I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17738

Why Are Opioid Prescribing Rates Higher in Rural Versus Urban Areas?

Alicia Modestino
Gary Young
Md Mahmudul Hasan
Jiesheng Shi
Md Noor E Alam

FEBRUARY 2025

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17738

Why Are Opioid Prescribing Rates Higher in Rural Versus Urban Areas?

Alicia Modestino
Northeastern University and IZA

Gary Young
Northeastern University

Md Mahmudul Hasan
University of Florida

Jiesheng Shi
Northeastern University

Md Noor E Alam
Northeastern University

FEBRUARY 2025

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Why Are Opioid Prescribing Rates Higher in Rural Versus Urban Areas?*

Patients in rural areas have higher rates of opioid use and overdose than those in urban areas that are linked to the greater prevalence and amounts of opioids prescribed. We merge individual claims data with county-level supply and demand factors to examine this relationship between geographical density and opioid prescribing. We find patients in rural areas are 10 percentage points more likely to receive an opioid prescription with about half of this differential attributable to the underlying health of the local population. A Blinder-Oaxaca decomposition reveals that roughly 80 percent of the remaining gap is explained by a combination of supply and demand factors. Allowing for the interaction of demand (e.g., working in a physically demanding occupation) and supply (e.g., healthcare delivery system) variables eliminates the gap. Our findings suggest several way states can reduce the gap in opioid prescribing between rural and urban areas, with possible downstream impacts on overdose and mortality.

JEL Classification: I14, I15, I18

Keywords: opioid, prescribing, density, health disparity, geography

Corresponding author:
Alicia Sasser Modestino
Northeastern University
School of Public Policy and Urban Affairs
310 Renaissance Park
360 Huntington Avenue
Boston, MA 021115
USA
E-mail: a.modestino@neu.edu

* We are grateful to Northeastern University and the Massachusetts Department of Public Health for financial support of this research. This work was supported with funding from the Massachusetts Department of Public Health (MDPH) through a contract with the Centers for Disease Control and Prevention (CDC), award number 6 NU17CE925012-03-01

I. Introduction

According to the latest data available from the 2022 National Survey on Drug Use and Health, people living in rural (non-metropolitan) areas use opioids at a higher rate (31.7 percent) than those living in urban (metropolitan) areas (26.5 percent), with even higher rates (36.0 percent) among those living in completely rural areas (SAMHSA, 2023). Previous studies have found that this disparity in opioid use is linked to greater prescribing, showing that the odds that a patient in a non-metropolitan area is prescribed an opioid is up to 50 percent higher than it is for a similar patient in an urban area (Prunuske et al., 2014) and that living in a non-metropolitan area is also associated with higher *amounts* of prescribed opioids (Guy Jr. et al., 2017). More importantly, higher rates of prescribing opioids in non-metropolitan areas have been shown to have important consequences for mortality, with researchers finding that lower population density is associated with higher overdose rates (Davlasheridze and Goetz, 2021).

This disparity in opioid prescribing by geography is present even when comparing patients that have similar characteristics, receive care in similar clinical settings, have the same type of insurance coverage and are subject to the same state regulations. For example, among veterans receiving care through the Veterans Health Administration, per capita opioid utilization was 30 percent higher among non-metropolitan versus metropolitan patients (Lund et al., 2019). Among Medicare Part D recipients, opioid prescribing rates ranged from 3 percent in more densely populated states such as New York to 11 percent in less densely populated states such as Utah (Kuo et al. 2016). In addition, this geographic variation in the prevalence of prescribed opioids across counties is greater than the geographic variation observed for other Medicare services related to pain conditions such as prescribing of other types of drugs and performing surgical procedures to reduce pain (e.g., lumbar fusion) (McDonald, Carlson, and Izrael, 2012).

Finally, the disparity in opioid prescribing across counties with varying density has even been documented within states, such as Massachusetts, suggesting that these differences are not limited to certain states or regions that are predominantly either metropolitan or non-metropolitan nor having particular regulatory environments. For example, prior research shows that Massachusetts counties with substantial rural populations in the western part of the state, such as Berkshire county, had opioid prescribing rates that were twice that of urban counties, such as Suffolk, which encompasses Boston, the state's largest metro area (Massachusetts

Department of Public Health, 2019). A concomitant disparity in the prevalence of opioid use disorder was also found across urban and rural counties in the state (Barocas et al., 2018).

Despite the increasing amount of research on geographic differences in opioid prescribing, no study has been able to simultaneously explore the range of supply-side (provide) factors while also controlling for the demand-side (patient) factors due to data limitations. As a result, previous studies have not been able to quantify the relative importance of each set of factors nor whether dynamic interactions exist between the demand and supply side. This has left policymakers with the unenviable task of pursuing multiple policies with little knowledge of the tradeoffs involved in the hopes of having an immediate impact on an ever-growing problem that has only been exacerbated further by the pandemic (Modestino 2021). If the difference in prescribing rates between urban and rural areas is largely due to health care access, delivery system characteristics, or prescribing behavior then these factors need to be prioritized to reduce excessive opioid prescribing that might contribute to dependency, abuse, overdose, or death (Wennberg, 1973). However, if the disparity by geographical density is primarily due to the characteristics of the local population or the underlying economic factors in those areas then supply-side interventions might not be the most effective approach relative to policies aimed at reducing patient demand for opioids such as improving occupational health and safety conditions and/or expanding safety net programs to reduce the severity of periods of economic distress.

We fill this gap in the literature by using a novel claims database to capture individual patient-level characteristics and combine this with county-level characteristics to examine the relationship between geographical density and opioid prescribing, during a period of time when opioid prescribing was still rising (2010-2014). Unlike most studies in the literature, we include both supply and demand side factors and focus on a broad-based, commercially insured population using the Massachusetts All-Payer Claims (MAPC) Database. By examining these factors within a single state (Massachusetts), we are able to eliminate the heterogeneity associated with the differential proliferation of various state regulations that have been implemented over time, producing more precise estimates. Finally, we examine a period of time immediately after the Great Recession where there was significant variation in both opioid prescribing and economic distress across more and less densely populated areas, even within states such as Massachusetts.

We find that on average, patients in non-metropolitan areas in Massachusetts are 10 percentage points more likely to receive an opioid prescription. About half of this differential is due to the underlying health of the local population. When we limit our analysis to three prevalent conditions for which an opioid is commonly prescribed (back pain, joint pain, and car accidents), we find that a little less than half of the remaining gap can be explained by supply side factors, such as differences in the health care delivery system. Although demographics play a large role on the demand side, particularly veteran status, health insurance type is also an important factor. A two-way Blinder-Oaxaca decomposition reveals that roughly 80 percent of the raw difference in opioid prescribing rates is explained by the inclusion of both sets of covariates, reducing the gap to roughly 1 percentage point. Allowing for the interaction of some demand-side (e.g., working in a physically demanding occupation) and supply-side (e.g., healthcare delivery system) variables further reduces this differential to be less than half of a percentage point and statistically insignificant. These findings suggest that economic conditions, such as the type of working conditions that patients might experience, can interact with the healthcare system in unforeseen ways and possibly give rise to more targeted interventions can reduce the persistent gap in opioid prescribing among more and less densely populated areas, with possible downstream impacts on overdose and mortality.

II. What factors affect opioid prescribing rates by geography?

A number of studies over the past decade have examined a variety of independent factors affecting opioid prescribing rates by geographical density on either the demand (patient) side or the supply (provider) side of the market. On the demand side, researchers have shown that differences in patient composition, economic distress, and opioid use disorder have all played a role in explaining the disparity in opioid prescribing rates across rural (non-metropolitan) and urban (metropolitan) areas. On the supply side, differences in access to insurance, the health care delivery system, and physician prescribing patterns have also been shown to be important factors. However, these prior studies have been unable to account for both supply and demand side factors simultaneously to determine the relative magnitudes of their contribution to differences in prescribing rates by geography. Moreover, no prior study has examined interactions between demand and supply factors that are likely to make prescribing differences between metropolitan and non-metropolitan areas particularly difficult to eliminate with a one-size-fits-all approach to changing policy or practice across both urban and rural areas.

Demand-Side Explanations

On the demand side, rural populations have a higher share of people among whom opioid prescribing is higher or for whom duration of treatment is greater due to underlying health conditions. For example, previous work has shown that non-metropolitan counties tend to have larger populations of older adults who have a higher prevalence of conditions associated with pain such as diabetes and arthritis (García et al., 2019, Guy Jr. et al., 2017). Higher rates of opioid prescribing are also associated with areas that have a larger percentage of non-Hispanic whites, a population that is more prevalent in non-metropolitan areas (Guy Jr. et al., 2017).

Economic factors have also been linked to differences in opioid prescribing by geography. For example, non-metropolitan areas have higher employment shares in industries that are more likely to lead to injuries that require pain medication such as construction, production, and transportation (Economic Research Service, 2018). In particular, workers employed in mining and construction industries are more likely than workers in other industries to receive opioids when receiving a prescription for pain medication and more likely to receive opioids on a longer-term basis and at higher doses (Themula and Liu, 2018). Among non-metropolitan counties, the highest drug mortality rates are disproportionately concentrated in counties dependent on mining and service sector jobs that also have high rates of opioid prescribing and greater use of fentanyl (Monnat, 2019; Monnat et al., 2019).

Finally, the link between economic distress and mental health may also drive differences in drug seeking behavior on the part of patients in rural versus urban areas. Non-metropolitan areas typically have lower labor force participation rates, slower employment growth, and higher unemployment rates among prime-working-age adults, which contribute to higher poverty rates in non-metropolitan (15.4 percent) versus metropolitan (11.9 percent) areas (Economic Research Service, 2018). Large job losses and stagnant wages, such as those observed in non-metropolitan areas, have been linked to individuals being more likely to engage in substance use to alleviate depression related to economic hardships (Dasgupta, Beletsky, and Ciccarone, 2018). Moreover, adults residing in rural geographic locations receive mental health treatment less frequently and often with providers with less specialized training, when compared to those residing in metropolitan locations (McCall-Hosenfeld, Mukherjee, and Lehman 2014; Stewart 2018).

As a result, the problem of economic distress, mental health, and the opioid crisis have become intertwined—with potentially deadly consequences. Nearly half of prime age men not in the labor force take pain medication on a daily basis, and in nearly two-thirds of these cases they take prescription pain medication (Krueger 2017). One study found that for every $10,000 reduction in net income per capita, the rate of opioid overdose increases by 10 percent (Davlasheridze and Goetz, 2021). Another found that opioid deaths and ED visits are predicted to rise when county unemployment rates temporarily increase (Hollingsworth, Ruhm and Simon, 2017). And these "deaths of despair"—drug overdoses, alcohol-related liver disease, and suicide—occur more frequently among adults without a college degree in non-metropolitan areas (Case and Deaton, 2020).

Supply-Side Explanations

On the supply (provider) side, differences in access to health care by insurance type and disparities in the health care delivery system have been shown to play a role in opioid prescribing differences by geography. For example, opioid prescribing is higher in areas with greater Medicaid enrollment (Guy Jr. et al., 2017) and within states, Medicaid generally plays a larger role in non-metropolitan areas (Foutz, Artiga, and Garfield, 2017). In terms of the health care delivery system, differences in both the types of facilities as well as the treatments available appear to contribute to the disparity in opioid prescribing by geography. For example, fewer hospital beds in non-metropolitan areas often leads to more rapid or frequent discharge to skilled nursing facilities (SNFs) after surgical procedures, and these facilities have also been shown to increase the likelihood of receiving an opioid prescription (Hubsky et al., 2020). Moreover, there are fewer pain specialists in non-metropolitan areas so patients are more likely to see a primary care physician such as a general or family practitioner. Primary care providers account for nearly half of all dispensed opioid prescriptions (Levy et al., 2015) and report multiple difficulties in weaning patients from chronic opioids, including medical contraindications of nonopioid alternatives and difficulty justifying weaning by stable long-term patients (Tong et al., 2019). In addition, non-metropolitan residents are less likely to use self-care interventions (yoga, meditation, exercise, acupuncture, relaxation techniques) compared with metropolitan residents, reportedly resulting in a 24 percentage point differential in the likelihood of taking an opioid for pain relief (Eaton et.al., 2018).

