Opioid Use Among Social Security Disability Insurance Applicants, 2013-2018

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Abstract

Prescription opioids are commonly used to treat pain among Social Security Disability Insurance (SSDI) beneficiaries. Opioid use among beneficiaries is of great public health concern given that beneficiaries account for a disproportionate share of opioid-related hospitalizations and deaths. Little is understood about the trajectory of such opioid use—is it a continuation of treatment patterns initiated prior to SSDI enrollment, or is the SSDI program itself a route to obtaining affordable prescription opioids? To shed light on this question, we estimated the prevalence of opioid use among SSDI applicants *at the time of application*. Using newly developed SSDI administrative data, we identified applicants who were taking prescription opioids by using a novel natural language processing algorithm to precisely identify opioid analgesics in free text medication entry fields on the application. We also examined changes in opioid use among applicants over time, by applicants' medical and demographic characteristics including their region of residence, and the association between application rates and local opioid prescribing rates. We find the prevalence of opioid use among SSDI applicants declined from 33% in 2013 to 24% in 2018. In contrast, the share of applicants reporting musculoskeletal impairments, which are commonly associated with chronic pain, was unchanged during this period. Opioid use was especially prevalent among applicants with musculoskeletal and back impairments (45% and 50%, respectively). Between 2013 and 2018, applications reporting opioid use declined across both sexes and all age groups and education levels examined. Applications reporting opioid use also declined across all regions in the US, though there was substantial variation in the magnitude of decline with the smallest declines seen in parts of the Midwest and Southeastern United States. Finally, we found that both levels and changes in the rates of SSDI applications overall, as well as applications reporting opioid use, were positively associated with local opioid prescribing rates such that communities with higher prescribing rates also had higher rates of SSDI application.

Keywords: Disability, Social Security Disability Insurance, Opioids, Pain

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Background

Chronic pain is a leading cause of work disability (Kapteyn et al., 2008; Krueger, 2017; Theis et al., 2018). Pain-related musculoskeletal (MSK) disorders in particular, such as back pain, neck pain and arthritis, account for a significant share of work disability owing to their high prevalence (Theis et al., 2018) and are the leading reason for receipt of Social Security Disability Insurance (SSDI) benefits (SSA, 2019). Moreover, the prevalence of pain among prime-age adults without a college degree is rising (Case et al., 2020), indicating that pain-related medical conditions are likely to comprise a growing share of the SSDI caseload into the future as well. Understanding changes in the prevalence and treatment of chronic pain is therefore of key importance to the SSDI program.

Among chronic pain therapies, prescription opioids have been increasingly scrutinized and discouraged in light of limited evidence to support their efficacy together with growing evidence of their adverse effects (Dumas and Pollack, 2008; Kosten and George, 2002; Krebs et al., 2018; Lee et al., 2011), including but not limited to addiction and overdose (Volkow and McLellan, 2016). Despite these concerns, prescription opioids are commonly used to treat pain among SSDI recipients (Meara et al., 2016; Morden et al., 2014): in 2015, it is estimated that 49% of SSDI beneficiaries received an opioid prescription, 26.5% received long-term opioid treatment (i.e., greater than 90 days' duration), and 7% received opioid prescriptions at high doses associated with an increased risk of overdose (i.e., greater than 100 morphine milligram equivalents) for a period of at least 30 days (Liaw et al., 2020). The high prevalence of long-term opioid treatment and high-dose prescribing among SSDI beneficiaries has been a source of particular public health concern, because such prescribing practices are associated with an increased risk of overdose (Adewumi et al., 2018; Von Korff et al., 2011). Indeed, SSDI recipients accounted for 24.5% of opioid overdose hospitalizations among individuals under age 65 in 2013 (Peters et al., 2018); and though SSDI recipients account for only 16% of Medicare beneficiaries (Cubanski et al., 2016), it is estimated that from 2012 to 2016 they accounted for 80.8% of opioid overdose deaths in Medicare (Kuo et al., 2019). Moreover, SSDI beneficiaries are exposed to other factors that contribute to their increased vulnerability to opioid-related adverse events, such as a higher underlying prevalence of chronic pain and psychiatric disorders (Kuo et al., 2019; Peters et al., 2018).

Research on prescription opioid treatment for pain in the SSDI population has focused primarily on existing beneficiaries, as beneficiaries become eligible for Medicare after a two-year waiting period, and thereafter treatment patterns can be readily examined using Medicare claims data. In contrast, very little is known about the prevalence of opioid use at the time of application and how opioid use varies by applicant characteristics, particularly on a national scale (Gebauer et al., 2019). Such information is potentially of tremendous value, however, to the disability research and policy community for several reasons. First, it can support the Social Security Administration's (SSA) efforts to better understand the burden of chronic pain and opioid treatment among future SSDI beneficiaries, and in particular whether there are specific geographic regions or subpopulations of applicants in whom opioid use is especially prevalent. This may in turn inform SSA's approach to initial and continuing reviews of medical evidence among applicants with chronic pain. Second, such information can assist both SSA and Medicare

in anticipating the vocational and medical supports that will be needed by such individuals should they qualify for SSDI benefits. Third, understanding the prevalence of opioid use at the time of application can indicate to what extent opioid treatment escalates following SSDI receipt, and whether features of the SSDI and Medicare programs might influence the trajectory of opioid use among beneficiaries. This is a critical first step to understanding how health care providers, Medicare and SSA together can achieve safer pain treatment in this especially vulnerable population. Finally, this information would be an important contribution to ongoing research efforts to understand how changes in the US opioid prescribing landscape have affected work-related functioning and disability claiming.

Developing national estimates of the prevalence of opioid use among SSDI applicants has proved challenging due to data constraints: comprehensive information about prescription drug use, SSDI applications and claiming is rarely combined in the same data source. SSDI applications themselves capture this information, which has been stored in an electronic database, SSA's Management Information Services Facility Electronic Disability Database (MEDIB), since 2007. A key challenge in analyzing the application data, however, is the large share of information entered into free text fields. Medications, for example, can be selected via a pre-populated drop-down list, entered as free text, or both. Wu et al. (2019a) found that between 2007 and 2017 40% of applicants reported their medications using both the drop-down and free text options, while 42% used free text entry only, illustrating the importance of examining the free text fields. Moreover, the share of applicants entering medications into free text fields has increased over time (Wu et al., 2019b), and it is therefore particularly important to account for free text data when examining temporal trends in medication use among SSDI applicants.

Wu and colleagues (2019a; 2020) have conducted the only other analyses examining the prevalence of opioid use among SSDI applicants using SSA administrative data. Using a random sample of 100,000 SSDI applicants in 2013 (4.5% of applicants in that year), they developed and tested a natural language processing (NLP) algorithm to identify opioid medication names in both the application free text fields and drop-down menu (Nadkarni et al., 2011; Wu et al., 2020). They then applied this algorithm to a 30% sample of SSDI applicants from 2007 to 2017, and estimated that the prevalence of opioid use at the time of application ranged from 26 to 32% depending on the year (Wu et al., 2019a).

In this study, we develop an alternative NLP algorithm to estimate the prevalence of opioid use among SSDI applicants using SSA administrative data. Our approach complements the innovative strategy developed by Wu and colleagues (2020), and contributes several additional strengths, notably: the use of a much larger training sample to identify possible opioid drug names, drawn from multiple years of application data; the exclusion of opioid-containing cough and cold medications to more precisely identify opioids used to treat pain; and leveraging data from other application free text fields to refine the classification of misspelled opioid names, and to identify opioids used to treat opioid use disorder (OUD) rather than pain.

We employ this algorithm for two purposes. First, we describe variation in opioid use among applicants over time, by applicants' medical and demographic characteristics, and by geographic region. We particularly focus on high-risk males, who we define as men without a college degree, aged 45-66. Second, we begin to explore whether the rates of application and, more

specifically, the rates of applications that report opioid use might be affected by policies designed to reduce the rate of opioid prescribing in the community. We show that community prescribing rates are significantly associated with application rates overall, and the rate of applications that report opioid use, even after adjusting for characteristics of the local environment. Thus, there is a relationship between community prescribing rates and both the rate and composition of disability applications. This analysis is a first step towards understanding the causal effects of excess opioid prescribing, and the attempts to counteract it, on disability applications.

