among physicians might be driven by physicians taking over the prescribing previously done by NPs. Since this mechanism would require that some NPs who were co-practicing with GPs leave these joint practices following the law changes, we examine whether granting NPs independent prescriptive authority for controlled substances changes the share of GPs who practice in the same clinics as NPs or the number of NPs per GP practice.

Recall that in our main analyses, we use information on patient zip codes to infer the practice counties of prescribing providers in each year of the sample (see Section III.A and Appendix B). To examine whether independent prescriptive authority affects co-practice patterns among GPs and NPs, we instead use the two snapshots of *exact* practice addresses in 2014 and 2018 provided by IQVIA. Calculating the share of GPs who had at least one NP practicing at their practice address and the average number of NPs per GP practice in each county in these two years, we compare how co-practice patterns changed from 2014 to 2018 in the 15 states that did not allow NPs to independently prescribe controlled substances by 2018 ("never-takers"), the 27 states with law changes in or before 2014 ("always-takers"), and the nine states with law changes between 2015 and 2018 ("switchers").

V Results

V.A Graphical evidence

Figure 2 provides an initial look at the impacts of competition by examining the relationship between the number of prescribers of controlled substances and prescribing patterns. In the figure, the number of NPs is set to zero until NPs are allowed to prescribe controlled substances independently. For each medication type, we consider the number of prescriptions per 1,000 people written by GPs and NPs (left subfigures) and the average number of prescriptions written by each prescribing GP (right subfigures) at the county-year level. These county-year observations are residualized from county and year fixed effects and grouped into deciles based on the number of GPs plus the number of NPs per 1,000 people.

The subfigures show a positive relationship between within-county changes in the number of prescribers per capita and the number of opioid prescriptions (panel (a)), controlled anti-anxiety prescriptions (panel (b)), and opioid and benzodiazepine co-prescriptions (panel (c)) per capita and per prescribing GP. While the positive association between the number of prescribers and prescriptions per capita may just reflect the impacts of better health care access in areas with more providers, the positive association between the number of prescribers per capita and the average number of prescriptions written by each prescribing GP is notable. Holding demand fixed, each prescribing GP should need to write fewer—rather than more—prescriptions in areas in which there is a greater concentration of other providers available to prescribe. However, while suggestive, these figures do not directly investigate the role of competition per se in driving increases in prescribing.

The role of law changes that shift the competitive landscape is investigated in Figure 3, which presents event-study estimates from estimation of equation (2).[22] Panels (a) and (b) show that there were no significant differences in trends in opioid and controlled anti-anxiety prescribing per 1,000 people between treatment and control counties in the years before the law changes. However, the prescribing of opioids and controlled anti-anxiety medications jumped when NPs were granted the authority to independently prescribe controlled substances. These effects were largely stable in the years following the law changes for opioids, while the effects steadily increased over the next three years for scheduled anti-anxiety medications. As shown in panel (c), co-prescribing of opioids and benzodiazepines per 1,000 people likewise increased when NPs were granted independent prescriptive authority. While there is some suggestion of a pre-trend for co-prescribing, there is nevertheless a clear jump in the year of the law change that persists for at least three years.

Figure 4 presents event studies that are analogous to those presented in Figure 3 except that they show the prescribing of controlled substances separately by NPs (left subfigures) and GPs (right subfigures).[23] The left subfigures show that prescribing per 1,000 people of opioids (panel (a)), controlled anti-anxiety medications (panel (b)), and co-prescribing of

[22]Results in Figure 3 are conditional on county-specific linear time trends estimated over the entire sample period. Results from specifications that exclude time trends and that include county-specific time trends predicted using only pre-period data (Goodman-Bacon, 2021) are presented in Figure A2(a). The results from these alternative specifications are very similar.

[23]As shown in Figure A2(c), the inclusion of time trends has little effect on the estimates for GPs. However, the inclusion of county-specific linear time trends—estimated over the entire sample period or predicted using only pre-period data—corrects for negative pre-trends in the outcomes among NPs (Figure A2(b)).

opioids and benzodiazepines (panel (c)) by NPs rose once they were granted the ability to prescribe these medications independently. These findings are not particularly surprising given that such increases were arguably the intent of the law changes. Strikingly, however, the right subfigures show that the prescribing of these medications by GPs also jumped when NPs were allowed to prescribe independently. If patients had merely switched from GPs to NPs following the law changes, prescribing among GPs should have fallen in tandem with the rise in NP prescribing. Hence, the simultaneous increases among NPs and GPs suggest a behavioral response on the part of GPs facing increased competition.

Figure A3 shows analogous figures for non-controlled anti-anxiety medications (left subfigures) and antidepressants (right subfigures). Although the estimates are less precise, they suggest that the prescribing of non-controlled anti-anxiety medications may have fallen slightly, which would be consistent with some replacement of non-controlled anti-anxiety medications with controlled alternatives such as benzodiazepines. Although most of the post-treatment event-time estimates are statistically insignificant at conventional levels, there is suggestive evidence that prescribing of antidepressants may also have risen after the law changes. This upward trend is largely due to (noisy) increases among GPs (panel (c)), which may reflect demand for antidepressants among patients and/or complementarities between antidepressants and benzodiazepines.

V.B Main estimates

Results from estimation of equation (3) are shown in Table 3. As outlined in Section IV, we consider the number of prescriptions per county-year written by all providers (columns (1)–(3)), NPs (columns (4)–(6)), and GPs (columns (7)–(9)) per 1,000 people for opioids, controlled anti-anxiety medications, and opioid and benzodiazepine co-prescribing. Panel (a) shows estimates using the full sample, and panel (b) shows estimates for the balanced panel of states that are observed for at least three years before and after NPs gained independent prescriptive authority for controlled substances. Panels (c) and (d) also consider this balanced panel but use the estimators proposed by Sun and Abraham (2021) and Borusyak et al. (2022), respectively, to correct for potential biases in two-way fixed effects models with staggered treatment adoption and heterogeneous treatment effects.

All four panels indicate that there are positive effects of allowing NPs to independently prescribe controlled substances on our primary prescription outcomes. However, comparing panels (a) and (b) suggests that it is important to consider a balanced panel—and that doing so yields somewhat larger effects on the prescribing of GPs. Comparing panels (b) and (c) suggests that given this balanced panel, correcting for staggered treatment adoption using the estimator proposed by Sun and Abraham (2021) increases the point estimates while reducing the standard errors. Comparing panels (b) and (d), we see that the estimates for GPs and NPs are very similar when using the estimator proposed by Borusyak et al. (2022), although the aggregate effects are slightly attenuated. Given the robustness of our main effects across estimators, we focus on estimates from the balanced panel without these proposed corrections moving forward.

The estimated effects in Table 3 are large. As shown in columns (1)–(3) of panel (b), allowing NPs to independently prescribe controlled substances leads to 44.3 more opioid prescriptions (8.8 percent relative to the baseline mean), 13.2 more controlled anti-anxiety prescriptions (7.5 percent), and 4.5 more co-prescriptions of opioids and benzodiazepines (16.7 percent) per 1,000 people at the county-year level. It is notable that the effect on co-prescribing, a dangerous practice, is so large.

Looking to the results by provider type, we see in columns (4)–(6) that the estimated effects on NP prescribing are positive, as expected. However, as shown in columns (7)-(9), the estimates for GPs are much larger, and the impacts on all three prescription outcomes are statistically significant. Comparing the estimates for GPs to those for all providers indicates that more than half of the total increases in prescribing come from GPs. The estimates in panel (b) show that granting NPs independent prescriptive authority for controlled substances leads the number of prescriptions written by GPs per 1,000 people at the county-year level to increase by 23.3 opioid prescriptions (10.0 percent relative to the GP-specific baseline mean), 8.5 controlled anti-anxiety prescriptions (7.9 percent), and 2.7 opioid and benzodiazepine co-prescriptions (16.3 percent).

Table 4 examines whether these increases in prescribing among NPs (columns (1)–(3)) and GPs (columns (4)–(6)) are driven by additional providers starting to prescribe the drug classes that we consider or additional prescriptions among already-prescribing providers.

Perhaps surprisingly, the results in panel (a) show that the law changes do not draw new providers of either type into prescribing controlled substances. Moreover, as shown in panel (b), there are no significant increases in the number of "frequent" prescribers.[24] Rather, increases in prescribing come from increases in the number of prescriptions per prescribing provider (panel (c)). Among prescribing GPs, allowing NPs to independently prescribe controlled substances leads to an average of 27.8 more opioid prescriptions, 12.1 more controlled anti-anxiety prescriptions, and 4.6 more opioid and benzodiazepine prescriptions per year. Compared to the respective baseline means, these estimates reflect increases of 9.9, 8.3, and 15.0 percent. While the point estimates are about half as large among prescribing NPs, the percent effects are even more pronounced given substantially lower baseline means among these providers.

Table 5 considers the effects of granting NPs independent prescriptive authority for controlled substances on the prescribing of non-controlled anti-anxiety medications and antidepressants by NPs (columns (1)–(2)) and GPs (columns (3)–(4)). Consistent with Figure A3, panel (a) shows that the number of antidepressant prescriptions per 1,000 people written by GPs increased somewhat following the law changes. While there is a slight increase in the number of antidepressant-prescribing GPs per 1,000 people (panel (b)), the increase in the number of antidepressants comes mainly from GPs writing more prescriptions per prescribing provider (panel (c)). Although the antidepressants that we consider are not controlled substances, antidepressants may be an example of a drug that is demanded by patients but prescribed to the marginal patient against a provider's better judgment given low efficacy in many cases and the risk of physical dependence. In turn, increased prescribing of antidepressants could explain some of the observed increases in the prescribing of benzodiazepines (the most common type of controlled anti-anxiety medication), as these medications are often prescribed to cope with symptoms induced by antidepressants (Bushnell et al., 2017).

[24]Table 4 uses our primary definition of "frequent" providers outlined in Section IV. That is, providers are required to both (1) write a given type of prescription in each month (or year for co-prescribing of opioids and benzodiazepines) and (2) be above the 25th percentile among all GPs who satisfy criterion (1). Figure A4 shows results from specifications that vary the percentile of GP prescribing that serves as the threshold for "frequent" prescribers. For most outcomes, the results are, if anything, more pronounced with a higher threshold.

V.C Additional analyses

Table 6 further investigates the effects on opioid prescribing among NPs (columns (1)–(3)) and GPs (columns (4)–(6)). Panel (a) shows that the increases in opioid prescribing are mainly driven by prescriptions for opioid-naïve patients. Allowing NPs to prescribe controlled substances independently leads GPs to write 22.5 more opioid prescriptions for opioid-naïve patients per 1,000 people at the county-year level (11.3 percent relative to the baseline mean) versus only 0.79 more opioid prescriptions for non-naïve patients (2.4 percent; estimate insignificant at conventional levels). This suggests that competition-induced increases in opioid prescribing put additional patients at risk of developing opioid use disorder.

The rest of Table 6 shows that the law changes do not affect the length of prescriptions, either for opioid-naïve or non-naïve patients (panel (b)). However, there are increases in the average MME per day supplied among both opioid-naïve and non-naïve patients, with the increases being almost 50 percent larger for non-naïve patients (panel (c)). The number of prescriptions with over 120 MME per day also increases among opioid-naïve patients (panel (d)). Given that the CDC recommends that providers start patients on the lowest effective dose and that they "avoid" or "carefully justify" increasing dosage to greater than 90 MME per day (CDC, 2016), this result is especially striking.

As outlined in Section IV, we conduct three additional tests to further probe whether it is indeed competition from NPs that is driving the increases in prescribing among GPs. Table 7 presents results from estimation of an augmented version of equation (3) that includes an interaction between the treatment indicator and an indicator denoting whether the number of NPs per GP was above that of the median county at the start of the sample period. The estimates bear out the hypothesis that NPs are more of a competitive threat to GPs in counties in which there are relatively more NPs who stand to gain independent prescriptive authority: the estimated effects for opioids (column (1)), controlled anti-anxiety medications (column (2)), and co-prescribing of opioids and benzodiazepines (column (3)) among GPs are 65.2, 118.4, and 68.7 percent higher, respectively, in counties with an above- versus below-median number of NPs per GP in 2006. Moreover, all of the impacts in the above-median counties are strongly statistically significant, whereas the estimates for opioids and controlled anti-anxiety medications are significant only at the 10 percent level in the below-median counties.

In addition to cross-sectional, geographic variation in the extent of exposure to increased competition following the law changes, there is also variation within locations based on physician specialty. Table 8 tests the hypothesis that physicians who face more direct competition from NPs will respond more strongly to the law changes. For reference, column (1) repeats the estimates for GPs from panel (b) of Table 3. As shown in columns (3) and (4), physicians in psychiatry/neurology and obstetrics/gynecology respond to increased competition from NPs by writing more opioid prescriptions (panel (a)), controlled anti-anxiety prescriptions (panel (b)), and co-prescriptions of opioids and benzodiazepines (panel (c)). Physicians in emergency medicine (column (2)) also respond by writing more opioid prescriptions. These findings are consistent with the fact that many NPs are certified in acute care medicine, psychiatry/mental health, and women's health (AANP, 2022). However, given that more NPs are certified in primary care than these other specialties, the results are unsurprisingly more precise and generally larger—both in levels and relative to the group-specific baseline means—among GPs.