Another factor on the supply side has been the prescribing habits of physician themselves which has become a key policy lever for states combatting the opioid crisis. There has been wide variation in opioid prescribing in terms of which conditions, how often, and how much, resulting in only weak consensus regarding the appropriate use of opioids for treating pain (McDonald, Carlson, and Izrael 2012). Even within individual hospitals, rates of opioid prescribing vary widely between low-intensity and high-intensity prescribers, with long-term opioid use being 30 percent higher among patients treated by high-intensity prescribers (Barnett, Olenski, and Jena, 2017). Other studies have shown that opioid prescribing in non-metropolitan areas is strongly influenced by providers' individual relationships with their patients (Click et al 2018), and that these relationships may lead to physician behavior that is less consistent with newer opioid prescribing guidelines (García et al., 2019).

As a result, differential regulation or enforcement of physician prescribing by state is also likely to explain the disparity in opioid prescribing rates by geography. For example, the implementation of state-run prescription drug monitoring programs (PDMPs) differs across predominantly urban versus rural states (García et al., 2019). "Must access" PDMPs that require providers to use the PDMP to check a patient's prescribing history in all circumstances, not only when they suspect abuse, are more common in high density (urban) states. These stricter PDMPs have been associated with stronger gatekeeping effects that prevent drug seeking across similar types of providers and patients by insurance type (e.g., Medicare Part D), whereas PDMPs without such provisions are found to have no such effect (Buchmueller and Carey, 2018).

Interactions between Demand and Supply Side Factors

Alternatively, there may be important interactions between demand and supply side factors that, in combination, may have greater explanatory power than either of these individual factors alone. For example, the combination of non-metropolitan areas having an industrial mix that skews towards jobs with higher injury rates plus a lack of access to alternative (non-opioid) pain treatments could account for a greater share of the disparity in opioid prescribing between rural (non-metropolitan) and urban (metropolitan) areas than either of these factors independently. We will explore these types of interactions between demand and supply side factors to better inform policy solutions that could be implemented in combination, rather than in isolation, such as the expansion of facilities and providers for alternative pain treatments in areas with particularly high concentrations of production and mining occupations.

Finally, we cannot discount that there may be other confounding influences that could be fueling the differences in opioid prescribing that we observe by geography. For example, access to medication-assisted treatment (MAT) facilities and alternative therapies for opioid-use disorder are limited in non-metropolitan areas, meaning opioid use disorder may go untreated (García et al., 2019; Lister et. al. 2020). During the time period that we study, many non-metropolitan counties in the U.S. did not have any physicians that had gone through the training to obtain the necessary federal waiver to prescribe MAT such as buprenorphine-naloxone (Rosenblatt, Andrilla, Catlin, and Larson 2015). Thus, we will also need to control for the potential confounding influence of greater opioid prescribing that arises from differential access to treatments related to opioid-use disorder across rural versus urban areas.

III. Data

We capture individual patient-level characteristics using a novel claims-level database and combine this with county-level characteristics to examine the relationship between geographical density and opioid prescribing. We focus on a broad-based, commercially insured population from the Massachusetts All-Payer Claims (MAPC) Database, during a period of time when opioid prescribing was still rising (2010-2014) and there was significant variation in economic distress by geography due to the housing and financial crisis in the wakes of the Great Recession. This data allows us to examine both supply and demand factors within a single state (Massachusetts) to eliminate the heterogeneity associated with the various state regulations that have been implemented over time.

To account for differences in the health status of patient populations in metropolitan versus non-metropolitan areas, we also examine specific conditions for which patients are most likely to receive an opioid prescription. This approach further reduces the heterogeneity in patient composition across geography to better examine the contribution of individual supply and demand factors. We generate our sample by first using the full MAPC database to determine the top 10 most common diagnoses that an opioid is typically prescribed for. Collectively, these diagnoses account for about half of all opioid claims in the MAPC database (See Table 1).Then, for each year in our study, we identify patients receiving a diagnosis for three of the top five of these most common conditions—back pain, joint disease, or passenger in a car accident. Collectively, these diagnoses account for nearly one-quarter of opioid claims in the MAPC database.[1]

[1] We exclude the other two diagnoses that were in the top five conditions for the following reasons: ICD-10 78 (Symptoms of Ill Defined Causes) since this is a catch-all diagnosis category and ICD-10 V7 (Bus Occupant Injured in Transport Accident) since bus accidents are less likely to occur in rural areas.

Table 1. Top Diagnoses for which an Opioid is Prescribed in the MAPC Database

First two digits of ICD-10 Code	Percentage of MAPC Opioid Claims	Condition	Sub-Condition
72	**11.59**	**Dorsopathies (Spinal Diseases) (720-724), Rheumatism (excluding spine) (725-729)**	**35% are unspecified back pains**
78	10.32	Symptoms of Ill Defined Causes (780-789) (Transient, cause cannot be identified)	28% Chest related, 24% Abdomen and Pelvis
71	**6.87**	**Arthropathies and Related Disorders (710-719) (Joint Diseases)**	**37% Osteoarthritis, 41% Other/unspecified**
V79	5.73	Bus occupant injured in transport accident	45% Accident with 2 or 3 wheel vehicle, 31% pedestrian
V59	**3.73**	**Occupant of pick-up truck or van injured**	**65% Non-collision accident like overturning**
25	2.68	Diabetes and other Endocrine Disorders (250-259)	88% Diabetes with no complication
27	2.47	Other Metabolic and Immunity Disorders (270-279)	54% Dyslipidemia
30	2.05	Neurotic Disorders (300-309) (Anxiety, Drug Dependence, Nondependent Abuse of Drugs)	34% Anxiety
42	2.11	Other forms of Heart Disease (420-429)	56% Heart arrythmia
59	2.52	Other diseases of the Urinary System (590-599)	41% Kidney Stone, 39% Other, such as UTI
Total	**50.07**		

Source: Authors' calculations using the Massachusetts All Payer's Claim Database.

Note: ICD-10 codes are from the International Classification of Diseases, Tenth Edition. Conditions that are highlighted in bold are those that were used in the analysis.

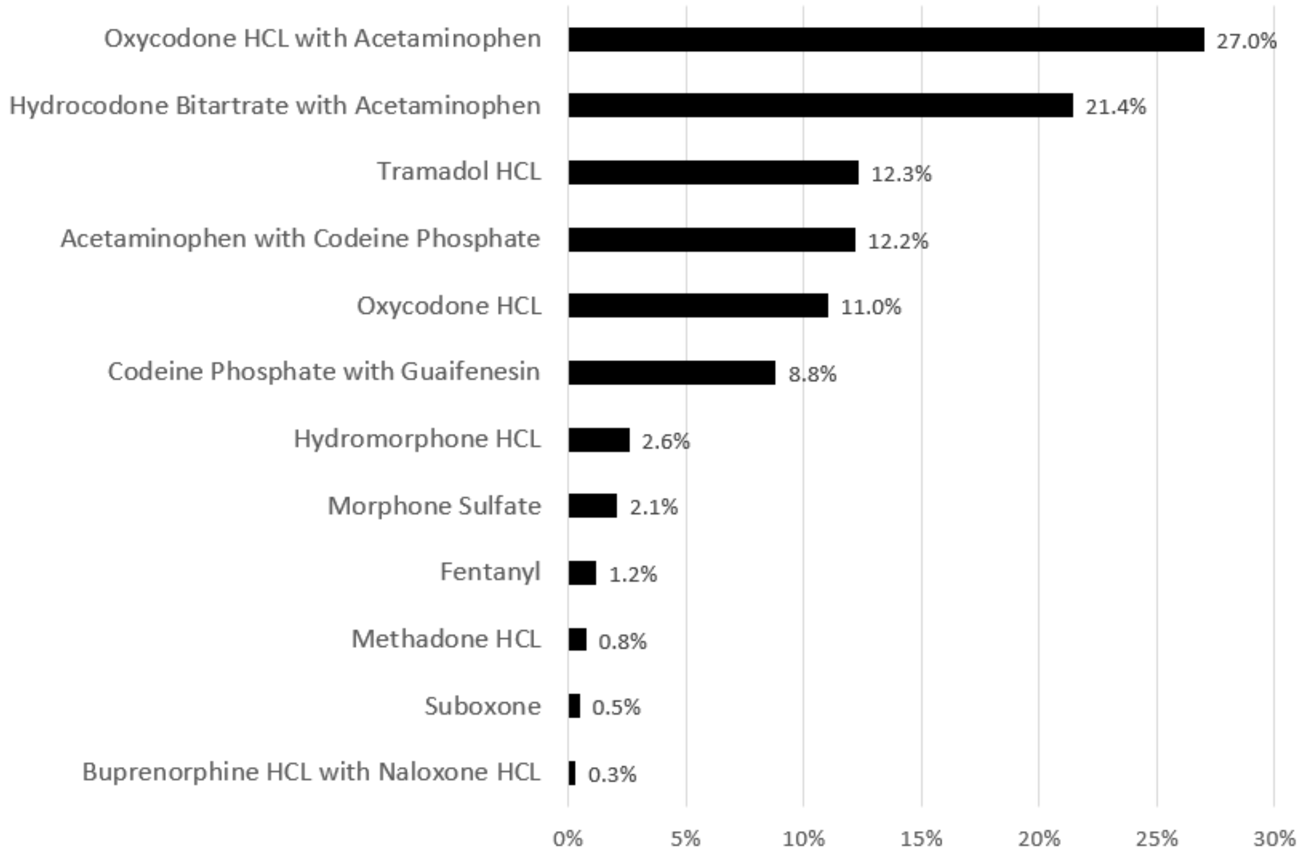
We then follow patients over time in the MAPC database as they moved through each stage of being diagnosed and receiving medical treatment over time, including whether or not they received an opioid as part of their treatment. First, we identify which patients received an opioid prescription based on a review of their pharmacy claims within 180 days of the first diagnosis of the three conditions that we study. We restrict our analysis to the 12 most commonly prescribed opioids which account for 99 percent of all opioid claims in our database (see Figure 1). We also collect the National Provider Identifier (NPI) of the clinicians involved in those claims and merge in the provider's specialty from the NPI Registry. Finally, we exclude patients who changed zip codes during our study period (2010-2014) which account for about 10 percent of unique patients in the dataset.

We then collapse the resulting claims-level dataset to the patient level and create an analytic dataset that includes both patient- and county-level characteristics. The patient-level characteristics come from the claims database and include our dependent variable which is whether or not the individual was prescribed an opioid during the 180-day treatment window as well as control variables such as basic demographics (e.g., age, sex), insurance type (e.g., HMO/self-pay, PPO, indemnity, public, and other non-specified), and provider specialty (14 specialties).[2] Note that we exclude individuals who were prescribed opioids that are commonly used for Medication Assisted Treatment (MAT) for opioid use disorder (OUD) such as buprenorphine.

