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The Effects of Opioids on Labor Market Outcomes and Use of Social Security Disability Insurance

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Abstract

Prescription opioids are widely used to treat pain. They can be beneficial by helping a person with a medical condition to manage pain and to be gainfully employed rather than seeking Social Security Disability Insurance (SSDI). On the other hand, opioids are addictive; their use may lead to substance abuse and an exit from the labor market. This paper investigates the effects of prescription opioids on labor market outcomes and the use of SSDI. Estimating the effects of prescription opioids is challenging because those prescribed opioids are likely to be different from those who were not, for example, in terms of their health conditions. To obtain causal estimates, I use marketing payments from opioid manufacturers and distributors to physicians as an instrument to predict opioid prescribing. I find that a higher opioid prescription rate has positive effects on labor market outcomes, although the effects are not precisely estimated. A higher opioid prescription rate also increases the use of SSDI. This result is puzzling because to apply for and continue receiving SSDI benefits, a person cannot work above the substantial gainful activity (SGA) threshold. This can be partially explained by the finding that a higher opioid prescription rate may increase both SSDI use and labor market activities through part-time employment.

Keywords: Opioids, Disability Insurance, Labor Supply (JEL H53, I12, I18, I38, J14, J22)

1 Introduction

While media coverage suggests a devastating impact of opioid abuse on communities, there is an important and legitimate medical use for opioids by workers. For example, opioids can help a person who has a medical condition to manage pain, be gainfully employed rather than seeking SSDI[1], and subsequently pay the Social Security payroll tax. Previous papers have shown that better pain management can lead to greater labor force participation. Garthwaite (2012) found that the sudden and unexpected withdrawal of one type of pain medication used to treat joint pain (Cox-2 inhibitors) from the market led to a decrease in the probability of working. Similarly, Bütikofer and Skira (2018) found in the context of Norway, the removal of the same pain medication from the market increased the use of sick leave and disability benefits.

On the other hand, opioid use can be harmful since they are a known addictive substance and might lead a worker to exit the labor force. Moreover, the efficacy of opioids in treating chronic, non-cancer pain such as back pain in the long term is unclear (CDC, 2019). The underlying condition that is causing the pain may impair work and ultimately lead a person to claim SSDI. Recent papers have shown that in the context of the US, prescription opioids have a negative effect on labor market outcomes. Harris et al. (2019) and Aliprantis et al. (2019) found that an increase in the opioid prescription rate leads to a lower labor force participation rate and a lower employment rate. Given that SSDI is primarily financed by payroll tax contributions, the effect of opioids on labor force participation is a particularly relevant issue.

The relationship between prescription opioids and SSDI is less studied, although it is known that opioids are widely used, particularly among SSDI applicants and beneficiaries. In 2011, around 30 percent of SSDI applicants reported using any opioid (Wu et al., 2019). The rate was even higher among Medicare recipients under age 65 who have a disability at 44 percent (Morden et al., 2014). The most common reason for receiving SSDI among disabled workers in 2017 was diseases related to the musculoskeletal system and connective tissue (32.7 percent of all disabled worker beneficiaries (SSA, 2018)); a common treatment for such conditions is prescription analgesics that include opioids (Morden et al., 2014).

This project explores whether opioids influence labor market outcomes and eventually, application and enrollment in SSDI. It focuses on working-age individuals with sufficient long and recent work experience required to qualify for SSDI and who may have some medical condition that may prevent them from full employment and necessitate them to take prescription opioids. An opioid prescription may affect labor market outcomes positively or negatively, and therefore could result in more or less SSDI use.

The main challenge in quantifying the effects of prescription opioids on labor market outcomes and SSDI is that workers prescribed an opioid medication may be different from those who are not. For example, the former may have more severe medical conditions that prevent them from working and increase the likelihood of successfully applying for SSDI. An empir-

[1] Social Security Disability Insurance (SSDI) pays cash benefits to workers who become permanently and severely disabled. It is funded through payroll tax under the Federal Insurance Contributions Act (FICA).

ical approach that does not take this potential selection bias into account would overstate the effects of opioids.

Some working papers that look into the relationship between opioids and labor market outcomes or SSDI have been descriptive (Krueger, 2017; Cutler et al., 2017), while other papers attempted to produce causal estimates (Laird and Nielsen, 2017; Aliprantis et al., 2019; Currie et al., 2019; Harris et al., 2019; Park and Powell, 2019). Strategies used by other researchers to address the endogeneity issue include using the opioid prescription rate for the elderly population as IV for illicit access to opioids for the younger, working population (Currie et al., 2019) and using the difference-in-differences set up in the context of OxyContin reformulation in 2010 (Park and Powell, 2019). Except for Park and Powell (2019), these papers focused on the effects of opioids on labor market outcomes, not SSDI.

This paper uses a novel approach to address the endogeneity issue. I use local area payments from pharmaceutical companies to physicians for opioid marketing, as an instrument to predict opioid use. The underlying idea is that, holding other factors constant (e.g. health conditions), doctors who receive marketing dollars are more likely to prescribe opioids than those who do not. Examples of such marketing include office visits by sales representatives from pharmaceutical companies and meals or dinners with company representatives outside of the physician's practice setting. Hadland et al. (2019) found that greater marketing expenditures are positively correlated with greater opioid prescriptions. There are other types of marketing, such as those directed towards patients through patient groups and discount cards. These types of marketing and how they interact with direct-to-physician marketing are outside the scope of this paper.

To my knowledge, this project is the first paper that investigates the effects of opioids on both labor market outcomes and SSDI using the IV approach. The method of this paper has the potential to produce causal estimates of the effect of opioid prescription rates on labor market outcomes and SSDI. The analysis is done at the county level.

An advantage of a county-level analysis, instead of an analysis at a more granular level is that the former can capture the effects from both the legitimate use of prescription opioids as well as the diverted or misuse of the same medication. Prescription opioids can be obtained through a retail pharmacy (which requires a physician's prescription) or the black market (whereby patients who were prescribed opioids resell their medications). Opioid marketing payments potentially increase the county-level supply of opioids through both channels. Moreover, a policy that regulates the prescribing of opioid medication would potentially be concerned with both ways of how opioids are eventually consumed.

A drawback of this paper is that it does not consider the interaction between prescription opioids and illicit opioids (e.g. heroin). Changes to the supply of prescription opioids may cause some individuals to consume more or less of the illicit substitutes. For example, Alpert et al. (2018) found that the introduction of an abuse-deterrent version of an opioid medication led to an increase in heroin use and heroin-related overdose deaths. Opioid marketing payments potentially affect the supply of prescription opioids. How this interacts with the use of illicit opioids and their combined effects on the labor market and SSDI use are not examined in this paper.

Using IV estimation, this paper finds that a higher opioid prescription rate in a county has positive effects on labor market outcomes by increasing labor force participation and reducing unemployment. However, the effects are not precisely estimated. Moreover, the positive effects of prescription opioids are confined only to the urban counties. On the other hand, greater opioid use increases the use of SSDI by increasing applications, awards, enrollment, and dollar amount of benefits paid. Given that some SSDI rules disincentivize work, it is puzzling to find that prescription opioids increase both labor market activities and SSDI use. This can be partially explained by the finding that a higher opioid prescription rate may increase both SSDI use and labor market activities through part-time employment.

The remainder of the paper is organized as follows: Section 2 describes the data used for estimation. Section 3 describes in detail the nature of marketing payments to physicians and how the payments are distributed across counties. Section 4 explains the methods used for estimation. Section 5 discusses results from the first-stage regressions and the causal estimates of the effects of prescription opioids on labor market outcomes and SSDI. Section 6 concludes the paper and addresses the limitations of the study.

2 Data and Summary Statistics

The analysis is done at the county level, primarily using publicly available data from multiple sources. The data is measured annually for years 2014 through 2017. The analysis is confined to these years because the data on opioid marketing payments are only available for August 2013 onwards. Table 1 presents the summary statistics of the data.

2.1 Data on Labor Market Outcomes

The data on labor market outcomes were obtained from the American Community Survey (ACS). There are four labor market outcomes examined in this paper: the labor force participation rate, the unemployment rate, the percentage of the population working full time, and the percentage of the population working less than full time. Full-time employment is defined as working 35 hours or more per week. All these outcomes pertain only to the population age 18-64.

2.2 Data on SSDI Outcomes

The data on SSDI outcomes come from the Social Security Administration (SSA). There are four measures of SSDI outcomes: the number of SSDI applications per 1,000 population, the number of SSDI awards per 1,000 population, the proportion of the population enrolled in SSDI, and the dollar amount of SSDI benefit per 1,000 population.