The remainder of Table 8 focuses on surgeons. As shown in column (5), orthopedic surgeons increase their prescribing of opioids when NPs are allowed to prescribe controlled substances independently. This result is expected given that orthopedic surgeons may face some competition in the form of alternatives to their services (e.g., pain management) from NPs. As predicted, there are no statistically significant effects for general surgeons (column (6)), a class of physicians who likely face little competitive pressure from NPs.

Our final test to probe whether changes in competition drive our findings examines how the law changes affect co-practice patterns among NPs and GPs. Recall from Section IV that this analysis uses the snapshots of exact practice addresses in 2014 and 2018 provided by IQVIA. As shown in Figure A5, around 65 percent of NPs (subfigure (a)) and 60 percent of GPs (subfigure (b)) were practicing at the same address as at least one provider of the other type in 2014. This figure declined for NPs by 2018, with more NPs practicing independently or with physicians in specialties outside of general practice. In contrast, the share of GPs co-practicing with NPs increased by 2018, as did the average number of NPs per GP practice (see Figure A6).

Importantly, these increases in co-practice patterns among GPs were more pronounced in treatment states. This provides strong evidence against the possibility that the observed increases in prescribing among GPs were driven by changes in workloads from NPs leaving their joint practices following the law changes.[25] As shown in Figure A5(b), the share of GPs co-practicing with at least one NP increased by 5.5 percentage points from 2014 to 2018 (9.3 percent relative to the baseline mean) in states that granted NPs independent prescriptive authority for controlled substances between 2015 and 2018 compared to around 5.0 percentage points (8.0 percent) in states that either did not allow NPs to prescribe independently by 2018 ("never-takers") or states that granted such authority by 2014 ("always-takers"). Moreover, as shown in Figure A6, the average number of NPs per GP practice in treatment states increased by 3.7 among all GPs (subfigure (a)) and by 4.6 among co-practicing GPs (subfigure (b)), changes that are again more pronounced than those observed in never-taker and always-taker states.

Table 9 turns to the question of whether the observed increases in prescribing are accompanied by increases in drug overdose deaths. In particular, we estimate analogues of equation (3) that consider the county-year number of fatal drug overdoses per million people involving any drug (column (1)), any opioid (column (2)), and prescription opioids (column (3)) as the outcome. In specifications without time trends (panel (a)), there is a marginally significant effect on fatal drug overdoses involving prescription opioids, with the law changes leading to 7.0 more prescription opioid fatalities per million people (14.8 percent relative to the baseline mean). However, as shown in panels (b) and (c), this effect is attenuated when we add either county-specific pre-trends following Goodman-Bacon (2021) or county-specific time trends estimated over the entire sample period as in our primary specification.[26]

[25] In addition to NPs, GPs often work with physician assistants (PAs). As their name suggests, PAs work directly under the supervision of a physician and do not have independent prescriptive authority. Table A1 shows that PAs write more prescriptions for opioids and controlled anti-anxiety medications and increase their co-prescribing of opioids and benzodiazepines when NPs are granted independent prescriptive authority. These results show that GP practices additionally respond to the law changes by increasing prescribing among non-physicians who are close substitutes to NPs. It further highlights that GPs often work with other providers who might also be able to absorb any excess workload in the event that NPs leave their joint practices.

[26] We include county-specific trends in our primary specification for prescription outcomes, as event studies

It is possible that the effects of increases in prescribing are balanced by increases in access to treatment for drug addiction. This would be consistent with results from Grecu and Spector (2019), who find that relaxing scope-of-practice laws increases access to treatment for opioid use disorders. Alternatively, it is possible that the impacts of increases in prescribing take longer than three years following the law changes to lead to measurable mortality effects.

V.D Robustness

The results of several robustness checks are summarized in Figure A8, which shows that the results are remarkably robust. In addition to showing estimates for the unbalanced panel and with the Sun and Abraham (2021) and Borusyak et al. (2022) corrections (as in Table 3), the figure provides estimates omitting demographic controls, omitting time trends, adding state-specific rather than county-specific linear time trends, including county-specific linear time trends predicted using only pre-period data (Goodman-Bacon, 2021), excluding states that switched before the beginning of the sample period from the set of control states, and taking only "never-taker" states as the controls.

The only change that noticeably affects our results is the omission of time trends in the regressions for prescription outcomes among NPs (subfigure (b)). This is not surprising: As shown in Figure A2, there are negative pre-trends among NPs in specifications without location-specific time trends. Since these pre-treatment differences in outcome trends bias the effects downward, the estimates for NPs in specifications without time trends are unsurprisingly smaller than in specifications with state- or county-specific time trends (predicted using only pre-period data or estimated over the entire sample period). Our primary specification therefore includes county-specific linear time trends, as there are no significant pre-treatment differences between treatment and control states in the prescription outcomes for NPs once we condition on these controls. We note, however, that our primary results focusing on the impacts of the law changes on GPs are not meaningfully affected by the

show pre-trends in prescribing among NPs in the absence of such controls (see Figure A2). In contrast, as shown in Figure A7, event studies for mortality show no pre-trends when time trends are not included (subfigure (a)), whereas including county-specific linear time trends introduces negative pre-trends (subfigure (c)). While the model without time trends (or with county-specific pre-trends) therefore appears to be more valid when examining drug mortality, we conclude that there is no strong evidence that laws granting NPs independent prescriptive authority affected drug overdose deaths.

inclusion (or exclusion) of time trends or any of the other alternative specifications that we consider.

VI Conclusion

We document the ways in which the prescribing practices of GPs change following increases in competition that are precipitated by changes in state-level scope-of-practice laws granting NPs the ability to prescribe controlled substances without physician oversight. We find that GPs respond to such legislation by increasing their prescribing of opioids and controlled anti-anxiety medications such as benzodiazepines. We further find that GPs increase their co-prescribing of opioids and benzodiazepines to the same patient on the same day, a behavior that the CDC strongly cautions against because it can lead to respiratory failure (CDC, 2016). There are also slight increases in GP prescribing of unscheduled antidepressants, which can be complements to controlled anti-anxiety medications. In contrast, there are no changes in the prescribing of non-controlled anti-anxiety medications, which are likely substitutes for medications directly affected by the law changes that we consider.

Three additional tests support the hypothesis that the increases in prescribing among GPs are driven by increased competition from NPs. First, the observed increases in GP prescribing are higher in areas with a greater number of NPs per GP at baseline. Second, changes in prescribing are concentrated in the specialties that compete most directly with NPs. Third, the law changes do not lead to reductions in the share of GPs practicing in the same clinics as NPs or in the number of NPs per GP practice. This last result indicates that our findings are not driven by increases in workloads among physicians resulting from newly independent NPs leaving their joint practices.

Examining the increases in opioid prescribing in greater depth shows that GPs increase the strength of opioid prescriptions and the number of very high-strength prescriptions in response to increased competition. Moreover, competition-induced increases in the number of opioid prescriptions are due predominately to increases among opioid-naïve patients, suggesting that competition among providers puts additional patients at risk of developing opioid use disorder. Our work focusing on the role of competition therefore adds another consideration to recent research showing that physician prescribing of opioids is driven in part by training (Schnell and Currie, 2018), beliefs about risks (Doctor et al., 2018), pharmaceutical marketing (Alpert et al., 2022; Arteaga and Barone, 2022), and provider altruism coupled with the existence of secondary markets (Schnell, 2017).

This paper begins to fill an important gap in the literature on the effects of competition in health care markets by focusing on competition at the individual provider level rather than at the level of the hospital or insurer. The results are consistent with the cautions of authors such as Gaynor et al. (2015) and McGuire (2000), who suggest that more competition will not always lead to improvements in patient care and can instead lead to excessive and even harmful service provision.

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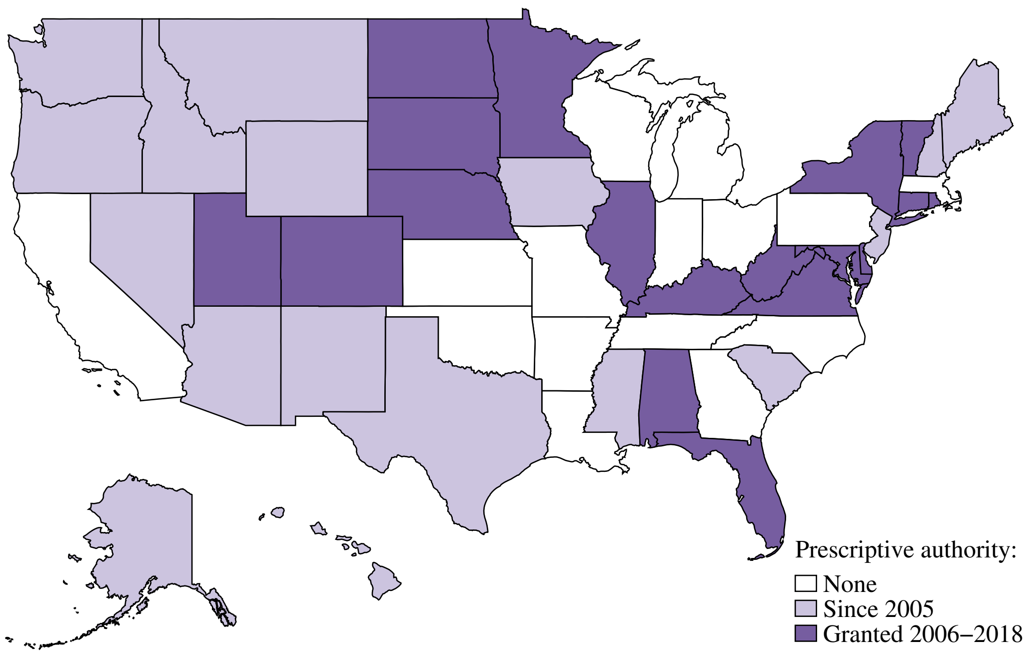
VII Figures

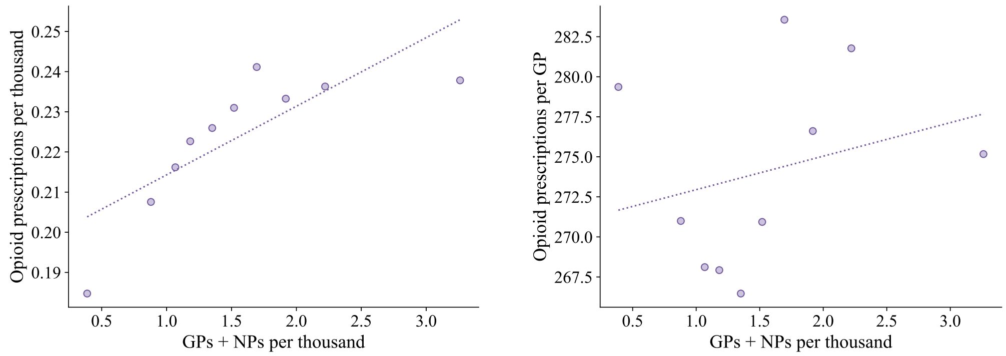
Figure 1: NP independent prescriptive authority for controlled substances: 2006–2018



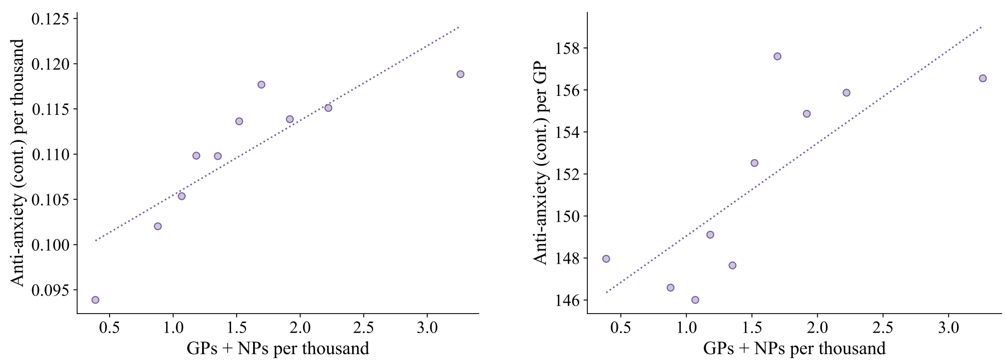
Notes: We consider states as having independent prescriptive authority if nurse practitioners (NPs) registered in the state have the statutory authority to prescribe controlled substances without physician collaboration or supervision. Years in which states granted NPs independent prescriptive authority come from Markowitz and McMichael (2020).