We then merge in county-level information from two sources. First, we use the Area Health Resource File (AHRF) to merge in information about the health care delivery system (e.g., number and type of providers and facilities per capita) to explore supply-side factors that may affect the quantity and type of treatment that are available. Second, we also use the American Community Survey 5-year Data (2010-2014) to merge in population-level demographics (e.g., race, insurance coverage, and veteran status) and economic conditions (e.g., unemployment rate, poverty rate, occupational distribution) to explore county-level demand-side factors that can affect underlying health conditions and treatment preferences.

[2] These patients account for less than one percent (5,634) of the sample so their exclusion does not affect our results.

Figure 1. Percentage of Unique Opioid Claims by Drug Prescribed, 2010



Source: Authors' calcualtions using the Massachusetts All-Payers Claims Database.

IV. Methods

To explore the relationship between population density and opioid prescribing, we first determine how best to measure density within a geographic region (e.g., zip code). Although the eastern part of Massachusetts is largely metropolitan, the western part of the state and the counties that make up the Cape Cod National Seashore, including the islands of Nantucket and Martha's Vineyard, are far less so. Focusing on this within-state geographical variation enables us to study population density on a more granular level (e.g., zip code tabulation areas) than the stark definitions of living in a metropolitan (urban) versus a non-metropolitan (rural) county.

We measure density using the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. This file contains the population, total area, and land area for each unique urban area-ZIP Code tabulation area (ZCTA).[3] We then used the zip code to ZCTA crosswalk to merge these measures into our patient level dataset by zip code. We created both a dummy variable for whether the zip code contains any part of an urban (metropolitan) ZCTAs as well as a continuous variable of the percentage of the zip code population that resides in an urban ZCTA. No matter which designation we use to measure density, we obtain results that were both quantitatively and qualitatively similar.[4] For exposition purposes, we report results using the dummy variable measure based on the Urban Area to Zip Code Tabulation Area Relationship File and report the continuous variable results in the appendix.

We then employed a logistic regression framework to determine the likelihood that an individual patient with one of the three conditions that we identified will receive an opioid prescription and how this varies by geographic density. We estimated this relationship separately for each of the three conditions because they reflect a range of experiences with treating pain. For example, back pain diagnoses are more reliant on patient perceptions of pain to determine whether treatment might require an opioid. In contrast, a diagnosis for joint disease is typically confirmed with a diagnostic test (e.g., x-ray, ultrasound, MRI) that can gauge severity and

---

[3] For records corresponding to parts of or entire ZCTA entities that do not overlap any 2010 urban area, the urban area code is 99999, the urban area name is "Not in a 2010 urban area", and the urban area population, housing unit count, total area, and land area values are null. The percent values relating to the urban area are also null. For more information please see: https://www2.census.gov/geo/pdfs/maps-data/data/rel/explanation_ua_zcta_rel_10.pdf

[4] As a robustness check, we also use the USDA Frontier and Remote Area (FRA) Codes For more information, please see https://www.ers.usda.gov/data-products/frontier-and-remote-area-codes/ . We also explored several other measures of county population density provided by the Census Bureau such as the Rural Urban Commuting Codes and the USDA Economic Research Service 2013 Rural-Urban Continuum Codes. While we get qualitatively similar results, these measures do not provide as much granularity as the ZCTA designations which vary within counties.

provide a less subjective determination of the need for an opioid prescription. Finally, being a passenger in a car accident, a largely random event, is plausibly exogenous to underlying conditions that might require an opioid, reducing confounding influences (e.g., drug-seeking behavior) from prior diagnoses. We estimate the relationship between density and opioid prescribing using equation (1):

$$P_{izct} = \alpha + \beta \text{ DENSITYz} + \text{PATIENTit} + \text{PROVIDERi} + \text{POPULATIONc} + \text{HCDELIVERYc} + \text{ECONOMICct} + \text{YEARt} + \varepsilon_{izct} \quad (1)$$

Where:

P_{izct} = indicator for whether patient *i* living in zip code *z* in county *c* in year *t* was prescribed an opioid

$DENSITY_z$ = measure of density at the zip code level *z* (dummy or continuous measure)

$PATIENT_i$ = vector of individual-level characteristics (e.g., age, gender, insurance type) for patient *i* measured at the time of diagnosis in year t

$PROVIDER_i$ = field of specialty (e.g., primary care, surgery) of the clinician involved in the majority of the claims for the primary conditions diagnosed for patient *i*

$POPULATION_c$ = vector of county-level population characteristics for county *c* measured at the start of the period in 2010 (e.g., percent white, percent of persons less than 65 without health insurance, percent of the population that are veterans)

$HCDELIVERY_c$ = vector of health care delivery system variables for county *c* measured at the start of the period in 2010 (e.g., number of hospital beds, skilled nursing facilities, active MDs and general practitioners—all measured in per capita terms)

$ECONOMIC_{ct}$ = vector of economic variables for county *c* measured annually from 2010-2014 (e.g., unemployment rate for individuals aged 16+, share of population below the poverty level, share of employment in physically demanding occupations)[5]

$YEAR_t$ = dummy variable for each year 2011-2014 (excluding the base year of 2010)

ε_{izct} = error term

Using this model, we estimate the relationship for each condition by sequentially adding to the model each group of independent variables separately to be able to compare our results to prior studies (see Figure A1 for a conceptual model). We then include all covariates in the final

[5] These broad occupation categories include production, transportation and material moving; natural resources (e.g., mining), construction, and maintenance; and services.

specification to simultaneously determine the relative contribution of supply and demand factors that are driving the relationship between density and opioid prescribing. We also perform a Blinder-Oaxaca decomposition to understand whether it is the endowments (mean levels) of these factors or the strength of the relationship (coefficients) of those factors that is more important in explaining the differences in opioid prescribing across metropolitan and non-metropolitan areas. Finally, we also explore interactions between the demand and supply side factors such as the share of workers in physically demanding production or transportation occupations and the health care delivery system to better understand the nuances that could be useful for guiding policy solutions.

V. Results

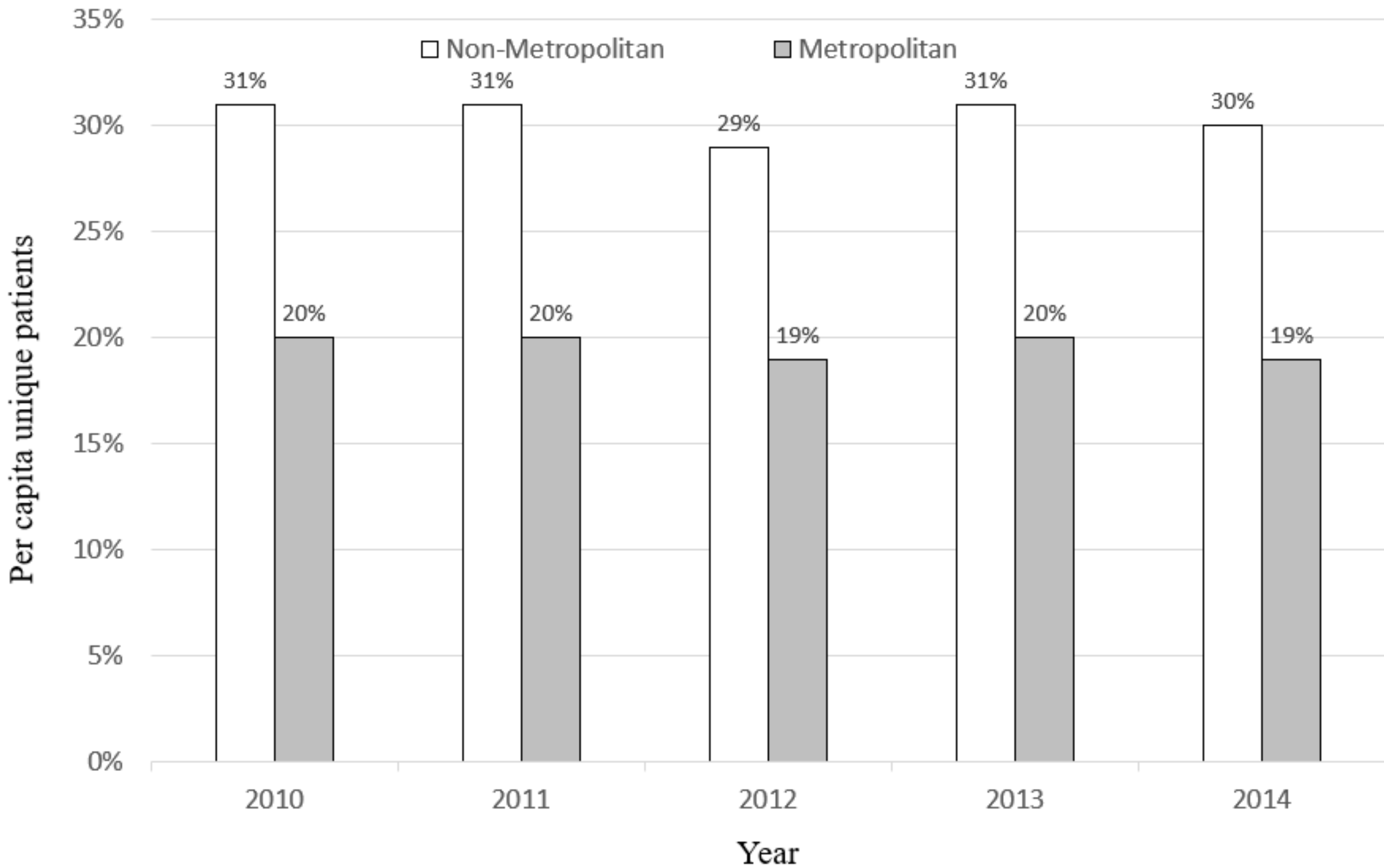
We find that much of the variation in opioid prescribing for urban (metropolitan) versus rural (non-metropolitan) areas is due to differences in the prevalence of the underlying clinical conditions (e.g., back pain). Figure 2 displays opioid prescribing rates over time across all conditions combined, not just the top ten, for metropolitan versus non-metropolitan areas.[6] Similar to prior studies, we find that overall prescribing rates across all conditions combined are 50 percent (10 percentage points) higher in non-metropolitan versus metropolitan areas of Massachusetts, without controlling for any covariates. However, Figure 3 shows that when we examine opioid prescribing rates across non-metropolitan and metropolitan areas for patients with similar conditions, such as back pain (ICD-10=72), the gap narrows to just 20 percent (5 percentage points). This indicates that roughly half of the disparity in opioid prescribing rates by geographical density in Massachusetts is driven by heterogeneity in the type of underlying clinical conditions of the population residing in those areas.

We then turn to examining which of the supply and demand side factors help explain the remaining disparity in opioid prescribing between metropolitan and non-metropolitan areas ***within*** each of our three clinical conditions. We start with one condition, back pain, to understand the baseline results and then compare to the other two conditions to understand whether back pain differs from conditions more easily diagnosed (e.g., joint pain) or conditions that occur at random (e.g., car accident injuries).

[6] For exposition purposes, here we are using a dummy variable (0/1) for whether the zip code contains any metropolitan ZCTA to classify patients as living in a non-metropolitan versus a metropolitan area.