There are a few limitations with regard to the data on SSDI applications and awards. First, the data exclude the states of Alaska and Hawaii. Second, due to data privacy concerns, SSA suppressed observations of counties that have less than 10 SSDI applications or awards. This affects 9.3 percent of observations. To address this issue, I substituted in 5 for suppressed

Table 1: Summary Statistics, 2014–2017

	Mean	Median	SD	N
# of opioid prescription per person	0.68	0.64	0.31	11,854
Labor force participation rate	76.69	77.37	4.62	12,568
Unemployment rate	7.85	7.55	2.54	12,568
SSDI applications per 1000 population	10.02	9.45	3.91	12,432
SSDI awards per 1000 population	3.35	3.04	1.50	12,432
% enrolled in SSDI	4.43	4.09	1.97	12,568
$ amount of SSDI benefits per 1000 population	52.10	48.51	22.37	12,568
% working full-time	50.40	50.75	5.27	12,568
% working less than full-time	27.21	27.00	3.64	12,568
$ amount of marketing payments per 1000 population	10.35	9.11	8.33	12,568
# of marketing payments per 1000 population	0.61	0.52	0.50	12,568
# of physicians receiving payments per 1000 population	0.12	0.11	0.09	12,568
% male	49.21	49.14	1.27	12,568
% white	73.48	75.90	16.49	12,568
Median age	37.91	37.40	4.25	12,568
Median household income ('000)	57.46	54.47	15.52	12,568
% under poverty	14.30	14.33	5.11	12,568
% with bachelor's degree or more	29.96	29.93	10.74	12,568
% age 65 and over	14.33	13.72	3.74	12,568
Ratio of physician to population	2.73	2.63	1.79	12,568
% veterans	6.56	6.45	2.57	12,568
Has shortage of physicians	0.03	0.00	0.18	12,568
% enrolled in old-age Medicare	14.65	14.13	3.72	12,460
% living in urban areas	80.91	92.48	24.46	12,568
Median house value ('000)	228.54	177.30	145.16	12,560
% with ambulatory difficulty	5.22	4.80	2.25	12,568
% with self-care difficulty	1.87	1.70	0.78	12,568

Source: American Community Survey (ACS), US Census Bureau, Social Security Administration (SSA), Centers for Disease Control and Prevention (CDC), Centers for Medicare and Medicaid Services (CMS), and Health Resources and Services Administration (HRSA).

observations. I also ran the analysis using other substitute values between 0 and 10, but it does not substantially change the results. Lastly, the data includes all types of SSDI applicants. A person can receive SSDI benefits as a disabled worker, a disabled widow(er) aged 50 to 65, or a disabled adult child of a disabled, retired, or deceased worker. The ideal measures of SSDI applications and awards would include only SSDI applicants who are disabled workers. In contrast, the data on SSDI enrollment and the dollar amount of benefits paid pertain only to beneficiaries who are disabled workers. In 2017, 86.4 percent of all beneficiaries were disabled workers (SSA, 2018).

2.3 Data on Other County-level Characteristics

There are three sources of data for county-level characteristics. The data on basic county-level demographics such as median age, level of education, and household income, come from the ACS. From the same source, I also obtained data on the median house value. The data on the number of physicians in the county come from the Area Health Resources Files (AHRF) system issued by the National Center for Health Workforce Analysis under the Health Resources and Services Administration (HRSA). I also obtained data on the percentage of the veteran population in the county and the main industry of the county from the same database. Lastly, the data on the level of urbanicity of a county come from the US Census Bureau. The level of urbanicity is measured by the proportion of the population in the county living in urban areas.

2.4 Data on Opioid Prescription Rate

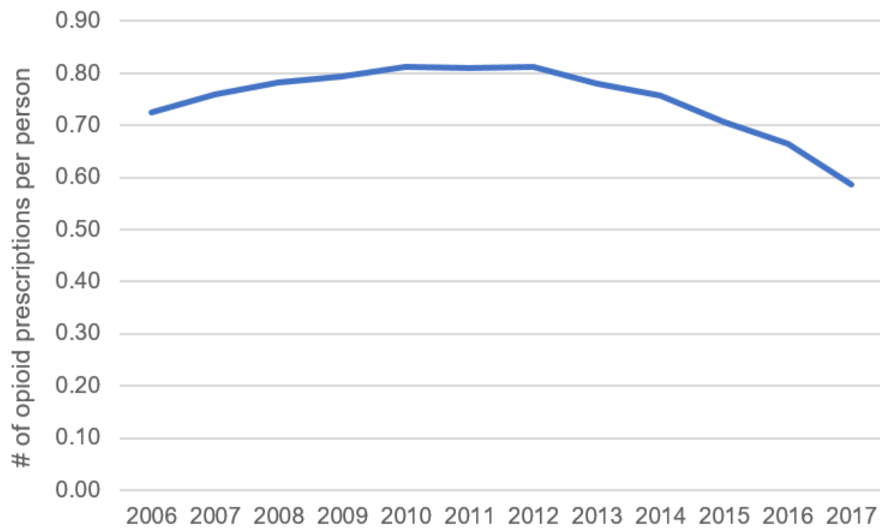
The data on the opioid prescription rate at the county level were obtained from the website of the Centers for Disease Control and Prevention (CDC). This measure covers opioid medications used for pain treatment. It excludes opioid medications meant for other medical uses such as cough and cold formulations containing opioids, as well as buprenorphine products and methadone used to treat opioid use disorder. Moreover, this variable captures opioid prescriptions filled at retail pharmacies and excludes mail-order opioids. It aggregates all prescriptions which were paid for by Medicare, Medicaid, private insurance, and cash and its equivalent.

The opioid prescription rate measures the *number* of opioid prescriptions per person in a county. A shortcoming of this measure of opioid use is that it does not capture the *amount* or *strength* of the opioids dispensed, which is sometimes measured in morphine milligram equivalents (MME). For example, one prescription may dispense stronger opioid medication compared to another prescription. The measure that I currently use (the number of opioid prescriptions per person) would not be able to capture this variation and would treat the magnitude of the two prescriptions as the same. Figure 1 shows the time trend of opioid prescription rates. In 2006 the rate was 0.72 opioid prescriptions per person. It steadily increased until it peaked in 2010 at 0.81. Since then the opioid prescription rate had substantially decreased. The rate was 0.59 in 2017.

2.5 Data on Opioid Marketing Payments

The data on payments from pharmaceutical companies to physicians for the promotion of opioid medications came from the Centers for Medicare and Medicaid Services (CMS). Under the Physician Payments Sunshine Act, a part of the Affordable Care Act of 2010, pharmaceutical companies are required to report to CMS payments made to physicians and teaching hospitals. CMS then compiles and publishes this data on its website. Data started to be collected in August 2013. For this paper, I used the datasets called "General Payment Data – Detailed Dataset," which exclude payments made to physicians for research activities or ownership interests (i.e. physicians owning shares of pharmaceutical companies).

Figure 1: Opioids Prescription Rate



The unit of observation in the original CMS dataset is a payment. Each payment comes with the following contextual information: the name and ID of the physician receiving the payment, address of the physician's practice, drugs or medical devices being marketed, pharmaceutical company making the payment, amount (in dollars), nature of payment (e.g. food, speaking fees, honoraria, gift, etc.) and form of payment (cash vs. in-kind).

To create a measure of direct marketing of opioids targeted towards physicians in an area (county), I further restricted the data as follows. First, I restricted the data to payments made to promote prescription opioids used in out-patient settings and exclude medications used to treat opioid abuse. Second, I restricted the data to payments in the form of food in order to address any potential issues with outliers. Compared to other forms of payments, the dollar amount of food payments varies less. For example, the interquartile range of food payments is $7, while the interquartile range of speaking fees or honoraria payments is $1,800. Moreover, food is the most common form of payment to physicians. They accounted for 94 percent of the total number of payments. The median food payment is $17. Other forms of payments tend to be more expensive and less equally distributed. For example, the median speaking fee or honorarium payment is $1,750 and this form of payments are disbursed to a very small percentage of physicians.

After restricting the data, the resulting dataset for 2014–2017 consists of 771,466 payments for food made to 81,186 physicians. These payments are collectively worth $13 million. The dollar amount per payment is $13 (median), $17 (mean). Conditional on receiving any payment, the number of payments per physician is 2 (median), 9 (mean). The dollar amount per physician is $40 (median), $160 (mean).

To create county-level measures of marketing payments, I geocoded physicians' addresses to retrieve the counties in which the physicians practice. Then, I collapsed the data to the county level and subsequently created three measures of marketing payments:

1. Total dollar amount of payments in the county in each year
2. Total number (count) of payments in the county in each year
3. Total number of physicians receiving marketing payments in the county in each year

3 Distribution of Opioid Marketing Payments Across Counties

As previously mentioned, data on marketing payments are available through CMS only for payments made in August 2013 onwards. Figure 2 illustrates the magnitude of total opioid marketing payments made to physicians, summed up across all counties. Between 2014 and 2016, the dollar amount of total opioid marketing payments increased from \$3.0 million to \$3.9 million. This figure decreases to \$1.3 million in 2018. The trend for the number of payments is similar. It increased from 155,693 payments in 2014 to 243,057 payments in 2016, and then decreased to 92,642 payments in 2018. In 2014, 41,380 physicians received marketing payments. This figure was relatively stable up to 2016, before it decreased to 12,035 physicians in 2018.

