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EMPLOYMENT OUTCOMES FOR SOCIAL SECURITY DISABILITY INSURANCE APPLICANTS WHO USE OPIOIDS

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Abstract

In this paper, we examine the relationship between self-reported opioid use and employment outcomes among Social Security Disability Insurance (SSDI) applicants. We followed a sample of 2009 applicants to SSDI for four years after the Social Security Administration (SSA) determined their application outcome. We drew our sample from SSA's Structured Data Repository (SDR) and supplemented the SDR with other SSA administrative data sources that provide information on application outcomes, annual earnings, and deaths. We used a machine-learning method to identify opioids in medication text fields in SDR data.

Our analysis addresses two questions: (1) How do employment and earnings patterns differ between SSDI applicants who did and did not use opioids at the time of application? and (2) What is the association between opioid use and employment outcomes among SSDI applicants? We estimated the association between opioid use at application and later employment outcomes through ordinary least squares regression, by using three measures of local opioid availability as instrumental variables and by a reduced-form ordinary least squares regression. Understanding these patterns and associations can improve understanding about the post-application economic well-being of SSDI applicants and may help policymakers identify ways to help this group.

The paper finds that:

- Applicants who self-reported opioid use at the time of application had lower employment rates in the first four years after determination compared to non-opioid users.
- Estimates from different estimation methods and for samples – including awarded and denied applicants – all suggest a negative and statistically significant association between (1) self-reported opioid use at application and (2) post-determination employment and earnings outcomes.
- Our results suggest that a 10 percent increase in the local opioid prescribing rate is associated with employment that is, at most, 0.3 of a percentage point lower, which is similar to the documented association among the broader U.S. population. While we know opioids are associated with lower employment, we do not know whether opioids *per se* contribute positively or negatively to this result.

The policy implications of the findings are:

- While we find that opioid use is associated with a similarly lower employment for SSDI applicants as for the broader population, the potential implications for SSDI applicants are particularly notable because opioid use is about 50 percent higher among SSDI applicants.
- More research on the role of opioids in determining employment outcomes may lead to a better understanding of employment trajectories for SSDI beneficiaries and of reapplication among denied applicants.

Introduction

Opioids permeated the American medical system in the late 1990s and continue to be pervasive more than 20 years later (U.S. Department of Health and Human Services 2019). Opioids gained prevalence in part through promotion by the pharmaceutical industry as a safe and effective solution for chronic pain. Opioid prescription rates peaked in 2010–2012, with 81 prescriptions written for every 100 Americans (Centers for Disease Control and Prevention [CDC] 2018). As the prevalence of opioids increased, so did the evidence of their potential harmful effects, such as addiction, misuse, and overdose. In 2017, the U.S. Department of Health and Human Services declared a public health emergency to address the so-called opioid epidemic. That same year, there were still 59 opioid prescriptions written for every 100 Americans. Furthermore, the average days of supply per opioid prescription rose consistently between 2006 and 2017 (CDC 2018).

The opioid epidemic is particularly notable for people with disabilities, who use opioids at a higher rate than the general population. Between one-quarter to one-third of applicants to Social Security Disability Insurance (SSDI) – the nation's largest safety net program for workers with disabilities – reported using opioids at the time of application in the period from 2007 to 2017 (Wu et al. 2020).[1] An even higher proportion of SSDI beneficiaries, 44 percent, filled at least one opioid prescription in 2011 (Morden et al. 2014). The comparatively high rate of opioid use among SSDI beneficiaries could be because many have serious health conditions, such as cancer, where opioid use might serve a therapeutic purpose. Further, a non-trivial proportion of SSDI beneficiaries have musculoskeletal conditions, which are also associated with opioid use (Mathieson et al. 2020).

If opioids deliver their intended therapeutic benefits, they could help facilitate work. Kilby (2015) finds that self-reported pain levels in hospital settings rise when states implement Prescription Drug Monitoring Programs intended to reduce opioid distribution (which may

[1] Our analysis sample includes those applying for disabled worker benefits, disabled adult child benefits, and disabled widow(er) benefits. Disabled worker benefits are paid out of the Social Security Disability Insurance Trust Fund, disabled adult child benefits are paid out of either the DI Trust Fund or the Old-Age and Survivors Insurance (OASI) Trust Fund, depending on whether the child's parent is disabled, retired, or deceased, and disabled widow(er) benefits are paid out of the OASI Trust Fund. Since these are all insurance payments based on disability, for simplicity we use the terms "Social Security Disability Insurance" and "SSDI" to include all three types of beneficiaries.

hinder the ability to work). There is also evidence that non-opioid pain relievers increase labor force participation and lower absenteeism (Garthwaite 2012; Bütikofer and Skira 2018).

However, there are also reasons to suspect that opioids could interfere with work. There is no evidence documenting the long-term effectiveness of opioids on pain and functioning (CDC 2016), and several studies show that opioids may worsen these outcomes (Frieden and Houry 2016). Opioids may also exacerbate problems with cognition and executive function (Schiltenwolf et al. 2014) and are associated with an increased risk of depression (Scherrer et al. 2016). In addition, opioids are associated with a high risk of dependence and abuse. Up to 26 percent of primary care patients who receive opioids for chronic pain become dependent (CDC 2016), and 21 to 29 percent of them misuse opioids (Vowles et al. 2015). Opioids were also responsible for more than 700,000 overdose deaths from 1999 to 2017 (CDC 2019). Further, Cutler et al. (2017) and Essak (2020) suggest that the wider availability of opioids is linked to increases in SSDI applications and awards.

Indeed, several studies document an association between opioids and a decline in employment-related outcomes. In the United States, Harris et al. (2019) document adverse effects on labor force participation, employment, and unemployment rates. They show that a 10 percent increase in county opioid prescriptions per capita reduces county-level labor force participation by 0.56 percentage points. Also in the United States, Aliprantis et al. (2019) finds that a 10 percent increase in local opioid prescription rates is associated with a decrease in the labor force participation rate of between 0.15 and 0.47 percentage points for men and between 0.15 and 0.19 percentage points for women. Likewise, Laird and Nelson (2016) document a notable effect of opioid prescription rates on labor force participation in Denmark. They find that a 10 percent increase in opioid prescriptions reduces labor force participation by 1.5 percentage points. Domestically, Krueger (2017) hypothesizes that as much as 20 percent of the observed decline in the male labor force participation rate between 1999 and 2015 might be attributed to an increase in opioid prescriptions. There are, however, also at least two United States studies that show null or some beneficial effects of opioids. Currie et al. (2019) find causal evidence of a positive effect of prescription opioids on employment for women – although no statistically significant relationship for men.

There are reasons to think that the relationship between opioids and employment might be different among those with disabilities. It is possible that opioids are overprescribed to the general population but appropriately prescribed to people with disabilities, who experience the potential benefits of opioids. However, if there is already a strained connection to work, it is also possible that opioids may have a notable harmful effect on employment outcomes among people with disabilities.

Overall, little is known about the relationship between opioids and employment outcomes among people with disabilities, and the existing literature yields somewhat conflicting results. Using state implementation of Prescription Drug Monitoring Programs as an instrument for individual opioid consumption, Kilby (2015) finds that a decrease in opioids is associated with increases in absenteeism among short-term disabled and injured workers. Savych et al. (2018) use local opioid prescribing patterns as an instrumental variable for opioid use and find no statistically significant effect of any opioid prescription within two years of injury on receipt of temporary disability; however, they find that longer-term opioid prescriptions – defined as three or more prescriptions in the second six months after an injury – triple the duration of temporary disability benefit receipt among workers with low back injuries. Harris et al. (2019) note that the relationship between opioid use, labor market outcomes, and disability is complicated, in part because it can be difficult to disentangle the causal relationship between opioids and disability.

We add to the literature by exploring the relationship between prescription opioids and employment outcomes among SSDI applicants. Specifically, we examine the following questions: (1) How do employment and earnings patterns differ between SSDI applicants who did and did not use opioids at the time of application? (2) What is the association between opioid use and employment outcomes among SSDI applicants? We focus on a cohort of individuals who applied for SSDI in 2009 and follow them for four years after their application outcome was determined.

We employ several estimation strategies to answer the second research question. Following Savych et al. (2018), we use county-level opioid prescribing patterns and opioid retail drug distribution by zip code as instrumental variables to estimate the causal effect of opioid use on employment outcomes. However, our instruments appear weak, and we are unable to draw causal conclusions. Rather, we refer to results from ordinary least squares and a reduced-form ordinary least squares regression that substitutes our would-be-instruments for an indicator of individual opioid use. Those results show a negative and statistically significant association between (1) self-reported opioid use at application and (2) post-determination employment and earnings outcomes. It is important to note that this study does not address the medical appropriateness of opioid use among SSDI applicants. Also, because we do not demonstrate a causal association, opioid use might be a proxy for the severity of a health condition.

Background

In 2019, more than 2 million Americans applied for SSDI Disabled Worker benefits (SSA 2020). To qualify, workers must have a sufficient work history in jobs covered by Social Security and must be younger than full retirement age. They must also have a physical or mental impairment – which has lasted or is expected to last for at least 12 months or result in death – that prevents substantial gainful activity (SGA). In 2021, SGA is defined as monthly work activity valued above $1,310 for non-blind beneficiaries. If awarded, beneficiaries receive cash benefits averaging about $1,100 per month and, generally after a two-year waiting period, Medicare.