Methods

We developed a deterministic NLP algorithm to identify opioids used to treat pain, and applied this algorithm to SSDI application data to answer the following research questions: 1) What share of SSDI applicants are taking prescription opioids at the time of application?; 2) Has the prevalence of opioid use at the time of application changed in recent years, and have there been any concurrent changes in the demographic or medical composition of the SSDI applicant pool?; 3) Does the prevalence of opioid use among SSDI applicants vary by applicant characteristics or geographic area?; and 4) Is there a relationship between community-level opioid prescribing rates and SSDI application rates? In this section, we describe our data and methodology in further detail.

Data

Our primary data source is SSA's MEDIB database. MEDIB is an administrative data source that stores information about SSA applicants collected on SSA Forms 16 and 3368 at the time of application.[1] These forms gather applicant demographic data (i.e., date of birth, sex,[2] educational attainment, zip code of residence), and information about applicants' medications, medical conditions, treatments and testing. The forms can be completed on paper or online, with or without assistance from SSA staff (by telephone or in person) or a claimants' representative. MEDIB also contains the applicant's primary and secondary medical diagnoses and initial determination made by the examiner. We use data on 8,614,482 applicants who submitted a claim to a Disability Determination Services office between the years 2013 and 2018, which represents a census of all SSDI applicants during this time period.[3]

Supplemental data sources include the Centers for Diseases Control and Prevention's (CDC) opioid prescribing data, from which we obtain area-level opioid prescribing rates annually from 2013 to 2018. We use five-year (2014-2018) population estimates from the U.S. Census Bureau's American Community Survey's (ACS) to calculate population-adjusted SSDI application rates.

Development and Testing of a Natural Language Processing Algorithm to Identify Opioid Use Among SSDI Applicants

[1] SSA Form 3368 is available here: https://www.ssa.gov/forms/ssa-3368-bk.pdf
[2] Sex is reported by the applicant but constrained to binary male/female categories.
[3] The sample counts differ from official statistics because we eliminate applications that appear to contain the same information. See Wu et al. (2019b) for discussion of applications that do not appear in the MEDIB.

As described above, on Form 3368 medication information can be reported either through a drop-down menu that is prepopulated with over 600 different medication names, or through free-text fields, or both (Wu et al., 2020). The majority of applicants report at least some medications in the free-text fields (Wu et al., 2019a). In order to more accurately estimate the percent of SSDI applicants taking opioids at the time of application, we therefore developed a deterministic NLP algorithm to identify opioids used to treat pain in free-text fields.

We used the following approach to develop the NLP algorithm. First, we developed a list of exact opioid identifiers which consisted of correctly spelled opioid analgesic names drawn from our master list of generic and brand names.[4] In a given medication entry free-text field, applicants commonly enter additional text beyond the medication name, such as the medication dosing or frequency (e.g. oxycodone 20mg); applicants may also enter multiple distinct medication names in a single free-text field. In order to identify these exact opioid word matches within a longer string of characters, our algorithm was therefore designed to search for opioid identifiers bounded on the left by the beginning of the string or a delimiter (i.e., a character that marks a separation between different words), and bounded on the right by the end of the string or a delimiter. Delimiters included blank spaces and certain types of punctuation (see **Appendix A** for details). This first step allowed us to identify exact, correctly spelled opioid matches in the free-text fields.

Identifying correctly spelled opioid matches is not enough, however: many free-text medication names in MEDIB are misspelled or in Spanish. Excluding misspellings would lead us to underestimate the prevalence of opioid use among SSDI applicants. Our second step was therefore to identify words that were possibly misspelled opioid analgesic names. We did this by searching all free-text medication entries in the universe of MEDIB 2013 to 2017 data for misspellings that were 1-edit distance from a correctly spelled opioid analgesic name (i.e., different by only one character). For longer opioid medication names that exceeded 10 characters (e.g. hydrocodone, hydromorphone), we also extracted 2-edit distance misspellings.[5]

Having extracted these misspellings, the next challenge was to distinguish those that were likely to be misspelled opioid names (i.e., unambiguous opioids, such as "oxycotin"), from those that could represent misspellings of other non-opioid drug names and were therefore less likely to be opioids (i.e., ambiguous opioids, such as "ultra" – a 1-edit distance misspelling of "ultram" that could be a fragment of numerous medication names). Distinguishing these types of

[4] We used a similar master list of opioid analgesics as in Zhu et al. Zhu W, Chernew ME, Sherry TB, Maestas N. Initial Opioid Prescriptions among U.S. Commercially Insured Patients, 2012–2017. New England Journal of Medicine 2019;380; 1043-1052.. This list contains both generic and brand names of opioid analgesics compiled from multiple sources: the Food and Drug Administration, the National Center for Injury Prevention and Control, the MarketScan 2016 Red Book and Red Book online. As in Zhu et al. Ibid., we excluded opioid-containing cough syrups and injectable opioids from our master list of opioid analgesic names; however, we included buprenorphine, methadone, their combinations and brand names in our master list, since buprenorphine and methadone can be used to treat chronic pain.

[5] Several Spanish-language versions of opioid analgesic names were captured when we extracted 1- or 2-edit distance misspellings (e.g., "hidrocodona" is the Spanish version of "hydrocodone", and is also a 2-edit distance misspelling of "hydrocodone"). These Spanish-language versions were then classified as unambiguous opioids, as described in the next paragraph. We did not search further for 1- or 2-edit distance misspellings of the Spanish-language versions.

misspellings is important for accurately estimating the prevalence of opioid use among applicants: including all ambiguous opioid misspellings, for instance, could potentially overstate the prevalence of opioid use among SSDI applicants. To distinguish unambiguous from ambiguous opioid misspellings, a general internist (Dr. Sherry, one of the study authors) reviewed our list of 1-edit and 2-edit distance misspellings of opioid names against a comprehensive online database of medication names,[6] using both phonetic and wildcard searches to determine whether any of these misspellings resembled non-opioid medication names. We classified 1-edit and 2-edit distance misspellings as unambiguous opioid misspellings if no similar non-opioid drug names were identified in the database; we classified them as ambiguous opioid misspellings if we identified one or more similar non-opioid drug names in the database.

All unambiguous opioid misspellings were considered to represent opioid names and were therefore added as opioid identifiers in our NLP algorithm. For ambiguous opioid misspellings, we developed additional systematic classification criteria for determining which misspellings to consider opioids and add as opioid identifiers to our algorithm. These criteria are detailed in **Appendix A**. Of note, they leverage an additional free-text data element in MEDIB, which is the "Reason for Medication" field. For each free-text medication entry, applicants have the option of also entering their reason for taking the medication in this distinct free-text field. After reviewing a sample of entries from the "Reason for Medication" field, we developed a list of words commonly used by applicants to describe pain or pain-related medical conditions (including common misspellings and Spanish-language versions), and used this information as part of our classification criteria for ambiguous opioid misspellings (see **Appendix A** for list of pain-related terms). Our rationale was that ambiguous misspellings were more likely to represent opioids in cases where an applicant reported that a medication was being used for pain. To our knowledge, ours is the first study to leverage this additional type of free-text medication information (i.e., the reason for medication) from MEDIB.

Our NLP algorithm therefore searched all applicants' free-text medication entries for words that matched our list of opioid identifiers, which ultimately included the following:

(1) Correct spellings of opioid generic and brand names from our master list;
(2) Unambiguous opioid misspellings;
(3) Ambiguous opioid misspellings that were clearly connected to the treatment of pain.

Having identified medication free-text entries containing opioid names, we then implemented two additional steps to further enhance the accuracy of our algorithm. First, we identified medication entries where an opioid was listed alongside additional words that indicated it was part of a cough or cold medication (e.g. "guaifenesin", an antitussive that may be formulated in combination with opioids), and removed such entries from our final estimates of the prevalence of opioid analgesic use. Words corresponding to cough and cold medications were identified from the comprehensive list of opioid-containing medications compiled by Zhu et al. (2019), and

[6] We used Drugs.com, an online database of over 24,000 medication names that are compiled from Wolters Kluwer Health, the American Society of Health-System Pharmacists, Cerner Multum and IBM Watson Micromedex and peer-reviewed. In addition to its comprehensiveness, a key advantage of this database is that it allows both phonetic and wildcard searches, which we leveraged to identify both opioid and non-opioid medication names similar to our misspelled medication names.

are listed in **Appendix A.** Second, we identified instances where methadone and buprenorphine were being used to treat opioid addiction rather than pain by leveraging information in the "Reason for Medication" free-text fields. We reviewed a sample of entries from the "Reason for Medication" field to identify words commonly used by applicants to describe opioid addiction, including common misspellings and Spanish-language versions (see **Appendix A** for list of terms). We then removed from our final estimates entries where buprenorphine or methadone were listed, and one of these addiction terms was listed as the reason for the medication. The rationale for both of these refinements was that our goal was to identify opioids used to treat pain primarily. Ultimately, only 0.2% of opioid medication entries were cases where buprenorphine or methadone was used for addiction treatment, and an even smaller share of opioid medication entries represented cough or cold medications.