Figure 2: Direct-to-physician Marketing of Opioids

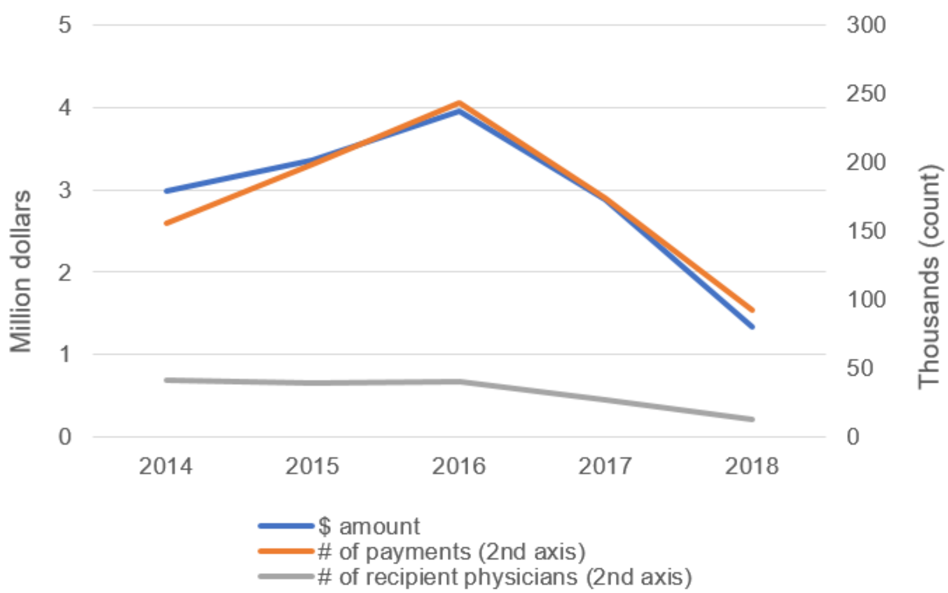
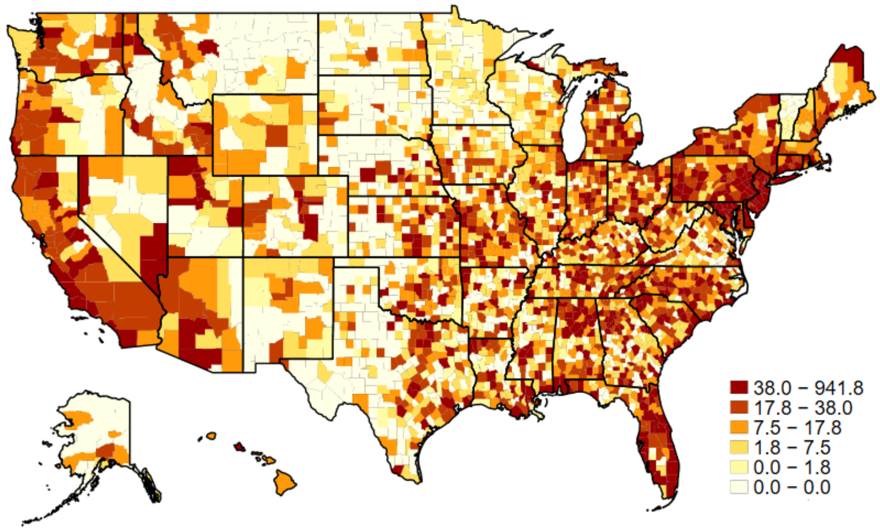


Figure 3 shows the distribution of opioid marketing payments across US counties, as measured by the total dollar amount of marketing payments received throughout 2014–2017, per 1,000 population. 26.5 percent of counties did not receive any marketing payments at all during the 2014–2017 period. The maps using other measures of marketing payments are similar and are not shown.

Another way to study the distribution of marketing payments is to look at how consistently counties receive marketing payments. As previously mentioned, 26.5 percent of counties did

Figure 3: Map of Marketing Payments, Total Dollar Amount in 2014–17, per 1,000 Population



not receive any marketing payments throughout 2014–2017. For the remaining counties, some counties receive payments intermittently (e.g. for 1 or 2 years out of 4), while others received marketing payments more consistently. See Table 2 for the breakdown.

Table 2: # of Years Each County Receive Marketing Payments, 2014–17

	# of counties	Percent
0 year (never received)	834	26.5
1 year	289	9.2
2 years	277	8.8
3 years	321	10.2
4 years	1,421	45.2
Total	3,142	100.0

Table 3 presents characteristics of counties which are separated based on the magnitude of the marketing payments that they received. 26.5 percent of counties did not receive any marketing payment during the 2014–2017 period. These counties make up the bottom 26 percent and are presented in column 1 of Table 3. For the remaining counties which receive at least one marketing payment, they are separated into two groups: the top 5 percent of counties that received the most marketing (shown in column 3) and the remaining counties (shown in column 2). The appendix contains a table with similar statistics when counties are separated into groups based on the number of years (out of four) that they received marketing payments.

Counties exposed to greater direct-to-physician marketing have (unconditionally) higher opioid prescription rates. The average opioid prescription rate in counties not exposed to any opioid marketing (bottom 26 percent) was 0.49, while the rate for counties in the top 5

Table 3: County Characteristics (mean), by Payments Received, 2014–2017

	(1) B 26% Mean	(2) M 69% Mean	(3) T 5% Mean
# of opioid prescription per person	0.49	0.83	1.14
Labor force participation rate	74.82	74.28	74.75
Unemployment rate	6.69	7.75	7.04
SSDI applications per 1000 population	11.89	12.42	13.58
SSDI awards per 1000 population	4.83	4.34	4.87
% enrolled in SSDI	5.50	6.06	6.30
$ amount of SSDI benefits per 1000 population	61.91	69.83	71.45
% working full-time	51.48	49.30	50.03
% working less than full-time	25.76	26.58	27.18
$ amount of marketing payments per 1000 population	0.00	5.30	23.01
# of marketing payments per 1000 population	0.00	0.35	1.55
# of physicians receiving payments per 1000 population	0.00	0.10	0.39
% male	50.99	49.78	48.95
% white	84.37	83.03	84.22
Median age	42.93	40.21	40.40
Median household income ('000)	45.59	48.69	46.89
% under poverty	15.44	15.81	16.27
% with bachelor's degree or more	17.96	21.39	24.46
% age 65 and over	19.17	16.62	17.33
Ratio of physician to population	0.56	1.45	2.79
% veterans	7.92	7.83	8.07
Has shortage of physicians	0.39	0.13	0.04
% enrolled in old-age Medicare	18.76	16.81	18.63
% living in urban areas	17.90	49.21	57.93
% living in mostly urban county	14.03	48.26	62.42
% living in mostly rural county	28.66	41.98	27.39
% living in completely county	57.31	9.76	10.19
Median house value ('000)	109.56	145.70	139.55
% with ambulatory difficulty	7.05	7.07	7.00
% with self-care difficulty	2.32	2.39	2.37
Observations	3,336	8,604	628

Source: American Community Survey (ACS), US Census Bureau, Social Security Administration (SSA), Centers for Disease Control and Prevention (CDC), Centers for Medicare and Medicaid Services (CMS), and Health Resources and Services Administration (HRSA).

percent was much higher at 1.14. The relationship between marketing payments and opioid prescription rate is discussed in more detail in the following sections.

Counties that received more marketing payments or received marketing payments more consistently tend to be more urban. 57.9 percent of the population in the counties in the top 5 percent live in urban areas. These counties also have a higher physician-to-population ratio at 2.79 physicians per 1,000 population. Recall that the marketing efforts measured by the payments were directed towards physicians. Thus, it is reasonable to find marketing payments to be positively correlated with the availability of physicians in the county. In contrast, counties that never received any marketing payments (the bottom 26 percent) tend to be more rural. Only 17.9 percent of the population in the counties in the bottom 26 percent live in urban areas. They also have a lower physician to population ratio at 0.56. Since these counties have fewer physicians per population, it follows that they receive less direct-to-physician marketing payments.

4 Methods

4.1 First-stage Regression

I start by estimating the first-stage regression:

$$Prate_{it} = \alpha_0 + \alpha_1 Marketing_{it} + \alpha_2 \mathbf{Controls}_{it} + \Omega_{st} + \varepsilon_{it} \tag{1}$$

$Prate_{it}$ is the number of opioid prescriptions per person in county i in year t. $Marketing_{it}$ is the number of physicians practicing in county i who had received marketing payments in year t, normalized to per 1,000 county population. $\mathbf{Controls}_{it}$ is a vector of the characteristics of county i in year t. The control variables are percent male, percent white, median age, median household income, percent under poverty, percent with bachelor's degree or more, ratio of physicians to population, indicator of physician shortage[2], indicators of urbanicity, median house value, and indicators of the main economic activity of the county. Ω_{st} is state-by-year fixed effect. This regression was run using the population size of the county as weights.

Fixed effects.

I chose to use state-by-year fixed effects instead of county fixed effects because I want to exploit variation across counties while flexibly controlling for state-level differences and time trends. The state-by-year fixed effects allow the state-level differences to vary by year and the by-year intercept to vary by state. An example of a state-specific factor that may affect the prescription rate is state laws regulating prescription of opioids, such as the Prescription

[2] The indicator for physician shortage depends on (a) the ratio of population to primary-care physicians and (b) whether primary care physicians in the surrounding counties are over-utilized or inaccessible to the population in the county under consideration.

Drug Monitoring Programs, which allow physicians and pharmacists to access a patient's prescription history.

I did not use county fixed effects because the variation in marketing payments within a county across years is not a good variation to use to predict the prescription rate. As previously discussed, a large proportion of counties did not receive any marketing payments or received payments intermittently during the 2014–2017 period, while the time trend of the prescription rate is more stable. To expand, 26.5 percent of counties did not receive any marketing payments throughout 2014-17, while another 18.0 percent received payments only 1 or 2 years out of 4. In contrast, the time trend of prescription rate for these counties is more consistent – prescription rate steadily decreased between 2014 and 2017.

For counties that received marketing payments more consistently (i.e. for 3 or 4 years out of 4), marketing payments and prescription rates moved in opposite directions over time. Between the 2014 and 2017, prescription rates steadily decreased. On the other hand, marketing payments first increased between 2014 and 2016, before sharply decreasing in 2017. Thus, variation in marketing payments within a county across years is not a good predictor of the prescription rate.