The SSDI application process may involve several steps and last for a prolonged period. Applicants begin by applying online, at a local SSA office, or via a toll-free phone number. SSA staff work with staff at the applicant's state Disability Determination Services office to make an initial determination based on non-medical criteria and medical evidence. If the initial determination is a denial, an applicant may appeal up to four levels: (1) reconsideration by the state Disability Determination Services, (2) hearing by an administrative law judge, (3) Social Security Appeals Council review, and (4) federal court review. Historically, about 22 percent of applicants are awarded at initial determination, 11 percent are awarded after appeal, and 64 percent are denied (SSA 2019, Chart 11). As of December 2019, SSDI provided benefits to nearly 10 million former workers with disabilities and their dependents (SSA 2020).

SSDI beneficiaries qualify for the program based on a wide range of physical and mental conditions; however, drug addiction or alcoholism on its own cannot merit an SSDI award. Before 1996, drug addiction or alcoholism of a severity that prevented SGA could be the primary medical basis for an SSDI award, and addictions could also be a contributing factor for those with other disabilities. In 1996, Congress ended medical eligibility for beneficiaries for whom drug addiction or alcoholism was a contributing factor material to the finding of disability. This change affected about 90,000 SSDI beneficiaries, about 58 percent of whom lost benefits because of the policy change – either because they did not reapply or reapplied and were denied (Stapleton et al. 1998).[2]

Although neither substance abuse nor substance use are qualifying conditions for SSDI, we might expect that a notable portion of SSDI applicants and beneficiaries use prescription medications (such as opioids), because this population is likely to have conditions that are associated with opioid use. For example, 30 percent of SSDI beneficiaries have musculoskeletal conditions (SSA 2019, Table 6), which are associated with opioid use (Mathieson et al. 2020). Opioids may be prescribed for many other conditions, including cancer (2.8% of beneficiaries) and injury (3.5% of beneficiaries). Indeed, in 2011, 32 percent of SSDI applicants and 44 percent of SSDI beneficiaries reported opioid use (Wu et al. 2020; Morden et al. 2014).

It is well documented that the employment outcomes of SSDI applicants differ based on whether they are awarded or denied benefits. This association was first established when Bound (1989) reported that, in the 1970s, between 40 to 45 percent of rejected male applicants over age 45 worked at some point in the previous year, compared to 5.5 to 7.5 percent of beneficiaries. The same paper documented that employed rejected applicants had annual earnings more than five times larger than that of employed beneficiaries. Von Wachter et al. (2011) update Bound's work and find that these differences persisted in the 1980s and 1990s and also among males ages 30–44. Chen and van der Klaauw (2008) include applicants of both genders and find that, in the 1990s, 21 percent of rejected applicants were employed, compared to 7 percent of beneficiaries. Several other studies produced similar evidence (Maestas et al. 2013; French and Song 2014).

The difference in employment outcomes by award decision could occur because those who are awarded benefits meet the strict SSDI eligibility criteria, including the inability to engage in SGA, while those who are denied benefits do not. In addition, it is possible that awarded beneficiaries could restrict employment to receive SSDI benefits (Schimmel et al. 2011). Specifically, beneficiaries have their cash benefits suspended or withheld in months in which they engage in SGA – the same concept used to determine initial program eligibility. There are some exceptions that allow beneficiaries to test work and earn an unlimited amount in up to 12 months while retaining cash benefits; collectively, the trial work period and grace

[2] Prescription medications, including methadone and narcotic pain medications, taken as prescribed are not considered under DI's drug addiction or alcoholism policy.

period. In our analysis estimating the relationship between opioid use and employment outcomes among SSDI applicants, we stratify results by application outcome.

Data and Study Sample

Our analysis is based on four SSA administrative data sources: the Structured Data Repository (SDR), the Data Analysis Support Hub (DASH), the Master Earnings File (MEF), and the Numerical Identification System (NUMIDENT).

We derived a sample of individuals who applied to SSDI in 2009 from SSA's SDR. Since 2007, SSA has electronically stored data from SSDI and Supplemental Security Income (SSI) applications in the SDR.[3] We selected a 30 percent random sample of initial-level SSDI applications in 2009, based on their case establishment date. For those who submitted multiple applications in 2009, we selected the first application.[4] Thus, there was one application per applicant in our sample. The sample included applicants ages 18–67 at the time of application who applied for SSDI disabled worker benefits, disabled adult child benefits, and disabled widow(er) benefits. The sample includes those who applied for SSDI only as well as those who concurrently applied for SSI (a means-tested income support program for people with disabilities).[5]

We obtained data on application outcomes from SSA's DASH. SSA's Office of Research, Demonstration, and Employment Support developed DASH to consolidate reporting and further enhance analytical and reporting capabilities. This platform includes data on final adjudication decisions and adjudication dates, but it does not include all determinations.[6] We

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[3] The SDR does not include all SSDI applications. Specifically, cases that do not undergo the standard disability determination process are not included in the SDR. These may include second (and higher order) applications in which the new application provides no new information from the previous application. The SDR also excludes technical denials that are screened out through the electronic application process. The electronic application interactively checks eligibility criteria such as age, covered employment, and current employment and discontinues the application if basic criteria are not met. Our data also exclude incomplete applications, such as cases in which the claimant dies before adjudication begins or cases in which the claimant does not wish to pursue the claim.

[4] Our analysis is based on first application to consistently assess the relationship between opioid use and employment, rather than relying on a mix of initial applications (for those with just one application) and second or later applications for others.

[5] We included applicants, even those who applied close to their full retirement age (67 years old for those born in 1960 and later). It is helpful to note that this likely includes beneficiaries who are unlikely to be in the labor force during our analysis period.

[6] A comparison of the 2010–2017 DASH to the SDR over the same period shows that the DASH excludes about 8 percent of cases included in the SDR. The most common cases missing from DASH are those determined by a SSA field office, such as "no determination," "SGA denial," and "collateral estoppel" cases: cases in which there is a prior favorable determination that generally must be adopted for the same period of the new claim.

used 2009–2011 DASH data on the final determination decision and determination date and restricted the sample to those who had a final determination by the end of 2014.[7]

Information on all employment-related outcomes comes from SSA's MEF. The MEF captures annual earnings (wages and self-employment income) reported to the Internal Revenue Service and subject to Social Security taxes. Less than 1 percent of our SDR 2009 sample was not in the MEF; we treated those non-matched applicants to the MEF as zero earners.[8] Finally, we merged to SSA's Numerical Identification System (NUMIDENT) for information on death.

Our initial sample included 580,542 applicants who applied for SSDI with or without applying for SSI in 2009. We excluded 45,626 records (7.8 percent of the initial sample) because they did not have records in the 2009, 2010, or 2011 DASH files. Because we need to obtain the final determination decision and date from DASH files, we were unable to include these cases in our analysis. We excluded an additional 1,198 cases (0.2 percent of the initial sample) because their cases were determined after 2014, and we excluded 2,287 cases (0.4 percent of the initial sample) that did not have a valid decision and decision date recorded in DASH.

Our final sample included 531,431 applicants. Most applicants received determination decisions (after all potential levels of appeal) in the year of or year after application: 49 percent of applicants received the final determination decision in 2009, and 35 percent received the decision in 2010. For others, the determination process was prolonged: 13 percent received the decision in 2011, 2 percent received it in 2012, and 0.7 percent received it in 2013 or 2014. We describe the sample characteristics below in Table 1.

Method

Our analytic approach included three main steps: (1) identification – from the analytic sample of 2009 SSDI applicants – of those who self-reported opioid use at the time of application, (2) examination of the employment and earnings patterns of applicants by SSDI

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[7] Most of 2009 applicants have their determination information in 2009 DASH file; some spread to 2010 and 2011 DASH files.

[8] Our analysis sample includes those applying for SSDI worker benefits, who must have earnings recorded in the MEF to be eligible for benefit receipt, as well as applicants for disabled adult child benefits and disabled widow(er) benefits, who do not need to have SSDI-covered earnings to qualify for benefits.

award outcomes and opioid status, and (3) use of an instrumental variable approach to isolate the effect of opioids on employment.

Identifying Opioid Use

As part of an SSDI application, applicants are required to complete a disability report that collects information including medical conditions, work activity, education and training, job history, and medical treatment. Applicants are specifically asked about medications and asked to report any prescription or non-prescription medicines being taken at the time of application. Applicants who apply online may select medications from a pull-down list of 630 medication names, enter their medications in a free-text field, or both. Applicants who complete a paper application must list their medications in a free-text field.

Most applicants reported medications as free-text entries, a format that is not immediately ready for research. Among those in our analytic sample of 2009 applicants who reported medications, 35 percent did so exclusively in free text and another 50 percent used free text along with the pull-down list. Historically, using information entered in free-text fields required manual coding, which is time-consuming and prone to error, in order to be used in quantitative analysis.