Figure 2: Changes in the number of prescribers and controlled substance prescribing

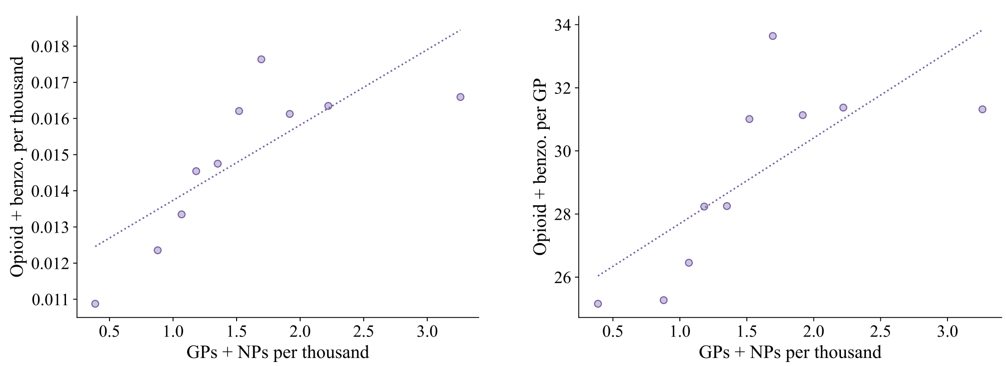
(a) Opioid prescriptions



(b) Anti-anxiety prescriptions



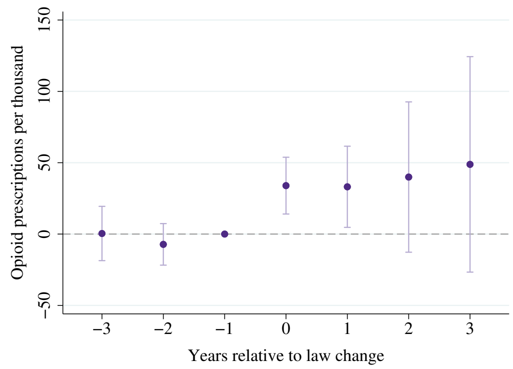
(c) Opioid + benzo. co-prescriptions



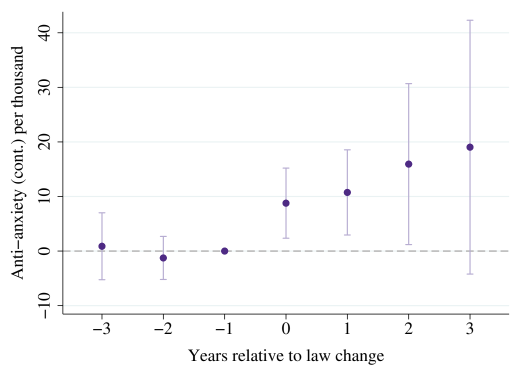
Notes: The above figures show the relationship between changes in the number of general practice physicians (GPs) and nurse practitioners (NPs) per 1,000 people and changes in measures of opioid prescribing (subfigure (a)), anti-anxiety controlled substance prescribing (subfigure (b)), and opioid and benzodiazepine co-prescribing (subfigure (c)) at the county-year level from 2006–2018. All relationships are conditional on county and year fixed effects. The left subfigure in each subplot considers the amount of a given prescribing behavior by GPs and NPs per 1,000 people; the right subfigure considers the average amount of a given behavior per GP. The number of GPs and NPs in a given county-year is based on our location assignment algorithm (see Appendix B); the number of NPs is set to zero until NPs are allowed to prescribe controlled substances independently in a given state. Counties are grouped into deciles accounting for approximately equal shares of the population based on the number of GPs and NPs per 1,000 people. The dotted line is the fitted line across deciles. Data come from the IQVIA LRx database.

Figure 3: Effects of NP independent prescriptive authority on aggregate controlled substance prescribing

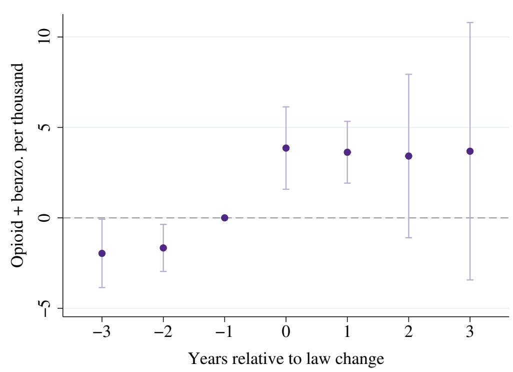
(a) Opioid prescriptions



(b) Anti-anxiety prescriptions



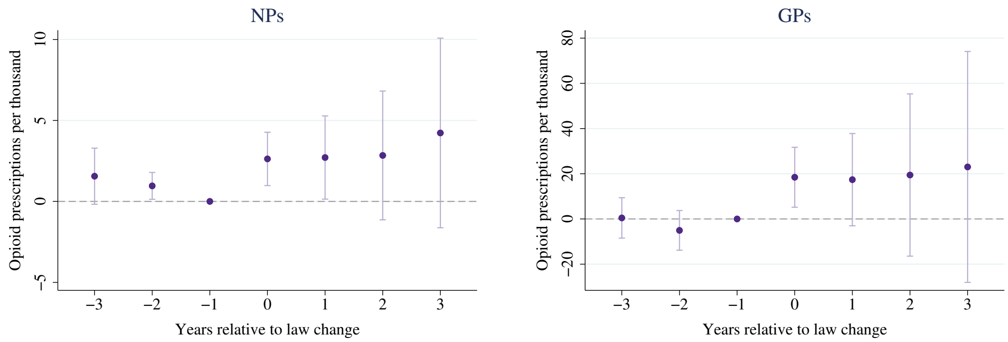
(c) Opioid + benzo. co-prescriptions



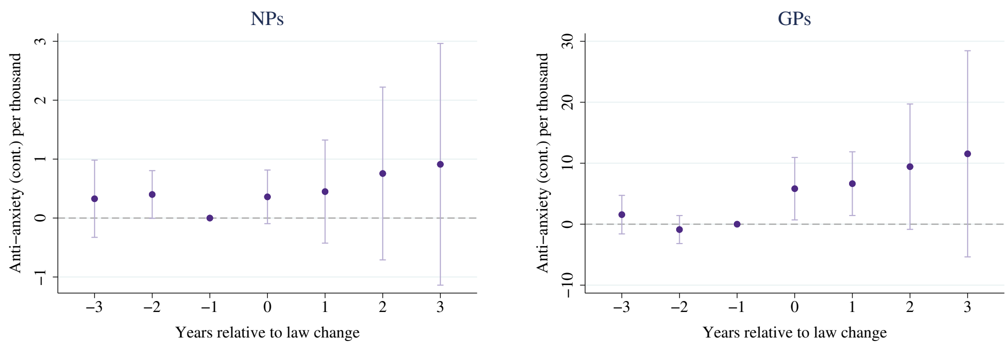
Notes: The above figures present coefficients and 95% confidence intervals from estimation of equation (2) using county-year–level data from 2006–2018. The outcome in subfigure (a) is the number of opioid prescriptions per 1,000 people, the outcome in subfigure (b) is the number of anti-anxiety controlled substance prescriptions per 1,000 people, and the outcome in subfigure (c) is the number of instances in which an opioid and benzodiazepine prescription were written for the same patient by the same provider on the same day per 1,000 people. To allow for a balanced panel, these figures consider effects in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database. See Figure A3(a) for analogous figures for non-controlled substance prescribing.

Figure 4: Effects of NP independent prescriptive authority on controlled substance prescribing by NPs and GPs

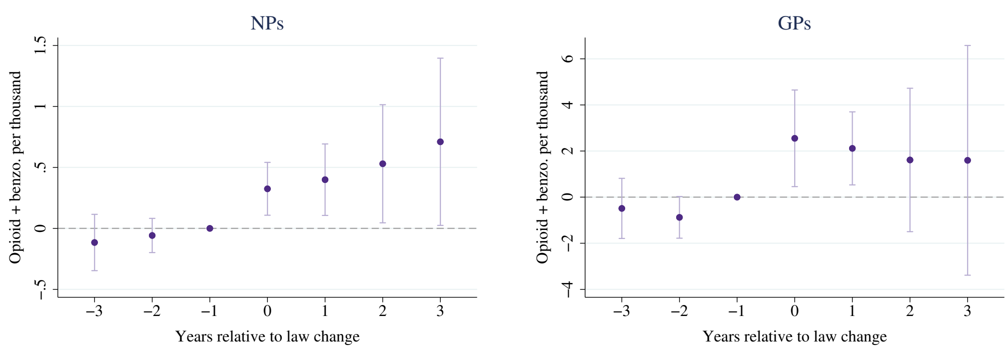
(a) Opioid prescriptions



(b) Anti-anxiety prescriptions



(c) Opioid + benzo. co-prescriptions



Notes: The above figures present coefficients and 95% confidence intervals from estimation of equation (2) using county-year–level data from 2006–2018. The left (right) subfigure in each subplot only considers prescriptions written by nurse practitioners [NPs] (physicians in general practice [GPs]). The outcome in subfigure (a) is the number of opioid prescriptions per 1,000 people, the outcome in subfigure (b) is the number of anti-anxiety controlled substance prescriptions per 1,000 people, and the outcome in subfigure (c) is the number of instances in which an opioid and benzodiazepine prescription were written for the same patient by the same provider on the same day per 1,000 people. To allow for a balanced panel, these figures consider effects in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database. See Figure A3(b) and (c) for analogous figures for non-controlled substance prescribing.

VIII Tables

Table 1: Number of prescribers and prescription shares by provider type

		Prescription shares				
		Controlled substances			Non-controlled substances	
	Unique providers (1)	Opioids (2)	Anti-anxiety (3)	Opioid + benzo. (4)	Anti-anxiety (5)	Anti-depressants (6)
a. 2006–2018						
Select physician specialties						
General practice	401,916	0.443	0.596	0.609	0.393	0.516
Emergency medicine	60,035	0.063	0.017	0.036	0.017	0.003
Psych. & neurology	95,655	0.018	0.162	0.024	0.204	0.236
Obstetrics & gyn.	62,200	0.026	0.015	0.014	0.012	0.025
General surgery	71,344	0.055	0.008	0.019	0.004	0.002
Orthopedic surgery	38,413	0.075	0.007	0.020	0.008	0.001
Nurse practitioners	269,015	0.068	0.075	0.064	0.163	0.117
Total providers	1,569,881	1.000	1.000	1.000	1.000	1.000
Total pres. (billions)		2.060	0.752	0.100	0.173	2.365
b. 2006						
Select physician specialties						
General practice	241,131	0.477	0.643	0.649	0.483	0.568
Emergency medicine	32,567	0.074	0.018	0.039	0.027	0.005
Psych. & neurology	59,902	0.022	0.163	0.034	0.181	0.259
Obstetrics & gyn.	40,759	0.033	0.018	0.014	0.016	0.035
General surgery	42,268	0.064	0.010	0.021	0.008	0.003
Orthopedic surgery	24,856	0.095	0.008	0.023	0.012	0.002
Nurse practitioners	56,608	0.028	0.030	0.026	0.046	0.048
Total providers	763,278	1.000	1.000	1.000	1.000	1.000
Total pres. (millons)		132.3	44.63	5.711	7.783	131.7
c. 2018						
Select physician specialties						
General practice	305,295	0.382	0.543	0.588	0.342	0.456
Emergency medicine	51,117	0.042	0.012	0.022	0.010	0.002
Psych. & neurology	71,910	0.014	0.166	0.017	0.193	0.210
Obstetrics & gyn.	45,325	0.020	0.011	0.012	0.009	0.018
General surgery	49,527	0.052	0.007	0.020	0.002	0.001
Orthopedic surgery	29,476	0.058	0.005	0.017	0.003	0.000
Nurse practitioners	201,764	0.119	0.132	0.102	0.267	0.196
Total providers	1,111,232	1.000	1.000	1.000	1.000	1.000
Total pres. (millons)		131.9	56.30	5.023	23.19	236.8

Notes: Observations are at the provider-year level. Total prescriptions reflect the total number of prescriptions written by providers of all types (including specialties not reported in the table) in the reported time period; prescription shares are calculated relative to these totals. “Opioid + benzo.” denotes instances of co-prescribing of an opioid and a benzodiazepine to the same patient by the same provider on the same day. Data come from the IQVIA LRx database.