A concern that may arise from using state-by-year fixed effects instead of county fixed effects is that there may be unobserved, time-invariant, county-specific factors that affect the prescription rate and are correlated with marketing payments. This would cause the coefficient of marketing payments (α_1) to be inconsistently estimated. To mitigate this issue, I controlled for county characteristics that may be correlated with both prescription rate and marketing payments. Examples of such characteristics would be physician-to-population ratio, urbanicity, and the main economic activity of the county.

Measure of marketing payments.

Marketing payments potentially increase the use of opioids by coaxing physicians to write more prescriptions. I chose to use only the number of physicians receiving marketing payments as an instrument instead of other measures of marketing payments such as the dollar amount of payments, the number of payment transactions, or using multiple measures of marketing payments simultaneously as instruments. This is because the number of physicians receiving payments is the best predictor of opioid prescription rates compared to other measures of marketing payments. Moreover, including other measures of marketing payments in the regression does not substantially improve the ability to predict the prescription rate. Other studies on physician marketing have also found similar results. Grennan et al. (2018) studied the effects of marketing payments for a type of medication called statins on physicians' prescribing behavior. The authors focused on payments in the form of meals and found that conditional on providing any meal, providing a more expensive meal does not increase prescription. Similarly, Carey et al. (2020) found that physicians who receive marketing payments prescribe more and this is spurred by low-dollar payments in the form of food.

I use the marketing payments in year t to predict opioid prescription rate in the same year t and the next year $(t+1)$ because there is evidence that the effects of marketing payments on physicians' prescribing dissipate over time. Mizik and Jacobson (2004) found that although physicians write more new prescriptions following a visit from a pharmaceutical salesperson, the effect tends to diminish within six months. Similarly, Carey et al. (2020) found that after receiving marketing payments, physicians prescribed more medication. However, this effect peaks six months after receiving the payment and decreases afterward.

Exclusion restriction.

A concern that may arise when using marketing payments as an instrument for prescription rate is that there may be unobserved factors that affect the outcomes of interests which are also correlated with marketing payments. To assess the risk of violating the exclusion restriction, it helps to understand how pharmaceutical firms decide where to distribute marketing payments. Recent lawsuits brought against opioid manufacturers for misrepresenting the risk of opioid addiction have shed some light on their marketing strategies. Besides direct marketing targeted towards physicians, opioid manufacturers also employed other methods to promote their products such as discount coupons for first-time opioid users and funding patient advocacy groups that promote the use of opioids (The People of the State of New York v. Purdue Pharma, 2019).

Furthermore, opioid manufacturers focused their marketing efforts on subsets of the population deemed to be more lucrative, the elderly and the veteran population. These groups were targeted because of their health insurance coverage (Commonwealth of Massachusetts v. Purdue Pharma, 2019). This insight regarding the subgroups of the population targeted by the opioid companies supports why marketing payments can serve as a feasible instrument. The outcomes of interest analyzed in this paper pertain to the working-age population. I investigated only the labor market outcomes of individuals age 18-64. Moreover, a worker's SSDI (as opposed to children or survivor's SSDI) is generally only available to individuals in the same age range. In contrast, the sub-population targeted by opioid manufacturers were the elderly (who are above working age) and the veterans (who constitute a small percentage of the population). Thus, opioid prescriptions are the most plausible channel through which marketing payments to physicians affect labor market outcomes and SSDI use.

4.2 Second-stage Regression

The specification of the second-stage regression is below.

$$Outcome_{it} = \beta_0 + \beta_1 \widehat{Prate}_{it} + \beta_2 \mathbf{Controls}_{it} + \Gamma_{st} + u_{it} \tag{2}$$

I examined the effects of prescription opioids on four types of labor market outcomes: the labor force participation rate, the unemployment rate, the percentage of the population working full time, and the percentage of the population working less than full time. In addition, there are four measures of SSDI use: the number of SSDI applications per 1,000 population, the number of SSDI awards per 1,000 population, the proportion of the population enrolled in SSDI, and the dollar amount of SSDI benefits per 1,000 population. Γ_{st}

is the state-by-year fixed effects. $\mathbf{Controls}_{it}$ is the same set of control variables as in the first-stage regression.

5 Results

In this section, I first describe the results from the first-stage regression. Next, I discuss the causal estimates of the effects of prescription opioids on labor market outcomes and SSDI use.

5.1 First-stage Regression Results

Section 3 briefly alludes to the positive correlation between opioid marketing payments and opioid prescriptions. This section further explores this relationship in the context of the first-stage regression. Table 4 presents the results of the first-stage regressions. Column 1 shows that increasing the number of physicians who are receiving marketing payments per 1,000 population by one unit would lead to a 0.90 per person increase in the number of opioid prescriptions. This is a large increase given that the mean number of opioid prescriptions per person is 0.68. However, the mean number of physicians receiving marketing payments per 1,000 population is 0.12, so an increase of 1 unit is also very large.

I also examined the one-year lag effect of marketing payment, i.e. the effect of marketing payment in the previous year on the prescription rate in the current year. The result is reported in column 2. The coefficient is smaller than the one in column 1. Increasing the number of physicians receiving marketing payments in the previous year per 1,000 population by one unit would lead to an increase in the number of opioid prescriptions in the current year by 0.81 per person.

The first-stage regression shows that marketing payments are a reasonable predictor of prescription rate. The appendix contains the full regression result with coefficients for the control variables as well as the results of first stage regressions using other measures of marketing payments as the instrument.

5.2 The Effects of Prescription Opioids on Labor Market Outcomes

Table 5 presents the causal estimates of the effect of prescription opioids on labor market outcomes. The number of physicians receiving marketing payments per 1,000 population is used as an instrument to predict the opioid prescription rate. The estimates suggest that prescription opioids have positive effects on labor market outcomes although the effects are not precisely estimated. Increasing the number of opioid prescriptions by one per person leads to an increase in the labor force participation rate by 1.11 percentage points. Moreover, increasing the opioid prescription rate by one unit leads to a decrease in the unemployment rate by 0.59 percentage points. Using lag values of the prescription rate yields roughly similar estimates. None of these estimates are statistically significant at the 10 percent level.

Table 4: 1st Stage Regression

	(1) Prate	(2) Prate
# of recipient physicians per 1000 population	0.90***	
	(0.09)	
# of recipient physicians per 1000 population, lag		0.81***
		(0.08)
Observations	11854	8894
R^2	0.67	0.67
F statistic	104.39	102.10
Prob F statistic	0.00	0.00
Mean # of opioid prescription per person	0.68	
Mean # of recipient physicians per 1000 population	0.12	

* p < 0.10, ** p < 0.05, *** p < 0.01
Standard errors are clustered at the county level and are reported in parentheses.
Regressions include (state × year) fixed effects.
Prate is the number of opioid prescriptions per person.
Controls included: percent male, percent white, median age, median household income, percent under poverty, percent with bachelor's degree or more, ratio of physician to population, indicator for physician shortage, indicators for urbanicity, median house value, main economic activity.

Given that other papers have found the effects of opioids on labor market outcomes to be negative (Harris et al., 2019; Aliprantis et al., 2019), these estimates are somewhat surprising. To make sense of the results, it may be useful to compare them to the "naive" regression of labor market outcomes on the opioid prescription rate without using any instrument. The estimates are shown in Table 6. Interestingly, the results from the "naive" regressions are the opposite of the results from the IV regressions. The estimates without using an instrument suggest that prescription opioids are negatively correlated with labor market outcomes. An increase in the number of opioid prescriptions by one per person is associated with a decrease in the labor force participation rate of 1.09 percentage points. On the other hand, the correlation between prescription opioids and the unemployment rate is imprecisely estimated. An increase in the number of opioid prescriptions by one per person is associated with a 0.17 percentage points decrease in the unemployment rate.

One way to rationalize the difference in the estimates from the naive regressions with those from the IV regressions is to consider how the marketing payments are distributed across counties. As previously discussed, counties that receive more marketing payments tend to be more urban. A concern that may arise would be that the labor market condition of a county is sensitive to its economic context. For example, more urban counties may have a more robust labor market with a higher labor force participation rate. The IV estimates may be picking up differences in the characteristics of the labor market between rural and urban

Table 5: IV Regression: Labor Market Outcomes

	(1) LFPR	(2) LFPR	(3) Urate	(4) Urate
Opioid prescription rate	1.11		–0.59	
	(0.71)		(0.36)	
Opioid prescription rate, lag		1.08		–0.53
		(0.70)		(0.35)
Observations	11854	8885	11854	8885
R^2	0.81	0.82	0.79	0.77
Mean # of opioid prescription per person		0.68		
Mean labor force participation rate		76.69		
Mean unemployment rate		7.85		

* p < 0.10, ** p < 0.05, *** p < 0.01
Standard errors are clustered at the county level and are reported in parentheses.
Regressions include (state × year) fixed effects.
Opioid prescription rate is the number of opioid prescriptions per person.
LFPR is the labor force participation rate.
Urate is the unemployment rate.
Controls included: percent male, percent white, median age, median household income, percent under poverty, percent with bachelor's degree or more, ratio of physician to population, indicator for physician shortage, indicators for urbanicity, median house value, main economic activity.

counties, instead of the variation in the predicted opioid prescription rate. In other words, the estimates which suggest that a higher opioid prescription rate leads to a greater labor force participation may actually be picking up the effect of a more robust labor market in urban counties. To address this concern, I included three control variables that capture the 'robustness' of the labor market in a county. The first control variable is a set of indicators for the level of urbanicity of a county. There are three levels of urbanicity: mostly urban, mostly rural, and completely rural[3]. The second is the median house value in the county. The third is a set of indicators for the main industry in the county. There are six categories of industry: farming, mining, manufacturing, recreation, government, and an indicator for not specializing in any particular industry.