To identify opioids in applicants' disability reports, we used a supervised machine-learning algorithm based on natural-language processing. This process included (1) separating free-text entries into individual tokens – single or multiple words that have meaning when grouped; (2) removing any tokens unlikely to be drugs, including those that started with a non-letter value, dictionary words, and common abbreviations; and (3) creating an algorithm to compare the remaining words to known lists of opioids. The algorithm included a certain tolerance for misspellings and phonetic spellings and underwent testing to fine-tune the approach. We ultimately achieved an accuracy rate of 99.9 percent when compared to a test sample manually coded by a pharmacist. We developed and used this method in previous work, which also provides more details about our algorithm (Wu et al. 2019, 2020). Using this approach, we created an application-level indicator for self-reported use of any opioids identified in the CDC's Oral Morphine Milligram Equivalents file and the National Library of Medicine's RxNorm.

Analyzing Employment and Earnings Outcomes by Opioid Use

We drew on wages and self-employment income in the MEF to describe the employment and earnings patterns for applicants in our analytic sample in the year their application was determined[9] and in the first four calendar years after that. Because determination could have occurred from 2009 through 2014, the window for employment and earnings outcomes ranges from 2009 through 2013 for those with cases determined in 2009 (49 percent of the sample) to as late 2014 through 2018 for those with cases determined in 2014 (0.2 percent of the sample).

We first constructed three outcome measures: (1) any employment, (2) average annual earnings, and (3) any engagement in annualized SGA. We determined any engagement in annualized SGA by comparing applicants' annual earnings to 12 times the SGA threshold for that year.[10,11] For example, in 2009, the annualized SGA amount was $11,760. We then used these measures to compare employment and earnings patterns among applicants stratified by opioid use as reported at application, determination decision, and gender.

Next, we examined the association between opioid use at SSDI application and subsequent employment outcomes, estimating the following ordinary least squares regression model:

$$Y_i = \beta_0 + \beta_1 \cdot Opioid_i + X_i\beta_2 + T_i\beta_3 + Y_{-2i}\beta_4 + \varepsilon_i \ (1)$$

In this model, Y_i is one of three employment outcomes for applicant *i*: (1) ever employed in any of the first four years after the year of determination; (2) the log of average earnings in the first four years after the year of determination,[12] and (3) any engagement in annualized SGA in any of the first four years after the year of determination. $Opioid_i$ is an indicator for self-reported opioid use at the time of application. X_i is a vector of baseline control variables including age, gender, education level, receipt of or planned medical care for a mental condition, concurrent application

[9] In this study, we define "determination" as including both determinations and decisions; it refers only to the final adjudication of the case after any appeals.
[10] The Social Security Act specifies a higher SGA amount for statutorily blind individuals, who account for about 2 percent of SSDI beneficiaries (Gubits et al. 2018). In 2009, the SGA threshold was $980 for non-blind beneficiaries and $1,640 for blind beneficiaries. Our data do not have information that allows us to identify statutorily blind applicants. Hence, we use the non-blind SGA amount for the entire sample.
[11] Because the MEF data measure annual earnings and SGA is measured on an annual level, our measure may incorrectly characterize beneficiaries relative to what would be recorded in SSDI administrative records for beneficiaries. However, administrative measures are not available for denied applicants.
[12] We use the log earnings because of the skewness of the earnings distribution. We add 1 for $0 in earnings when conducting the log transformation, because the log of 0 is infinity and the log of 1 is 0.

to SSI, geographic region, and the county-level unemployment rate. We also included the determination outcome as a baseline control variable in one specification of equation (1) and conduct alternate specifications in which we estimate separate regressions for those who were awarded and those who were denied benefits. T_i is a dummy variable for the year of SSDI application determination, and Y_{-2i} is employment outcome two years prior to benefit determination; controlling for employment outcomes prior to determination aims to guard against the Ashenfelter dip.[13] Finally, we tested a specification in which we excluded those who had died before the end of the fourth year after determination, because this group may have a different employment trajectory due to their health condition.

Instrumental Variable Approach

Applicants who reported using opioids at the time of application may differ from those who did not on important dimensions that are not observed in the data, and these differences may contribute to different employment outcomes. First, opioid use may increase with the severity of disability (which is unobservable but can adversely affect employment). In this scenario, the ordinary least squares estimates could incorrectly attribute adverse employment outcomes to opioid use, rather than to severe disability. Second, opioid use could be associated with unobserved differences in propensity to return to work. For example, workers who have a higher propensity for work might also be more likely to fill opioid prescriptions as a tool to facilitate their employment. Alternatively, workers less prone to work may be undeterred by the potential for opioids to interfere with work and seek opioid prescriptions. We do not know, a priori, the direction of this association and, hence, the direction of bias due to this unobserved propensity.

Accordingly, we used an instrumental variable approach to estimate the causal effect of opioid use on employment outcomes. Following the work of Savych et al. (2018), we used local prescribing patterns to instrument for individual opioid prescriptions. This approach assumes that local prescribing patterns influence whether an individual is prescribed opioids but do not directly affect employment outcomes. Specifically, we estimate the following first-stage regression:

$$Opioid_i = \alpha_0 + X_i\alpha_1 + T_i\alpha_2 + \alpha_3 LOPP_i + \upsilon_i \quad (2)$$

[13] The Ashenfelter dip refers to the empirical regularity that the mean earnings of participants in employment and training programs generally decline in years prior to intervention. In our situation, controlling for the employment and earnings outcomes at two-year prior to the determination helps captures the pre-trends before the determination.

We used two data sources and constructed three different instruments, $LOPP_c$, for applicant *i*. First, we measured 2009 local prescribing patterns using county prescribing rates, which record the annual retail opioid prescriptions dispensed per 100 persons (CDC 2020).[14] These rates are available for 87.5 percent of U.S. counties. Counties may be excluded if they had no retail pharmacies, if no pharmacies in the county were sampled, or if the prescriptions were attributed to a more populous adjacent county. The excluded counties tend to be sparsely populated, and this measure was available for 98.5 percent of our sample.[15] Prescribing rates for opioids varied widely across counties, ranging from 1 prescription per 100 persons in Chambers County, Texas, to 520 prescriptions per 100 persons in Martinsville, Virginia. To account for the skewness of the data, we took the logarithm of CDC county prescribing rates.

The other data source we used is based on the Drug Enforcement Administration's Automated Reports and Consolidated Ordering System (ARCOS). Drug manufacturers and distributors are required to report sales of certain controlled substances, including opioids, through ARCOS in an effort to identify illegal activity and combat the opioid epidemic. ARCOS reports retail drug distribution at the three-digit zip code level, which generally represents larger areas than do counties, but information is available for nearly all (99.9 percent) three-digit zip codes.[16]

We constructed two versions of instrumental variables based on ARCOS data; both draw on ARCOS data for opioid drugs that were tracked by ARCOS and also in CDC's list of opioids. The first version is the logarithm of the total weight of retail opioid drugs distributed in each three-digit zip code in 2009, divided by the population in the 3-digit zip code. The second version is calculated using a weighted total incorporating morphine milligram equivalents (MME) factors, hence giving more weight to opioid drugs that have a higher MME.

In the second stage of our two-stage least squares estimation, we regress employment outcomes on all exogenous regressors in equation (1) except opioid use [equation (3)]. Rather,

[14] Opioid prescriptions include buprenorphine, codeine, fentanyl, hydrocodone, hydromorphone, methadone, morphine, oxycodone, oxymorphone, propoxyphene, tapentadol, and tramadol. Cough and cold formulations containing opioids and buprenorphine products typically used to treat opioid use disorder, as well as methadone dispensed through methadone treatment programs, were not included.
[15] The sample members who were counties that were excluded from CDC data were excluded from our instrumental variable and reduced form analyses.
[16] About nine percent of our analysis sample had more than one addresses in our data. Multiple addresses occurred because some applicants updated their address when appealing a determination decision. We are unable to distinguish which address are linked with the initial application from those associated with the appeal. In these cases, we used an algorithm to randomly select an address to be used.

the predictions of opioid use at the individual level ($\widehat{Opioid_i}$) are included in the second stage model.

$$Y_i = \beta_0 + \beta_1 \cdot \widehat{Opioid_i} + X_i\beta_2 + T_i\beta_3 + Y_{-2i}\beta_4 + \varepsilon_i \text{ (3)}$$

We estimate the two-stage least squares separately for each instrumental variable. As with all instrumental variable analyses, we were unable to assess the validity of our instruments at the outset of analysis. However, as mentioned in the introduction and described in more detail when we discuss and interpret results, we believe the instruments suffer from weak instrument bias.

The Reduced-Form Regression

We also estimate the reduced-form ordinary least squares regression of association between local opioid prescribing patterns and the subsequent employment outcomes:

$$Y_i = \beta_0 + \beta_1 \cdot LOPP_c + X_i\beta_2 + T_i\beta_3 + Y_{-2i}\beta_4 + \varepsilon_i \text{ (4)}$$

The advantage of this approach is that the local opioid prescribing pattern could be correlated with the probability of an individual's reported opioid use but does not suffer from the endogeneity concerns associated with using the measure of individual-level opioid use. The reason for this is that local opioid prescribing patterns are independent of important unobservables of individual employment behaviors, like severity of disability and propensity to work. In this analysis, we account for other local economic indicators, such as the county unemployment rate. As described previously, $LOPP_c$ is local opioid prescription pattern, which takes the form of one of three instrument variables we constructed for applicant *i*: (1) the logarithm of county prescribing rates based on CDC data, (2) the logarithm of the per-capita weighted sum of retail opioid drugs distributed in the 3-digit zip code based on ARCOS data, and (3) the logarithm of the per-capita weighted sum using MME factors of retail opioid drugs distributed in the 3-digit zip code.