Figure 2. Unique Patients Per Capita Receiving an Opioid Prescription in Massachusetts

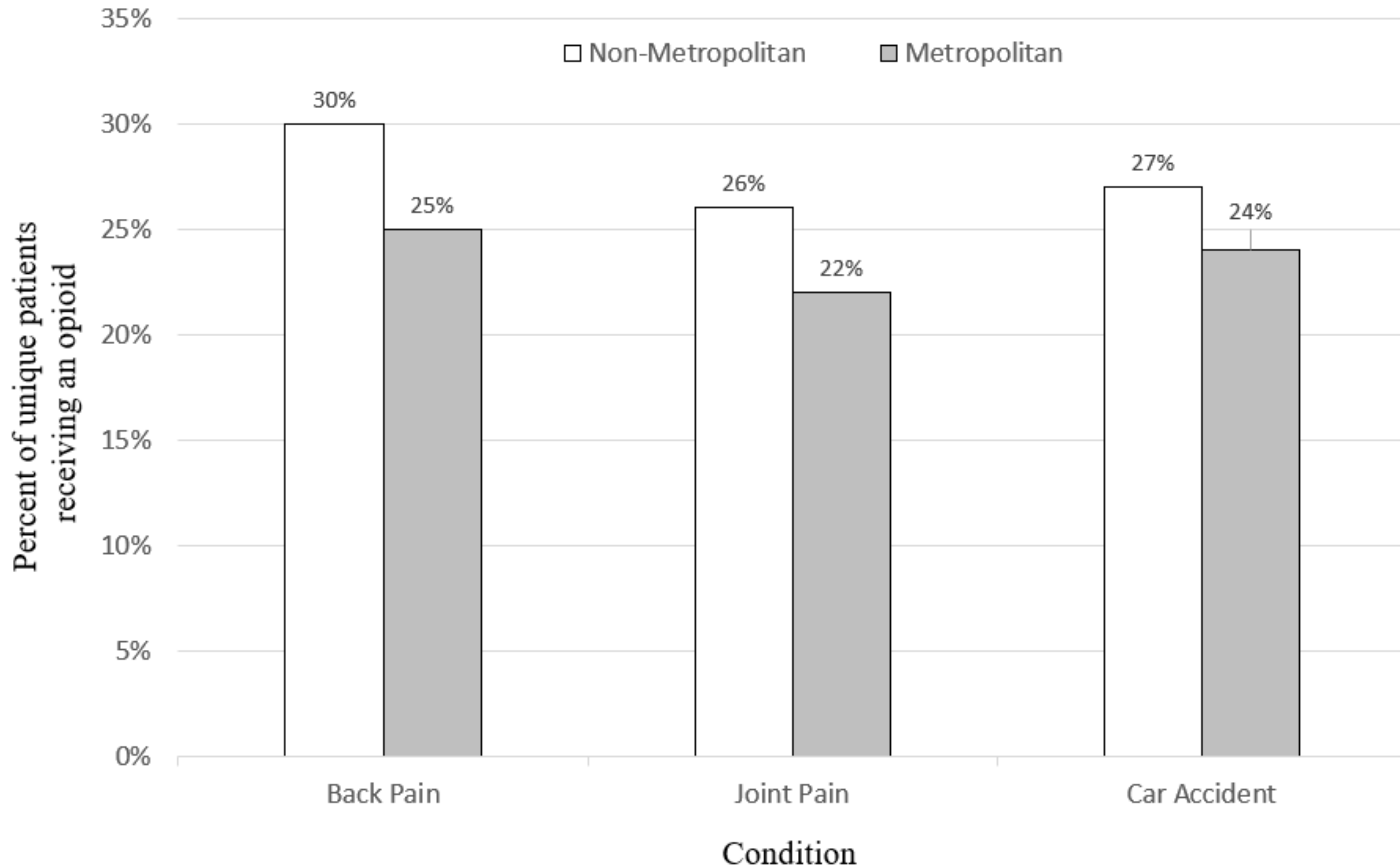
All Conditions



Sources: Authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau.

Note: For exposition purposes, here we are using a dummy variable (0/1) for whether the zip code contains any urban ZCTA to classify patients as living in an metropolitan versus a non-metropolitan area. In each case, the numerator is the number of unique patients who have filed a claim for an opioid prescription and the denominator is the population count in each area type (metropolitan or non-metropolitan) and each year.

Figure 3. Likelihood of Receiving an Opioid by Underlying Condition in Massachusetts, 2010-2014



Sources: Authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau.
Note: For exposition purposes, here we are using a dummy variable (0/1) for whether the zip code contains any urban ZCTA to classify patients as living in a metropolitan versus a non-metropolitan area. For each condition, the numerator is the number of unique patients receiving a diagnosis who have filed a claim for an opioid prescription and the denominator is the total number of patients receiving a diagnosis in each area type (metropolitan versus a non-metropolitan) between 2010 and 2014.

Panel A of Table 2 reports the descriptive statistics for patients diagnosed with back pain by population density for the dependent variable as well as for each of the patient-level covariates in Equation (1). As one would expect, our continuous density measure confirms that the share of the zip code tabulation area (ZCTA) population that lives in an urban area is significantly higher (14.9 percentage points) for patients living in a metropolitan versus a non-metropolitan area. Moreover, back-pain patients that live in a non-metropolitan area are 4.9 percentage points more likely to be prescribed an opioid, and have a higher number of opioid claims, compared to those living in a metropolitan area.

We also find that non-metropolitan areas do indeed exhibit greater prevalence for a variety of factors that are positively correlated with higher opioid prescribing. For example, non-metropolitan areas have a higher proportion of back pain patients who are age 65 years and older and have public health insurance (primarily Medicaid)—both of which have been associated with higher opioid prescribing. In addition, back pain patients in non-metropolitan areas are more likely to have medical claims from an ER, primary care physician, diagnostic clinician, or end-of-life provider—specialties linked to higher opioid prescribing. In contrast, non-metropolitan back pain patients are less likely to have claims from a pain specialist who may be more likely to follow newer protocols that limit opioid prescribing or a clinician at a rehab or other medical facility who may offer alternative treatments (e.g., physical therapy) for pain.

Panel B of Table 2 confirms that patients suffering from back pain in non-metropolitan areas also live in communities with county-level characteristics that are associated with higher rates of opioid prescribing that can affect the standard of care that they receive. For example, these non-metropolitan areas have higher population shares of whites and veterans—groups that have been shown to be more likely to receive an opioid prescription, which may affect local prescribing practices. Prior research shows that this channel operates independently from the patient's own demographic characteristics as providers often apply population-level treatment patterns across all of the patients they treat in their medical practices (Wennberg, 1973).

Similarly, patients exhibiting back pain in non-metropolitan areas also live in counties with different health care delivery systems and economic conditions. For example, these areas have fewer hospital beds but more skilled nursing facilities—the latter of which have been associated with increased opioid prescribing. There are also fewer physicians per capita overall but a greater share of general practitioners who have been shown to account for nearly half of all

Table 2. Descriptive Statistics for Sample of Patients Receiving a Diagnosis for Back Pain (2010-2014)

Panel A. Patient Level Variables

	Metropolitan (Urban)		Non-Metropolitan (Rural)		Difference in Means
	Mean	Std. Dev.	Mean	Std. Dev.	(Rural-Urban)
Density Measures					
Lives in a non-metropolitan (rural) area	0.000	0.000	1.000	1.000	1.000 ***
Percent of zip code population in a metropolitan (urban) area	0.708	0.333	0.559	0.375	-0.149 ***
Dependent Variables: Opioid Prescribing					
Percent prescribed an opioid	0.247	0.431	0.295	0.456	0.049 ***
Number of opioid claims per patient	0.651	2.310	0.987	4.450	0.336 ***
Independent Variables					
Demographics					
Percent male	0.449	0.497	0.451	0.498	0.002
Percent age 18-24	0.082	0.275	0.079	0.270	-0.003 *
Percent age 25-34	0.146	0.353	0.128	0.334	-0.018
Percent age 35-44	0.170	0.375	0.166	0.372	-0.004 *
Percent age 45-54	0.216	0.411	0.219	0.413	0.003 *
Percent age 55-64	0.185	0.388	0.193	0.395	0.008 **
Percent age 65+	0.202	0.401	0.215	0.411	0.013 ***
Insurance Type					
HMO/self-pay	0.391	0.488	0.409	0.492	0.018 **
PPO	0.229	0.420	0.165	0.372	-0.063 ***
Indemnity	0.128	0.334	0.108	0.311	-0.019 **
Public (Medicare, Medicaid, VA)	0.230	0.230	0.290	0.290	0.060 ***
Other (not specified)	0.026	0.158	0.028	0.165	0.003
Provider Speciality					
Pain	0.017	0.130	0.010	0.100	-0.007 **
Alternative pain treatment (e.g., chiropracter, physical therapy)	0.057	0.231	0.064	0.245	0.008 **
Addiction	0.000	0.022	0.001	0.037	0.001
Mental health	0.015	0.122	0.016	0.125	0.001
ER/critical care	0.031	0.173	0.045	0.208	0.014 ***
Rehab	0.079	0.270	0.056	0.230	-0.023 ***
Dental	0.001	0.037	0.001	0.024	-0.001
Surgery	0.052	0.222	0.049	0.217	-0.003
General/family practitioner	0.094	0.291	0.123	0.328	0.029 ***
Internal medicine	0.091	0.287	0.105	0.307	0.015 ***
End of life (hospice, palliative care)	0.013	0.114	0.022	0.148	0.009 **
Diagnostic (e.g., radiology, pathology, immunology)	0.151	0.358	0.163	0.369	0.012 ***
Non-MD (e.g., nurse, PA)	0.005	0.067	0.007	0.082	0.002
Medical Facility (e.g., hospital)	0.237	0.425	0.192	0.394	-0.045 ***
Veteran Adminsitration / Military	0.000	0.009	0.000	-0.016	0.000
Other	0.005	0.067	0.007	0.082	0.002
Number of Patients	1,011,515		342,549		-668,966

Panel B. County Level Variables

	Metropolitan (Urban)		Non-Metropolitan (Rural)		Difference in Means
	Mean	Std. Dev.	Mean	Std. Dev.	(Rural-Urban)
<u>Population Demographics</u>					
Percent white	0.794	0.099	0.845	0.054	0.05 ***
Percent persons under 65 without health insurance	0.008	0.000	0.008	0.000	0.00
Percent population veterans	0.104	0.031	0.135	0.018	0.03 ***
<u>Health Care Delivery System</u>					
Hospital beds per 10,000 residents	15.424	21.841	14.419	16.011	-1.01
Skilled nursing facility beds per 10,000 population	70.511	11.938	82.658	16.869	12.15 ***
Total active MDs per 10,000 population	52.490	37.374	30.973	8.882	-21.52 ***
General/family care specialists per 10,000 population	19.960	4.710	23.280	12.860	3.32 **
<u>Economic Conditions</u>					
Unemployment rate, age 16+	0.067	0.014	0.079	0.014	0.01 ***
Poverty rate	0.106	0.042	0.132	0.029	0.03 ***
Percent employed in production, transportation, material moving occupations	0.083	0.021	0.120	0.020	0.04 ***
Percent employed in natural resource, construction, maintenance occupations	0.072	0.019	0.083	0.015	0.01 **
Percent employed in service occupations	0.162	0.029	0.178	0.018	0.02 **
Number of Patients	1,011,515		342,549		

Source: Patient-level variables are based on the authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. County-level demographic and health care delivery system variables are from the Area Health Resource File. County-level labor market variables are from the American Community Survey.

Notes: For exposition purposes, here we are using a dummy variable (0/1) for whether the zip code contains any urban ZCTA to classify patients as living in a metropolitan versus a non-metropolitan area. Within this classification we also show descriptive statistics for the density variable used in our regressions which is the percentage of the ZCTA population that lives in a metropolitan area. See Table 1 for a list of covariates contained in each group. ***Indicates statistical significance at the one percent level, ** at the five percent level, and * at the ten percent level.

dispensed opioid prescriptions. In terms of economic conditions, patients suffering from back pain in non-metropolitan areas also face higher unemployment rates, greater poverty, and a labor market with a greater share of employment opportunities in physically demanding production, transportation, construction and service sector occupations—all of which have been shown to contribute to greater opioid prescribing, overdose, and mortality.