We refined the accuracy of our algorithm through multiple rounds of testing on MEDIB medication entries, and independent hand-checking of results by two research team members to identify necessary modifications. Our final algorithm was tested on a sample of 1200 medication entries and demonstrated an accuracy rate of 99.92%: there were 0 instances of false positives, and a false negative rate of 0.17%.

Statistical Analyses

For each year from 2013 to 2018, we used the MEDIB data to estimate overall SSDI application rates per 100 relevant population[7] and the rate of applications mentioning opioid use, in which an applicant reported using an opioid analgesic in either the free-text fields (as ascertained by our NLP algorithm) or via the drop-down menu. In addition, we estimated application rates by sex, age group (ages 18-44 or 45-66 at the time of application),[8] education level (less than high school, high school only or some college, completed college),[9] primary or secondary medical impairments (MSK, mental impairment, both MSK and mental impairment)

[7] For the overall application rate, opioid rate, MSK impairment rate, back impairment rate, mental impairment rate, MSK with mental impairment rate, and pain or other symptoms rate, the denominator was the number (in hundreds) of adults ages 18-64 derived from the ACS data; for the application rates for each education category, the denominator was the number (in hundreds) of adults ages 25-64 with the respective level of education; for all other groups, the denominator was the number (in hundreds) of individuals corresponding to the population specified in the numerator (e.g., for the application rate among males, the denominator was the number (in hundreds) of males ages 18-64).

[8] Our sample of SSA applicants includes a few individuals age 65 and 66 – full retirement age during this time period was 66, and some 66 year-olds apply for backdated benefits if their disabilities began when they were 64 or 65. Therefore there is slight misalignment between the age range of our sample and the ACS-derived denominators, which extend up to age 64, but this misalignment is very minor since very few individuals apply for SSDI beyond age 64.

[9] Our data include highest year of education completed, but do not include degree completion (with the exception of GED earned); we therefore used years of education to classify applicants into the groups less than high school, high school only or some college, and completed college.

and mentioning the presence of "pain or other symptoms,"[10] on a national level.[11] We also estimated the rate of applications among high risk males, defined here as males ages 45-66 who did not complete college, among whom the prevalence of pain, functional limitations, and labor force nonparticipation has increased over time (Case and Deaton, 2015; Krueger, 2017).[12] In each year, we calculated the share of applicants and the share of initially allowed applicants within each of these subgroups of interest. Pooling all years of data, we then examined the share of applicants within specific demographic and medical impairment groupings who reported opioid use, and the share of applicants reporting opioid use who were then initially allowed. We also examined changes in the rate of applications reporting opioid use within each of these subgroups from 2013 to 2018.

To characterize geographic variation in the rate and share of SSDI applications mentioning opioid use, we estimated and compared application rates by couma. Coumas are small geographic areas that represent a blend of counties and public use microdata areas (PUMAs). In the case of counties that are large, populous and comprised of multiple PUMAs, the county is the couma; in cases where counties are smaller, sparsely populated and multiple such counties are assigned to a PUMA, the PUMA is the couma (Case and Deaton, 2017). This approach assures that each couma has a minimum population size of 100,000, reducing measurement error relative to using small, sparsely populated counties as units of analysis. MEDIB data contains applicants' 5-digit zip code of residence, therefore all 5-digit zip codes were crosswalked to coumas (see **Appendix B** for a description of the crosswalk).

Finally, we used linear regressions to examine the association between couma-level opioid prescribing rates and SSDI application rates overall, as well as the rate of applications mentioning opioid use. Our models adjusted for couma fixed effects to control for time invariant differences across coumas, as well as year fixed effects to control for secular trends in opioid prescribing and SSDI application rates. Opioid prescribing rates are reported by the CDC at the county-level – since counties are fully nested within coumas,[13] we estimated couma-level prescribing rates as the population-weighted average of the rates for all counties assigned to that couma. Population estimates and characteristics from the ACS are also reported at the county-level and are thus readily crosswalked to the couma-level.

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[10] SSA Form 3368 explicitly asks applicants if their work-limiting medical conditions cause "pain or other symptoms". Note that this is a different data element than the "Reason for Medication" field described above, which is a free-text field in which applicants may report the reasons they are taking each medication listed on the form. These two data elements collect different information: the former asks about symptoms the patient is experiencing, whereas the latter – which we use to identify likely opioid analgesics – provides the indications for the applicants' medications.

[11] When calculating application rates, the following rates used the full age range of applicants from 18 to 66: overall application rate, rate of applications mentioning opioid use, application rates among males and females, and application rates by primary or secondary medical impairment. All other application rate calculations restricted the age range as described in the text.

[12] Kreuger (2017) finds that females ages 45-64 who did not complete college are not similarly at risk for pain, opioid use, and SSDI application, unless they report their reason for labor force nonparticipation is something other than home responsibilities.

[13] We used the county-couma crosswalk provided as an online data appendix to Case & Deaton Case A, Deaton A. 2017. Mortality and Morbidity in the 21st Century. (Ed)^(Eds), Brookings Papers on Economic Activity, vol. Spring 2017. 2017., available at https://www.brookings.edu/bpea-articles/mortality-and-morbidity-in-the-21st-century/.

Results

SSDI Applications, Initial Allowances and the Prevalence of Opioid Use, 2013-2018

When combining medication information from both the drop-down list and free text entries, we estimate that the overall prevalence of prescription opioid analgesic use among SSDI applicants between 2013 and 2018 was 30.5%. Only 0.2% of SSDI applicants reported using buprenorphine and methadone for opioid addiction. In contrast, when using medication data from the drop-down list only, we estimate the prevalence of opioid analgesic use to be 11.8% during this same time period. This substantial discrepancy illustrates the importance of combining data from both the medication drop-down list and free text fields to accurately estimate the prevalence of opioid use – or use of any other medication – among SSDI applicants. Accordingly, all findings related to the prevalence of opioid use that are reported in this study are based on medication data from both the drop-down list and free text fields.

Table 1 describes trends in SSDI applications and initial allowances yearly from 2013 to 2018 – overall, by demographic subgroups of interest (**Panel A**) and by medical subgroups of interest (**Panel B**). The latter group includes applicants reporting opioid analgesic use, applicants reporting a MSK disorder, back disorder, mental disorder or both a MSK and mental disorder as either their primary or secondary impairment, and applicants reporting "pain or other symptoms." We examined these categories of impairments because MSK and mental disorders are the two leading reasons for SSDI awards, and within the MSK disorder category, back disorders are the leading type (Meseguer, 2013). **Panels A** and **B** report, for each subgroup of interest, the rate of applications, and the share of total applications and initial allowances corresponding to that subgroup. For example, among males in 2018, the application rate was 0.62 per 100 relevant population, male applicants accounted for 50% of the total applicant pool, and male applicants accounted for 57% of initial allowances. **Panel B** reports the same statistics for medical subgroups of interest.

Table 1 shows that the overall rate of SSDI applications per 100 adults ages 18-64 fell sharply during this time period, from a rate of 0.81 per 100 relevant population in 2013 to a rate of 0.62 in 2018. The overall share of applications that were initially allowed was unchanged at 33%. The sex and age composition of the applicant pool remained largely unchanged during this time period (**Panel A**). Of note, in each year equal numbers of men and women submitted applications, but men were far more likely to be initially allowed. In all years, adults ages 45-66 accounted for nearly two-thirds of applications and an even higher share of initial allowances (i.e., 84%). The share of applicants who had not completed high school fell slightly from 2013-2018, from 20% to 17%, while the share of applicants who had completed college increased slightly from 9% to 11%. The share of applicants who were high-risk males (i.e., ages 45-66, and who had not completed college) was unchanged from 2013 to 2018.

Turning to medical characteristics (**Panel B**), the rate of applications reporting opioid analgesic use, and the share of all applicants and initially allowed applicants reporting opioid use all fell substantially from 2013 to 2018. The rate of applications reporting opioid use fell from 0.27 to 0.15 (per 100 adults age 18-64), a decline of almost 45%. The share of applicants reporting opioid use fell from 33% to 24%, and the share of initially allowed applicants reporting

opioid use fell from 35% to 26%. In contrast, the share of applicants and initially allowed applicants reporting pain-related symptoms or conditions (i.e., MSK disorders overall and back disorders) was largely unchanged. Application rates declined among these impairment categories, tracking the overall decline in applications.