Results

Characteristics of SSDI Applicants

In Table 1, we present characteristics of the analytic sample by application outcomes and opioid use at the time of application. The majority of the sample (54.8 percent) were awarded benefits. The first two columns show the characteristics for beneficiaries by opioid use, and the next two columns show the same for denied applications. Overall, 30.3 percent of our sample reported using opioids at the time of application. Opioid use was higher among those awarded benefits: 34.0 percent among beneficiaries versus 25.8 percent among denied applicants. This result is consistent with Wu et al. 2020, which finds that applicants who reported opioid use are statistically more likely to be awarded benefits. In both studies, the relationship between opioid use and award is descriptive and does not indicate causality.

Allowed SSDI applicants differed from denied applicants across several domains (Table 1). Beneficiaries were generally less healthy: they were more likely to die by the fourth year after the determination. Beneficiaries also had a higher likelihood of visiting a physician for physical conditions compared to denied applicants; however, they were less likely to visit a physician for a mental condition. Beneficiaries were less likely to be employed or to have earned above SGA at the calendar year of application. These outcomes are consistent with the design of SSDI, which is meant to support those with the most severe disabilities impacting work. There are other observed differences between allowed and denied applicants, such as those in education, gender, and SSDI only application. There are also presumably unobserved differences, which reinforces the need to estimate the relationship between opioids and employment separately by award status.

Applicants who self-reported using opioids at the time of SSDI application differ from those who did not, regardless of award decision. Relative to applicants who did not report opioid-use at the time of application, opioid users were more likely to be female and were more likely to be SSDI only applicants. These findings are consistent with our prior work (Wu et al. 2020). As indicated by several measures, applicants who used opioids were also in poorer health compared with non-users. They were more likely to be a recipient of or have planned medical care for a physical condition (99.9 percent versus 96.8 percent for beneficiaries; 99.7 percent versus 92.0 percent for denied applicants) and to die by the fourth year after determination (17.6 percent versus 14.3 percent for beneficiaries; 6.0 percent versus 5.4 percent for denied applicants), but they were less likely to visit a physician for a mental condition (37.8 percent versus 40.6 percent for beneficiaries; 40.9 percent versus 45.1 percent for denied applicants).

Table 1. *Characteristics, by Determination Outcome and Opioid Use*

Characteristic	Beneficiaries			Denied applicants		
	Reported opioid use	Did not report opioid use		Reported opioid use	Did not report opioid use	
Average age	49.76	49.07	***	42.23	41.24	***
Female (%)	48.48	44.25	***	52.26	47.11	***
Education[a]			***			***
Less than high school (%)	20.01	22.77		25.02	29.33	
High school (%)	47.20	46.29		47.98	47.07	
Some college (%)	22.14	19.31		20.78	17.01	
College and above (%)	10.10	11.12		6.12	6.38	
Missing education (%)	0.54	0.52		0.10	0.22	
SSDI only applicants(%)	63.17	56.56	***	40.73	32.92	***
Receipt of or planned medical care for a physical condition (%)	99.86	96.79	***	99.71	92.01	***
Receipt of or planned medical care for a mental condition (%)	37.81	40.60	***	40.89	45.06	***
Died by the fourth year after determination (%)	17.59	14.33	***	6.01	5.36	***
Employed in the calendar year of application (%)	36.06	37.56	***	44.71	47.24	***
Average earnings in the calendar year of application ($)	4,219	4,147		4,730	4,088	***
Proportion earned above SGA in the calendar year of application (%)	11.12	10.15	***	13.83	11.13	***
Number of observations	99,091	192,125		62,040	178,175	

Note: *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.
[a] chi-square test is conducted on categorical variables.
Source: Authors' calculation based on 2009 Structured Data Repository data merged with 2009–2011 Data Analysis Support Hub and Master Earnings File data.
SGA = substantial gainful activity.

Opioid users were less likely than non-opioid users to be employed at calendar year (2009) of application (36.1 percent versus 37.6 percent for beneficiaries; 44.7 percent versus 47.2 percent for denied applicants). We find that, while there is no statistically significant difference in average earnings at the time of application for beneficiaries who used opioids relative to non-opioid users, denied opioid users earned more relative to denied non-opioid users ($4,730 versus $4,088). Both allowed and denied opioid users were more likely to have earned above SGA relative to non-opioid users (11.1 percent for allowed opioid users versus 10.2 percent for allowed non-users; 13.8 percent for denied opioid users versus 11.1 percent for denied non-users). Differences in characteristics by opioid use and award status may contribute to some of differences we see in employment outcomes, so it is important to control for these observable differences in the subsequent analysis.

Post-Determination Employment and Earnings Patterns by Opioid Use

In this section, we present post-determination employment and earnings patterns by determination decision and by opioid use at application. In Figure 1, we present employment rates in the year of and in the first four years after determination.

Across the four applicant groups (awarded opioid user, awarded opioid non-user, denied opioid user, and denied opioid non-user), the employment rate declined over time. The most notable decline was among beneficiaries: the employment rate in the year after determination was less than half the rate in the year of determination and continued to gradually fall for the next three years.

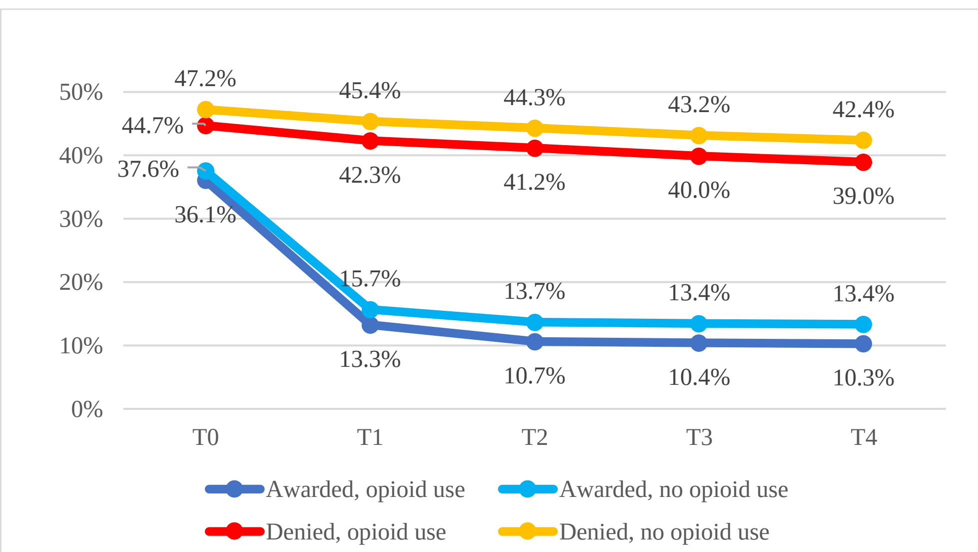
The decline in employment after determination was primarily influenced by beneficiaries whose cases were determined in the same year of the application (Appendix, Figure A1). Among beneficiaries with 2009 applications and determinations, 55 percent of opioid non-users and 58 percent of opioid users were employed in 2009 and 16 and 18 percent were employed in 2010, respectively. This could signal that the onset of disability interfered with their ability to work. Further, many worked partially in the year they applied. Their partial year earnings and employment in 2009 mostly reflects the pre disability determination period and 2010 represents a full post disability determination earnings period.

Among beneficiaries who learned of their award in 2010 or later, the employment rate was already low at the calendar year of determination and the decline was much less pronounced. For example, among beneficiaries who had cases determined in or after 2011, employment rates ranged between 12 to 15 percent in the year of determination and fell slightly to 11 to 13 percent four years after determination.

Beneficiaries continued to have lower employment rates than denied applicants in the year of and each of the first four years after determination (Figure 1). The gap in employment across beneficiaries and denied applicants grew over time as the employment rate among beneficiaries declined. In the year of determination, denied applicants were about 9 percentage points more likely than beneficiaries to be employed, while in the fourth year after determination, denied applicants were about 29 percentage points more likely to be employed than beneficiaries.

Among both awarded and denied applicants, those who self-reported using opioids at the time of application were less likely to be employed compared to non-opioid users. For example, in the year of determination, 47 percent of denied applicants who did not report opioid use were employed compared to 45 percent of denied applicants who reported opioid use. This difference persisted and gradually increased over time to about a 3-percentage point difference. A similar pattern exists among beneficiaries. In the year of determination, 38 percent of beneficiaries who did not report opioid use were employed, compared to 36 percent of awarded opioid users. In the fourth year after determination, 13 percent of those who did not report opioid use and 10 percent of opioid users were employed.