Continuing with our analysis of back pain patients, Table 3 estimating the relationship between density and opioid prescribing, reporting the coefficient on our indicator of whether a patient lives in a predominantly non-metropolitan area from equation (1). Each column sequentially adds both the patient- and county-level covariates to estimate their contribution to opioid prescribing for back pain.[7] We find that some individual characteristics are more important than others for explaining the differential in prescribing rates by geography.[8] For example, column (2) in Panel A reveals that controlling for basic patient demographics (e.g., age, gender, and their interaction) reduces the coefficient on the population density variable by only 2.4 percent.[9] However, controlling for patient insurance type (e.g., PPO, HMO, indemnity, self-pay, and public) reduces the coefficient on the population density variable by 23 percent, suggesting that the greater reliance of patients living in non-metropolitan areas on public health insurance is an important factor in explaining higher opioid prescribing rates. Indeed, prior research has shown that Medicaid is associated with higher rates of opioid prescribing in sparsely populated areas (Quinones 2015), and that this disparity largely reflects greater levels of disability and chronic illness in the populations that Medicaid serves (Goodman-Bacon and Sandoe, 2017). In contrast, controlling for the specialty of the patient's provider slightly increases the coefficient on the density variable suggesting that the provider mix at the patient level is not a factor. Overall, we find that the patient-level characteristics that we can measure from the medical claims data can only explain about 20 percent of the difference in urban versus rural opioid prescribing rates.

Panel B of Table 3 reveals that the county-level population covariates can explain a much larger share of the variation in opioid prescribing across metropolitan and non-metropolitan

[7] We find similar results when using our continuous density measure captured by percent of the zip code population that lives in a metropolitan area and also when measuring the dependent variable as the number of opioid claims per patient (see Table A1).
[8] See Table A2 and A3 for similar estimates reported for joint conditions (ICD-10=71) and car accidents (ICD-10=V59) respectively.
[9] For example, the coefficient on the density variable is 0.049 without including any other independent variables but falls to 0.047 (a 2.4 percent reduction) when controlling for patient demographics in column (2).

Table 3. Estimating the Relationship between Density and Opioid Prescribing: Back Pain (2010-2014)

Panel A. Controlling for Patient Level Variables

	Dependent Variable: Patient was Prescribed an Opioid (0/1)				
	1	2	3	4	5
Indicator for Non-Metropolitan (Rural) Area	**0.049 *****	**0.047 *****	**0.037 *****	**0.052 *****	**0.039 *****
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Controlling for Patient Demographics	NO	YES	NO	NO	YES
Controlling for Patient Insurance Type	NO	NO	YES	NO	YES
Controlling for Patient Provider Specialty	NO	NO	NO	YES	YES
Number of observations	1,354,064	1,354,064	1,354,064	1,354,064	1,354,064
R-squared	0.037	0.048	0.070	0.046	0.091
Percent of urban-rural difference explained	-----	-2.4%	-23.3%	6.9%	-19.2%

Panel B. Controlling for County Level Variables

	Dependent Variable: Patient was Prescribed an Opioid (0/1)				
	1	2	3	4	5
Indicator for Non-Metropolitan (Rural) Area	**0.049 *****	**0.025 *****	**0.030 *****	**0.018 *****	**0.011 *****
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Controlling for Population Demographics	NO	YES	NO	NO	YES
Controlling for Health Care Delivery System Variables	NO	NO	YES	NO	YES
Controlling for Economic Conditions	NO	NO	NO	YES	YES
Number of observations	1,354,064	1,354,064	1,354,064	1,354,064	1,354,064
R-squared	0.037	0.039	0.039	0.039	0.040
Percent of urban-rural difference explained	-----	-49%	-38%	-63%	-78%

Source: Patient-level variables are based on the authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. County-level demographic and health care delivery system variables are from the Area Health Resource File. County-level labor market variables are from the American Community Survey.

Notes: See Table 1 for a list of covariates contained in each group. Each coefficient is from a separate regression.
***Indicates statistical significance at the one percent level, ** at the five percent level, and * at the ten percent level.

areas. Including county population demographics in Column (2) reduces the coefficient on the density variable by roughly half. This result suggests that the patient composition of less densely populated areas, such as having a higher share of whites and veterans for whom opioids are prescribed more often, is an important driver of differential prescribing patterns by geography.

We also find that macro factors related to the health care delivery system and economic conditions are equally, if not more, important in explaining opioid prescribing differences across metropolitan and non-metropolitan areas. Column (3) of Panel B shows that including covariates measuring the both the capacity of the health care delivery system as well as the types of facilities or providers reduces the coefficient on the population density variable by about 38 percent. This is due in part to the greater reliance on skilled nursing facilities and general practitioners in more rural areas, both of which are associated with higher opioid prescribing rates.[10] Column (4) indicates that economic conditions are also an important driver, reducing the coefficient on the population density variable by about 70 percent when we add in controls for unemployment, poverty, and the share of employment in physically demanding occupations.

Although each of these sets of factors plays a role in explaining the disparity in opioid prescribing that we observe by geography, it's not clear whether this is simply due to these factors being more prevalent in non-metropolitan areas or whether there is a different mechanism at work. For example, is it the case that greater opioid prescribing in more non-metropolitan areas is solely due to the higher share of veterans in those areas or is it also the case that veterans living in non-metropolitan areas are also more likely to receive an opioid? To disentangle these effects, we perform a Blinder-Oaxaca decomposition which divides the gap in opioid prescribing between metropolitan and non-metropolitan areas into two components.[11] The first component is explained by the differences in the levels (or "endowments") of the observed related factors between metropolitan and non-metropolitan areas. The second component represents the residual part that cannot be explained by differences in the factors themselves but instead arises from the "differential effect" of the observed factors (e.g., difference in the magnitude of regression coefficients) across metropolitan and non-metropolitan areas.

---

[10] See Table A4 in the appendix for the detailed output showing the coefficients on each independent variable.
[11] Most applications of the technique can be found in the labor market and discrimination literature. For meta studies, see, e.g., Stanley and Jarrell (1998) or Weichselbaumer and Winter-Ebmer (2005). However, the method can also be useful in other fields. In general, the technique can be employed to study group differences in any (continuous and unbounded) outcome variable. For example, O'Donnell et al. (2008) use it to analyze health inequalities by poverty status.

We do this by first estimating separate regression models, one for metropolitan areas and one for non-metropolitan areas. We then perform the decomposition of the disparity in opioid prescribing, Y, as:

$$\Delta\overline{Y} = [\beta^1 \left(\overline{X}^1 - \overline{X}^2\right)] + [\overline{X}^2 \left(\beta^1 - \beta^2\right)] \qquad (2)$$

where $\overline{X}$ is a row vector of average values of the explanatory variables and β is a vector of coefficient estimates for each group 1 (metropolitan) and 2 (non-metropolitan). In this case, the coefficient estimates of group 1, β_1, have been assumed to be as the reference.

Table 4 reports the results of the two-way Blinder-Oaxaca decomposition when we include all of the individual- and county-level covariates. Roughly 80 percent of the raw difference in opioid prescribing rates is explained by the inclusion of both sets of covariates, reducing the coefficient on the density measure from 0.049 to 0.039. Among the explained portion, differences in patient insurance type, county demographics and county economic conditions account for most of the disparity in opioid prescribing. Interestingly, once we account for the other covariates, the difference in the characteristics of the healthcare delivery system in metropolitan versus non-metropolitan areas serve to increase the disparity. This could be due to the larger differences in capacity observed by density with metropolitan areas having more hospital beds and active medical doctors per capita than non-metropolitan areas. Yet when we examine the unexplained portion of the gap in prescribing rates by density, we observe that the differential effect of the healthcare delivery system and the economic conditions across rural and urban areas is significant. Most notably, the share of general practitioners per capita and the share of employment in physically demanding occupations.[12] This suggests that greater opioid prescribing in rural versus urban areas is driven in part by different practice patterns where patients living in areas with similar healthcare settings and/or similar economic conditions are treated differently.

[12] See table A5 for detailed regression output showing the coefficients from each regression model separately for the metropolitan and non-metropolitan samples.

Table 4. Oaxaca Decomposition of Patient and County Factors for Back Pain Patients (2010-2014)

	Dependent Variable: Patient was Prescribed an Opioid (0/1)			
	Coefficient	Std. Error	Sig.	Percent Explained
Metropolitan (Urban)	0.247	(0.0004)		
Non-Metropolitan (Rural)	0.295	(0.0008)		
Difference	0.049	(0.0009)	***	
Percent of difference that is:				
Explained	0.039	(0.0010)	***	80.4%
Unexplained	0.010	(0.0013)	***	19.6%
Percent explained due to differences in endowments:				
Patient demographics	0.000	(0.0001)	*	0.3%
Patient insurance type	0.013	(0.0002)	***	27.1%
Patient provider specialty	-0.004	(0.0001)	***	-7.5%
County demographics	0.019	(0.0012)	***	39.9%
County health care delivery system	-0.017	(0.0017)	***	-34.2%
County economic conditions	0.027	(0.0014)	***	55.3%
Year	0.000	(0.0002)		-0.6%
Percent unexplained due to differences in coefficients:				
Patient demographics	-0.009	(0.0073)		-17.9%
Patient insurance type	-0.117	(0.0164)	***	-240.1%
Patient provider specialty	0.009	(0.0046)	**	18.8%
County demographics	-0.036	(0.1262)		-74.9%
County health care delivery system	-0.116	(0.0325)	***	-239.2%
County economic conditions	-0.173	(0.0644)	***	-357.2%
Year	0.010	(0.0088)		20.9%
Constant	0.442	(0.1588)	***	909.2%

Source: Patient-level variables are based on the authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. County-level demographic and health care delivery system variables are from the Area Health Resource File. County-level labor market variables are from the American Community Survey.

Notes: See Table 1 for a list of covariates contained in each group.
***Indicates statistical significance at the one percent level, ** at the five percent level, and * at the ten percent level.

Table 5 summarizes and compares the supply and demand side contributions across the three most common medical conditions in our study: back pain, joint pain, and car accidents. Supply side factors include all the of the patient- and county-level health care delivery system variables. The demand side factors include both the patient and county-level demographics as well as county economic conditions. Across all three medical conditions, the results are quite similar with the demand side factors explaining a higher share of the overall difference in prescribing rates by population density. Overall, our model explains less of the variation in opioid prescribing for the set of patients who had received an opioid as a result of being a passenger in a car accident, particularly among the demand-side factors. This finding stems from certain demographic characteristics, such as age and veteran status, having lower explanatory power for opioid prescribing associated with a car accident compared to the other two conditions. In contrast, these demand side factors help explain both the higher prevalence as well as the greater likelihood of being prescribed an opioid for back pain and joint diseases in urban versus rural areas.

Despite having controlled separately for a range of demand and supply side factors, there remains a small but statistically significant difference in opioid prescribing across more versus less populated areas. It could be the case that the interaction between certain demand and supply side factors also contributes to the likelihood of opioid prescribing. For example, prior research shows that the majority of patients with work-related injuries are treated by primary care physicians such as general and family practitioners but most community-based physicians have little or no formal training in occupational health care (Merrill et al., 1990). Thus, opioid prescribing rates may be higher in less populated areas because patients who work in physically demanding jobs are more likely to be treated by primary care physicians who are more likely to prescribe an opioid. To test this, we interact the county-level health care delivery system variables with the occupation variables. Table 5 reveals that when we add these interaction terms, the difference in opioid prescribing rates between more and less densely populated areas becomes statistically insignificant. This finding is also consistent with the Blinder-Oaxaca decomposition which indicated that the remaining unexplained portion of the gap was due to differential effects related to the healthcare delivery system and economic conditions.