A natural next step in explaining the results would be to explore whether the effects of prescription opioids on labor market outcomes vary by the urbanicity of the county. To do this, I use the percentage of the population in the county who lives in urban areas as a measure of urbanicity. I created indicators for quartiles based on this measure and interacted

[3]The indicators depend on the proportion of the population living in urban areas. A mostly urban county has more than 50 percent of its population living in urban areas. A mostly rural county has 0.1 to 50 percent of its population living in urban areas. A completely rural county has 0 percent of its population living in urban areas.

Table 6: Naive Regression: Labor Market Outcomes

	(1) LFPR	(2) LFPR	(3) Urate	(4) Urate
Opioid prescription rate	−1.09***		0.17	
	(0.25)		(0.15)	
Opioid prescription rate, lag		−1.04***		0.13
		(0.24)		(0.15)
Observations	11854	8885	11854	8885
R^2	0.82	0.83	0.79	0.77
Mean # of opioid prescription per person			0.68	
Mean labor force participation rate			76.69	
Mean unemployment rate			7.85	

* p < 0.10, ** p < 0.05, *** p < 0.01
Standard errors are clustered at the county level and are reported in parentheses.
Regressions include (state × year) fixed effects.
Opioid prescription rate is the number of opioid prescriptions per person.
LFPR is the labor force participation rate.
Urate is the unemployment rate.
Controls included: percent male, percent white, median age, median household income, percent under poverty, percent with bachelor's degree or more, ratio of physician to population, indicator for physician shortage, indicators for urbanicity, median house value, main economic activity.

them with the opioid prescription rate. The regression specification is below.

$$\begin{aligned} Outcome_{it} = \gamma_0 &+ \gamma_1 \widehat{Prate}_{it} \cdot 1stQuartile + \gamma_2 \widehat{Prate}_{it} \cdot 2ndQuartile \\ &+ \gamma_3 \widehat{Prate}_{it} \cdot 3rdQuartile + \gamma_4 \widehat{Prate}_{it} \cdot 4thQuartile \\ &+ \gamma_5 \mathbf{Controls}_{it} + \Theta_{st} + \nu_{it} \end{aligned} \tag{3}$$

Θ_{st} is the state-by-year fixed effects. $\mathbf{Controls}_{it}$ is the same vector of county characteristics as in previous regressions. The estimates of the heterogeneous effects of prescription opioids on labor market outcomes are shown in Table 7.

The results suggest that the effects of prescription opioids on the labor force participation may vary according to how urban a county is. The effects are positive for counties in the first, third, and fourth quartiles, although they are not precisely estimated. On the other hand, the effect is negative for counties in the second quartile and it is precisely estimated. An increase in the number of opioid prescriptions by one per person leads to a decrease in the labor force participation rate by 2.00 percentage points for counties in the second quartile.

Table 7: IV Regression: Labor Market Outcomes, with Interactions

	(1) LFPR	(2) LFPR	(3) Urate	(4) Urate
1st quartile × Opioid prescription rate	0.09		0.08	
	(1.12)		(0.54)	
2nd quartile × Opioid prescription rate	−2.00**		0.05	
	(0.89)		(0.39)	
3rd quartile × Opioid prescription rate	0.14		−0.38	
	(0.84)		(0.44)	
4th quartile × Opioid prescription rate	1.21		−0.79**	
	(0.77)		(0.40)	
1st quartile × Opioid prescription rate, lag		0.20		−0.33
		(1.10)		(0.55)
2nd quartile × Opioid prescription rate, lag		−1.86**		0.01
		(0.86)		(0.40)
3rd quartile × Opioid prescription rate, lag		0.19		−0.43
		(0.92)		(0.45)
4th quartile × Opioid prescription rate, lag		1.19		−0.70*
		(0.76)		(0.39)
Observations	11854	8885	11854	8885
R^2	0.82	0.83	0.79	0.77
Mean # of opioid prescription per person			0.68	
Mean labor force participation rate			76.69	
Mean unemployment rate			7.85	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered at the county level and are reported in parentheses.
Regressions include (state × year) fixed effects.
Opioid prescription rate is the number of opioid prescriptions per person.
LFPR is the labor force participation rate.
Urate is the unemployment rate.
Controls included: percent male, percent white, median age, median household income, percent under poverty, percent with bachelor's degree or more, ratio of physician to population, indicator for physician shortage, indicators for urbanicity, median house value, main economic activity.
The quartile is based on the percentage of the population in a county who lives in urban areas.

The results using lag values of opioid prescription rates are similar.

It is plausible for prescription opioids to have positive effects in a more urban setting because it may be easier for a person with a disability to find employment in urban areas than in rural areas. For example, there are more employers in urban areas which can accommodate workers with a disability. Moreover, there may also be more work opportunities which are less physically demanding in urban areas than there are in a rural setting.

On the other hand, prescription opioids decrease the unemployment rate for counties in the third and fourth quartile, although the effect is only precisely estimated for counties in the fourth quartile. Increasing the number of opioid prescriptions by one per person leads to a decrease in the unemployment rate of 0.79 percentage points for counties in the fourth quartile. In contrast, increasing opioids prescribing in counties in the first and second quartiles increases unemployment, although the effects are not precisely estimated. The results using lag values of opioid prescription rates are similar.

5.3 The Effects of Prescription Opioids on SSDI Use

Tables 8 and 9 present causal estimates of the effects of prescription opioids on SSDI-related outcomes. The results suggest that a higher opioid prescription rate results in greater use of SSDI. An increase in the number of opioid prescriptions by one per person leads to an increase of 6.02 SSDI applications and 2.05 SSDI awards per 1,000 population. Moreover, increasing the prescription rate by one unit leads to an increase in the percentage of the population age 18-64 enrolled in SSDI by 1.30 percentage points and an increase in the dollar amount of SSDI benefits per 1,000 population by $14.00. Estimates using lag values of the prescription rate are similar. These effects are precisely estimated. Moreover, using other measures of marketing payments as the instrument does not change the results substantially. The appendix contains regression results using different measures of marketing payments as the instrument.

It is perplexing to find results suggesting that a higher opioid prescription rate leads to greater participation in the labor force and at the same time greater use of SSDI. To apply for and continue receiving SSDI benefits, beneficiaries must refrain from engaging in substantial gainful activities (SGA), which in 2019 is equivalent to earning more than $1,220 per month. This requirement may discourage attachment to the labor market. Thus, a greater proportion of the population applying for and enrolling in SSDI may lead to lower labor force participation. However, the results suggest the opposite.

One explanation that may rationalize this contradictory finding is that a higher opioid prescription rate may increase the percentage of the population on SSDI but may also increase labor force participation through part-time employment below the SGA threshold. Table 10 shows the causal estimates of the effects of prescription opioids on full-time and less than full-time work. Full-time employment is defined as working 35 hours or more per week. The estimates suggest that prescription opioids promote both full-time and less than full-time employment. Increasing the number of opioid prescriptions by one per person leads to an increase in the proportion of the population age 18-64 who are working full-time by 0.46 percentage point and those working less than full-time by 1.38 percentage points. The effects for full-time work are not precisely estimated, while the estimates for less than full-time work are statistically significant at the 10 percent level.

Table 8: IV Regression: SSDI Outcomes (Applications and Awards)

	(1) SSDI app	(2) SSDI app	(3) SSDI awards	(4) SSDI awards
Opioid prescription rate	6.02***		2.05***	
	(0.95)		(0.32)	
Opioid prescription rate, lag		5.51***		1.81***
		(0.86)		(0.28)
Observations	11790	8837	11790	8837
R^2	0.81	0.81	0.82	0.80
Mean # of opioid prescription per person			0.68	
Mean # of SSDI applications per 1000 population			10.02	
Mean # of SSDI awards per 1000 population			3.35	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered at the county level and are reported in parentheses.
Regressions include (state × year) fixed effects.
Opioid prescription rate is the number of opioid prescriptions per person.
SSDI app is the number of SSDI applications per 1,000 population.
SSDI awards is the number of SSDI awards per 1,000 population.
Controls included: percent male, percent white, median age, median household income, percent under poverty, percent with bachelor's degree or more, ratio of physician to population, indicator for physician shortage, indicators for urbanicity, median house value, main economic activity.

6 Conclusion

Opioid medication is widely used to treat pain. It can have a positive impact by helping a person with medical conditions to manage pain and be employed rather than seeking SSDI. On the other hand, the efficacy of opioids in treating chronic pain in the long term is unclear and they are known to be an addictive substance. Their use may lead a person to become addicted, exit the labor force, and eventually claim SSDI. This paper explores the impact of prescription opioids on the working-age population by examining their labor market outcomes and use of SSDI. The analysis is done at the county level.

To obtain causal estimates, this paper uses marketing payments from pharmaceutical companies to physicians to promote opioids, as an instrument to predict opioid prescriptions. The underlying idea is that physicians exposed to marketing from opioid manufacturers are more willing to prescribe opioids to their patients than physicians who were not exposed. The first stage regression demonstrates that marketing payments strongly predict opioid prescriptions.