Table 1: SSDI Applications, Initial Allowances and Applicant Characteristics Including Opioid Analgesic Use, 2013-2018

	Year					
	2013	2014	2015	2016	2017	2018
Applicants per 100	0.81	0.78	0.73	0.69	0.65	0.62
Initial Allowance Rate	33%	32%	32%	32%	33%	33%
Panel A: Applicant Demographic Characteristics						
Male	0.82	0.78	0.73	0.69	0.65	0.62
Share of Applicants	50%	49%	49%	50%	50%	50%
Share of Initial Allowances	56%	56%	57%	57%	57%	57%
Female	0.81	0.79	0.74	0.69	0.65	0.63
Share of Applicants	50%	51%	51%	50%	50%	50%
Share of Initial Allowances	44%	44%	43%	43%	43%	43%
Age 18-44	0.49	0.46	0.43	0.41	0.38	0.36
Share of Applicants	35%	34%	34%	34%	34%	33%
Share of Initial Allowances	16%	15%	15%	15%	16%	16%
Age 45-66	1.27	1.23	1.15	1.09	1.03	0.99
Share of Applicants	65%	66%	66%	66%	66%	67%
Share of Initial Allowances	84%	85%	85%	85%	84%	84%
Less than HS	1.74	1.59	1.44	1.31	1.19	1.12
Share of Applicants	20%	19%	19%	18%	17%	17%
Share of Initial Allowances	17%	17%	16%	16%	15%	15%
HS only or Some College	1.15	1.12	1.05	0.99	0.94	0.89
Share of Applicants	67%	67%	68%	68%	68%	68%
Share of Initial Allowances	62%	62%	62%	62%	62%	62%
College	0.27	0.28	0.27	0.26	0.25	0.25
Share of Applicants	9%	10%	10%	10%	11%	11%
Share of Initial Allowances	11%	11%	11%	11%	11%	11%
High-risk Male	1.62	1.55	1.44	1.38	1.29	1.24
Share of Applicants	28%	28%	28%	29%	28%	28%
Share of Initial Allowances	38%	38%	38%	39%	38%	38%
Panel B: Applicant Medical Characteristics						

Opioid Use	0.27	0.26	0.24	0.21	0.18	0.15
Share of Applicants	33%	33%	32%	30%	28%	24%
Share of Initial Allowances	35%	35%	34%	32%	29%	26%
Musculoskeletal Impairment	0.34	0.33	0.31	0.30	0.27	0.26
Share of Applicants	41%	42%	43%	43%	42%	42%
Share of Initial Allowances	37%	37%	37%	37%	36%	36%
Back Impairment	0.20	0.20	0.18	0.17	0.16	0.15
Share of Applicants	25%	25%	25%	25%	24%	24%
Share of Initial Allowances	20%	20%	20%	20%	19%	19%
Mental Impairment	0.11	0.11	0.10	0.10	0.10	0.10
Share of Applicants	13%	14%	14%	14%	15%	15%
Share of Initial Allowances	8%	8%	7%	7%	8%	8%
MSK and Mental Impairment	0.02	0.02	0.02	0.02	0.02	0.02
Share of Applicants	3%	3%	3%	3%	3%	3%
Share of Initial Allowances	1%	1%	1%	1%	1%	1%
Pain/Other Symptoms	0.76	0.73	0.69	0.65	0.61	0.58
Share of Applicants	93%	94%	94%	94%	94%	94%
Share of Initial Allowances	94%	94%	94%	94%	94%	94%

Notes:
Applicants per 100 = # Applicants with Characteristic of Interest/ Relevant Population * 100
Initial Allowance Rate = # Applicants Initially Allowed / # Total Applicants
Share of Applicants= # Applicants with Characteristic of Interest / # Total Applicants
Share of Initial Allowances = # Applicants with Characteristic of Interest Initially Allowed / # Total Initially Allowed
Education categories add to less than 100 percent because some applicants do not report their education level.

In summary, the overall rate of SSDI applications in the population, as well as the share of SSDI applicants and initially allowed applicants reporting opioid use, declined substantially from 2013 to 2018 even though the share of applicants reporting MSK impairments, which are commonly associated with chronic pain, was unchanged. The demographic composition of the applicant pool was also largely unchanged during this time period.

Prevalence of Opioid Use by SSDI Applicant Characteristics

Pooling data from 2013 to 2018, **Table 2** describes the prevalence of opioid use within key applicant subgroups of interest. It also reports the percent of applicants using opioids who are initially allowed within each subgroup, compared to the percent of initially allowed applicants in the subgroup as a whole. For example, 29% of male applicants reported opioid use during this time period, and 39% of male applicants reporting opioid use were initially allowed compared to 37% of all male applicants who were initially allowed. The percent of applicants reporting opioid use was similar across all demographic groups examined (age, sex, education level) at approximately 30%. Across all demographic groups, applicants reporting opioid use were initially allowed at a slightly higher rate than for the applicant pool as a whole, but this difference was generally small (i.e., 2 percentage points). The highest prevalence of opioid use was observed among applicants with MSK disorders (45%) and specifically back disorders

(50%). Within each of these two impairment categories, however, the percent of applicants reporting opioid use who were initially allowed was similar to the overall percent of applicants with that impairment who were initially allowed (e.g., 28% of all applicants reporting MSK disorders, and 29% of all applicants reporting both an MSK disorder and opioid use, were initially allowed).

Table 2: Prevalence of Opioid Use by SSDI Applicant Characteristics, 2013-2018

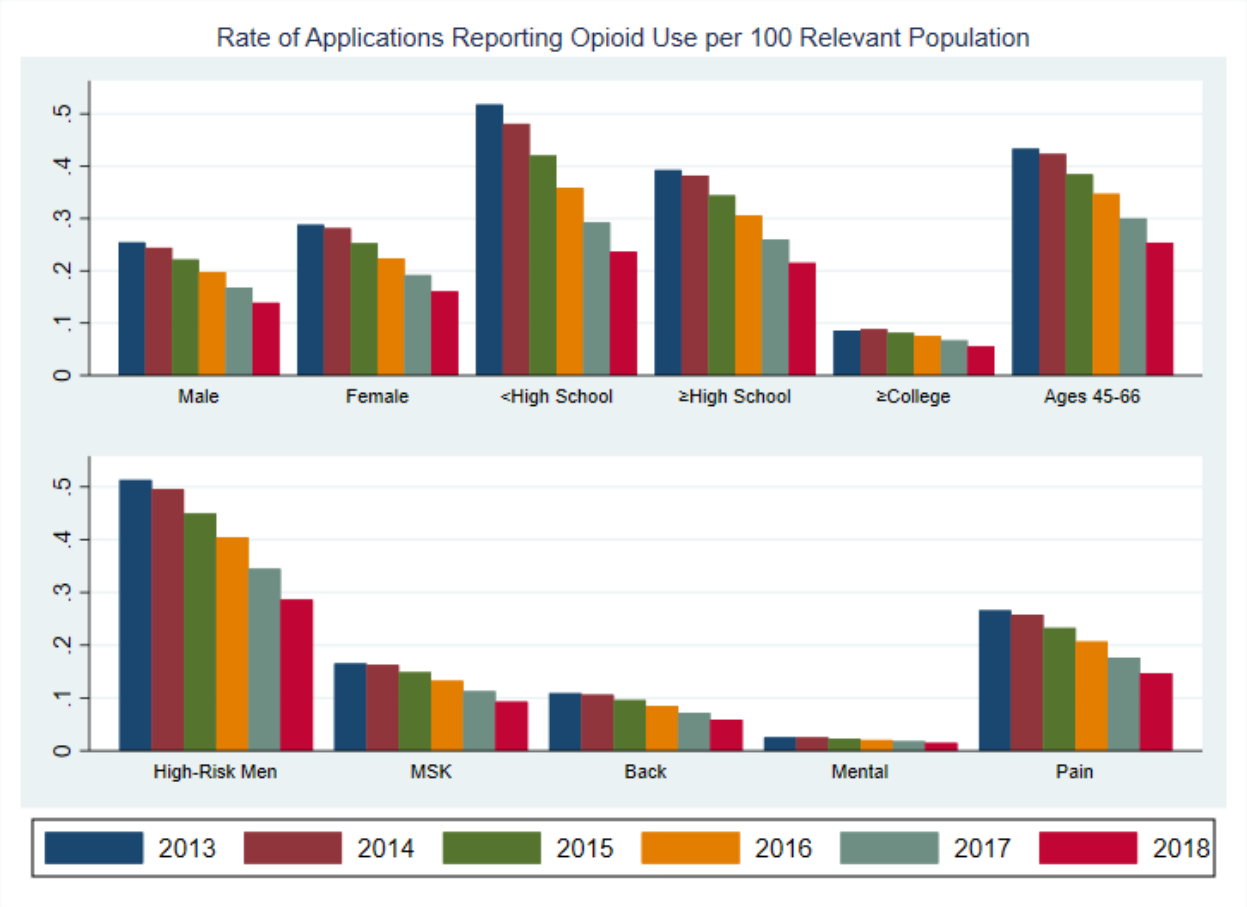
	Percent Applicants Reporting Opioid Use	Percent Applicants Reporting Opioid Use Initially Allowed	Percent of All Applicants Initially Allowed
	[1]	[2]	[3]
Sex			
Male	29%	39%	37%
Female	32%	30%	28%
Education			
Less than HS	28%	30%	28%
HS only or Some College	31%	31%	30%
College	29%	36%	36%
Age			
Ages 18-44	28%	13%	15%
Ages 45-66	32%	44%	42%
Other			
High-risk Men	29%	46%	44%
Impairments			
Musculoskeletal	45%	29%	28%
Back	50%	27%	26%
Mental	21%	18%	18%
MSK and Mental	45%	14%	14%
Pain/Other Symptoms	32%	34%	33%