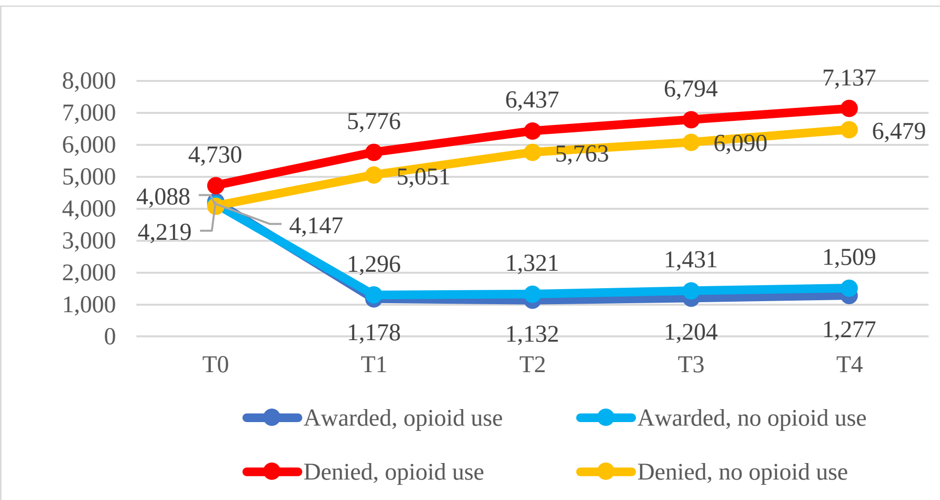
Figure 1. *Proportion Employed, by Determination Outcome and Opioid Use*



Note: T0 represents the year of determination; T1 represents the first year after determination; T2 represents the second year after determination; T3 represents the third year after determination; and T4 represents the fourth year after determination. All differences by determination outcome and by opioid use are statistically significant at 1 percent level.
Source: Authors' calculation based on 2009 Structured Data Repository data merged with 2009–2011 Data Analysis Support Hub and Master Earnings File data.

Among those awarded benefits, earnings followed a somewhat similar pattern as employment: total annual earnings were highest in the year of determination and fell sharply in the first year after determination (Figure 2).[17] After that point, however, earnings gradually increased in each year. This suggests that those who remain employed are those with higher earnings. Average annual earnings for opioid and non-opioid users awarded benefits were similar in the year of determination, but those without opioid use had earnings that were higher in each of the four years after determination. For example, in the fourth year after determination, beneficiaries who did not use opioids earned an average of $1,509, compared to $1,277 among beneficiaries who reported opioid use at the time of application.

Figure 2. *Mean Annual Earnings, by Determination Outcome and Opioid Use*



Note: T0 represents the year of determination; T1 represents the first year after determination; T2 represents the second year after determination; T3 represents the third year after determination; and T4 represents the fourth year after determination. All differences by determination outcome and by opioid use are statistically significant at 1 percent level, except among awardees by opioid use at T0.
Source: Authors' calculation based on 2009 Structured Data Repository data merged with 2009–2011 Data Analysis Support Hub and Master Earnings File data.

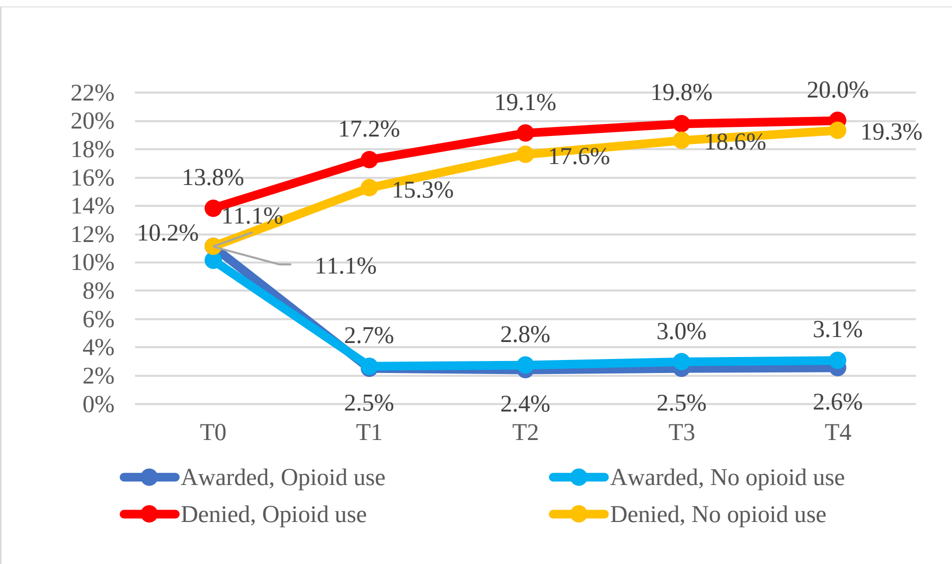
The relationship between earnings and opioid use among denied applicants was different than the relationship between earnings and opioid use among beneficiaries. Earnings were higher among denied applicants who use opioids than for denied applicants who did not use opioids (Figure 2). In the year of determination, denied applicants who used opioids had

[17] Again this also reflects the annual nature of the earnings data in that the year of award includes pre-disability months. Earnings will be small for those who apply early in the year and larger for those who apply later.

earnings that were about 16 percent higher than among denied applicants who did not use opioids ($4,730 versus $4,088), and an earnings gap persisted through the fourth year after determination. These differences are almost entirely driven by male applicants (Appendix, Figure A2).[18]

Like the pattern we observe for mean earnings, we find that the proportion that earned above SGA is highest for denied opioid users (Figure 3). Among denied applicants, the gap between opioid users and non-users is largest in the year of determination (13.8 percent versus 11.1 percent, respectively) and begins to converge over the subsequent four years. Among beneficiaries, non-opioid users are slightly more likely to have earned above SGA post SSDI determination.

Figure 3. *Proportion Earned Above SGA, by Determination Outcome and Opioid Use*



Note: T0 represents the year of determination; T1 represents the first year after determination; T2 represents the second year after determination; T3 represents the third year after determination; T4 represents the fourth year after determination. All differences by determination outcome and by opioid use are statistically significant at 1 percent level.
Source: Authors' calculation based on 2009 Structured Data Repository data merged with 2009–2011 Data Analysis Support Hub and Master Earnings File data.

[18] Appendix Figure A2 describes the post-determination employment and earnings patterns by gender. We find that denied female non-users are slightly more likely to be employed than their male counterparts, but they earn less. The pattern of higher earnings for denied opioid users is primarily driven by males. For males who were denied and used opioids at application, annual earnings are about $5,406 at the year of determination and $8,677 four years after determination. The corresponding numbers for males who were denied and did not use opioids are $5,018 and $7,055.

Collectively, these trends suggest a negative correlation between self-reported opioid use and employment and earnings outcomes among beneficiaries, but a positive correlation between opioid use and earnings among denied applicants. However, these relationships appear to vary based on factors other than opioid use, including determination year and gender (Appendix, Figures A1 and A2). In the next section, we estimate the relationship between opioid use and employment outcome, controlling for gender and determination year as well as other observable characteristics that potentially influence employment and earnings.

Association between Opioid Use and Employment and Earnings Outcomes: Ordinary Least Squares Estimates

The results of the regression model presented in equation (1) indicate that opioids generally have either a negative or no association with employment-related outcomes (Table 2). Opioid use at the time of application was associated with a decline of 3 percentage points in the likelihood of any employment in the first four years after determination. This decline is statistically significant at the 1 percent level and represents a 7.5 percent decline relative to the mean employment rate of 39.8 percent in this period. The estimated association between opioids and employment was the same among the sample excluding those who died by the end of the fourth year after determination, and only looked at beneficiaries, but was slightly larger among denied applicants.[19] All estimates were statistically significant.

Opioid use was associated with statistically significant lower earnings. Specifically, opioid use at the time of application was associated with a 24 percent decline in earnings over the four-year period. The magnitude of the reduction in earnings was slightly smaller among the sample excluding those who died by the end of the fourth year after determination and among the sample of all beneficiaries. The decline was larger for denied applicants, with a 29 percent decline in earnings over the four-year period. All estimates were statistically significant.

Opioid use was associated with a statistically significant reduction in SGA engagement in all specifications. Among all applicants, opioid use was associated with a 1 percentage point decline in SGA that was statistically significant at the 1 percent level. This represents a 6 percent reduction relative to the 16.4 percent of all applicants who engaged in SGA. This

[19] We also tested by awarded decision and excluding those who died by T4. The results are largely similar.

association held among those who were alive through the end of the analysis period – although it was smaller in magnitude – as well as for both awarded and denied applicants.

Consistent with what we observed from descriptive patterns, SSDI award is negatively associated with post-determination employment outcomes. For example, being awarded benefits was associated with a decline of 32 percentage points in the likelihood of any employment in the first four years after determination. This decline is statistically significant at the 1 percent level. The difference could occur because those who are awarded benefits are unable to engage in SGA, whereas this might not be true of denied applicants, also, awarded beneficiaries may restrict employment to maintain eligibility for SSDI benefits. We also find that pre-determination employment outcomes are positively correlated with post-determination employment outcomes. Those who worked two years before determination are 23 percentage points more likely to work in the first four years after determination.