This paper finds that prescription opioids have positive effects on labor market outcomes, although the effects are not statistically significant. Increasing the number of opioid pre-

Table 9: IV Regression: SSDI Outcomes (Enrollment and Dollar Amount of Benefits)

	(1) % in SSDI	(2) % in SSDI	(3) $ SSDI	(4) $ SSDI
Opioid prescription rate	1.30***		14.00***	
	(0.28)		(3.64)	
Opioid prescription rate, lag		1.38***		14.93***
		(0.29)		(3.68)
Observations	11854	8885	11854	8885
R^2	0.87	0.87	0.85	0.86
Mean # of opioid prescription per person			0.68	
Mean % enrolled in SSDI			4.43	
Mean $ amount of SSDI benefit per 1000 population			52.10	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered at the county level and are reported in parentheses.
Regressions include (state × year) fixed effects.
Opioid prescription rate is the number of opioid prescriptions per person.
% in SSDI is the percentage of population enrolled in SSDI.
$ SSDI is the dollar amount of SSDI benefits paid per 1,000 population.
Controls included: percent male, percent white, median age, median household income, percent under poverty, percent with bachelor's degree or more, ratio of physician to population, indicator for physician shortage, indicators for urbanicity, median house value, main economic activity.

scriptions by one per person leads to an increase in the labor force participation rate of 1.11 percentage points. Moreover, prescription opioids lower the unemployment rate; increasing the prescription rate by one unit leads to a 0.59 percentage point drop in the unemployment rate. However, these positive effects of prescription opioids tend to be confined only to urban counties.

Prescription opioids also raise the use of SSDI. Increasing the prescription rate by one unit leads to an increase of 6.02 SSDI applications and 2.05 SSDI awards per 1,000 population. Moreover, increasing the prescription rate by one unit leads to an increase in the percentage of the population who are enrolled in SSDI by 1.30 percentage points and an increase in the dollar amount of SSDI benefits per 1,000 population by $14.00.

The effects of prescription opioids by increasing both labor market activities and SSDI use seem contradictory because some SSDI rules, such as the substantial gainful activity (SGA) threshold, disincentive work. This can be partially explained by the finding that a higher opioid prescription rate may increase both SSDI use and labor market activities through part-time employment. I find that increasing the opioid prescription rate by one unit increases the percentage of the population working less than full-time by 1.38 percentage points. The effects on full-time employment are also positive but imprecisely estimated.

Table 10: IV Regression: Full-time and Less than Full-time Work

	(1) % full-time	(2) % full-time	(3) % $<$ full-time	(4) % $<$ full-time
Opioid prescription rate	0.46 (0.76)		1.38* (0.83)	
Opioid prescription rate, lag		0.32 (0.76)		1.52* (0.85)
Observations	11854	8885	11854	8885
R^2	0.84	0.84	0.62	0.61
Mean # of opioid prescription per person			0.68	
Mean % working full-time			50.40	
Mean % working less than full-time			27.21	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered at the county level and are reported in parentheses.
Regressions include (state × year) fixed effects.
Opioid prescription rate is the number of opioid prescriptions per person.
% full-time is the percentage of the population working full-time (35 hours or more per week).
%¡full-time is the percentage of the population working less than full-time
Controls included: percent male, percent white, median age, median household income, percent under poverty, percent with bachelor's degree or more, ratio of physician to population, indicator for physician shortage, indicators for urbanicity, median house value, main economic activity.

One limitation of the paper is that it does not consider the interaction between prescription opioids and illicit opioids. Marketing payments increase the supply of prescription opioids, which may then affect the use of illicit opioids. The effects of *illicit* opioids on labor market outcomes and SSDI are not examined here. Another limitation is that the time frame of the analysis is relatively short. I used data for 2014 through 2017. Some effects of prescription opioids may take longer to materialize. This paper is unable to examine these aspects of opioid use. Future studies may address these limitations.

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Appendix

Table 11: Characteristics of County, based on Number of Years Receiving Marketing Payments, 2014–17

	0 year Mean	1 year Mean	2 years Mean	3 years Mean	4 years Mean
# of opioid prescription per person	0.49	0.67	0.75	0.88	0.91
Labor force participation rate	74.82	74.21	73.55	73.25	74.72
Unemployment rate	6.69	7.39	7.53	7.67	7.81
SSDI applications per 1000 population	11.89	12.55	12.95	13.18	12.25
SSDI awards per 1000 population	4.83	4.47	4.63	4.65	4.24
% enrolled in SSDI	5.50	6.17	6.55	6.67	5.84
$ amount of SSDI benefits per 1000 population	61.91	69.53	74.90	76.00	67.70
% working full-time	51.48	50.16	49.65	48.99	49.21
% working less than full-time	25.76	25.93	25.51	26.05	27.10
$ amount of marketing payments per 1000 population	0.00	0.69	1.88	2.72	9.44
# of marketing payments per 1000 population	0.00	0.04	0.12	0.21	0.63
# of physicians receiving payments per 1000 population	0.00	0.03	0.06	0.09	0.15
% male	50.99	50.47	50.02	49.99	49.45
% white	84.37	83.88	84.90	85.76	82.01
Median age	42.93	41.74	41.74	41.00	39.44
Median household income ('000)	45.59	44.93	44.87	45.51	50.72
% under poverty	15.44	16.20	16.39	16.47	15.52
% with bachelor's degree or more	17.96	17.43	17.78	18.54	23.88
% age 65 and over	19.17	18.10	18.07	17.40	15.94
Ratio of physician to population	0.56	0.78	0.83	0.92	1.98
% veterans	7.92	7.70	7.88	8.04	7.82
Has shortage of physicians	0.39	0.25	0.27	0.17	0.06
% enrolled in old-age Medicare	18.76	17.77	18.00	17.41	16.44
% living in urban areas	17.90	28.49	31.41	37.42	60.51
% mostly urban counties	14.03	24.91	22.74	28.35	64.04
% mostly rural counties	28.66	41.52	55.60	60.75	33.57
% completely rural counties	57.31	33.56	21.66	10.90	2.39
Median house value ('000)	109.56	117.50	117.60	127.62	160.32
% with ambulatory difficulty	7.05	7.41	7.66	7.86	6.70
% with self-care difficulty	2.32	2.51	2.54	2.62	2.28
Observations	3,336	1,156	1,108	1,284	5,684

Source: American Community Survey (ACS), US Census Bureau, Social Security Administration (SSA), Centers for Disease Control and Prevention (CDC), Centers for Medicare and Medicaid Services (CMS), and Health Resources and Services Administration (HRSA).

Table 12: Different Measures of Marketing Payments as Instrument, No Lag

	(1) Prate	(2) Prate	(3) Prate	(4) Prate	(5) Prate	(6) Prate
$ amount of payments per 1000 pop	0.01***			−0.00*	0.00	
	(0.00)			(0.00)	(0.00)	
# of payments per 1000 pop		0.13***		0.17***		0.04***
		(0.02)		(0.03)		(0.02)
# of recipient physicians per 1000 pop			0.90***		0.85***	0.72***
			(0.09)		(0.09)	(0.08)
% male	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% white	0.01***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Median age	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Median household income ('000)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% under poverty	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% with B.S. or more	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% age 65 and over						
Ratio physician:population	0.01**	0.01**	0.00	0.01**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% veterans						
Has shortage of physicians	−0.13***	−0.12***	−0.12***	−0.12***	−0.12***	−0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Median house value ('000)	−0.00***	−0.00**	−0.00**	−0.00*	−0.00**	−0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mostly rural	0.29***	0.29***	0.26***	0.28***	0.26***	0.27***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Mostly urban	0.39***	0.37***	0.34***	0.37***	0.34***	0.34***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Farm-dependent	−0.18***	−0.17***	−0.18***	−0.17***	−0.18***	−0.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Mining-dependent	0.06	0.06	0.06	0.06	0.06	0.06
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Manufacturing-dependent	0.02	0.03*	0.02*	0.02*	0.02*	0.02*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Federal/State gov-dependent	0.01	0.01	0.00	0.01	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Recreation	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	11854	11854	11854	11854	11854	11854
R^2	0.65	0.66	0.67	0.66	0.67	0.67
F statistic	53.88	72.93	104.39	43.02	57.26	50.29
Prob F statistic	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
Prate is the number of opioid prescriptions per person.
The F-statistic tests whether all instruments are jointly equal to zero
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Different Measures of Marketing Payments as Instrument, with Lag