Table 2: Average county-level prescription outcomes by treatment status

	Control states			States with law changes		
	2006–2018 (1)	2006 (2)	2018 (3)	2006–2018 (4)	2006 (5)	2018 (6)
Number of states	33			18		
a. General practice physicians						
Prescriptions per thousand						
Opioids	231.2	216.4	159.5	207.7	197.8	141.8
Anti-anxiety (cont.)	109.8	95.45	92.73	110.5	96.26	94.86
Opioid + benzo.	14.89	12.41	9.122	14.86	12.20	8.798
Anti-anxiety (non-cont.)	16.97	12.65	24.87	16.23	12.26	22.91
Antidepressants	303.6	251.2	337.4	290.3	246.4	313.5
Prescribing providers per thousand						
Opioids	0.809	0.747	0.787	0.845	0.780	0.814
Anti-anxiety (cont.)	0.714	0.671	0.693	0.742	0.691	0.717
Opioid + benzo.	0.492	0.483	0.403	0.488	0.467	0.404
Anti-anxiety (non-cont.)	0.569	0.533	0.601	0.588	0.550	0.618
Antidepressants	0.794	0.717	0.833	0.841	0.752	0.887
Average prescriptions per prescribing provider						
Opioids	286.5	288.3	203.2	247.6	252.9	174.9
Anti-anxiety (cont.)	153.5	141.1	133.7	147.2	135.4	130.2
Opioid + benzo.	29.56	25.15	22.14	28.39	23.76	20.25
Anti-anxiety (non-cont.)	29.00	23.43	40.21	26.18	21.36	35.64
Antidepressants	376.9	344.0	400.8	344.8	323.5	357.0
Unique providers	290,476	161,240	204,056	161,930	79,891	101,239
b. Nurse practitioners						
Prescriptions per thousand						
Opioids	37.35	12.86	52.23	27.17	11.16	38.52
Anti-anxiety (cont.)	14.99	4.826	23.63	11.27	3.702	20.56
Opioid + benzo.	1.753	0.577	1.647	1.191	0.343	1.381
Anti-anxiety (non-cont.)	7.011	1.245	19.00	6.692	1.112	18.72
Antidepressants	68.07	20.69	141.3	67.48	21.96	143.2
Prescribing providers per thousand						
Opioids	0.286	0.142	0.420	0.284	0.167	0.394
Anti-anxiety (cont.)	0.238	0.110	0.379	0.224	0.117	0.362
Opioid + benzo.	0.111	0.048	0.151	0.096	0.045	0.135
Anti-anxiety (non-cont.)	0.208	0.081	0.381	0.213	0.093	0.384
Antidepressants	0.305	0.142	0.508	0.333	0.175	0.543
Average prescriptions per prescribing provider						
Opioids	101.6	61.74	105.6	72.72	48.67	80.34
Anti-anxiety (cont.)	49.56	29.70	55.35	36.28	22.69	51.28
Opioid + benzo.	11.44	6.846	8.768	8.464	5.582	7.772
Anti-anxiety (non-cont.)	23.46	10.25	43.58	21.20	8.955	40.58
Antidepressants	170.1	97.02	246.7	155.5	92.66	233.1
Unique providers	186,708	35,791	134,699	101,130	20,817	67,065

Notes: Observations are at the county-year level, and averages are weighted by population. "States with law changes" refers to states that granted NPs the ability to independently prescribe controlled substances between 2006 and 2018; "Control states" refers to all other states. "Opioid + benzo." denotes instances of co-prescribing of an opioid and a benzodiazepine to the same patient by the same provider on the same day. Data come from the IQVIA LRx database.

Table 3: Effects of NP independent prescriptive authority on controlled substance prescribing

	All providers			Nurse practitioners			General practice physicians		
Prescriptions per 1,000:	Opioids	Anti-anxiety	Opioid + benzo.	Opioids	Anti-anxiety	Opioid + benzo.	Opioids	Anti-anxiety	Opioid + benzo.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
a. Unbalanced panel									
Post law change	44.113	11.331	4.088	5.184	2.977	0.651	19.286	5.356	2.243
	(11.951)	(3.810)	(1.436)	(2.096)	(1.733)	(0.267)	(8.337)	(3.570)	(1.235)
	[<0.001]	[0.005]	[0.006]	[0.017]	[0.092]	[0.018]	[0.025]	[0.140]	[0.075]
Relative to mean	0.080	0.063	0.150	0.203	0.313	0.491	0.083	0.050	0.137
b. Balanced panel									
Post law change, 0–3 years	44.279	13.222	4.467	2.643	0.388	0.454	23.296	8.452	2.660
	(16.575)	(4.565)	(1.148)	(1.405)	(0.431)	(0.192)	(11.320)	(3.276)	(1.031)
	[0.010]	[0.006]	[<0.001]	[0.066]	[0.372]	[0.022]	[0.045]	[0.013]	[0.013]
Relative to mean	0.088	0.075	0.167	0.104	0.041	0.343	0.100	0.079	0.163
c. Sun and Abraham (2021)									
Post law change, 0–3 years	46.108	14.086	5.364	2.190	0.285	0.411	25.488	9.232	3.353
	(13.462)	(3.304)	(0.686)	(1.056)	(0.395)	(0.149)	(8.734)	(2.008)	(0.442)
	[0.001]	[<0.001]	[<0.001]	[0.043]	[0.473]	[0.008]	[0.005]	[<0.001]	[<0.001]
Relative to mean	0.091	0.080	0.201	0.086	0.030	0.311	0.110	0.086	0.206
d. Borusyak, Jaravel, and Spiess (2022)									
Post law change, 0–3 years	36.242	10.105	3.755	2.522	1.429	0.642	23.555	6.974	3.055
	(15.719)	(4.218)	(1.982)	(2.401)	(0.916)	(0.474)	(8.687)	(2.922)	(1.190)
	[0.021]	[0.017]	[0.058]	[0.293]	[0.119]	[0.175]	[0.007]	[0.017]	[0.010]
Relative to mean	0.072	0.058	0.140	0.099	0.151	0.486	0.101	0.065	0.188
Baseline mean	504.4	175.5	26.75	25.45	9.473	1.322	232.1	107.4	16.28
Observations	40,911	40,911	40,911	40,911	40,911	40,911	40,911	40,911	40,911

Notes: The above table reports coefficients, standard errors (in parentheses), and p-values [in brackets] from estimation of equation (3) using county-year–level data from 2006–2018. Outcomes are the number of prescriptions of a given type written by providers of a given type per 1,000 people. "Opioid + benzo." denotes instances of co-prescribing of an opioid and a benzodiazepine to the same patient by the same provider on the same day. Columns (1)–(3) consider prescriptions written by all providers, columns (4)–(6) consider prescriptions written by nurse practitioners, and columns (7)–(9) consider prescriptions written by physicians in general practice. Panel (a) considers the effects of all 18 law changes from 2006–2018, panel (b) only considers the effects 0–3 years after the law change in the 11 states with law changes from 2009–2015, and panels (c) and (d) apply the estimators proposed by Sun and Abraham (2021) and Borusyak et al. (2022) to this balanced panel, respectively. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. The baseline mean is measured as the average across all counties in 2010. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Table 4: Effects of NP independent prescriptive authority on extensive and intensive margins of controlled substance prescribing

	Nurse practitioners			General practice physicians		
	Opioids	Anti-anxiety	Opioid + benzo.	Opioids	Anti-anxiety	Opioid + benzo.
	(1)	(2)	(3)	(4)	(5)	(6)
a. Prescribing providers per thousand						
Post law change, 0–3 years	0.000	–0.014	–0.003	–0.007	–0.013	–0.001
	(0.010)	(0.006)	(0.003)	(0.012)	(0.011)	(0.008)
	[0.966]	[0.024]	[0.472]	[0.562]	[0.258]	[0.914]
Baseline mean	0.247	0.189	0.087	0.833	0.735	0.517
Relative to mean	0.000	–0.074	–0.034	–0.008	–0.018	–0.002
b. Frequent prescribers per thousand						
Post law change, 0–3 years	0.004	0.001	0.001	0.011	0.002	0.006
	(0.002)	(0.001)	(0.002)	(0.007)	(0.004)	(0.007)
	[0.122]	[0.587]	[0.641]	[0.157]	[0.568]	[0.357]
Baseline mean	0.045	0.027	0.050	0.377	0.283	0.384
Relative to mean	0.090	0.037	0.020	0.029	0.007	0.016
c. Average prescriptions per prescribing provider						
Post law change, 0–3 years	13.227	5.862	2.771	27.793	12.081	4.593
	(5.221)	(1.627)	(0.899)	(11.151)	(3.821)	(1.778)
	[0.014]	[<0.001]	[0.003]	[0.016]	[0.003]	[0.013]
Baseline mean	83.86	39.72	11.20	281.6	145.3	30.57
Relative to mean	0.158	0.148	0.247	0.099	0.083	0.150
Observations	40,911	40,911	40,911	40,911	40,911	40,911

Notes: The above table reports coefficients, standard errors (in parentheses), and p-values [in brackets] from estimation of equation (3) using county-year–level data from 2006–2018. The outcome in panel (a) is the number of providers of a given type who are observed writing prescriptions of a given type per 1,000 people; the outcome in panel (b) is the number of "frequent" prescribers of a given type per 1,000 people, where "frequent" is defined as both (1) writing a given type of prescription in each month (or year for opioid-benzo. co-prescribing) and (2) being above the 25th percentile of prescribing among all GPs who satisfy criterion (1); and the outcome in panel (c) is the average number of prescriptions of a given type written by providers of a given type. "Opioid + benzo." denotes instances of co-prescribing of an opioid and a benzodiazepine to the same patient by the same provider on the same day. Columns (1)–(3) consider nurse practitioners, and columns (4)–(6) consider physicians in general practice. To allow for a balanced panel, this table considers the effects 0–3 years after the law change in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. The baseline mean is measured as the average across all counties in 2010. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Table 5: Effects of NP independent prescriptive authority on non-controlled substance prescribing

	Nurse practitioners		General practice physicians	
	Anti-anxiety (1)	Antidepressants (2)	Anti-anxiety (3)	Antidepressants (4)
a. Prescriptions per thousand				
Post law change, 0–3 years	–0.693	–1.161	0.286	12.453
	(0.590)	(2.489)	(0.520)	(5.285)
	[0.245]	[0.643]	[0.585]	[0.022]
Baseline mean	2.831	38.76	12.94	259.5
Relative to mean	–0.245	–0.030	0.022	0.048
b. Prescribing providers per thousand				
Post law change, 0–3 years	–0.005	–0.003	–0.002	0.012
	(0.006)	(0.008)	(0.009)	(0.013)
	[0.415]	[0.720]	[0.836]	[0.346]
Baseline mean	0.152	0.244	0.560	0.792
Relative to mean	–0.033	–0.012	–0.004	0.015
c. Average prescriptions per prescribing provider				
Post law change, 0–3 years	–0.935	4.197	0.816	13.993
	(0.507)	(3.583)	(0.751)	(4.490)
	[0.071]	[0.247]	[0.282]	[0.003]
Baseline mean	14.87	129.2	22.60	324.1
Relative to mean	–0.063	0.032	0.036	0.043
Observations	40,911	40,911	40,911	40,911

Notes: The above table reports coefficients, standard errors (in parentheses), and p-values [in brackets] from estimation of equation (3) using county-year–level data from 2006–2018. The outcome in panel (a) is the number of prescriptions of a given type written by providers of a given type per 1,000 people, the outcome in panel (b) is the number of providers of a given type who are observed writing prescriptions of a given type per 1,000 people, and the outcome in panel (c) is the average number of prescriptions of a given type written by providers of a given type. Columns (1)–(2) consider nurse practitioners, and columns (3)–(4) consider physicians in general practice. To allow for a balanced panel, this table considers the effects 0–3 years after the law change in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. The baseline mean is measured as the average across all counties in 2010. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Table 6: Effects of NP independent prescriptive authority on opioid prescribing by patient type

	Nurse practitioners			General practice physicians		
	Overall	Opioid naive	Non-opioid naive	Overall	Opioid naive	Non-opioid naive
	(1)	(2)	(3)	(4)	(5)	(6)
a. Prescriptions per thousand						
Post law change, 0–3 years	2.643	2.224	0.419	23.296	22.507	0.792
	(1.405)	(1.178)	(0.340)	(11.320)	(10.802)	(0.915)
	[0.066]	[0.065]	[0.224]	[0.045]	[0.042]	[0.391]
Baseline mean	25.45	20.44	5.013	232.1	199.2	32.94
Relative to mean	0.104	0.109	0.084	0.100	0.113	0.024
b. Average days supplied per prescription						
Post law change, 0–3 years	–0.005	–0.019	–0.017	–0.091	–0.088	–0.117
	(0.205)	(0.204)	(0.132)	(0.132)	(0.142)	(0.154)
	[0.980]	[0.925]	[0.897]	[0.494]	[0.540]	[0.450]
Baseline mean	3.250	3.255	2.081	10.46	10.94	6.882
Relative to mean	–0.002	–0.006	–0.008	–0.009	–0.008	–0.017
c. Average MME per day supplied						
Post law change, 0–3 years	28.234	22.430	30.582	26.906	23.874	33.260
	(10.883)	(9.631)	(12.267)	(8.765)	(8.553)	(10.391)
	[0.012]	[0.024]	[0.016]	[0.003]	[0.007]	[0.002]
Baseline mean	189.3	156.3	198.3	388.0	339.1	479.8
Relative to mean	0.149	0.144	0.154	0.069	0.070	0.069
d. Prescriptions with >120 MME daily per thousand						
Post law change, 0–3 years	1.342	1.091	0.250	5.814	5.842	–0.028
	(0.719)	(0.540)	(0.252)	(2.707)	(2.551)	(0.546)
	[0.068]	[0.048]	[0.326]	[0.037]	[0.026]	[0.959]
Baseline mean	8.644	6.278	2.366	75.94	61.63	14.31
Relative to mean	0.155	0.174	0.106	0.077	0.095	–0.002
Observations	40,911	40,911	40,911	40,911	40,911	40,911