Table 2. *Association between Applicant Opioid Use in 2009 and Post-Determination Employment and Earnings Outcomes*

	All sample applicants (N=531,431)		Excluding applicants who died by T4 (N=473,188)		All beneficiaries (N=291,216)		All denied applicants (N=240,215)	
Any employment at T1, T2, T3, or T4								
Any opioid use	-0.03	***	-0.03	***	-0.03	***	-0.04	***
Awarded benefit	-0.32	***	-0.32	***	---	---	---	---
Outcome at two years before determination	0.23	***	0.23	***	0.14	***	0.30	***
Mean earnings in T1 through T4[a]								
Any opioid use	-0.24	***	-0.22	***	-0.22	***	-0.29	***
Awarded benefit	-3.03	***	-3.05	***		---		---
Outcome at two years before determination	0.22	***	0.23	***	0.12	***	0.33	***
Ever earned above SGA at T1, T2, T3, or T4								
Any opioid use	-0.01	***	-0.00	***	-0.01	***	-0.01	***
Awarded benefit	-0.24	***	-0.25	***	---	---		---
Outcome at two years before determination	0.24	***	0.15	***	0.04	***	0.26	***

Note: *** Statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.
[a] The logarithm of mean earnings in T1 through T4.
T refers to year of SSDI application determination.
SGA = substantial gainful activity.

Instrumental Variable Estimates

We implemented an instrumental variable approach to isolate the variation in individual opioid use driven by local prescribing patterns, rather than by individual characteristics or preferences. For this approach to be valid, two key underlying assumptions for the instrumental variable estimate must hold. First, the instrument must be relevant. That is, local opioid prescribing patterns must have a demonstrable effect on applicant opioid use. Second, the instrument must be exogenous. That is, local prescribing patterns should not affect employment outcomes other than indirectly through applicant opioid use.

We present the first-stage results in Table 3, which help inform the instrument relevance. As discussed in the method section, we estimate separately for each instrumental variable and for each sample we explored. The table shows that all three instruments are associated with a statistically significant increase in the likelihood of self-reported opioid use among all analysis samples and instruments. The first-stage regression yields *F*-statistics at 37 or above, which are well above the benchmarks for instrument strength (Stock and Yogo 2005). However, the magnitude of the estimates is small. The largest estimate implies that a 10 percentage point increase in the local area opioid prescribing rate is associated with a 0.6 percentage point increase in the likelihood that SSDI applicants reported any opioid prescriptions at the time of the application. Overall, these results raise concern about the strength of our instrument. Note that we also tested versions of the instruments that were not logged and found qualitatively similar results.[20]

While we cannot directly test the exclusion restriction, we believe that local prescribing patterns are not correlated with unobserved individual characteristics that affect applicant employment outcomes, conditional on the controls. Notably, we control for the county-level unemployment rate, which may affect both the local prescribing patterns and employment outcomes.

[20] Because the weak instrument bias tends to get worse as we add more weak instruments, we did not use more than one instrumental variable in our equation.

Table 3. *First-Stage Ordinary Least Squares Estimates*

	All sample applicants (N=531,431)		Excluding applicants who died by T4 (N=473,188)		All beneficiaries (N=291,216)		All denied applicants (N=240,215)	
	Coef	*F*-value	Coef	*F*-value	Coef	*F*-value	Coef	*F*-value
The logarithm of county prescribing rates, CDC data[a]	0.06***	118	0.06***	114	0.06***	105	0.06***	106
The logarithm of the per-capita weighted sum of retail opioid drugs distributed in the 3-digit zip code, ARCOS data[b]	0.04***	62	0.04***	61	0.05***	65	0.04***	47
The logarithm of the per-capita weighted sum using MME factors of retail opioid drugs distributed in the 3-digit zip code, ARCOS data[b]	0.03***	47	0.03***	44	0.04***	51	0.03***	37

Note: *** Statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.
[a] Standard errors clustered at county level.
[b] Standard errors clustered at the 3-digit zip code level.
T refers to year of SSDI application determination.
ARCOS = Automated Reports and Consolidated Ordering System; CDC = Centers for Disease Control and Prevention; MME = morphine milligram equivalents.

In Table 4, we present the two-stage least squares (2SLS) estimates of the effect of any self-reported opioid use on employment outcomes among the entire analytic sample using CDC county-level prescribing patterns as an instrument. We find that the sign of our 2SLS estimates is the same as the ordinary least squares (OLS) estimates presented in Table 2, but the magnitudes are much larger. For example, OLS shows that opioid use at the time of application is associated with a 3 percentage point decline in the likelihood of any employment in the first four years after determination, while 2SLS estimate shows a 32 percentage point decline. The magnitudes of the 2SLS estimates heighten our concerns about the validity of our instrumental variables. Because the correlation (and, therefore, also the covariance) between the instrument and the endogenous variable is small, the IV may suffer from weak instrument bias. The weak correlation between the IV and the endogenous variable may lead to serious bias in the 2SLS estimates (Bound et al. 1995).

Although 2SLS estimates can be larger than OLS estimates, our concerns about the instrument remain. Specifically, 2SLS estimates the local average treatment effect (LATE), while OLS estimates the average treatment effect (ATE). Differences between LATE and ATE estimates may arise due to the heterogeneity in the studied sample. Applied to our analysis, the population for whom the IV has any influence could be different from the general population, and the impact of opioid use on this population is larger. However, the magnitude of the difference we observe is difficult to explain by the difference between LATE and ATE.

The estimates based on retail drug distribution by zip code (ARCOS) are presented in Appendix Table B1 and are largely consistent with the estimates using CDC county-level prescription rates as an instrument. Hence, we believe that all three instrument variables we constructed suffer from weak instrument bias that lead to improbably large 2SLS estimates.

Reduced-Form Model Estimates

In Table 4, we also present the reduced form model estimates of the relationship between local opioid prescribing patterns and employment outcomes, as well as a comparison with the OLS and 2SLS estimates. As we discussed in the previous section, the reduced form approach enables us to correlate the local opioid prescribing pattern with the probability of an individual's reported opioid use but does not suffer from the endogeneity concerns associated with using the measure of individual-level opioid use. The reduced form estimates show that a 10 percent increase in local opioid prescribing rate per 100 persons is associated with a 0.2 percentage point decline in the likelihood of any employment in the first four years after determination, a 1.8 percent decline in earnings over the four-year period, and a 0.2 percentage point decline in the likelihood of earning above SGA. In Appendix Table B1, we summarize the reduced form estimates using the other two instrument variables based on ARCOS data. The results across all three reduced form estimates are largely consistent.

Table 4. *Estimates from OLS, 2SLS, and Reduced Form Regressions Using All Sample Members (N=531,431), CDC Data as Instrument*

	OLS estimates		**IV estimates** The logarithm of county prescribing rates, CDC data		**Reduced form estimates**	
Any employment at T1, T2, T3, or T4						
Any opioid use	-0.03	***	-0.32	***		
Local opioid prescribing patterns					-0.02	***
Awarded benefit	-0.32	***	-0.30	***	-0.32	***
Outcome at two years before determination	0.23	***	0.23	***	0.23	***
Mean earnings in T1 through T4[a]						
Any opioid use	-0.24	***	-3.01	***		
Local opioid prescribing patterns					-0.18	***
Awarded benefit	-3.03	***	-2.85	***	-3.04	***
Outcome at two years before determination	0.22	***	0.23	***	0.22	***
Ever earned above SGA at T1, T2, T3, or T4						
Any opioid use	-0.01	***	-0.29	***		
Local opioid prescribing patterns					-0.02	***
Awarded benefit	-0.24	***	-0.22	***	-0.24	***
Outcome at two years before determination	0.14	***	0.15	***	0.14	***

Note: The IV and reduced form estimates for subgroups are available from authors upon request.
*** Statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.
[a] Mean earnings are in logarithm form.
T refers to year of SSDI application determination.
CDC = Centers for Disease Control and Prevention; IV = instrumental variable; OLS = ordinary least squares; SGA = substantial gainful activity; 2SLS = two-stage least squares.

Discussion

This paper contributes to our understanding of the relationship between self-reported opioid use and employment outcomes among individuals with disabilities. To our knowledge, this is the first study to investigate this relationship among SSDI applicants. Among a cohort of SSDI applicants who applied for the program in 2009, we find lower rates of employment and earnings among beneficiaries who reported opioid use compared to those who did not. Among denied applicants, we find that opioid users are less likely to be employed, but, among those who are employed, earnings are higher. However, these relationships could vary based on factors other than opioid use, such as gender and the length of time between application and determination; this variation emphasizes the importance of controlling for these characteristics.

Controlling for characteristics observable in our data, estimates from OLS, 2SLS, and reduced form models suggest a negative and statistically significant association between (1) self-reported opioid use at application and (2) post-determination employment and earnings outcomes. While the magnitude of coefficients varies across different models, these observed relationships consistently suggest that opioid use (and local opioid availability) negatively relates to post-determination employment outcomes among SSDI applicants. This relationship holds among all sample members, in the subsample for which we excluded those who had died before the end of the fourth year after determination, and separately among beneficiaries and applicants who were denied benefits.

The magnitude of our OLS and reduced form estimates is similar to estimates for the broader population; we do not focus on the results of our 2SLS estimates because of their weak relationship with individual opioid use and the notably larger magnitude of the results in comparison to the OLS estimates. Among the larger population of people with and without disabilities, previous research has found that a 10 percent increase in opioid prescriptions reduces labor force participation by 0.2 to 0.6 percentage points (Harris et al. 2019; Aliprantis et al. 2019). Our results suggest that a 10 percent increase in the local opioid prescribing rate is associated with, at most, a 0.3 percentage point decline in employment. Although our results are not directly comparable for several reasons – including that the previous literature focused on labor force participation rather than employment – they suggest that, for SSDI applicants, opioid use has a negative association with employment that is similar in magnitude to the broader population of people with and without disabilities in the United States.