Table 5. Exploring Supply versus Demand Factors across Conditions (2010-2014)

	Dependent Variable: Patient was Prescribed an Opioid (0/1)		
	Back Pain	Joint Disease	Car Accident
Indicator for Rural Area	**0.049** ***	**0.045** ***	**0.041** ***
	(0.001)	**(0.001)**	**(0.002)**
Covariates			
Supply Side Factors	0.028 ***	0.027 ***	0.027 ***
	(0.001)	(0.001)	(0.002)
Demand Side Factors	0.017 ***	0.016 ***	0.021 ***
	(0.001)	(0.001)	(0.002)
Both Supply and Demand Side Factors	0.009 ***	0.008 ***	0.011 ***
	(0.001)	(0.001)	(0.002)
Including Supply and Demand Side Interactions	0.002	0.003 *	0.001
	(0.001)	(0.002)	(0.002)
Percent of urban-rural difference explained			
Supply Side Factors	-43.2%	-41.1%	-34.2%
Demand Side Factors	-65.1%	-63.7%	-48.1%
Both Supply and Demand Side	-81.9%	-82.3%	-71.9%
Including Supply and Demand Side Interactions	-96.0%	-93.8%	-97.2%
Number of observations	1,354,064	1,064,536	446,798
R-squared	0.094	0.097	0.100

Source: Patient-level variables are based on the authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. County-level demographic and health care delivery system variables are from the Area Health Resource File. County-level labor market variables are from the American Community Survey.

Notes: Supply side factors include patient insurance type, patient provider specialty, and county-level health care delivery system.

Demand side factors include patient demographics, county-level demographics, and county-level economic conditions.

Each coefficient is from a separate regression.

***Indicates statistical significance at the one percent level, ** at the five percent level, and * at the ten percent level.

V. Conclusion

Although at first glance there might seem to be little role for policy in addressing higher opioid prescribing in less densely populated areas, our results suggest some key areas for consideration. On average, patients in non-metropolitan areas are 10 percentage points more likely to receive an opioid prescription. About half of this differential (5 percentage points) stems from the underlying health conditions of residents, for which there is likely less of a role for policy. However, when we limit the scope to a particular diagnosis, a little less than half of the remaining gap can be explained by supply side factors, such as differences in the health care delivery system. Although demographics play a large role on the demand side, particularly veteran status, health insurance type is also an important factor. This suggests that there may be important differences in the coverage of alternative pain treatments (e.g., physical therapy) that could be addressed through health insurance regulation under the Affordable Care Act.

Yet there are complex interactions that also suggest the need for policy to further consider the local context. Once we limit the scope to a particular diagnosis, the inclusion of both demand and supply side factors reduces the gap to roughly 1 percentage point. Allowing for the interaction of some demand-side (e.g., working in a physically demanding occupation) and supply-side (e.g., healthcare delivery system) variables further reduces this differential to be less than half of a percentage point and statistically insignificant. This finding indicates that economic conditions, such as the type of working conditions that patients might experience, can interact with the healthcare system in unforeseen ways and give rise to more targeted interventions. For example, medical boards might consider occupational health care a continuing education requirement for primary care physicians who practice in areas with a high share of workers in physically demanding jobs.

Finally, there is a larger literature documenting differences in physician practice behavior across geographic areas suggesting that providers become conditioned to follow local guidelines and practices (Wennberg 1973). If this is the case, then it will be important for state and federal agencies to consider implementing more targeted guidelines for opioid prescribing that go beyond the number of pills prescribed to regulate the dosage in milligrams that is recommended for specific conditions. These guidelines could be incorporated as part of the Rural Communities Opioid Response Program (RCORP), which addresses barriers to treatment for substance use disorder (SUD), including opioid use disorder (OUD). Alternatively, greater patient education about whether an opioid prescription is needed and/or desirable can help patients better advocate for their own pain management while managing the risks associated with opioid use. Regardless of the policy strategy that is adopted, this study demonstrates that there are clear, tangible drivers that states can address in the near-term to reduce the persistent gap in opioid prescribing among more and less densely populated areas, with possible downstream impacts on overdose and mortality.

References

Barocoas, J., White, L., Wang, J., Walley, A., LaRochelle, M., Bernson, D., Land, T., Morgan, J., Samet, J., and Linas, B. (2018). Estimated Prevalence of Opioid Use Disorder in Massachusetts, 2011-2015: A Capture-Recapture Analysis. *American Journal of Public Health,* Dec;108(12):1675-1681. https://pubmed.ncbi.nlm.nih.gov/30359112/

Barnett, M. L., Olenski, A. R., & Jena, A. B. (2017). Opioid-prescribing patterns of emergency physicians and risk of long-term use. *New England Journal of Medicine*, 376(7), 663-673. https://pubmed.ncbi.nlm.nih.gov/28199807/

Buchmueller, T. C., & Carey, C. (2018). The effect of prescription drug monitoring programs on opioid utilization in medicare. American Economic Journal: Economic Policy, 10(1), 77-112. https://www.aeaweb.org/articles?id=10.1257/pol.20160094

Case, A., & Deaton, A. (2020). Deaths of Despair and the Future of Capitalism. Princeton University Press. https://www.amazon.com/Deaths-Despair-Future-Capitalism-Anne/dp/069119078X

Click IA, Basden JA, Bohannon JM, Anderson H, & Tudiver F.(2018). Opioid prescribing in rural family practices: a qualitative study. *Substance Use & Misuse*;53:533–40. https://pubmed.ncbi.nlm.nih.gov/28857643/

Davlasheridze, M. & Goetz, S. J. (2021). Explaining spatial disparities in drug overdoses, 1970-2014. *Review of Regional Studies*, Vol. 51, Issue 3, December 21. https://rrs.scholasticahq.com/article/31015-explaining-spatial-disparities-in-fatal-drug-overdoses-1970-2016

Dasgupta, N., Beletsky, L., & Ciccarone, D. (2018). Opioid crisis: no easy fix to its social and economic determinants. *American Journal of Public Health*, 108(2), 182-186. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5846593/

Eaton, L. H., Langford, D. J., Meins, A. R., Rue, T., Tauben, D. J., & Doorenbos, A. Z. (2018). Use of self-management interventions for chronic pain management: A comparison between rural and nonrural residents. *Pain Management Nursing*, 19(1), 8-13. https://www.sciencedirect.com/science/article/abs/pii/S1524904217303892

Economic Research Service. 2018. Rural America at a Glance, 2018 Edition. Economic Information Bulletin No. (EIB-200), November. https://www.ers.usda.gov/publications/pub-details/?pubid=90555

Foutz, J., Artiga, S., & R. Garfield. (2017). The Role of Medicaid in Rural America. Kaiser Family Foundation, Issue Brief, April. https://www.kff.org/medicaid/issue-brief/the-role-of-medicaid-in-rural-america/

García, M. C., Heilig, C. M., Lee, S. H., Faul, M., Guy, G., Iademarco, M. F., ... & Gray, J. (2019). Opioid Prescribing Rates in Nonmetropolitan and Metropolitan Counties Among
Goodman-Bacon, A. and E. Sandoe. (2017). Did Medicaid Expansion Cause The Opioid

Epidemic? There's Little Evidence That It Did. *Health Affairs*: Forefront, August 23. https://www.healthaffairs.org/content/forefront/did-medicaid-expansion-cause-opioid-epidemic-there-s-little-evidence-did

Primary Care Providers Using an Electronic Health Record System—United States, 2014–2017. *Morbidity and Mortality Weekly Report*, 68(2), 25 https://www.cdc.gov/mmwr/volumes/68/wr/pdfs/mm6802a1-H.pdf

Guy Jr, G. P., Zhang, K., Bohm, M. K., Losby, J., Lewis, B., Young, R., ... & Dowell, D. (2017). Vital signs: changes in opioid prescribing in the United States, 2006–2015. MMWR. *Morbidity and Mortality Weekly Report*, 66(26), 697. https://pubmed.ncbi.nlm.nih.gov/28683056/

Hollingsworth, A., Ruhm, C., and Simon, K. (2017). Macroeconomic conditions and opioid abuse. *Journal of Health Economics*. 56 : 222–233.

Hubsky, A., Noble, B., Hartung, D., Tjia, J., Lapane, K., & J. Furuno. (2020). Opioid prescribing on discharge to skilled nursing facilities. *Pharmacoepidemiology and Drug Safety*, September: 29(9):1183-1188. https://pubmed.ncbi.nlm.nih.gov/32725962/

Krueger, A. B. (2017). Where have all the workers gone? An inquiry into the decline of the US labor force participation rate. *Brookings Papers on Economic Activity*, Fall(2), 1-87. https://pubmed.ncbi.nlm.nih.gov/30739945/

Kuo, Y. F., Raji, M. A., Chen, N. W., Hasan, H., & Goodwin, J. S. (2016). Trends in opioid prescriptions among Part D Medicare recipients from 2007 to 2012. *The American Journal of Medicine*, 129(2), 221-e21. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4718856/

Levy, B., Paulozzi, L., Mack, K. A., & Jones, C. M. (2015). Trends in opioid analgesic–prescribing rates by specialty, US, 2007–2012. *American Journal of Preventive Medicine*, 49(3), 409-413. https://pubmed.ncbi.nlm.nih.gov/25896191/

Lister, J. J., Weaver, A., Ellis, J. D., Himle, J. A., & Ledgerwood, D. M. (2020). A systematic review of rural-specific barriers to medication treatment for opioid use disorder in the United States. *The American Journal of Drug and Alcohol Abuse*, *46*(3), 273–288. https://doi-org.ezproxy.neu.edu/10.1080/00952990.2019.1694536

Lund, B. C., Ohl, M. E., Hadlandsmyth, K., & Mosher, H. J. (2019). Regional and Rural–Urban Variation in Opioid Prescribing in the Veterans Health Administration. *Military Medicine.* https://academic.oup.com/milmed/article/184/11-12/894/5492691

Massachusetts Department of Public Health (2019). MA Prescription Monitoring Program County-Level Data Measures (2019 Quarter 1). https://www.mass.gov/doc/prescription-monitoring-program-pmp-data-county-overview-may-2019/download

McCall-Hosenfeld JS, Mukherjee S, Lehman EB. (2014). The prevalence and correlates of lifetime psychiatric disorders and trauma exposures in urban and rural settings: results from the national comorbidity survey replication (NCS-R). *PLoS ONE*; 9(11): e112416. doi: 10.1371/journal.pone.01124164

McDonald, D. C., Carlson, K., & Izrael, D. (2012). Geographic variation in opioid prescribing in the US. *The Journal of Pain*, 13(10), 988-996. https://pubmed.ncbi.nlm.nih.gov/23031398/

Merrill, R., Pransky, G., Hathaway, J. and Scott, D. (1990). Illness and the workplace: a study of physicians and employers. *Journal of Family Practice.* Jul;31(1):55-8. https://pubmed.ncbi.nlm.nih.gov/2362176/Modestino, A. (2021). How Opioid Overdoses Reached Crisis Levels. EconoFact, November 19. https://econofact.org/how-opioid-overdoses-reached-crisis-levels

Monnat, S. (2019). The Contributions of Socioeconomic and Opioid Supply Factors to Geographic Variation in US Drug Mortality Rates. *Journal of Rural Studies.* Volume 68, May 2019, Pages 319-335. https://www.sciencedirect.com/science/article/abs/pii/S0743016717312500

Monnat, S., Peters, D. Berg, M. & Hochstetler, A. (2019). Using Census Data to Understand County-Level Differences in Overall Drug Mortality and Opioid-Related Mortality by Opioid Type. *American Journal of Public Health*. 2019 August; 109(8): 1084–1091. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6611117/

O'Donnell,O., vanDoorslaer, E., Wagstaff, A. & Lindelow, M. (2008). Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation. Washington, DC: The World Bank. https://openknowledge.worldbank.org/entities/publication/8c581d2b-ea86-56f4-8e9d-fbde5419bc2a

Prunuske, J. P., Hill, C. A. S., Hager, K. D., Lemieux, A. M., Swanoski, M. T., Anderson, G. W., & Lutfiyya, M. N. (2014). Opioid prescribing patterns for non-malignant chronic pain for rural versus non-rural US adults: a population-based study using 2010 NAMCS data. *BMC Health Services Research*, 14(1), 563. https://pubmed.ncbi.nlm.nih.gov/25407745/

Quinones, S. (2016). Dreamland: the true tale of America's opiate epidemic. Paperback edition. New York, Bloomsbury Press.