	(1) Prate	(2) Prate	(3) Prate	(4) Prate	(5) Prate	(6) Prate
$ amount of payments per 1000 pop, lag	0.01***			−0.00*	0.00	
	(0.00)			(0.00)	(0.00)	
# of payments per 1000 pop, lag		0.12***		0.16***		0.04***
		(0.01)		(0.03)		(0.01)
# of recipient physicians per 1000 pop, lag			0.81***		0.77***	0.63***
			(0.08)		(0.08)	(0.08)
% male	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% white	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Median age	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Median household income ('000)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% under poverty	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% with B.S. or more	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% age 65 and over						
Ratio physician:population	0.01*	0.01*	0.00	0.01**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
% veterans						
Has shortage of physicians	−0.14***	−0.13***	−0.12***	−0.13***	−0.12***	−0.12***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Median house value ('000)	−0.00***	−0.00**	−0.00**	−0.00**	−0.00**	−0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mostly rural	0.27***	0.26***	0.24***	0.26***	0.24***	0.24***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Mostly urban	0.35***	0.33***	0.31***	0.33***	0.31***	0.31***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Farm-dependent	−0.16***	−0.16***	−0.16***	−0.16***	−0.16***	−0.16***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Mining-dependent	0.06	0.06	0.05	0.06	0.05	0.05
	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
Manufacturing-dependent	0.03*	0.03*	0.02*	0.03*	0.02*	0.02*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Federal/State gov-dependent	0.01	0.01	0.00	0.01	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Recreation	−0.01	−0.01	−0.02	−0.01	−0.02	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	8894	8894	8894	8894	8894	8894
R^2	0.66	0.67	0.67	0.67	0.67	0.68
F statistic	50.63	73.15	102.10	43.65	54.31	48.48
Prob F statistic	0.00	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
Prate is the number of opioid prescriptions per person.
The F-statistic tests whether all instruments are jointly equal to zero
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Compare IVs: Labor Force Participation Rate

	(1) \$ amount	(2) # payments	(3) # physicians	(4) All 3
Opioid prescription rate	2.23*	1.90**	1.11	1.21*
	(1.16)	(0.89)	(0.71)	(0.69)
% male	−0.08	−0.08	−0.10*	−0.09*
	(0.06)	(0.06)	(0.06)	(0.06)
% white	−0.02**	−0.02**	−0.02**	−0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
Median age	−0.28***	−0.27***	−0.26***	−0.26***
	(0.04)	(0.03)	(0.03)	(0.03)
Median household income ('000)	−0.11***	−0.11***	−0.10***	−0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
% under poverty	−0.81***	−0.80***	−0.79***	−0.79***
	(0.04)	(0.03)	(0.03)	(0.03)
% with B.S. or more	0.15***	0.15***	0.14***	0.14***
	(0.02)	(0.02)	(0.02)	(0.02)
% age 65 and over				
Ratio physician:population	−0.04	−0.04	−0.02	−0.02
	(0.05)	(0.05)	(0.05)	(0.05)
% veterans				
Has shortage of physicians	−0.46*	−0.50**	−0.62***	−0.60***
	(0.26)	(0.23)	(0.21)	(0.21)
Median house value ('000)	0.00**	0.00*	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
Mostly rural	0.36	0.46	0.70**	0.67**
	(0.43)	(0.37)	(0.32)	(0.32)
Mostly urban	1.17**	1.31***	1.64***	1.60***
	(0.58)	(0.48)	(0.42)	(0.41)
Farm-dependent	2.58***	2.52***	2.38***	2.40***
	(0.34)	(0.31)	(0.29)	(0.29)
Mining-dependent	−0.24	−0.22	−0.16	−0.17
	(0.42)	(0.41)	(0.38)	(0.38)
Manufacturing-dependent	0.51***	0.51***	0.53***	0.52***
	(0.17)	(0.17)	(0.17)	(0.17)
Federal/State gov-dependent	−0.14	−0.14	−0.13	−0.13
	(0.22)	(0.22)	(0.22)	(0.22)
Recreation	0.36	0.35	0.34	0.34
	(0.29)	(0.29)	(0.28)	(0.28)
Observations	11854	11854	11854	11854
R^2	0.80	0.81	0.81	0.81

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Compare IVs: Unemployment Rate

	(1) $ amount	(2) # payments	(3) # physicians	(4) All 3
Opioid prescription rate	0.67	−0.50	−0.59	−0.90**
	(0.63)	(0.43)	(0.36)	(0.35)
% male	−0.06*	−0.09***	−0.09***	−0.09***
	(0.03)	(0.03)	(0.03)	(0.03)
% white	−0.07***	−0.06***	−0.06***	−0.06***
	(0.00)	(0.00)	(0.00)	(0.00)
Median age	0.06***	0.08***	0.08***	0.09***
	(0.02)	(0.02)	(0.01)	(0.01)
Median household income ('000)	0.04***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
% under poverty	0.23***	0.25***	0.25***	0.26***
	(0.02)	(0.02)	(0.02)	(0.02)
% with B.S. or more	−0.08***	−0.09***	−0.09***	−0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
% age 65 and over				
Ratio physician:population	−0.01	0.01	0.01	0.02
	(0.03)	(0.04)	(0.04)	(0.04)
% veterans				
Has shortage of physicians	0.22	0.05	0.04	−0.00
	(0.15)	(0.13)	(0.12)	(0.12)
Median house value ('000)	−0.00***	−0.00***	−0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Mostly rural	−0.18	0.17	0.19	0.29
	(0.24)	(0.19)	(0.18)	(0.18)
Mostly urban	−0.04	0.45*	0.49**	0.62***
	(0.33)	(0.25)	(0.23)	(0.22)
Farm-dependent	−1.06***	−1.27***	−1.28***	−1.34***
	(0.19)	(0.17)	(0.16)	(0.16)
Mining-dependent	−0.31*	−0.22*	−0.22*	−0.20
	(0.16)	(0.13)	(0.13)	(0.13)
Manufacturing-dependent	−0.29***	−0.27***	−0.26***	−0.26***
	(0.09)	(0.09)	(0.09)	(0.09)
Federal/State gov-dependent	−0.16	−0.14	−0.14	−0.14
	(0.12)	(0.12)	(0.12)	(0.12)
Recreation	0.36**	0.35**	0.35**	0.34**
	(0.18)	(0.17)	(0.17)	(0.17)
Observations	11854	11854	11854	11854
R^2	0.79	0.79	0.79	0.78

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Compare IVs: SSDI Applications

	(1) $ amount	(2) # payments	(3) # physicians	(4) All 3
Opioid prescription rate	6.00***	5.33***	6.02***	5.66***
	(1.36)	(1.05)	(0.95)	(0.90)
% male	−0.16***	−0.17***	−0.16***	−0.16***
	(0.04)	(0.04)	(0.04)	(0.04)
% white	−0.06***	−0.05***	−0.06***	−0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Median age	0.15***	0.17***	0.15***	0.16***
	(0.03)	(0.02)	(0.02)	(0.02)
Median household income ('000)	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
% under poverty	0.16***	0.17***	0.16***	0.17***
	(0.03)	(0.03)	(0.03)	(0.03)
% with B.S. or more	−0.16***	−0.16***	−0.16***	−0.16***
	(0.02)	(0.02)	(0.01)	(0.01)
% age 65 and over				
Ratio physician:population	0.21***	0.22***	0.21***	0.21***
	(0.06)	(0.06)	(0.06)	(0.06)
% veterans				
Has shortage of physicians	0.62***	0.52***	0.62***	0.57***
	(0.24)	(0.20)	(0.19)	(0.18)
Median house value ('000)	−0.00***	−0.00***	−0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Mostly rural	−1.63***	−1.43***	−1.64***	−1.53***
	(0.47)	(0.38)	(0.36)	(0.35)
Mostly urban	−2.08***	−1.80***	−2.09***	−1.94***
	(0.62)	(0.50)	(0.47)	(0.44)
Farm-dependent	−0.40	−0.52*	−0.39	−0.46
	(0.33)	(0.29)	(0.29)	(0.28)
Mining-dependent	−0.32	−0.27	−0.32	−0.29
	(0.29)	(0.29)	(0.28)	(0.29)
Manufacturing-dependent	−0.20	−0.18	−0.20	−0.19
	(0.17)	(0.17)	(0.17)	(0.17)
Federal/State gov-dependent	0.16	0.17	0.16	0.16
	(0.17)	(0.17)	(0.17)	(0.17)
Recreation	−0.28	−0.29	−0.28	−0.29
	(0.19)	(0.20)	(0.19)	(0.20)
Observations	11790	11790	11790	11790
R^2	0.81	0.81	0.81	0.81

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Compare IVs: SSDI Awards

	(1) \$ amount	(2) # payments	(3) # physicians	(4) All 3
Opioid prescription rate	1.72***	1.81***	2.05***	2.02***
	(0.45)	(0.35)	(0.32)	(0.30)
% male	−0.06***	−0.06***	−0.06***	−0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
% white	−0.01***	−0.01***	−0.01***	−0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Median age	0.08***	0.07***	0.07***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
Median household income ('000)	0.01	0.01	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
% under poverty	0.03***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
% with B.S. or more	−0.05***	−0.05***	−0.05***	−0.05***
	(0.01)	(0.00)	(0.00)	(0.00)
% age 65 and over				
Ratio physician:population	0.05***	0.05***	0.04***	0.04***
	(0.02)	(0.02)	(0.02)	(0.02)
% veterans				
Has shortage of physicians	0.13*	0.14**	0.17***	0.17***
	(0.08)	(0.07)	(0.06)	(0.06)
Median house value ('000)	−0.00**	−0.00**	−0.00**	−0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Mostly rural	−0.42***	−0.44***	−0.51***	−0.50***
	(0.15)	(0.13)	(0.12)	(0.12)
Mostly urban	−0.56***	−0.59***	−0.69***	−0.68***
	(0.20)	(0.17)	(0.16)	(0.15)
Farm-dependent	−0.05	−0.04	0.01	0.00
	(0.11)	(0.10)	(0.10)	(0.10)
Mining-dependent	−0.03	−0.03	−0.05	−0.05
	(0.11)	(0.11)	(0.10)	(0.10)
Manufacturing-dependent	0.01	0.01	0.00	0.00
	(0.06)	(0.06)	(0.06)	(0.06)
Federal/State gov-dependent	0.10**	0.10**	0.10**	0.10**
	(0.05)	(0.05)	(0.05)	(0.05)
Recreation	−0.07	−0.06	−0.06	−0.06
	(0.07)	(0.07)	(0.07)	(0.07)
Observations	11790	11790	11790	11790
R^2	0.82	0.82	0.82	0.82