Notes:
[1]: # Applicants with Characteristic of Interest who Report Opioid Use / # Applicants with Characteristic of Interest
[2]: # Applicants with Characteristic of Interest Reporting Opioid Use who are Initially Allowed/ # Applicants with Characteristic of Interest who Report Opioid Use
[3]: # Applicants with Characteristic of Interest who are Initially Allowed / # Applicants with Characteristic of Interest

We also examined changes in the rate of SSDI applications reporting opioid use per 100 relevant population, by demographic and medical subgroups of interest, for each year from 2013 to 2018 (**Figure 1**). Except for applicants who had completed college, for every other subgroup examined, the rate of applications reporting opioid use declined each year. Among applicants who had completed college, the rate of applications reporting opioid use increased slightly from

2013 to 2014 but declined each year thereafter. Declines in opioid use over time therefore occurred across all subgroups of interest.

Figure 1: Changes in the Characteristics of SSDI Applicants Reporting Opioid Use, 2013-2018



Geographic Variation in Opioid Use Among SSDI Applicants

Though opioid use among SSDI applicants overall and among key demographic and medical subgroups has fallen considerably in recent years, there remains geographic variation in the percent of applicants reporting opioid use. **Figure 2** shows the variation in the percent of applicants reporting opioid use by couma in 2018, our most recent year of data. Coumas with a higher percent of applicants reporting opioid use are generally concentrated in the Midwest, the Southeast and the West.

Figure 2: Variation in the Percent of Applicants Using Opioids by Couma, 2018

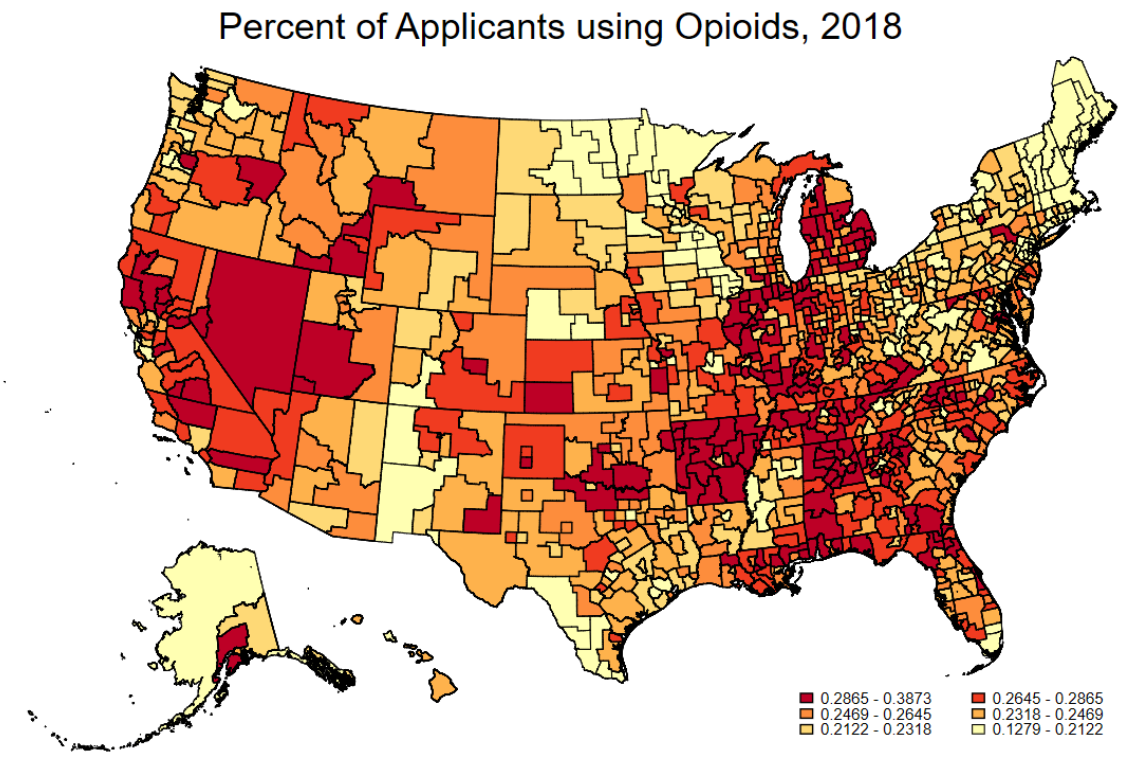


Table 3 describes geographic variation in changes in opioid use among SSDI applicants from 2013 to 2018, using an index of applications reporting opioid use. For each couma in each year, the index is calculated as the rate of applications reporting opioid use in that year divided by the rate of applications reporting opioid use in 2013. Values of the index less than 1 therefore indicate a decline in the rate of applications reporting opioid use in a given couma and year relative to 2013. **Table 3** reports the yearly mean, median, standard deviation, minimum and maximum values of the index across coumas. For each year from 2014 to 2018, the mean value of the index across all coumas fell relative to 2013, with a steeper decline after 2016. From 2014 to 2017, rates of applications reporting opioid use increased relative to 2013 in at least some coumas, as evidenced by a maximum index value greater than 1. By 2018, however, the maximum index value was 0.96, indicating that rates of applications reporting opioid use had fallen across every single region of the US relative to 2013.

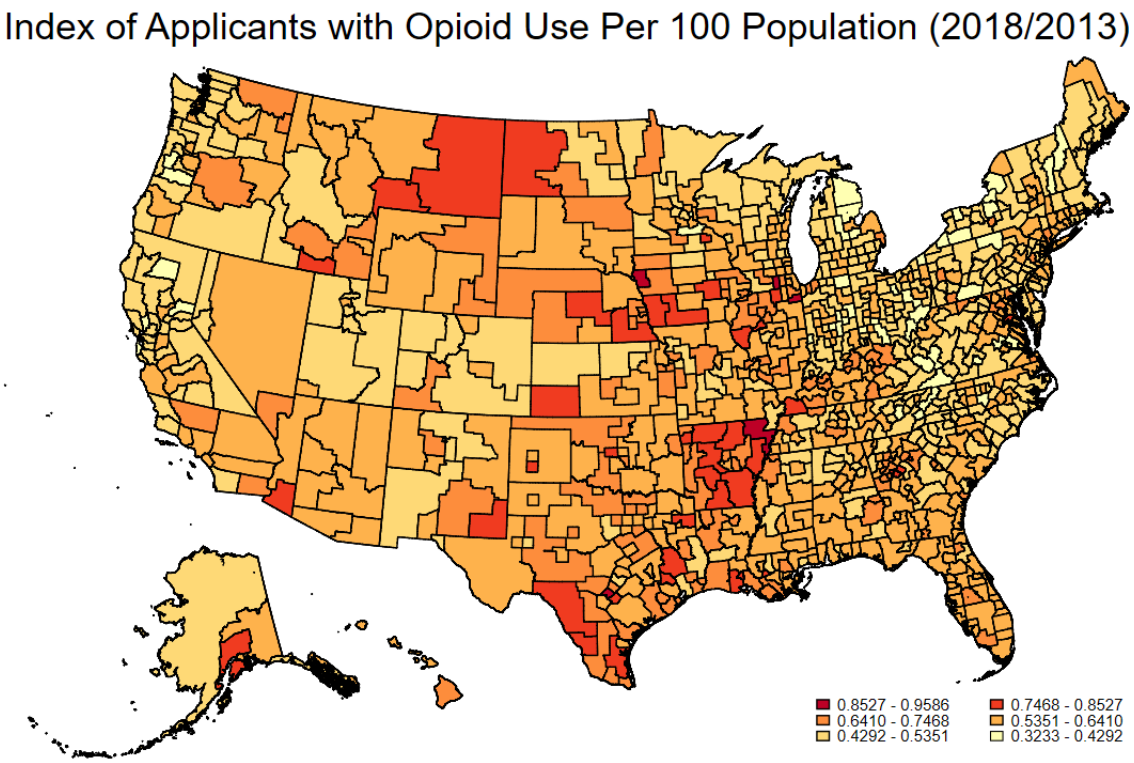
Table 3: Geographic Variation in the Rate of Applications Reporting Opioid Use by Couma, 2013-2018