Notes: The above table reports coefficients, standard errors (in parentheses), and p-values [in brackets] from estimation of equation (3) using county-year–level data from 2006–2018. For each patient and provider type, the outcome in panel (a) is the number of opioid prescriptions per 1,000 people, the outcome in panel (b) is the average number of days supplied per opioid prescription, the outcome in panel (c) is the average daily morphine milligram equivalents (MMEs) per opioid prescription, and the outcome in panel (d) is the number of opioid prescriptions with greater than 120 MME daily per 1,000 people. Columns (1)–(3) consider prescriptions written by nurse practitioners, and columns (4)–(6) consider prescriptions written by physicians in general practice. Columns (1) and (4) consider prescriptions written for all patients, columns (2) and (4) consider prescriptions written for patients who did not fill an opioid prescription in the past six months ("opioid naive"), and columns (3) and (6) consider prescriptions written for patients who filled an opioid prescription in the past six months ("non–opioid naive"). To allow for a balanced panel, this table considers the effects 0–3 years after the law change in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. The baseline mean is measured as the average across all counties in 2010. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Table 7: Effects of NP independent prescriptive authority on GP controlled substance prescribing by exposure to NPs

	General practice physicians		
Prescriptions per 1,000:	Opioids (1)	Anti-anxiety (2)	Opioid + benzo. (3)
Post law change, 0–3 years (β_1)	19.763	6.377	2.242
	(11.504)	(3.238)	(1.007)
	[0.092]	[0.054]	[0.031]
× Above median (β_2)	12.890	7.550	1.540
	(6.117)	(4.437)	(1.732)
	[0.040]	[0.095]	[0.378]
$\beta_1 + \beta_2$	32.653	13.927	3.782
	(11.950)	(4.979)	(1.848)
	[0.009]	[0.007]	[0.046]
Baseline mean (below median)	227.6	105.3	15.42
Baseline mean (above median)	273.4	126.9	24.22
Relative to mean (below median)	0.087	0.061	0.145
Relative to mean (above median)	0.119	0.110	0.156
Observations	40,911	40,911	40,911

Notes: The above table reports coefficients, standard errors (in parentheses), and p-values [in brackets] from estimation of an augmented version of equation (3) that includes an interaction between the treatment indicator and an indicator denoting whether the county had an above-median number of nurse practitioners (NPs) per general practice physicians (GPs) among treatment states in 2006 using county-year–level data from 2006–2018. Outcomes are the number of prescriptions of a given type written by GPs per 1,000 people. "Opioid + benzo." denotes instances of co-prescribing of an opioid and a benzodiazepine to the same patient by the same provider on the same day. To allow for a balanced panel, this table considers the effects 0–3 years after the law change in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. The baseline mean is measured as the average across all counties of a given type in 2010. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Table 8: Effects of NP independent prescriptive authority on controlled substance prescribing across physician specialties

	General practice (1)	Emergency medicine (2)	Psych. & neurology (3)	Obstetrics & gyn. (4)	Orthopedic surgery (5)	General surgery (6)
a. Opioids per thousand						
Post law change, 0–3 years	23.296	2.321	0.756	0.814	3.083	0.361
	(11.320)	(0.819)	(0.325)	(0.370)	(1.668)	(0.553)
	[0.045]	[0.007]	[0.024]	[0.032]	[0.070]	[0.517]
Baseline mean	232.1	33.95	10.19	14.11	41.18	28.10
Relative to mean	0.100	0.068	0.074	0.058	0.075	0.013
b. Anti-anxiety per thousand						
Post law change, 0–3 years	8.452	0.147	1.846	0.193	0.050	0.068
	(3.276)	(0.097)	(0.945)	(0.114)	(0.060)	(0.068)
	[0.013]	[0.137]	[0.057]	[0.098]	[0.416]	[0.322]
Baseline mean	107.4	3.273	28.61	2.909	1.341	1.553
Relative to mean	0.079	0.045	0.065	0.066	0.037	0.044
c. Opioid + benzo. per thousand						
Post law change, 0–3 years	2.660	0.128	0.025	0.090	0.021	0.094
	(1.031)	(0.054)	(0.053)	(0.033)	(0.050)	(0.047)
	[0.013]	[0.137]	[0.057]	[0.098]	[0.416]	[0.322]
Baseline mean	16.28	1.106	0.719	0.457	0.590	0.524
Relative to mean	0.163	0.116	0.035	0.197	0.036	0.179
Observations	40,911	40,911	40,911	40,911	40,911	40,911

Notes: The above table reports coefficients, standard errors (in parentheses), and p-values [in brackets] from estimation of equation (3) using county-year–level data from 2006–2018. Outcomes are the number of prescriptions of a given type written by providers of a given type per 1,000 people. "Opioid + benzo." denotes instances of co-prescribing of an opioid and a benzodiazepine to the same patient by the same provider on the same day. To allow for a balanced panel, this table considers the effects 0–3 years after the law change in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. The baseline mean is measured as the average across all counties in 2010. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Table 9: Effects of NP independent prescriptive authority on fatal drug overdoses

Fatal overdoses per 1,000,000:	All drugs (1)	All opioids (2)	Prescription opioids (3)
a. No time trends			
Post law change, 0–3 years	4.691	6.918	6.982
	(13.127)	(14.359)	(3.993)
	[0.722]	[0.632]	[0.087]
Relative to mean	0.038	0.101	0.148
b. County-specific pre-trends			
Post law change, 0–3 years	–1.671	3.023	2.909
	(7.925)	(8.156)	(2.619)
	[0.834]	[0.712]	[0.272]
Relative to mean	–0.013	0.044	0.062
c. County-specific time trends			
Post law change, 0–3 years	–9.695	–6.583	0.103
	(14.742)	(14.026)	(2.380)
	[0.514]	[0.641]	[0.966]
Relative to mean	–0.078	–0.097	0.002
Baseline mean	124.0	68.21	47.16
Observations	40,911	40,911	40,911

Notes: The above table reports coefficients, standard errors (in parentheses), and p-values [in brackets] from estimation of equation (3) using county-year–level data from 2006–2018. Outcomes are the number of fatal overdoses involving any drug (column (1)), any opioid (column (2)), and prescription opioids (column (3)) per 1,000,000 people. To allow for a balanced panel, this table considers the effects 0–3 years after the law change in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects and all time-varying, county-level controls listed in Figure A1. Panel (b) further includes county-specific linear pre-trends following Goodman-Bacon (2021), and panel (c) includes county-specific linear time trends estimated over the entire sample period. The baseline mean is measured as the average across all counties in 2010. Standard errors are clustered by state. Outcome data come from the NVSS database.

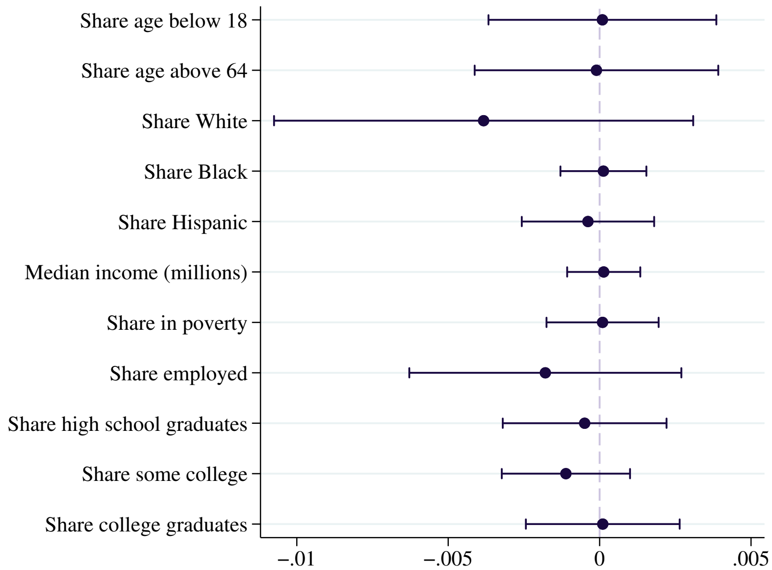
For Online Publication

The Effects of Competition on Physician Prescribing

Currie, Li, and Schnell (2023)

A Supplementary figures and tables

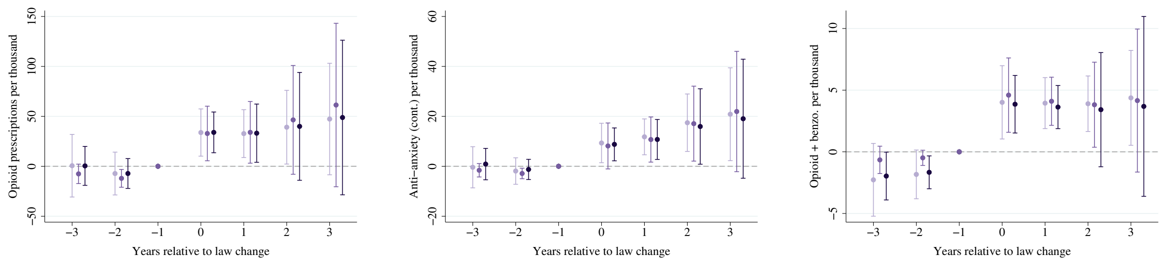
Figure A1: Relationship between changes in NP independent prescriptive authority and county-level socio-demographics



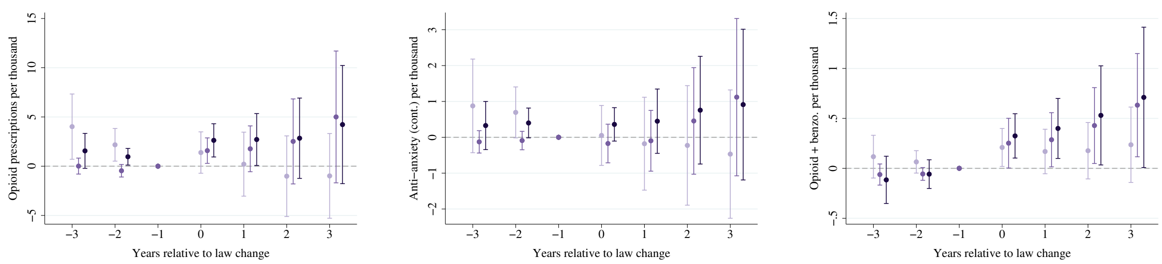
Notes: The above figure presents coefficients and 95% confidence intervals from estimation of balancing analogues of equation (3) using county-year–level data from 2006–2018. Each row presents output from a separate regression in which the potential confounder denoted on the y-axis is the dependent variable. To allow for a balanced panel, this figure considers the effects 0–3 years after the law change in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in the figure except the potential confounder being used as the outcome. Standard errors are clustered by state. Data on county characteristics come from the ACS, and data on the dates of law changes granting NPs independent prescriptive authority for controlled substances come from Markowitz and McMichael (2020).