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Compare IVs: Percent Enrolled in SSDI

	(1) \$ amount	(2) # payments	(3) # physicians	(4) All 3
Opioid prescription rate	1.03**	1.20***	1.30***	1.32***
	(0.51)	(0.37)	(0.28)	(0.28)
% male	−0.09***	−0.09***	−0.09***	−0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
% white	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Median age	0.18***	0.18***	0.18***	0.18***
	(0.01)	(0.01)	(0.01)	(0.01)
Median household income ('000)	0.01*	0.01*	0.01*	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)
% under poverty	0.12***	0.11***	0.11***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)
% with B.S. or more	−0.07***	−0.07***	−0.07***	−0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
% age 65 and over				
Ratio physician:population	0.09***	0.08***	0.08***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
% veterans				
Has shortage of physicians	0.10	0.12	0.14*	0.14**
	(0.10)	(0.08)	(0.07)	(0.07)
Median house value ('000)	−0.00***	−0.00***	−0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Mostly rural	−0.31*	−0.37**	−0.40***	−0.40***
	(0.18)	(0.15)	(0.13)	(0.13)
Mostly urban	−0.68***	−0.75***	−0.79***	−0.80***
	(0.24)	(0.18)	(0.16)	(0.15)
Farm-dependent	−0.85***	−0.82***	−0.80***	−0.80***
	(0.14)	(0.13)	(0.12)	(0.12)
Mining-dependent	−0.14	−0.15	−0.16	−0.16
	(0.16)	(0.15)	(0.15)	(0.15)
Manufacturing-dependent	0.10	0.10	0.10	0.10
	(0.11)	(0.11)	(0.11)	(0.10)
Federal/State gov-dependent	0.00	0.00	0.00	0.00
	(0.07)	(0.07)	(0.07)	(0.07)
Recreation	−0.39***	−0.39***	−0.39***	−0.39***
	(0.13)	(0.13)	(0.13)	(0.13)
Observations	11854	11854	11854	11854
R^2	0.87	0.87	0.87	0.87

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Compare IVs: $ Amount of SSDI Benefits

	(1) $ amount	(2) # payments	(3) # physicians	(4) All 3
Opioid prescription rate	13.04**	14.25***	14.00***	14.41***
	(6.18)	(4.64)	(3.64)	(3.59)
% male	−1.21***	−1.19***	−1.19***	−1.19***
	(0.25)	(0.25)	(0.25)	(0.25)
% white	0.04	0.04	0.04	0.04
	(0.05)	(0.05)	(0.04)	(0.04)
Median age	2.25***	2.23***	2.23***	2.22***
	(0.14)	(0.12)	(0.11)	(0.11)
Median household income ('000)	0.28***	0.28***	0.28***	0.28***
	(0.07)	(0.07)	(0.07)	(0.07)
% under poverty	1.20***	1.18***	1.19***	1.18***
	(0.16)	(0.15)	(0.14)	(0.14)
% with B.S. or more	−0.85***	−0.84***	−0.85***	−0.84***
	(0.09)	(0.08)	(0.07)	(0.07)
% age 65 and over				
Ratio physician:population	0.83***	0.80***	0.81***	0.80***
	(0.27)	(0.26)	(0.26)	(0.26)
% veterans				
Has shortage of physicians	1.39	1.57	1.53*	1.59*
	(1.19)	(1.01)	(0.92)	(0.91)
Median house value ('000)	−0.03***	−0.03***	−0.03***	−0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Mostly rural	−4.07*	−4.44**	−4.36***	−4.48***
	(2.24)	(1.87)	(1.69)	(1.67)
Mostly urban	−7.64***	−8.15***	−8.04***	−8.22***
	(2.86)	(2.28)	(2.00)	(1.96)
Farm-dependent	−11.50***	−11.28***	−11.32***	−11.25***
	(1.73)	(1.56)	(1.48)	(1.47)
Mining-dependent	0.14	0.06	0.08	0.05
	(2.07)	(2.01)	(2.01)	(2.00)
Manufacturing-dependent	1.07	1.05	1.05	1.04
	(1.12)	(1.10)	(1.10)	(1.10)
Federal/State gov-dependent	0.38	0.37	0.37	0.37
	(0.87)	(0.87)	(0.87)	(0.87)
Recreation	−3.31**	−3.29**	−3.30**	−3.29**
	(1.55)	(1.53)	(1.53)	(1.52)
Observations	11854	11854	11854	11854
R^2	0.85	0.85	0.85	0.85

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Compare IVs: Percent Working Full-time

	(1) \$ amount	(2) # payments	(3) # physicians	(4) All 3
Opioid prescription rate	1.15	1.08	0.46	0.58
	(1.19)	(0.94)	(0.76)	(0.74)
% male	0.05	0.05	0.04	0.04
	(0.07)	(0.06)	(0.06)	(0.06)
% white	−0.03***	−0.03***	−0.03***	−0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Median age	−0.19***	−0.18***	−0.17***	−0.18***
	(0.04)	(0.03)	(0.03)	(0.03)
Median household income ('000)	−0.07***	−0.07***	−0.07***	−0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
% under poverty	−0.93***	−0.92***	−0.92***	−0.92***
	(0.03)	(0.03)	(0.03)	(0.03)
% with B.S. or more	0.06***	0.05***	0.05***	0.05***
	(0.02)	(0.02)	(0.02)	(0.02)
% age 65 and over				
Ratio physician:population	0.12**	0.12**	0.13**	0.13**
	(0.06)	(0.06)	(0.06)	(0.06)
% veterans				
Has shortage of physicians	−0.23	−0.24	−0.33	−0.31
	(0.25)	(0.23)	(0.21)	(0.21)
Median house value ('000)	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Mostly rural	0.08	0.10	0.29	0.25
	(0.43)	(0.37)	(0.32)	(0.32)
Mostly urban	−0.12	−0.09	0.17	0.12
	(0.59)	(0.50)	(0.43)	(0.42)
Farm-dependent	2.95***	2.94***	2.83***	2.85***
	(0.36)	(0.34)	(0.32)	(0.32)
Mining-dependent	−0.02	−0.01	0.03	0.02
	(0.32)	(0.31)	(0.29)	(0.30)
Manufacturing-dependent	0.57***	0.57***	0.58***	0.58***
	(0.17)	(0.17)	(0.16)	(0.17)
Federal/State gov-dependent	−0.58**	−0.58**	−0.58**	−0.58**
	(0.27)	(0.27)	(0.27)	(0.27)
Recreation	−1.88***	−1.88***	−1.89***	−1.88***
	(0.25)	(0.25)	(0.25)	(0.25)
Observations	11854	11854	11854	11854
R^2	0.84	0.84	0.84	0.84

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Compare IVs: Percent Working Less than Full-time

	(1) \$ amount	(2) # payments	(3) # physicians	(4) All 3
Opioid prescription rate	0.10	1.10	1.38*	1.59**
	(1.35)	(1.00)	(0.83)	(0.81)
% male	0.00	0.02	0.02	0.03
	(0.06)	(0.06)	(0.06)	(0.06)
% white	0.09***	0.09***	0.09***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)
Median age	−0.15***	−0.17***	−0.18***	−0.18***
	(0.03)	(0.03)	(0.03)	(0.03)
Median household income ('000)	−0.05***	−0.05***	−0.05***	−0.06***
	(0.02)	(0.02)	(0.02)	(0.02)
% under poverty	0.21***	0.19***	0.19***	0.18***
	(0.04)	(0.03)	(0.03)	(0.03)
% with B.S. or more	0.20***	0.21***	0.21***	0.21***
	(0.02)	(0.02)	(0.02)	(0.02)
% age 65 and over				
Ratio physician:population	−0.21***	−0.23***	−0.24***	−0.24***
	(0.07)	(0.08)	(0.08)	(0.08)
% veterans				
Has shortage of physicians	−0.25	−0.11	−0.07	−0.04
	(0.27)	(0.24)	(0.22)	(0.22)
Median house value ('000)	−0.00**	−0.00**	−0.00**	−0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Mostly rural	0.69	0.39	0.31	0.24
	(0.47)	(0.38)	(0.34)	(0.33)
Mostly urban	1.49**	1.07**	0.95**	0.86**
	(0.64)	(0.50)	(0.44)	(0.43)
Farm-dependent	0.47	0.64**	0.69**	0.73**
	(0.37)	(0.33)	(0.31)	(0.31)
Mining-dependent	0.17	0.10	0.08	0.06
	(0.25)	(0.25)	(0.24)	(0.25)
Manufacturing-dependent	0.21	0.19	0.19	0.19
	(0.18)	(0.18)	(0.18)	(0.18)
Federal/State gov-dependent	1.43***	1.41***	1.41***	1.41***
	(0.30)	(0.30)	(0.30)	(0.30)
Recreation	2.70***	2.71***	2.72***	2.72***
	(0.38)	(0.37)	(0.37)	(0.37)
Observations	11854	11854	11854	11854
R^2	0.63	0.62	0.62	0.62

Standard errors in parentheses
Regressions include (state × year) fixed effects.
Standard errors clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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