Year	Index Mean	Index Median	Index SD	Index Minimum	Index Maximum
2013	1.00	1.00	0.00	1.00	1.00
2014	0.98	0.97	0.09	0.69	1.44
2015	0.89	0.88	0.10	0.55	1.35
2016	0.80	0.78	0.11	0.47	1.39
2017	0.68	0.67	0.10	0.40	1.15
2018	0.56	0.55	0.09	0.32	0.96

Notes: Index for Year *t* = Application Rate in Year *t*/Application Rate in 2013. SD = standard deviation. There are 976 observations in each year.

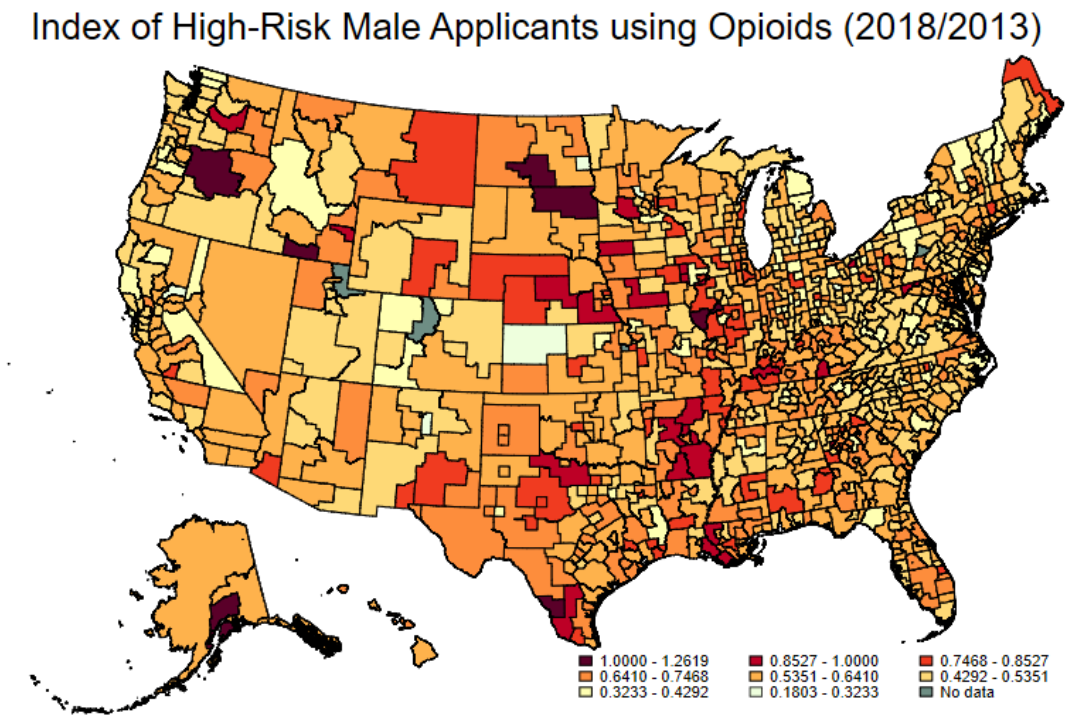
In each year, the discrepancy between the minimum and maximum index values by couma indicates that rates of applications reporting opioid use fell far more rapidly in some regions than others. To illustrate this variation in changes over time, **Figure 3** displays the index value for each couma in 2018 – coumas with higher index values (shown in red) experienced a smaller decline in the rate of applications reporting opioid use from 2013 to 2018. The smallest declines—and thus areas where opioid use was relatively persistent—were observed in Arkansas, southern Texas and Louisiana, and other pockets in the Midwest. Conversely, the largest declines in the rate of applications reporting opioid use occurred in parts of upstate New York, Pennsylvania, Virginia, Ohio, Indiana and Michigan.

Figure 3: Changes in the Rate of Applications Reporting Opioid Use by Couma in 2018 Relative to 2013



While the overall rate of applications reporting opioid use fell across every region of the US between 2013 and 2018, this was not the case for high-risk males. **Figure 4** displays the index value for high-risk males in each couma in 2018. In most regions, rates of applications reporting opioid use among high-risk males also fell during this time period, but the decline was smaller than that seen for the overall applicant pool and in select regions, the rate of applications reporting opioid use actually increased.

Figure 4: Changes in the Rate of Applications Reporting Opioid Use by Couma in 2018 Relative to 2013, High-Risk Males



High-risk males are defined as males without a college degree and aged 45-66.

Variation in Applications Reporting Opioid Use by Area-Level Opioid Prescribing Rates

Lastly, we examined the relationship between the rate of SSDI applications overall and applications reporting opioid use, according to the overall level of opioid prescribing in a given couma as measured using CDC data on opioid prescribing rates per 100 adults. The top row of **Table 4** reports the estimated coefficient on opioid prescribing rates for models that regress the SSDI application rate (column 1) or rate of applications reporting opioid use (column 2) in a given couma-year on couma-year opioid prescribing, adjusting for couma and year fixed effects. We find a positive, statistically significant relationship between the rate of opioid prescribing in a community and the rate of SSDI applications overall, as well as applications reporting opioid use. Column (1) indicates that an increase in the opioid prescribing rate by 10 prescriptions per 100 adults is associated with an increase in the SSDI application rate of 0.0352 per 100 adults ages 18-64, while column (2) finds this change is associated with a slightly smaller increase in the rate of SSDI applications reporting opioid use, of 0.0275 per 100 adults ages 18-64.

Table 4: Association Between Couma-Level Opioid Prescribing Rates, SSDI Applications and Applications Reporting Opioid Use, 2013-2018

	(1)	(2)
	Application Rate	Rate of Applicants Taking Opioids

Prescribing Rate	0.00352***	0.00275***
	(0.000364)	(0.000210)
Constant	0.781***	0.0500
	(0.0709)	(0.0410)
Couma Fixed-Effects	Yes	Yes
Year Fixed-Effects	Yes	Yes
Observations	5856	5856
Adjusted R-squared	0.957	0.941
Mean Dependent Variable	0.85	0.27

Standard errors in parentheses, clustered by couma * p<0.05, ** p<0.01, *** p<0.001

Discussion

The SSDI program has historically been affected by the opioid crisis, with earlier studies finding that a large share of SSDI beneficiaries used opioid analgesics at high doses to treat pain (Liaw et al., 2020; Meara et al., 2016; Morden et al., 2014). Little is known, however, about the trajectory of opioid use in this population, and in particular whether opioid use began before or after enrollment in SSDI. To inform this issue, we estimated the prevalence of opioid use at the time of SSDI application, and how opioid use varies by applicants' demographic and medical characteristics, or by geographic region. Our study sheds light on these questions by using administrative applications data and a novel NLP algorithm to accurately estimate the prevalence of opioid analgesic use among SSDI applicants, by leveraging information from application free text fields.

We find that opioid use remains prevalent among SSDI applicants: in 2018, the most recent year of data available, 1 in 4 SSDI applicants reported opioid analgesic use at the time of application. Among the subgroup of applicants with back and other MSK impairments, opioid use rates were notably higher: 50% of applicants with back impairments were already taking prescription opioids at the time of application, while 45% of applicants with MSK impairments and 45% of applicants reporting both a MSK and a mental impairment were taking opioid analgesics at the time application.