Limitations

When interpreting our results, it is important to recognize several limitations of the analysis. First, because the SDR has limited research-ready data on the characteristics of applicants, our estimates of the relationship between opioid use and subsequent labor market outcomes do not control for several factors that may be important determinants of post-determination employment outcomes – such as the applicant's type of impairment, overall health status, and work history.

In addition, the statistics in this paper are based on self-reported opioid use among applicants. Generally, survey respondents tend to underreport stigmatized behaviors, and there is a documented tendency of drug users to underreport drug use in surveys, particularly illicit drug use (Center for Behavioral Health Statistics and Quality 2014; Fendrich et al. 2004). Although our data are from administrative rather than survey data, it still seems likely that non-prescription opioid use is underreported, and it is also possible that the degree of underestimation varies by applicant subgroup. This measurement error may contribute to estimation bias.

Finally, we are not able to produce causal evidence on the relationship between opioid use and employment outcomes, because our instruments suffer from weak instrument bias that leads to improbably large and hard to interpret 2SLS estimates. It is also possible that the exclusion restriction is not satisfied even though we control for a host of individual-level characteristics and county-level unemployment rates. For example, local prescribing patterns may proxy for unobserved local area characteristics, such as pessimistic expectations of the economy that may influence both opioid use and employment outcomes. In OLS estimates, self-reported opioid use may be a marker for unobserved dimensions of disability severity or for unobserved worker characteristics related to employment and earnings outcomes.

Conclusion

This study represents an important first step in documenting the association between opioid use and employment outcomes among SSDI applicants. While the association for this subgroup appears to be similar to that the larger population, the implications are particularly important for SSDI applicants. SSDI applicants include a larger share of opioid users than in the broader population. In 2016, 29 percent of this group self-reported opioid use (Wu et al. 2020), compared to 19 percent of the U.S. population (Mytelka et al. 2018). Hence, any adverse associations with employment outcomes will be particularly pronounced among SSDI applicants.

We find that the negative association between self-reported opioid use and post-determination employment and earnings holds among both awarded and denied applicants. This finding suggests that future research can inform SSA about several aspects of the SSDI program. For instance, a better understanding of the role of opioids in employment may lead to a better understanding of employment trajectories for SSDI beneficiaries. Future research could also investigate whether opioid use might contribute to SSDI reapplication.

Finally, although the results point to a negative association between opioid use and employment outcomes, this study does not address the medical appropriateness of opioid use among SSDI applicants. Rather, it focuses on the employment and earnings effects of opioid use for this population. Because we do not demonstrate a causal association, our measures of opioid use could be conflated with unmeasured factors, such as disability severity or attachment to the labor force.

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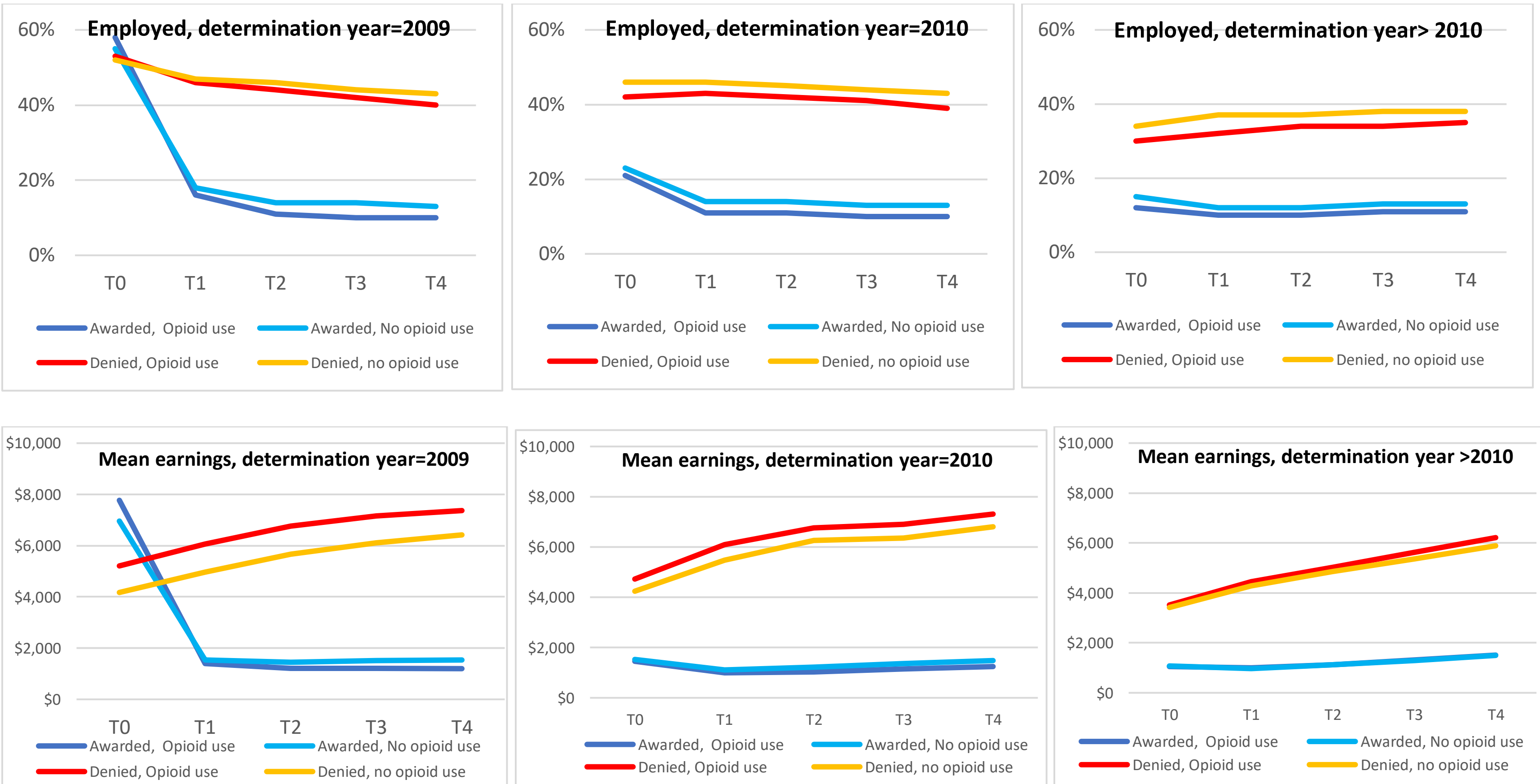
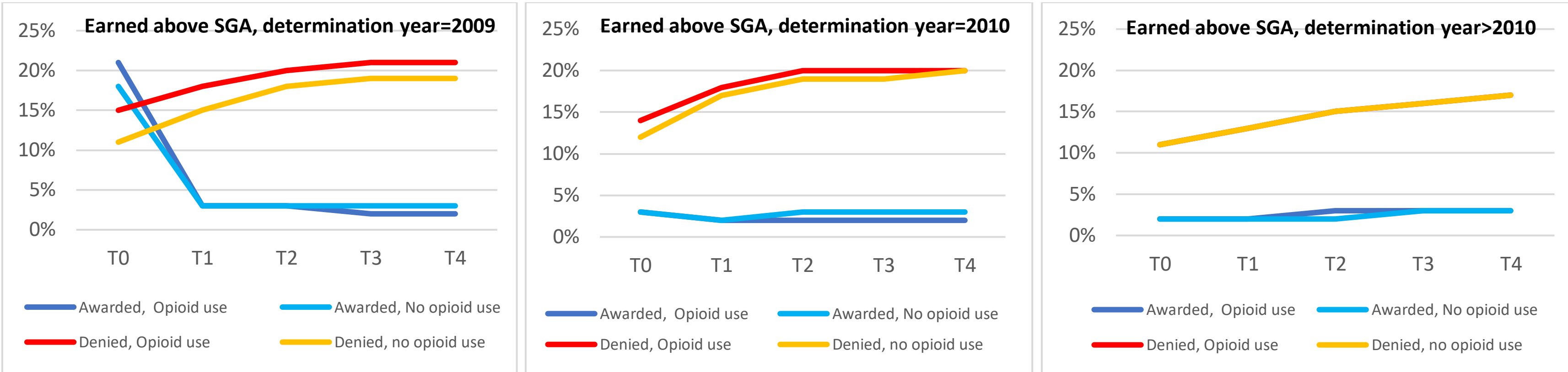
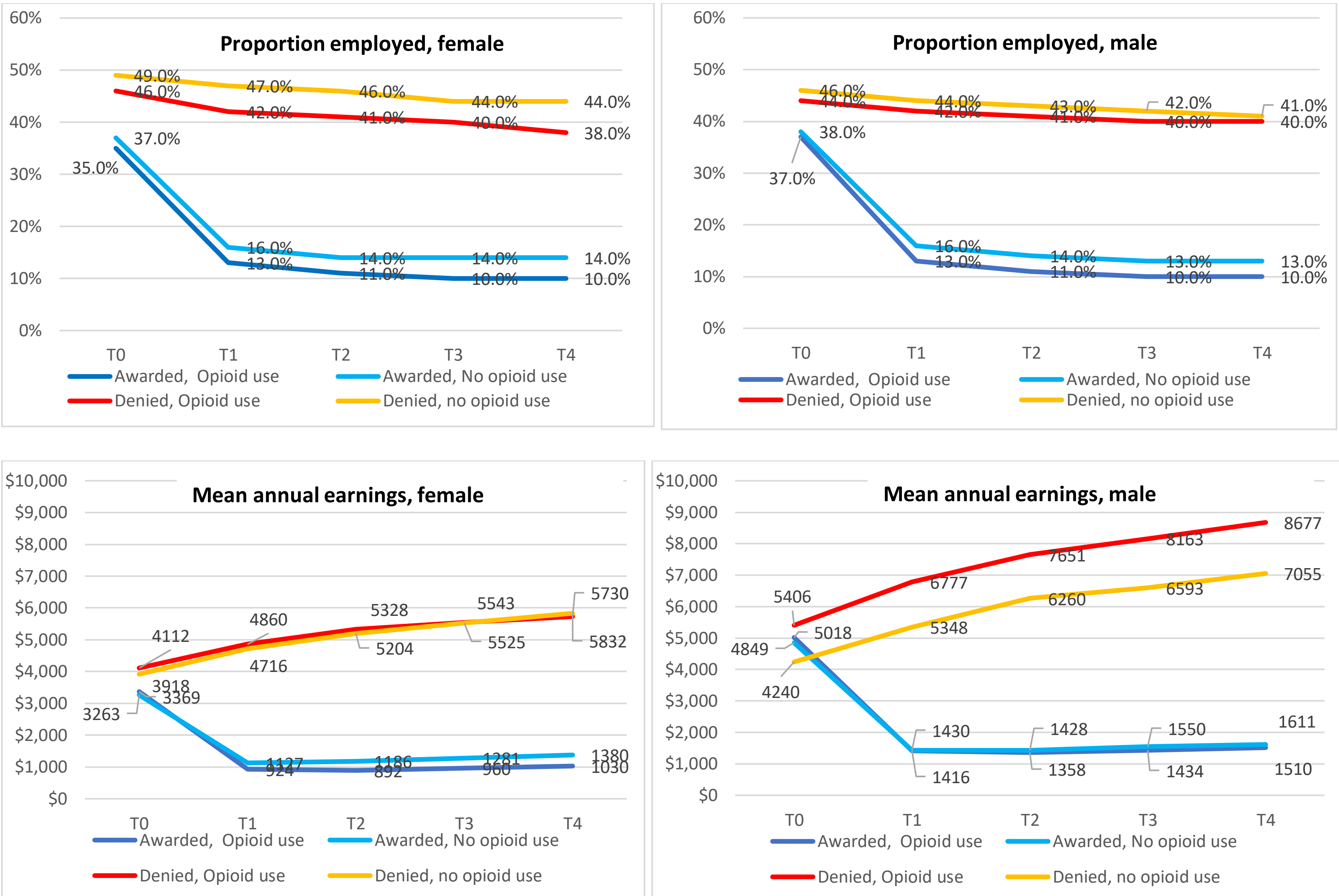
Appendix Figure A1. *Employment and Earnings Outcomes, by Determination Year*