Figure A2: Alternative time trends: Effects of NP independent prescriptive authority on controlled substance prescribing

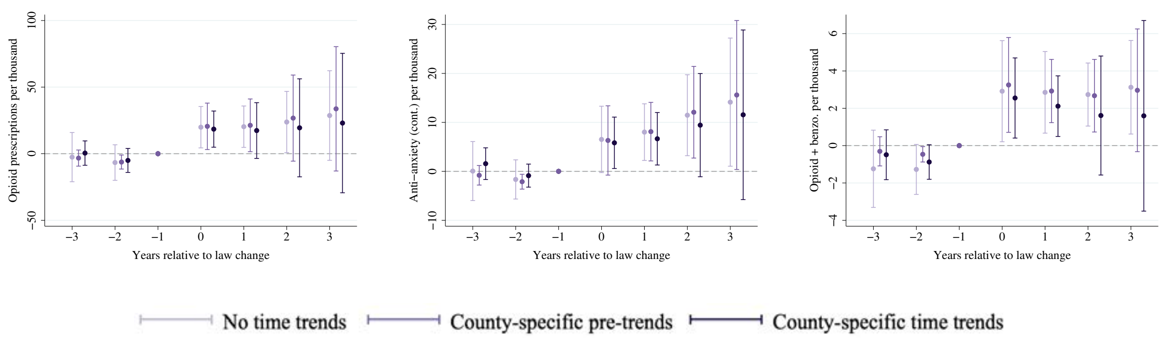
(a) All providers



(b) Nurse practitioners



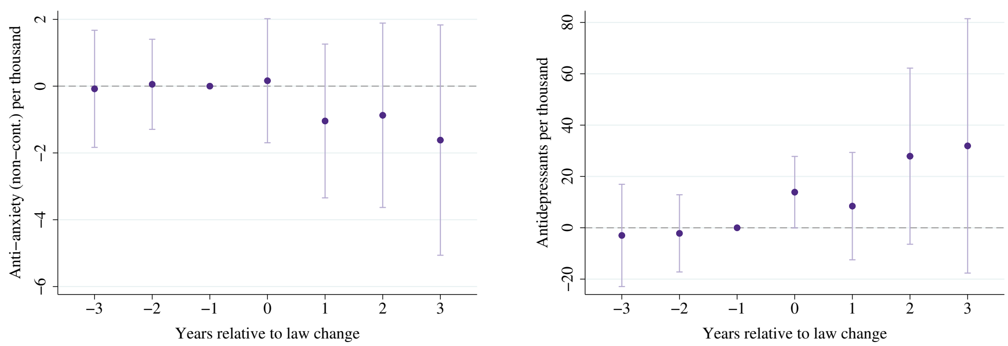
(c) General practice physicians



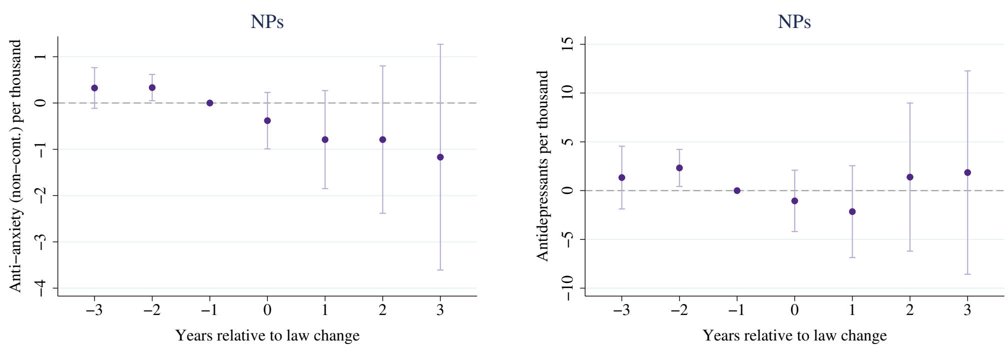
Notes: The above figures present coefficients and 95% confidence intervals from estimation of equation (2) using county-year–level data from 2006–2018. Outcomes are the number of opioid prescriptions per 1,000 people (left subfigures), the number of anti-anxiety controlled substance prescriptions per 1,000 people (middle subfigures), and the number of instances in which an opioid and benzodiazepine prescription were written for the same patient by the same provider on the same day per 1,000 people (right subfigures) by a given provider type. Subfigure (a) considers prescriptions written by all providers, subfigure (b) considers prescriptions written by nurse practitioners, and subfigure (c) considers prescriptions written by physicians in general practice. To allow for a balanced panel, these figures consider effects in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects and all time-varying, county-level controls listed in Figure A1. The light dots and bars are from specifications without time trends; the medium dots and bars are from specifications that include county-specific linear pre-trends following Goodman-Bacon (2021); the dark dots and bars are from specifications that include county-specific linear time trends estimated over the entire sample period. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Figure A3: Effects of NP independent prescriptive authority on non-controlled substance prescribing

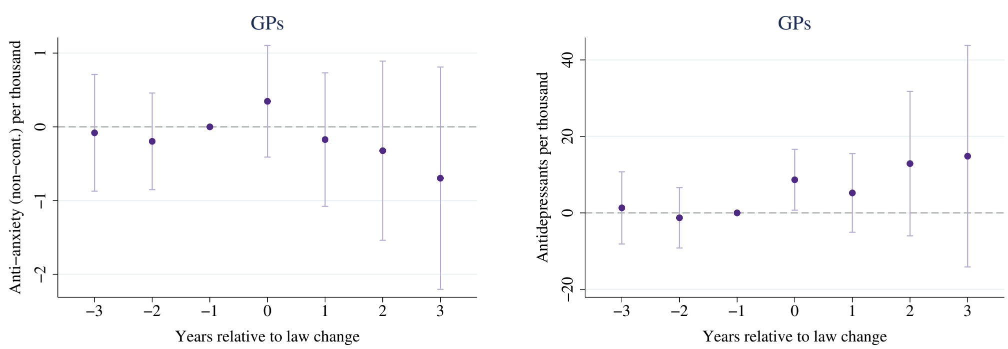
(a) All providers



(b) Nurse practitioners



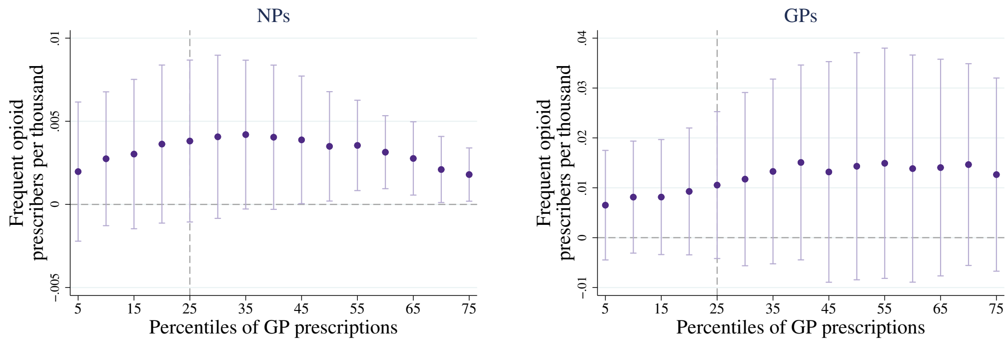
(c) General practice physicians



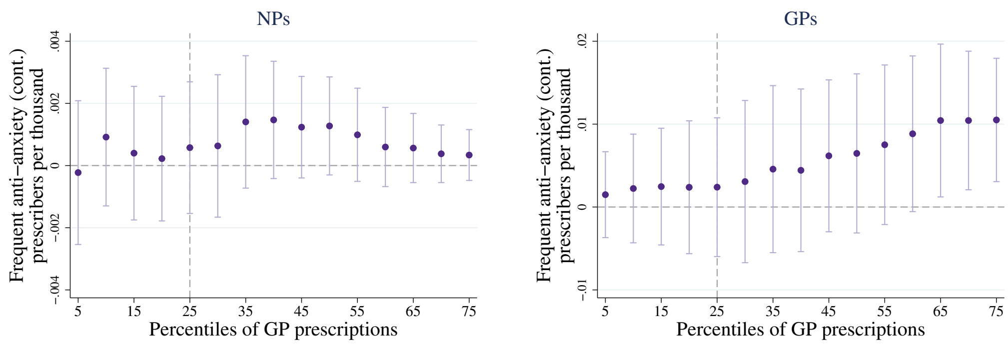
Notes: The above figures present coefficients and 95% confidence intervals from estimation of equation (2) using county-year–level data from 2006–2018. The outcome in the left (right) subfigure in each subplot is the number of prescriptions for non-controlled anti-anxiety medications (antidepressants) written by a given provider type per 1,000 people. Subfigure (a) considers prescriptions from all providers, subfigure (b) considers prescriptions written by nurse practitioners (NPs), and subfigure (c) considers prescriptions written by physicians in general practice (GPs). To allow for a balanced panel, these figures consider effects in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Figure A4: Alternative definitions: Effects of NP independent prescriptive authority on number of "frequent" prescribers

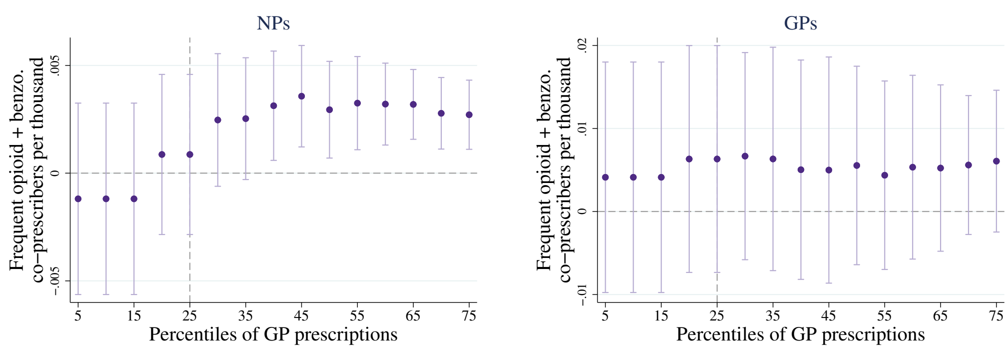
(a) Opioid prescribers



(b) Anti-anxiety prescribers



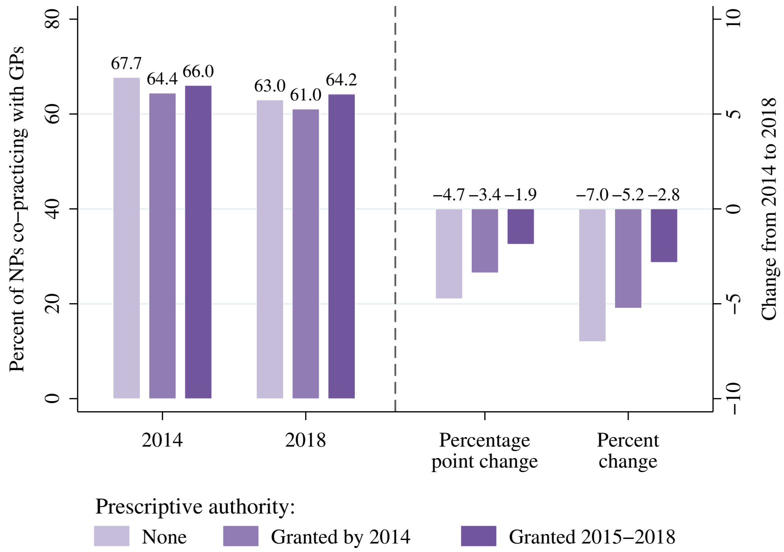
(c) Opioid + benzo. co-prescribers



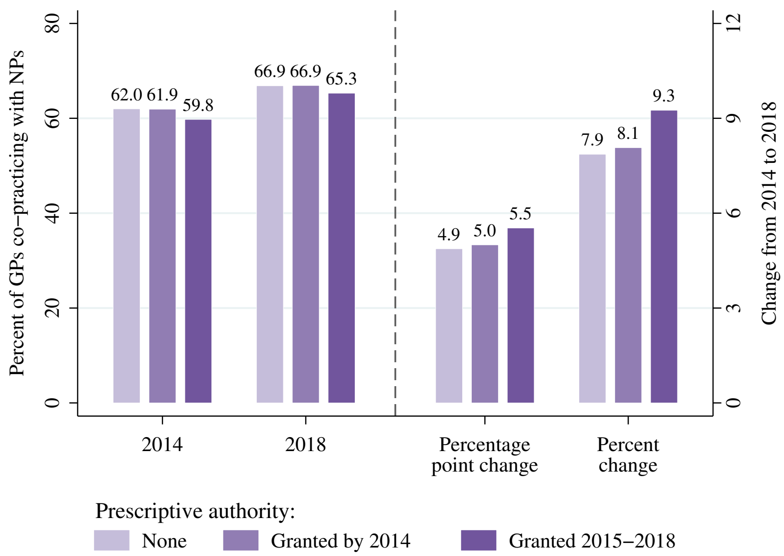
Notes: The above figures present coefficients and 95% confidence intervals from estimation of equation (3) using county-year–level data from 2006–2018. Each coefficient comes from a separate regression in which the outcome is an alternative definition of the number of "frequent" prescribers of a given type per 1,000 people; the left (right) subfigures consider the number of NPs (GPs). "Frequent" is defined as both (1) writing a given type of prescription in each month (or year for opioid-benzo. co-prescribing) and (2) being above the xth percentile of prescribing among all GPs who satisfy criterion (1), where x is defined on the x-axis. To allow for a balanced panel, these figures consider the effects 0–3 years after the law change in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Figure A5: Co-practice patterns of NPs and GPs in 2014 and 2018