The share of applicants using opioids has fallen considerably in recent years, however. In a span of only five years, from 2013 to 2018, the prevalence of opioid use among applicants decreased from 33% to 24%. Declines in the rate of applications reporting opioid use were observed across every demographic group and medical impairment group examined. Of note, during this same time period the share of SSDI applications for MSK impairments – a leading cause of pain-related disability – remained steady, and among applicants with MSK impairments the rate of applications reporting opioid use decreased. The decline in opioid use at the time of application therefore does not appear to be explained by changes in the composition of medical impairments within the applicant population.

While the overall rate of applications reporting opioid use declined in every region of the US between 2013 and 2018, we observed considerable variation in the magnitude of these declines. Notably, declines in applicants taking opioids were smallest in certain parts of the Midwest and Southeastern US. Among high-risk males, the rate of applications reporting opioid use actually increased in several areas.

Thus, while the opioid crisis remains intertwined with the SSDI program, our findings indicate that its footprint has decreased significantly in recent years. A key unanswered question remains what factors have contributed to this decline in the prevalence of opioid use among SSDI applicants. We find that the levels of SSDI applications overall and those reporting opioid use are positively associated with local opioid prescribing rates (i.e., areas with higher opioid prescribing rates also have higher rates of SSDI applications and applications reporting opioid use). This finding raises the possibility that local practice patterns with respect to pain management influence the SSDI program. Indeed, owing to the proliferation in recent years of policy initiatives aiming to abate the harms of the opioid crisis, opioid prescribing rates have declined substantially throughout much of the country. Further research is needed, however, to provide evidence of a causal relationship between opioid prescribing rates and SSDI claiming, since it is likely that areas with higher community-level prescribing also have people in more pain, which could independently account for increased SSDI applications.

Our analysis also identifies several regions of the US for which the rate of applications reporting opioid use has declined more slowly during this time period. A closer examination of the policy and health care environment in these regions may yield further insights as to why the rate of applications reporting opioid use remains persistently high. We also found marked geographic variation in changes in applications reporting opioid use among high-risk men specifically (i.e., men ages 45 to 66 who have not completed college), with some regions achieving large declines while a few actually witnessed increases. Given this subpopulation is at elevated risk for pain and functional limitations, examining the factors explaining geographic variations in SSDI claiming overall and applications reporting opioid use is particularly important.

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Appendix A: Additional Details on the Development of a Deterministic Natural Language Processing Algorithm to Identify Opioid Analgesics

The appendix provides supplementary information about our approach to developing a deterministic NLP algorithm to identify opioid analgesics.

Delimiters

The following types of punctuation, in addition to blank spaces, were used to identify distinct words within a string of characters in a free text field: commas, semi-colons, colons, periods, forward slashes, back slashes, open parentheses, close parentheses, and hyphens.

Of note, several opioid names contain delimiters within the name itself: Co-gesic, MS Contin, Oxy IR, Tylenol 3 and Tylenol 4. To identify these specific intact opioid names within a string of characters, we used a pattern matching approach in which the opioid identifier itself included the delimiter in the middle of the word.

Classification Rules for Ambiguous Opioid Misspellings

We classified ambiguous opioid misspellings according to the following rules:

1) Ambiguous misspellings that were similar to the names of non-opioid drugs used to treat pain were considered non-opioids.

2) For ambiguous misspellings that were similar to the names of non-opioid drugs that are not used to treat pain:
    a. If the edit distance between the ambiguous misspelling and the non-opioid drug name was less than 4 (i.e., the ambiguous misspelling was fairly similar to the non-opioid drug name), the ambiguous misspelling was classified as an opioid only if the applicant listed one of the pain terms below in the "reason for medication" field. For ambiguous misspellings of buprenorphine, methadone and their brand-name versions, the same rule was used except the misspelling was classified as an opioid if the applicant listed either one of the pain or addiction terms below.

    b. If the edit distance between the ambiguous misspelling and the non-opioid drug name was 4 or greater (i.e., the ambiguous misspelling was substantially closer to the original opioid medication than the non-opioid alternative), the ambiguous misspelling was classified as an opioid.
        i. Example: "methasone" could be a 1-edit distance misspelling of "methadone", or a 4-edit distance misspelling of "betamethasone", and under this rule would be classified as an opioid.

c. For any edit distance, if the ambiguous misspelling was phonetically far more similar to a specific opioid drug name than the non-opioid alternative, it was classified as an opioid regardless of the listed "reason for medication".
    i. Example: "noraco" could be a 1-edit distance misspelling of "Norco" (an opioid) or a 2-edit distance misspelling of "Nora-BE" (a non-opioid); given the high phonetic similarity between "noraco" and "Norco", this misspelling was classified as an opioid regardless of the listed "reason for medication".

Of note, the rationale for rule 1 was that for a given misspelling of an opioid drug name, if the similar non-opioid drug was also used to treat pain, then information from the "reason for medication" field would not help us in making an assignment. In these cases, we conservatively assigned the ambiguous misspelling as a non-opioid.

List of Pain-Related Terms

We reviewed a sample of free-text medication entries together with their corresponding "reason for medication" free-text entries to identify terms in the latter that indicated the presence of pain. We included terms that either clearly indicated the presence of pain or a similar sensation as a symptom, or that reflected painful conditions for which the primary treatments used are analgesics (e.g. arthritis). We did not include painful conditions for which medications other than analgesics are commonly used (e.g. cancer). We included common misspellings and Spanish versions of certain terms. Our list of pain-related terms was supplemented by the investigators with several additional, commonly used pain terms.

Pain
Pains
Arthritis
Artritis
Arhtritis
Headache
Headaches
Headake
Headakes
Fibromyalgia
Fibromialgia
Dolor
Dolores
Migraine
Migraines
Migrana
Migranas
Migrane
Migranes
Herniated disk
Herniated disc

Herniated disks
Herniated discs
Disco herniado
Discos herniados
Bulging disc
Bulging discs
Bulging disk
Bulging disks
Osteoarthritis
Osteoartritis
Neuropathy
Neuropatia
Ache
Aches
Spasm
Spasms
Muscle spasm
Muscle spasms
Espasmos musculares
Muscle aches
Muscle ache
Backpain
Analgesia
Analgesic
Injury
Injuries

List of Opioid Addiction-Related Terms

We reviewed a sample of free-text medication entries together with their corresponding "reason for medication" free-text entries to identify terms in the latter that indicated the presence of opioid addiction. We included common misspellings and Spanish versions of certain terms. Our list of was supplemented by the investigators with several additional, commonly used addiction-related terms.

Opioid use disorder
OUD
Opioid dependence
Opioid dependency
Opioid addiction
Opioid blocker
Opiate dependence
Opiate dependency
Opiate addiction
Opiate blocker
Opiod dependence

Opiod dependency
Opiod addiction
Opiod blocker
Opiod addition
Opiod antagonist
Addiction
Addicted
Adiccion
Adiction
Addicition
Drug management
Drug treatment
Drug dependence
Drug addiction
Drug problem
Drug problems
Drug abuse
Drug and alcohol abuse
Drug user
Drug history
Withdrawal
Withdrawl
Heroin
Heroin addiction
Substance abuse
Craving
Cravings
Detox
Detoxification
Medication assisted treatment
Chemical dependency
Get off drugs
Get off opioids
Get off opiates

List of Cough and Cold Medication-Related Terms

Among medication entries that contained opioid names, when any of the drug names below were also present, we considered the opioid to be part of a cough/cold medicine formulation and therefore excluded it from our final count of opioid analgesics.

Generic Names

The following is a list of generic drug names or classes (e.g. antihistamine) that are commonly used in opioid-containing cough and cold medications. Note that some of these medication names (e.g. pseudoephedrine) are typically abbreviated. The list below shows

abbreviations in parentheses alongside the full drug name – when any of these abbreviations was present, we also considered the entry to represent a cough/cold medicine formulation.