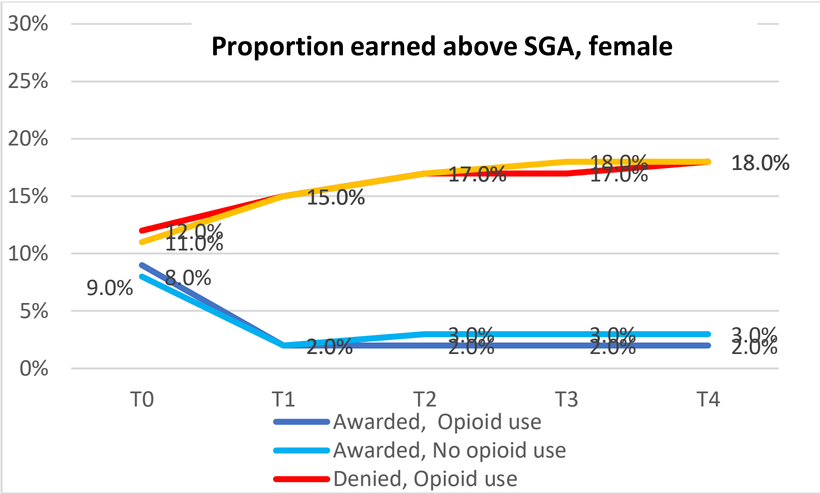


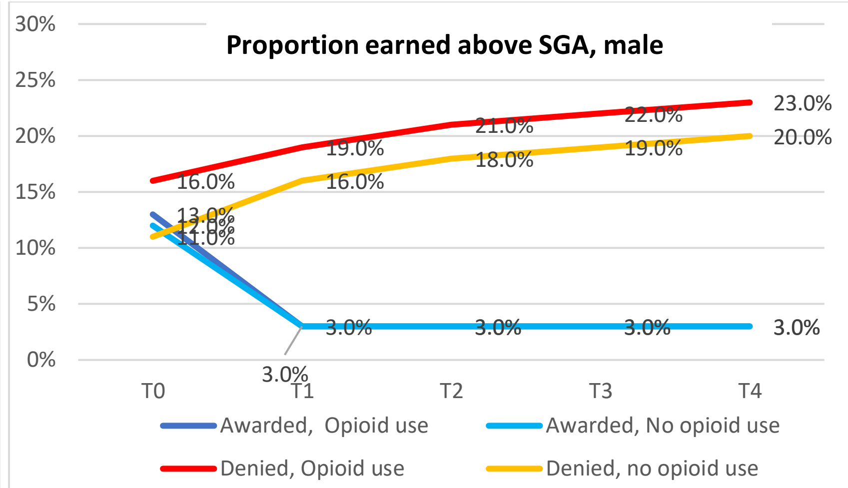


Note: T0 represents the year of determination; T1 represents the first year after determination; T2 represents the second year after determination; T3 represents the third year after determination; T4 represents the fourth year after determination.
Source: Authors' calculation based on 2009 Structured Data Repository data merged with 2009–2011 Data Analysis Support Hub and Master Earnings File data.

Appendix Figure A2. *Employment and Earnings Outcomes, by Gender*







Note: T0 represents the year of determination; T1 represents the first year after determination; T2 represents the second year after determination; T3 represents the third year after determination; T4 represents the fourth year after determination.

Source: Authors' calculation based on 2009 Structured Data Repository data merged with 2009–2011 Data Analysis Support Hub and Master Earnings File data.

Appendix Table B1. *Estimates from OLS, 2SLS, and Reduced-Form Regressions Using All Sample Members*

	OLS estimates		IV estimates (CDC data)		IV estimates (ARCOS data)		IV estimates (ARCOS data, weighted based on MME)		Reduced form estimates (CDC data)		Reduced form estimates (ARCOS data)		Reduced form estimates (ARCOS data, weighted based on MME)	
Any employment at T1, T2, T3, or T4														
Any opioid use	-0.03	***	-0.32	***	-0.34	***	-0.42	***						
Local opioid prescribing patterns									-0.02	***	-0.01	***	-0.01	***
Awarded benefit	-0.32	***	-0.30	***	-0.30	***	-0.29	***	-0.32	***	-0.32	***	-0.32	***
Outcome at two years before determination	0.23	***	0.23	***	0.23	***	0.23	***	0.23	***	0.23	***	0.23	***
Mean earnings in T1 through T4[a]														
Any opioid use	-0.24	***	-3.01	***	-3.17	***	-3.76	***						
Local opioid prescribing patterns									-0.18	***	-0.13	***	-0.13	***
Awarded benefit	-3.03	***	-2.85	***	-2.84	***	-2.80	***	-3.04	***	-3.04	***	-3.04	***
Outcome at two years before determination	0.22	***	0.23	***	0.23	***	0.23	***	0.22	***	0.22	***	0.22	***
Ever earned above SGA at T1, T2, T3, or T4														
Any opioid use	-0.01	***	-0.29	***	-0.29	***	-0.33	***						
Local opioid prescribing patterns									-0.02	***	-0.01	***	-0.01	***

Awarded benefit	-0.24	***	-0.22	***	-0.22	***	-0.22	***	-0.24	***	-0.24	***	-0.24	***
Outcome at two years before determination	0.14	***	0.15	***	0.15	***	0.15	***	0.14	***	0.14	***	0.14	***

Note: T refers to year of SSDI application determination.
*** Statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.
[a] Mean earnings are in logarithm form.
ARCOS = Automated Reports and Consolidated Ordering System; CDC = Centers for Disease Control and Prevention; IV = instrumental variable; MME = morphine milligram equivalents; OLS = ordinary least squares; SGA = substantial gainful activity; 2SLS = two-stage least squares.
Source: Authors' calculation based on 2009 Structured Data Repository data merged with 2009–2011 Data Analysis Support Hub and Master Earnings File data.

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