(a) Nurse practitioners



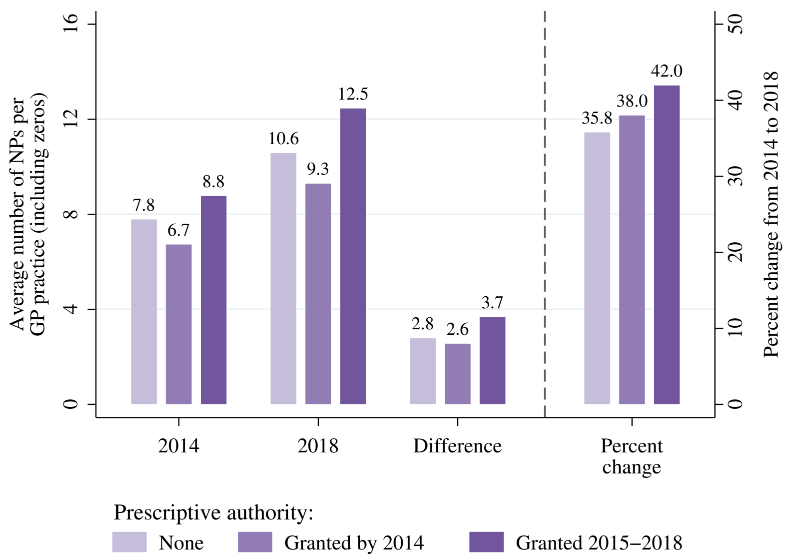
(b) General practice physicians



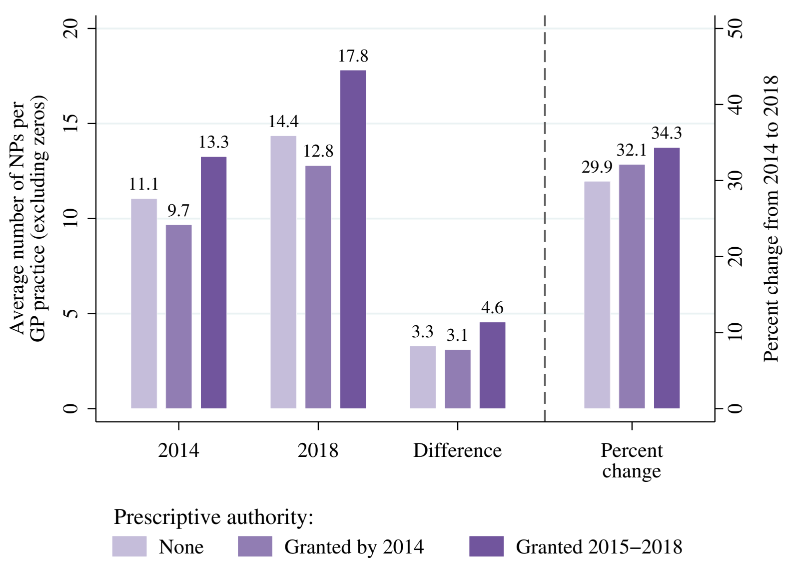
Notes: The above figures report co-practice patterns among nurse practitioners (NPs) and physicians in general practice (GPs) in states that did not allow NPs to independently prescribe controlled substances by 2018 (light purple), states that granted NPs independent prescriptive authority for controlled substances by 2014 (medium purple), and states that granted NPs the ability to independently prescribe controlled substances between 2015 and 2018 (dark purple). The left two panels in each subfigure show the population-weighted average of county-year level percents of a given provider type (NPs in subfigure (a) and GPs in subfigure (b)) who were observed practicing in the same clinic as at least one provider of the other type (GPs in subfigure (a) and NPs in subfigure (b); "co-practicing") in 2014 (first panel) and 2018 (second panel). The right two panels show the population-weighted average percentage point changes (third panel) and percent changes (fourth panel) in these shares from 2014 to 2018. Outcome data come from the location snapshots provided by IQVIA and include the exact practice addresses for all providers in the IQVIA data in 2014 and 2018.

Figure A6: Number of NPs per GP practice in 2014 and 2018

(a) Including zeros



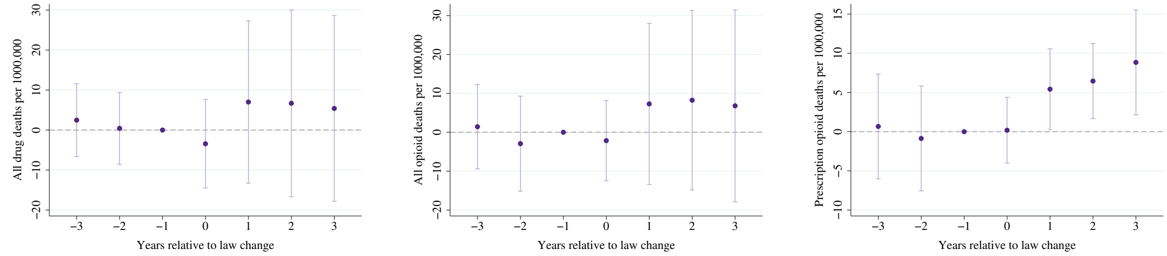
(b) Excluding zeros



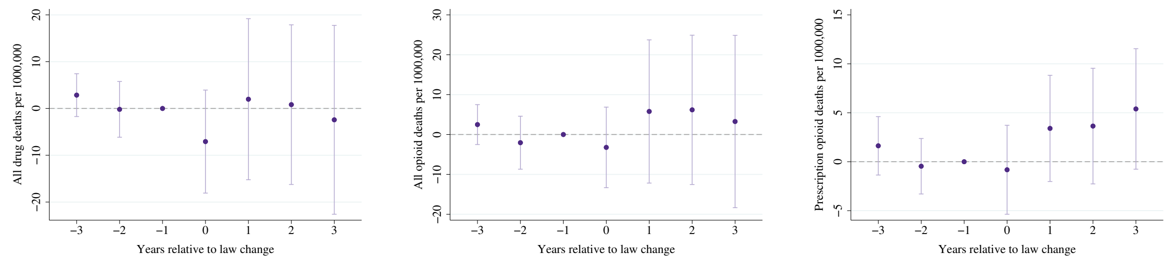
Notes: The above figures report the average number of nurse practitioners (NPs) observed working in the same practice as each physician in general practice (GP) in states that did not allow NPs to independently prescribe controlled substances by 2018 (light purple), states that granted NPs independent prescriptive authority for controlled substances by 2014 (medium purple), and states that granted NPs the ability to independently prescribe controlled substances between 2015 and 2018 (dark purple). The left two panels in each subfigure show the population-weighted average of the county-year number of NPs who were observed practicing in the same clinic as each GP in 2014 (first panel) and 2018 (second panel); subfigure (a) includes GPs with no NPs in their practice in these calculations whereas subfigure (b) excludes such zeros. The right two panels show the population-weighted average level changes (third panel) and percent changes (fourth panel) in these averages from 2014 to 2018. Outcome data come from the location snapshots provided by IQVIA and include the exact practice addresses for all providers in the IQVIA data in 2014 and 2018.

Figure A7: Effects of NP independent prescriptive authority on fatal drug overdoses

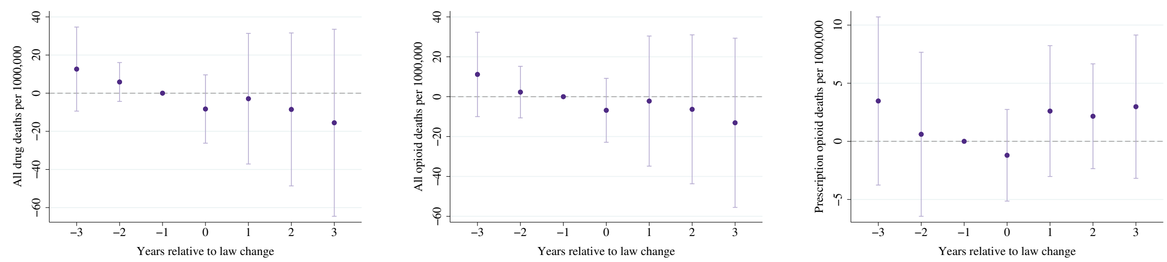
(a) No time trends



(b) County-specific pre-trends



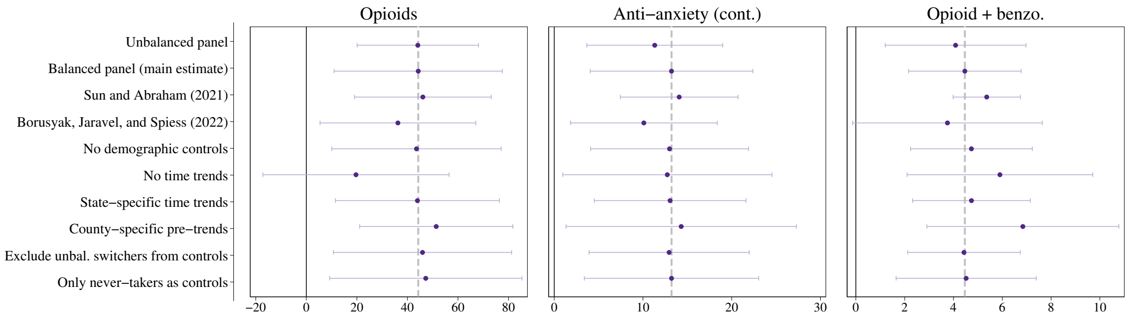
(c) County-specific time trends



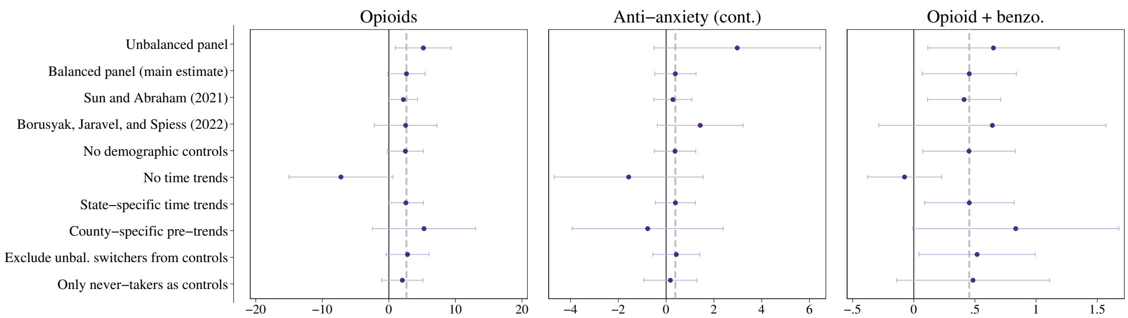
Notes: The above figures present coefficients and 95% confidence intervals from estimation of equation (2) using county-year–level data from 2006–2018. Outcomes are the number of fatal overdoses per 1,000,000 people involving any drug (left subfigures), any opioid (middle subfigures), and prescription opioids (right subfigures). To allow for a balanced panel, these figures consider effects in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects and all time-varying, county-level controls listed in Figure A1. Subfigure (b) further includes county-specific linear pre-trends following Goodman-Bacon (2021), and subfigure (c) includes county-specific linear time trends estimated over the entire sample period. Standard errors are clustered by state. Outcome data come from the NVSS database.

Figure A8: Robustness: Effects of NP independent prescriptive authority on controlled substance prescribing

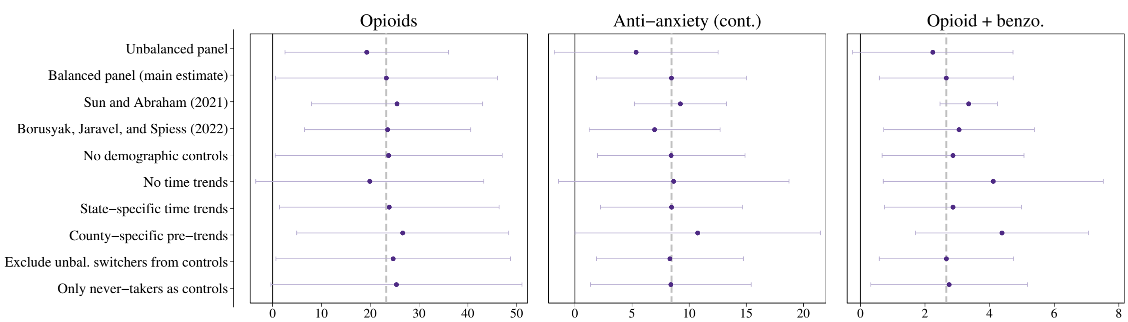
(a) All providers



(b) Nurse practitioners



(c) General practice physicians



Notes: The above figure presents coefficients and 95% confidence intervals from estimation of equation (3) using county-year–level data from 2006–2018. Each row presents output from a separate regression using the specification denoted on the y-axis. The dashed vertical line in each subfigure displays the coefficient estimate from our baseline specification (as reported in Table 3); this specification considers a balanced panel of the 11 states with law changes between 2009-2015 and includes county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. Outcomes are the number of prescriptions of a given type written by providers of a given type per 1,000 people. "Opioid + benzo." denotes instances of co-prescribing of an opioid and a benzodiazepine to the same patient by the same provider on the same day. Panel (a) considers prescriptions written by all providers, panel (b) considers prescriptions written by nurse practitioners, and panel (c) considers prescriptions written by physicians in general practice. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

Table A1: Effects of NP independent prescriptive authority on controlled substance prescribing by PAs

	Physician assistants		
	Opioids (1)	Anti-anxiety (2)	Opioid + benzo. (3)
a. Prescriptions per thousand			
Post law change, 0–3 years	4.843	1.060	0.529
	(2.688)	(0.546)	(0.245)
	[0.078]	[0.058]	[0.035]
Baseline mean	29.01	5.385	1.136
Relative to mean	0.167	0.197	0.466
b. Prescribing providers per thousand			
Post law change, 0–3 years	0.011	0.002	0.006
	(0.006)	(0.005)	(0.006)
	[0.067]	[0.638]	[0.297]
Baseline mean	0.180	0.134	0.081
Relative to mean	0.061	0.015	0.074
c. Average prescriptions per prescribing provider			
Post law change, 0–3 years	22.017	4.332	3.008
	(9.457)	(1.834)	(0.693)
	[0.024]	[0.022]	[<0.001]
Baseline mean	135.9	32.53	11.95
Relative to mean	0.162	0.133	0.252
Observations	40,911	40,911	40,911

Notes: The above table reports coefficients, standard errors (in parentheses), and p-values [in brackets] from estimation of equation (3) using county-year–level data from 2006–2018. The outcome in panel (a) is the number of prescriptions of a given type written by physician assistants per 1,000 people, the outcome in panel (b) is the number of physician assistants who are observed writing prescriptions of a given type per 1,000 people, and the outcome in panel (c) is the average number of prescriptions of a given type people written by prescribing physician assistants. To allow for a balanced panel, this table considers the effects 0–3 years after the law change in the 11 states with law changes between 2009–2015. The regressions include county and year fixed effects, county-specific linear time trends, and all time-varying, county-level controls listed in Figure A1. The baseline mean is measured as the average across all counties in 2010. Standard errors are clustered by state. Outcome data come from the IQVIA LRx database.