Guaiacolsulfonate
Pseudoephedrine (pse, pseudo, pseudoeph, pseudoephedri)
Guaifenesin (gg, gua, guai, guaif, guaifen)
Chlorcyclizine
Chlorpheniramine (chlorphenir, chlorphen, cpm)
Pheniramine (phenir)
Dexchlorpheniramine
Brompheniramine (bpm, bromphen)
Phenylephrine (phenyleph, phen, phenyl)
Promethazine (prometh)
Dextromethorphan (dm)
Terpin
Phenylpropanolamine (phenylpropanolam, phenylprop, ppa, phenyl)
Pyrilamine (pyril, pyr)
Carbinoxamine
Homatropine
Antihistamine (antihist)
Calcium iodide (ci)
Ammonium chloride (ammonium cl, am.cl)
Potassium chloride (pot.cl)
Diphenhydramine (diphen)
Bromodiphenhydramine (bromodi)
Triprolidine
Cocillana
Tolu
Phenyltoloxamine (phenyltolox, phenyl)
Iodinated glycerol
Triprolidine
Phenindamine
Phenergan

Brand Names

The following is a list of brand name drugs that, when used in combination with an opioid name, indicate that the medication is used for cough/cold. Some of these medication names are typically abbreviated, so the list below includes common abbreviations.

a.c.	Alamine	Anaplex
ac	Allerfrin	Anatuss
Actacin	Allfen	Aprodine
Actagen	Ambifed	Ascomp
Actifed	Anamine	Atridine

Atuss
Ban-tuss
Beeze
Bio-tuss
Biotussin
Brom-cort
Bromanate
Bromarest
Bromatane
Bromcomp
Bromotuss
Bromphenex
Bromplex
Bromtane
Brovex
Chemdal
Chemtussin
Cheraol
Cheratussin
Cherralex
Chlorgest
Cleartuss
Co-histine
Codahistine
Codal
Codatuss
Codecon
Codehist
Codiclear
Codimal
Codituss
Coditussin
Cofed
Coldcough
Comtussin
Conex
Cordron
Cotane
Cotatate
Cotuss
Cough
Cyndal
Cytuss
De-chlor
Decohistine
Decongest
Decongestant
Deconsal
Delhistine
Deproist
Dexphen
Diamine
Dicomal
Dihistine
Dimetane
Ditussin
Drocon
Drotuss
Duohist
Duradal
Duraganidin
Echotuss
Ed-tuss
Efasin
Endacof
Endagen
Endal
Enditussin
Endotuss
Enplus
Entuss
Etnergan
Excof
Execlear
Extendryl
Gani-tuss
Genecof
Giltuss
Glyatuss
Glyceryl
Guaiacolate
Guaiatussin
Guaifen
Guaituss
Guaitussin
Guiadex
Guiamid
Guiaphen
Guiatuscon
Guiatuss
Guiatussin
Halotussin
Hi-tuss
Highland
Hist
Histadyl
Histafed
Histex
Histinex
Histussin
Hycomal
Hydex
Hydro-tussin
Hydrocof
Hydron
Hydrophene
Hyphen
Iocen
Iodal
Iodoglyce
Iodur
Iofen
Iophen
Iotussin
J-max
J-tan
Jaycof
K-phen
Kg-dal
Kgs
Liqui-histine
Liqui-tuss
Liquicough
Liquitussin
Lortuss
Mallergan
Mar-cof
Maxi-tuss
Maxifed
Maxiflu
Maxiphen
Maxitussin
Med-hist
Medent
Medi-tuss
Meditussin
Midahist
Midatane

Minto-chlor
Mintuss
Monte-g
Multi-hist
Myhistine
Myodine
Myphetane
Mytussin
Naldecon
Nalex
Normatane
Notuss
Novadrin
Novadyne
Novagest
Novahistine
Novamor
Novatex
Novatuss
Novene
Nudal
Oridol
Pancof
Par-glycerol
Para-hist
Pediatex
Pericol
Phanatuss
Phenaca
Phendal
Phenerex
Phenflu
Phenhist
Phenylhistine
Pneumotussin
Poly hist
Poly-histine
Poly-tussin
Polytine
Pro-clear
Pro-cof
Pro-life
Pro-red
Proclan
Prolex
Promist
Protex
Protuss
Pseudodine
Q-tuss
Quindal
Relacon
Relasin
Relcof
Rhinacon
Rindal
Robafen
Robichem
Robitussin
Rolatuss
Romilar
Rondec
Ru-tuss
Ryna
Scot-tussin
Sk-terpin
Spen-histine
Tercodryl
Tosmar
Touro
Tri-phen-pyrl
Triacin
Triafed
Triaminic
Triant
Trifed
Trihist
Trimal
Triposed
Tusana
Tusdec
Tuss
Tusscough
Tusshistine
Tussi-organidin
Tussiden
Tussidin
Tussin
Tussive
Tusso
Tuzistra
Uni multihist
Uni-tricof
Uni-tuss
Vanacof
Vanex
Vetuss
Virtussin
Well-tuss
Welltuss
Winstamine
Xpect
Z-cof
X-cof
Zodryl
Zotex
Ztuss

Other Cough/Cold Terms

We also considered medication entries containing opioid names to represent cough/cold formulations if either of the terms “cough” or “cold” were present in the same entry.

Appendix B: Approach to Crosswalking Five-Digit Zip Codes to Coumas

MEDIB data reports applicants' 5-digit zip code (zip5) of residence. Therefore to analyze geographic variation at the couma-level, we must crosswalk zip5's to coumas. We use a two step approach in which we first crosswalk zip5s to zip code tabulation areas (ZCTAs), and then crosswalk ZCTAs to coumas.

ZCTAs are geographic areas constructed by the Census Bureau to roughly represent the United States Postal Service (USPS) zip5s.[14] The ZCTA code assigned to an area corresponds to the most frequently occurring zip5 code within that area – therefore, while in most cases the ZCTA and zip5 code for a given address will match, in some cases they may differ, which is why crosswalking zip5s to ZCTAs is a necessary initial step. We do this using the zip5-to-ZCTA crosswalk provided by the Uniform Data System (UDS) Mapper,[15] a joint initiative by the Health Resources and Services Administration (HRSA), John Snow Inc., and the American Academy of Family Physicians that is intended to support analyses evaluating the geographic reach of the Section 330 Health Center Program.[16]

Having crosswalked all applicant zip5s to ZCTAs, we then crosswalk ZCTAs to coumas, starting with the Census Bureau's ZCTA-county relationship file. For a given ZCTA-county pair, this relationship file gives the 2010 Census population for the overlapping geographic area that is common to both the ZCTA and the county, the percentage of the ZCTA's population within the overlapping area, and the percentage of the county's population within the overlapping area. We modify this relationship file by aggregating all counties to their respective coumas, using the county-couma crosswalk developed by Case and Deaton (2017),[17] which yields a ZCTA-couma relationship file. Note that counties are fully nested within coumas, so aggregating counties to coumas is straightforward.

We then use the ZCTA-couma relationship file to assign ZCTAs to coumas. In cases where a ZCTA is fully nested within a couma, all applicants assigned to that ZCTA are assigned to the couma. In cases where a given ZCTA overlaps with multiple coumas (i.e., is not fully nested within a single couma), we assign applicants from that ZCTA to a couma probabilistically, based on the percent population in the ZCTA apportioned to each couma in the ZCTA-couma relationship file. For example, suppose ZCTA A overlaps with both Couma B and Couma C, with 30% of ZCTA A's population in Couma B and 70% in Couma C. Our crosswalk will therefore assign each applicant from ZCTA A to Couma B with a probability of 0.3, and to Couma C with a probability of 0.7.

A limitation of the crosswalk is that the most recent Census ZCTA-county relationship file was created in 2010 and therefore the percent of a ZCTA's population assigned to a particular county reflects the 2010 value. Since more recent data apportioning ZCTA populations

[14] Additional details on the construction of ZCTAs are available here: https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html
[15] UDS Mapper's zip5 to ZCTA crosswalk is available here: https://www.udsmapper.org/zcta-crosswalk.cfm
[16] Additional information about UDS Mapper is available here: https://www.udsmapper.org/about.cfm
[17] We used the county-couma crosswalk provided as an online data appendix to Case & Deaton Case A, Deaton A. 2017. Mortality and Morbidity in the 21st Century. (Ed)^(Eds), Brookings Papers on Economic Activity, vol. Spring 2017. 2017., available at https://www.brookings.edu/bpea-articles/mortality-and-morbidity-in-the-21st-century/.

to counties is not available, we must therefore assume that the distribution of a ZCTA's population among counties (and hence coumas) during our study period (2013-2018) is similar to 2010.

Appendix C: Comparison of Natural Language Processing Algorithm Results to Wu and Colleagues

Our NLP algorithm identifies a similar share of SSDI applicants taking opioids as Wu and colleagues (Wu et al., 2019a), for each year of overlap in our analyses, as shown in **Table C1** below.

Table C1: Estimates of Percent Applicants Taking Opioids by Year

Year	**2013**	**2014**	**2015**	**2016**	**2017**
Wu et al. 2019	31%	32%	30%	28%	26%
Our Estimates	33%	33%	32%	30%	28%