Rosenblatt, R. A., Andrilla, C. H. A., Catlin, M., & Larson, E. H. (2015). Geographic and specialty distribution of US physicians trained to treat opioid use disorder. *The Annals of Family Medicine*, 13(1), 23-26. https://psycnet.apa.org/record/2015-05244-004

Stanley, T.D. and Jarrell, S.B. (1998) Gender Wage Discrimination Bias? A Meta-Regression Analysis. *Journal of Human Resources*, 33, 947-973. https://doi.org/10.2307/146404

Stewart EG. (2018). Suicide in rural areas In: Stewart EG, ed. Mental Health in Rural America: A Field Guide. New York: Routledge.

Substance Abuse and Mental Health Services Administration. (2023). 2022 National Survey on Drug Use and Health (NSDUH), Detailed Tables, Table 1.99B. Washington D.C., November 13. https://www.samhsa.gov/data/release/2022-national-survey-drug-use-and-health-nsduh-releases#detailed-tables

Themula, V., & Liu, T. (2018). Correlates of Opiod Dispensing. Workers Compensation Research Institute, Working Paper, December. https://www.wcrinet.org/reports/correlates-of-opioid-dispensing

Tong, S. T., Hochheimer, C. J., Brooks, E. M., Sabo, R. T., Jiang, V., Day, T., & Krist, A. H. (2019). Chronic Opioid Prescribing in Primary Care: Factors and Perspectives. *The Annals of Family Medicine*, 17(3), 200-206 https://www.annfammed.org/content/17/3/200.short

Weichselbaumer, D. and Winter-Ebmer, R. (2005) A Meta-Analysis of the International Gender Wage Gap. *Journal of Economic Surveys*, 19, 479-511. https://doi.org/10.1111/j.0950-0804.2005.00256.x

Wennberg, John E. MD, MPH, "Small Area Variations in Health Care Delivery" (1973). Open Dartmouth: Peer-reviewed articles by Dartmouth faculty. 4003. https://digitalcommons.dartmouth.edu/facoa/4003

Figure A1. Conceptual Model of Covariates

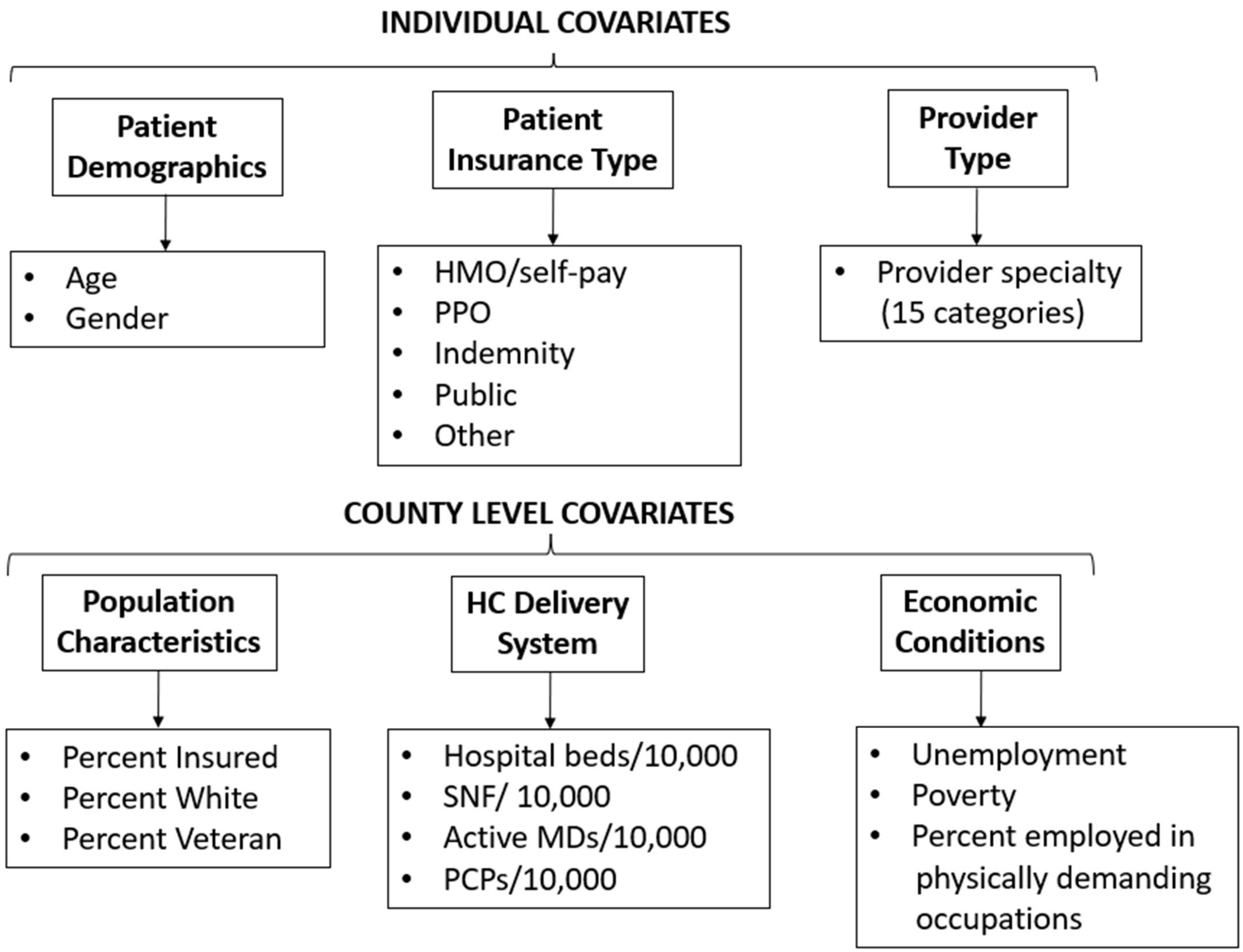


Table A1. Estimating the Relationship between Density and Opioid Prescribing: Alternative Measures

Panel A. Controlling for Patient Level Variables

Dependent Variable	**Patient was Prescribed an Opioid (0/1)**		**Number of opioid claims per patient**	
Independent Variable	Percent of zip code population in a metropolitan (urban) area		Lives in an non-metropolitan (rural) area	
Indicator for Non-Metropolitan (Rural) Area	**0.031** ***	**0.025** ***	**0.322** ***	**0.284** ***
	(0.001)	**(0.001)**	**(0.006)**	**(0.006)**
Controlling for Patient Demographics	NO	YES	NO	YES
Controlling for Patient Insurance Type	NO	YES	NO	YES
Controlling for Patient Provider Specialty	NO	YES	NO	YES
Number of observations	1,354,064	1,354,064	1,354,064	1,354,064
R-squared	0.035	0.090	0.019	0.035
Percent of urban-rural difference explained	-----	-19.2%	-----	-11.8%

Panel B. Controlling for County Level Variables

Dependent Variable	**Patient was Prescribed an Opioid (0/1)**		**Number of opioid claims per patient**	
Independent Variable	Percent of zip code population in a metropolitan (urban) area		Lives in an non-metropolitan (rural) area	
Indicator for Non-Metropolitan (Rural) Area	**0.031** ***	**0.001**	**0.322** ***	**0.134** ***
	(0.001)	**(0.001)**	**(0.006)**	**(0.009)**
Controlling for Population Demographics	NO	YES	NO	NO
Controlling for Health Care Delivery System Variables	NO	YES	YES	NO
Controlling for Economic Conditions	NO	YES	NO	YES
Number of observations	1,354,064	1,354,064	1,354,064	1,354,064
R-squared	0.035	0.040	0.039	0.020
Percent of urban-rural difference explained	-----	-95%	-----	-58%

Source: Patient-level variables are based on the authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. County-level demographic and health care delivery system variables are from the Area Health Resource File. County-level labor market variables are from the American Community Survey.

Notes: See Table 1 for a list of covariates contained in each group. Each coefficient is from a separate regression.
***Indicates statistical significance at the one percent level, ** at the five percent level, and * at the ten percent level.

Table A2. Estimating the Relationship between Density and Opioid Prescribing: Joint Pain

Panel A. Controlling for Patient Level Variables

	Dependent Variable: Patient was Prescribed an Opioid (0/1)				
	1	2	3	4	5
Indicator for Non-Metropolitan (Rural) Area	**0.045** ***	**0.045** ***	**0.036** ***	**0.048** ***	**0.036** ***
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Controlling for Patient Demographics	NO	YES	NO	NO	YES
Controlling for Patient Insurance Type	NO	NO	YES	NO	YES
Controlling for Patient Provider Specialty	NO	NO	NO	YES	YES
Number of observations	1,064,536	1,064,536	1,064,536	1,064,536	1,064,536
R-squared	0.036	0.047	0.069	0.042	0.087
Percent of urban-rural difference explained	-----	-0.7%	-21.3%	5.8%	-19.7%

Panel B. Controlling for County Level Variables

	Dependent Variable: Patient was Prescribed an Opioid (0/1)				
	1	2	3	4	5
Indicator for Non-Metropolitan (Rural) Area	**0.045** ***	**0.025** ***	**0.030** ***	**0.017** ***	**0.010** ***
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Controlling for Population Demographics	NO	YES	NO	NO	YES
Controlling for Health Care Delivery System Variables	NO	NO	YES	NO	YES
Controlling for Economic Conditions	NO	NO	NO	YES	YES
Number of observations	1,064,536	1,064,536	1,064,536	1,064,536	1,064,536
R-squared	0.036	0.038	0.038	0.038	0.039
Percent of urban-rural difference explained	-----	-45%	-34%	-62%	-77%

Source: Patient-level variables are based on the authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. County-level demographic and health care delivery system variables are from the Area Health Resource File. County-level labor market variables are from the American Community Survey.

Notes: See Table 1 for a list of covariates contained in each group. Each coefficient is from a separate regression.
***Indicates statistical significance at the one percent level, ** at the five percent level, and * at the ten percent level.