B Provider practice locations

Our extract of the IQVIA data contains an exact practice address for each provider in 2014 and 2018. However, our empirical design requires that we know the county of each prescriber in each year over our 13-year sample (2006–2018). We therefore designed and implemented a location assignment algorithm that uses information on the zip codes of the patients who filled the prescriptions written by each provider in each year to infer the county of each provider annually. The idea behind the algorithm is simple: if, for example, a provider predominately writes prescriptions for patients in Baltimore County, Maryland, but then begins writing prescriptions predominately for patients in Cook County, Illinois, then we assume that the provider moved from Baltimore to Chicago when the locations of her patients changed.

Our location assignment algorithm is implemented as follows. First, for each provider-month, we calculate the share of the provider's total prescriptions across all three of the drug classes included in our data extract (opioids, anti-anxiety medications, antidepressants) that were filled by patients in each zip code. Starting with the zip code with the highest share of prescriptions for that provider, we then add additional zip codes in order of descending prescription shares until we have a set of zip codes covering at least 90 percent of the provider's prescriptions in that month.[27] We call this starting set of zip codes the provider's "monthly practice area."

To determine provider moves, we then compare the monthly practice area in month t to the monthly practice area in month $t-2$.[28] We say that a move potentially occurred between month t and month $t-2$ if there is no overlap between the set of zip codes in the monthly practice areas across these two months. We use a two-period lagged comparison group to

[27]We select zip codes covering 90 percent of prescriptions, rather than only choosing the zip code with the highest share, to avoid having providers "flip-flop" between zip codes across months. For example, suppose that a provider wrote 60 (40) percent of her prescriptions for patients in zip code A (B) in month 1, 40 (60) percent of her prescriptions for patients in zip code A (B) in month 2, and 60 (40) percent of her prescriptions for patients in zip code A (B) in month 3. If we only considered the zip code with the highest share of prescriptions, it would appear as if the provider moved from zip code A to zip code B and then back to zip code A. Rather, the provider was serving a consistent area throughout—a pattern that is accurately captured with our 90 percent threshold.

[28]If a given provider wrote zero prescriptions in month $t-2$, then the monthly practice area in month $t-2$ is not defined. When this occurs, we compare the monthly practice area in month t to the monthly practice area in month $t-x$, where $x > 2$ is the unique x such that (1) the provider wrote zero prescriptions in months $t-x+1$ through $t-2$ and (2) the provider wrote a positive number of prescriptions in month $t-x$.

account for the fact that mid-month moves will result in prescriptions being written to patients in both the origin and destination locations in the month of the move. For example, suppose that a provider wrote 60 (40) percent of her prescriptions for patients in zip code A (B) in month $t-2$, 30 (20) (30) (20) percent of her prescriptions for patients in zip code A (B) (C) (D) in month $t-1$, and 60 (40) percent of her prescriptions for patients in zip code C (D) in month t. If we compared the monthly practice areas in periods t and $t-1$ and periods $t-1$ and $t-2$, we would determine that the provider did not move (since there is always some overlap in the set of zip codes in these adjacent period comparisons). Rather, the provider likely moved from an area with zip codes A and B to an area with zip codes C and D in period $t-1$, a pattern which is accurately captured with our two-period lagged comparison group.

With the months of potential moves identified, we then redefine time spells to be periods between moves rather than months. That is, if a provider was writing prescriptions for patients in overlapping monthly practice areas (as defined above) in months t_1 through t_n, but then began writing prescriptions for patients in a new set of overlapping monthly practice areas in months t_{n+1} through t_N, then we would define months t_1 through t_n as one spell and months t_{n+1} through t_N as another. We call this starting set of spells the provider's "initial spell set."

Below, we assign a specific location to each provider-spell by taking the zip code with the highest share of the provider's prescriptions across that spell. In principle, the most frequent zip code could be the same across two consecutive spells for the same provider. As this is inconsistent with the idea that the provider moved between spells, we iterate on the above procedure until the zip code with the highest share of the provider's prescriptions at the spell level differs across consecutive spells for the same provider.

In particular, after identifying the initial spell set for each provider as outlined above, we determine the set of zip codes needed to cover 90 percent of each provider's prescriptions within each spell. We then compare the practice area in spell t to the practice area in spell $t-1$ and say that a move occurred between these spells if there is no overlap between the set of zip codes in these spell-level practice areas. If a move did not occur between two spells, we merge the spells in question, calculate the practice area for this new spell, and compare the new spell's practice area to the practice area of the spell a period before. We iterate on this procedure—that is, redefining spells, defining spell-level practice areas, and identifying potential moves—until there is no overlap in the practice areas of consecutive spells. This ensures that the zip code with the highest share of prescriptions in each provider-spell changes across identified moves. We use a zip code to county crosswalk provided by the U.S. Department of Housing and Urban Development to assign counties to the most frequent zip code in each provider-spell and use this county as the provider's location for the period covered by the spell.[29]

We can compare the practice counties that we assign to providers in 2014 and 2018 using our algorithm to the practice counties provided by IQVIA in the same years.[30] These snapshots of addresses from IQVIA are the company's best assessment of each provider's location in each of these years based on information from various sources. Reassuringly, our algorithm assigns the same county (state) as IQVIA for 66.6 (89.7) percent of providers in 2018. Unsurprisingly, our algorithm is more accurate for more frequent prescribers, with 76.4 (94.8) percent of prescriptions in 2018 being written by providers whose county (state) we assign in accordance with the IQVIA data. A similar pattern is observed in 2014, with our location assignment algorithm assigning the same county (state) as IQVIA for 53.5 (73.0) percent of providers and 64.8 (81.9) percent of prescriptions.

Comparing our constructed panel of provider locations to one constructed from the National Plan and Provider Enumeration System (NPPES)—a data source that is commonly used to track provider locations over time—suggests that physician moves are significantly underreported in the NPPES.[31] Using our location assignment algorithm, we find that among

[29]The crosswalk is available here: https://www.huduser.gov/portal/datasets/usps_crosswalk.html.

[30]We can further compare the practice counties that we infer in 2018 using our location assignment algorithm to those provided in the 2018 AMA Masterfile, an input into IQVIA's 2018 location snapshot. Physicians are added to the AMA Masterfile when they receive their medical education number; practice locations among physicians who have since moved will therefore be outdated unless the provider choses to update their information with the AMA, and there is little incentive to do so. Our algorithm identifies the same county (state) of practice for 54.2 (84.7) percent of the 84.4 percent of physicians in the IQVIA data who can be linked to the 2018 AMA Masterfile.

[31]Another source of data that is commonly used to identify provider locations is the Centers for Medicaid and Medicare Services' "Physician Compare" database. While these data come from billing records and therefore should in principle have updated address information for providers, it unfortunately only includes a subsample of providers. For example, only 49.3 percent of providers in the IQVIA data in 2018 are also in Physician Compare.

the 94.7 percent of providers in the IQVIA data who can be linked to the NPPES, an average of 13.6 (6.4) percent moved counties (states) annually over the periods 2008–2013 and 2015–2018 (the years for which the NPPES is available through NBER). Among the same set of providers and years in the NPPES, annual cross-county (cross-state) moves are reported for an average of only 4.4 (2.5) percent of providers. This underreporting of provider moves in the NPPES is perhaps not surprising given that providers enter the NPPES when they apply for a National Provider Identifier (NPI) and have little reason to update their location information subsequently. Nevertheless, it highlights the limitations of the NPPES and motivates our use of a data-driven location assignment algorithm.

C Alternative micro-foundation: demand inducement

In Section II, we introduced a model of physician behavior that can rationalize an increase in prescribing among physicians following an increase in competition. This framework formalized the idea that the elasticity of patient demand to service use is increasing in competition; as such, physician behavior shifts toward the preferences of marginal patients in the presence of increased competition to retain demand.

Alternative models of physician behavior can also be used to micro-found our finding that increased competition leads to increases in prescribing of certain medications. Notably, models of demand inducement likewise deliver this result. In these models, the effect operates through an income effect: When competition increases, physicians lose patients, thereby reducing their income. Given diminishing marginal utility of income, physician utility is more responsive to changes in income at lower levels of income, and thus, inducing demand—which is assumed to have a constant marginal cost—is now more appealing. Competition therefore increases optimal demand inducement, putting upward pressure on service provision.

We formalize this intuition below in a standard model of physician-induced demand. In particular, we present a framework that closely follows the one outlined in Gruber and Owings (1996) and McGuire (2000) but that is framed for the case of prescription opioids. We only discuss prescription opioids for simplicity, though the same model holds for addictive anti-anxiety drugs and other controlled substances.

Following the literature on physician-induced demand, suppose that physician utility is given by $U = U(Y, I)$, where Y is income and I is demand inducement. In the case of prescription opioids, I can be thought of as inducing demand for prescription opioids among patients who would be better off with some other treatment. We assume that utility is increasing in income ($U_Y > 0$) at a decreasing rate ($U_{YY} < 0$), while utility is decreasing in demand inducement ($U_I < 0$) at a decreasing rate ($U_{II} < 0$). Let the number of patients that a doctor treats at baseline be given by N, and let $\alpha(I)$ be the fraction of patients who are prescribed opioids. Since prescribing is increasing in demand inducement, we have that $\alpha_I > 0$. We further assume that $\alpha_{II} = 0$, $U_{YI} = 0$, $U_{IY} = 0$.

Let R_{OP} be the full revenue associated with treatment including prescription opioids, and let R_{noOP} be the full revenue associated with treatment that does not include opioids. Since it is often simpler and less time consuming to prescribe opioids to a patient rather than providing some other treatment, we assume that $R_{OP} > R_{noOP}$.[32] Moreover, although we are not explicitly modeling the dynamics, R_{OP} will further exceed R_{noOP} if prescribing opioids increases the probability that patients return for future visits (e.g., for refills).

Physicians choose the level of inducement to maximize their utility subject to a budget constraint. The physician's problem can therefore be written as:

$$\max_{I} \; U(Y, I) \;\; s.t. \; Y = N \cdot \left(R_{OP} \cdot \alpha(I) + R_{noOP} \cdot (1 - \alpha(I))\right).$$

Assuming that utility is separable in income and inducement, taking the derivative with respect to I and setting it equal to zero yields the following the first-order condition:

$$[I] \quad U_Y \cdot N \cdot \alpha_I \cdot (R_{OP} - R_{noOP}) + U_I = 0.$$

This first-order condition shows that the physician decides how much demand to induce by trading off the utility from additional income that prescribing opioids provides against the disutility of inducing demand.

Now, suppose that NPs are granted independent prescriptive authority for controlled substances. Since some patients will now find it preferable to see an NP, N goes down for a given physician. Fully differentiating the first-order condition and rearranging, we obtain:

$$\frac{\partial I}{\partial N} = -\frac{1}{U_{II}} \alpha_I \left(R_{OP} - R_{noOP}\right) U_Y \left(\frac{U_{YY} Y}{U_Y} + 1\right).$$

It is reasonable to assume that the absolute value of the elasticity of marginal utility with respect to income, $\frac{U_{YY} Y}{U_Y}$, is greater than one.[33] In this case, $\frac{U_{YY} Y}{U_Y} + 1 < 0$ and $\frac{\partial I}{\partial N} < 0$. Therefore, as N goes down, physicians induce more demand for prescription opioids. Although

[32] To see this, consider a patient with lower back pain. If the physician decides to prescribe opioids, the provider can quickly write a prescription and move on to the next patient. If the doctor instead decides to focus on non-opioid treatment, an alternative treatment regime might involve counseling the patient to lose weight or coordinating with other providers to incorporate physiotherapy, cognitive behavioral therapy, and other interventions into the patient's treatment program.

[33] For example, Layard et al. (2008) estimate that the elasticity of marginal utility with respect to income ranges from 1.19 to 1.34 using surveys covering over 50 countries between 1972 and 2005.

physicians may dislike prescribing unnecessary opioids (i.e., they experience disutility from inducing demand), a drop in their revenue resulting from increased competition increases the marginal utility of revenue sufficiently to increase such prescribing.