Table A3. Estimating the Relationship between Density and Opioid Prescribing: Car Accidents

Panel A. Controlling for Patient Level Variables

	Dependent Variable: Patient was Prescribed an Opioid (0/1)				
	1	2	3	4	5
Indicator for Non-Metropolitan (Rural) Area	**0.041** ***	**0.038** ***	**0.033** ***	**0.039** ***	**0.024** ***
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Controlling for Patient Demographics	NO	YES	NO	NO	YES
Controlling for Patient Insurance Type	NO	NO	YES	NO	YES
Controlling for Patient Provider Specialty	NO	NO	NO	YES	YES
Number of observations	446,798	446,798	446,798	446,798	446,798
R-squared	0.002	0.074	0.087	0.046	0.119
Percent of urban-rural difference explained	-----	-6.1%	-19.8%	-4.3%	-40.1%

Panel B. Controlling for County Level Variables

	Dependent Variable: Patient was Prescribed an Opioid (0/1)				
	1	2	3	4	5
Indicator for Non-Metropolitan (Rural) Area	**0.041** ***	**0.031** ***	**0.036** ***	**0.019** ***	**0.018** ***
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Controlling for Population Demographics	NO	YES	NO	NO	YES
Controlling for Health Care Delivery System Variables	NO	NO	YES	NO	YES
Controlling for Economic Conditions	NO	NO	NO	YES	YES
Number of observations	446,798	446,798	446,798	446,798	446,798
R-squared	0.002	0.043	0.043	0.043	0.044
Percent of urban-rural difference explained	-----	-24%	-11%	-54%	-56%

Source: Patient-level variables are based on the authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. County-level demographic and health care delivery system variables are from the Area Health Resource File. County-level labor market variables are from the American Community Survey.

Notes: See Table 1 for a list of covariates contained in each group. Each coefficient is from a separate regression.

***Indicates statistical significance at the one percent level, ** at the five percent level, and * at the ten percent level.

Table A4. Estimating the Relationship between Density and Opioid Prescribing Detailed Regression Coefficients: Back Pain (2010-2014)

	Dependent Variable: Patient was Prescribed an Opioid (0/1)				
Independent Variable	Coefficient	Standard Error	P>	95% Confidence Interval	
Lives in a non-metropolitan (rural) area	0.009	0.001	0.000	-0.011	-0.006
Demographics					
Percent male	-0.005	0.002	0.002	-0.008	-0.002
Percent age 18-24	0.018	0.002	0.000	0.014	0.022
Percent age 25-34	0.059	0.002	0.000	0.056	0.062
Percent age 35-44	0.094	0.002	0.000	0.091	0.098
Percent age 45-54	0.119	0.002	0.000	0.116	0.122
Percent age 55-64	0.126	0.002	0.000	0.122	0.129
Percent age 65+		(omitted)			
Male*Percent age 18-24	-0.017	0.003	0.000	-0.023	-0.011
Male*Percent age 25-34	-0.021	0.003	0.000	-0.026	-0.017
Male*Percent age 35-44	-0.021	0.002	0.000	-0.025	-0.016
Male*Percent age 45-54	-0.005	0.002	0.022	-0.009	-0.001
Male*Percent age 55-64	0.004	0.002	0.062	0.000	0.009
Male*Percent age 65+		(omitted)			
Insurance Type					
HMO/self-pay	0.154	0.002	0.000	0.150	0.159
PPO	0.015	0.002	0.000	0.010	0.019
Indemnity	-0.059	0.003	0.000	-0.064	-0.054
Public (Medicare, Medicaid, VA)	0.152	0.002	0.000	0.147	0.156
Other (not specified)		(omitted)			
Provider Speciality					
Pain	0.233	0.003	0.000	0.227	0.239
Alternative pain treatment (e.g., chiropracter, physical therapy)	0.000	0.002	0.878	-0.003	0.004
Addiction	0.021	0.014	0.120	-0.006	0.048
Mental health	0.063	0.003	0.000	0.057	0.069
ER/critical care	0.085	0.002	0.000	0.080	0.089
Rehab	0.016	0.002	0.000	0.013	0.019
Dental	-0.035	0.011	0.001	-0.056	-0.014
Surgery	0.006	0.002	0.001	0.002	0.009
General/family practitioner	-0.009	0.001	0.000	-0.012	-0.006
Internal medicine	0.008	0.001	0.000	0.005	0.011
End of life (hospice, palliative care)	0.012	0.003	0.000	0.006	0.018
Diagnostic (e.g., radiology, pathology, immunology)	0.018	0.001	0.000	0.016	0.021
Non-MD (e.g., nurse, PA)	-0.013	0.005	0.012	-0.023	-0.003

Medical Facility (e.g., hospital)	0.073	0.001	0.000	0.070	0.075
Veteran Adminsitration / Military	-0.113	0.032	0.000	-0.176	-0.051
Other		(omitted)			
Population Demographics					
Percent white	-0.285	0.024	0.000	-0.332	-0.239
Percent persons under 65 without health insurance	-0.365	0.025	0.000	-0.415	-0.315
Percent population veterans	0.589	0.031	0.000	0.528	0.649
Health Care Delivery System					
Hospital beds per 10,000 residents	4.721	0.395	0.000	3.948	5.495
Skilled nursing facility beds per 10,000 population	-0.036	0.732	0.961	-1.471	1.400
Total active MDs per 10,000 population	5.755	0.508	0.000	4.759	6.751
General/family care specialists per 10,000 population	-3.780	6.528	0.563	-16.575	9.016
Economic Conditions					
Unemployment rate, age 16+	0.370	0.087	0.000	0.201	0.540
Poverty rate	-0.802	0.052	0.000	-0.903	-0.701
Percent employed in production, transportation, material moving occupations	1.485	0.064	0.000	1.360	1.610
Percent employed in natural resource, construction, maintenance occupations	0.700	0.058	0.000	0.585	0.814
Percent employed in service occupations	-0.470	0.065	0.000	-0.597	-0.343
Year Dummies					
2010		(omitted)			
2011	0.214	0.002	0.000	0.211	0.218
2012	0.222	0.002	0.000	0.217	0.226
2013	0.184	0.002	0.000	0.180	0.189
2014	0.197	0.003	0.000	0.192	0.202
Number of observations			1,354,064		
R-squared			0.094		

Source: Patient-level variables are based on the authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. County-level demographic and health care delivery system variables are from the Area Health Resource File. County-level labor market variables are from the American Community Survey.

Notes: See Table 1 for a list of covariates contained in each group. Each coefficient is from a separate regression.
***Indicates statistical significance at the one percent level, ** at the five percent level, and * at the ten percent level.

Table A5. Oaxaca Decomposition of Patient and County Factors for Back Pain Patients, Separate Models for Metropolitan and Non-Metropolitan Areas (2010-2014)

	Dependent Variable: Patient was Prescribed an Opioid (0/1)					
	Metropolitan Areas			Non-Metropolitan Areas		
	Coefficient	Standard Error	P>	Coefficient	Standard Error	P>
Independent Variable						
Demographics						
Percent male	-0.151	0.019	0.000	-0.162	0.030	0.000
Percent age 18-24	0.213	13.900	0.000	0.366	0.025	0.000
Percent age 25-34	0.451	30.450	0.000	0.483	0.024	0.000
Percent age 35-44	0.597	41.790	0.000	0.581	0.023	0.000
Percent age 45-54	0.658	45.310	0.000	0.544	0.024	0.000
Percent age 55-64	-0.028	-1.870	0.061	-0.166	0.024	0.000
Percent age 65+		(omitted)			(omitted)	
Male*Percent age 18-24	0.003	0.023	0.908	-0.026	0.038	0.484
Male*Percent age 25-34	-0.006	0.022	0.803	0.053	0.036	0.145
Male*Percent age 35-44	0.101	0.021	0.000	0.099	0.035	0.004
Male*Percent age 45-54	0.143	0.022	0.000	0.175	0.035	0.000
Male*Percent age 55-64	0.114	0.022	0.000	0.116	0.036	0.001
Male*Percent age 65+		(omitted)			(omitted)	
Insurance Type						
HMO/self-pay	1.129	0.020	0.000	0.672	0.029	0.000
PPO	0.348	0.020	0.000	-0.229	0.031	0.000
Indemnity	-0.335	0.022	0.000	-1.008	0.034	0.000
Public (Medicare, Medicaid, VA)	0.959	0.020	0.000	0.921	0.029	0.000
Other (not specified)		(omitted)			(omitted)	
Provider Speciality						
Pain	-0.093	0.014	0.000	1.030	0.039	0.000
Alternative pain treatment (e.g., chiropracter, physical therapy)	-0.217	0.120	0.000	0.048	0.021	0.021
Addiction	0.272	0.021	0.070	0.279	0.102	0.006
Mental health	0.360	0.016	0.000	0.364	0.033	0.000
ER/critical care	0.065	0.012	0.000	0.521	0.022	0.000
Rehab	0.000	0.014	0.000	-0.038	0.022	0.081
Dental	-0.023	0.023	0.973	-0.067	0.023	0.003
Surgery	-0.169	0.012	0.320	0.107	0.029	0.000
General/family practitioner	-0.400	0.078	0.000	0.034	0.017	0.045
Internal medicine	0.063	0.010	0.000	0.192	0.173	0.266
End of life (hospice, palliative care)	-0.254	0.040	0.000	0.056	0.016	0.000
Diagnostic (e.g., radiology, pathology, immunology)	0.360	0.010	0.000	0.085	0.050	0.089
Non-MD (e.g., nurse, PA)	-0.519	0.365	0.000	0.356	0.015	0.000
Medical Facility (e.g., hospital)	-0.048	0.010	0.155	-1.589	0.465	0.001

Veteran Adminsitration / Military	-1.010	0.242	0.000	-0.062	0.017	0.000
Other		(omitted)			(omitted)	
Population Demographics						
Percent white	-1.010	0.242	0.000	-1.089	0.390	0.005
Percent persons under 65 without health insurance	0.000	0.000	0.458	0.000	0.000	0.005
Percent population veterans	3.788	0.302	0.000	3.041	0.480	0.000
Health Care Delivery System						
Hospital beds per 10,000 residents	12.629	2.544	0.000	83.933	9.647	0.000
Skilled nursing facility beds per 10,000 population	9.097	9.207	0.323	-33.647	10.776	0.002
Total active MDs per 10,000 population	31.809	3.551	0.000	-41.068	19.530	0.035
General/family care specialists per 10,000 population	-393.744	67.502	0.000	-62.180	122.657	0.612
Economic Conditions						
Unemployment rate, age 16+	-1.062	0.800	0.184	0.244	1.173	0.835
Poverty rate	-0.903	0.452	0.046	-4.052	0.699	0.000
Percent employed in production, transportation, material movin	6.767	0.413	0.000	0.782	0.838	0.351
Percent employed in natural resource, construction, maintenanc	6.220	0.646	0.000	-1.676	0.529	0.002
Percent employed in service occupations	-3.969	0.649	0.000	1.965	0.883	0.026
Year Dummies						
2010		(omitted)			(omitted)	
2011	1.426	0.015	0.000	1.514	0.033	0.000
2012	1.436	0.019	0.000	1.583	0.037	0.000
2013	1.266	0.018	0.000	1.365	0.036	0.000
2014	1.315	0.023	0.000	1.237	0.035	0.000
Number of observations		1,011,515			342,549	
R-squared		0.089			0.100	

Source: Patient-level variables are based on the authors' calculations using the Massachusetts All Payer's Claim Database and the Urban Area to ZIP Code Tabulation Area (ZCTA) Relationship File from the Census Bureau. County-level demographic and health care delivery system variables are from the Area Health Resource File. County-level labor market variables are from the American Community Survey.

Notes: See Table 1 for a list of covariates contained in each group. Each coefficient is from a separate regression.

***Indicates statistical significance at the one percent level, ** at the five percent level, and * at the ten percent level.