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ARE THERE "HOT SPOTS" OF PRIMARY IMPAIRMENTS AMONG NEW SSDI AWARDEES – AND DO WE KNOW WHY?

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Abstract

This paper examines local-level variation in the primary disabling conditions of new awardees for Social Security Disability Insurance (SSDI) from 2005 through 2018. It uses data from the Social Security Administration's Disability Analysis File data linked to other publicly available information from the American Community Survey and Area Health Resource File. The analysis is at the level of U.S. Census Bureau Public Use Microdata Areas (PUMAs). The paper documents the share of awards in each PUMA and year in one of five impairment group categories, selected to align with areas of strong policy interest. In each impairment group, the paper identifies "hot spots" as PUMAs in which the share of awards for that condition is in the top 10 percent relative to other PUMAs in the same year. The paper documents the geographic variation in award shares and hot spots using maps and uses regression analysis to explore relationships between SSDI award shares by impairment group and a range of PUMA-level factors. The findings are descriptive and should not be interpreted causally.

We find that:

- SSDI awards by impairment groups have geographic patterns that show important variation across state lines as well as within state borders. The share of awards for musculoskeletal disorders is higher in PUMAs in Appalachia and into the southeast, while award shares for mental disorders are highest in New England – persistently so in in Vermont, and New Hampshire. Award shares for circulatory and respiratory disorders are higher in the Mississippi Delta region and northward along the Mississippi River to and through Illinois and Indiana. There are no obvious patterns for the neoplasms, infectious diseases, injuries category nor the systems diseases category.
- The general geographic patterns that show cross- and within-state differences are stable over time, but PUMA "hot spots" are not always the same in each year. In most cases, this simply reflects PUMAs that are just above the 90th percentile in some years and just below in others, rather than large swings in award shares within PUMAs over time. Nonetheless, areas with high award shares in particular impairment groups do persist over time.

- Regression analysis shows that demographic and socioeconomic factors explain part of the observed variation in award shares, but the estimated effects are small, suggesting that other factors may be critical determinants of local-level variation in award shares.

The policy implications of the findings are:

- When considering future caseload patterns, it may be important to consider local-level predictors of new awards, overall and by impairment type. Some of the factors that might affect award shares for certain disabling conditions include environmental exposures and features of the disability determination process (such as distance to a field office and examiner stringency). Because of concerns about multicollinearity, it is difficult to incorporate the full range of observable factors that might affect awards by impairment category. Additionally, other factors such as the efficacy of legal representation when filing claims or social networks and attitudes toward benefit receipt may be important determinants of SSDI award patterns but more difficult to measure in a way that would allow for them to be incorporated into a regression model.
- Qualitative research on geographic patterns in new benefit awards may help SSA better understand program trends, as well as the supports that new beneficiaries might need if they want to consider leaving the program rolls.

Introduction

Each year, the Social Security Administration (SSA) makes around three-quarters of a million new awards for Social Security Disability Insurance (SSDI) benefits.[1] While the financial and economic criteria used to determine awards are the same across the nation, award rates for SSDI vary across and within states, reflecting a mix of demographic, economic, health, and social factors (Schimmel Hyde et al. 2021). In addition to variation in award rates, the share of awards within a given impairment group could vary locally, reflecting a similar range of factors. Local-level statistics on the types of disabling conditions faced by new awardees may inform SSA about areas with specific needs among applicants or beneficiaries. For example, areas with significantly higher-than-average award shares for respiratory conditions may have different support needs than areas where awards for mental health conditions are higher-than-average. Understanding geographic patterns in disabling condition awards may help SSA project changes in the disability rolls and may be informative for SSA or other agencies in assisting beneficiaries.

In this manuscript, we explore local-level variation in the primary disabling conditions of new SSDI awards from 2005 through 2018. We use SSA administrative data to document the share of awards in each local area that is in one of five impairment group categories. We selected the impairment groups to align with areas of strong interest in disability policy, including mental and musculoskeletal disorders, which represent a large share of total awards in recent decades (SSA, 2019).

For each impairment group, we identify "hot spots" as areas in which the share of awards for that condition is in the top 10 percent relative to other areas in the same year. As we describe in what follows, we consider award shares at the level of the U.S. Census Bureau Public Use Microdata Area (PUMA), which is defined to include at least 100,000 individuals. PUMAs are defined within state borders, but often encompass more than a single county. We use PUMAs because they are large enough to minimize the masking of cells due to SSA guidelines, and because we are able to link information on award shares to publicly available annual area-level data from other federally-collected, nationally representative data.

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[1] The number of awards has been falling in recent years, with a precipitous decline in 2020, likely reflecting office closures due to COVID-19 (https://www.ssa.gov/oact/STATS/dibStat.html).

We find substantial heterogeneity in the share of SSDI awards within impairment groups across the country, with variation both across- and within-state. For example, the share of awards
for mental disorders are highest in New England, in an area that spans parts of Massachusetts, as well as New Hampshire and Vermont. This suggests that state and local policies and conditions may be important determinants not just of overall disability awards, but for awards within particular impairment groups. Our findings echo other work that has documented geographic variation in outcomes for individuals with disabilities and variations in SSA disability benefit receipt and beneficiary outcomes (Coe et al. 2011; Gettens et al., 2018; Nichols et al. 2017; Rupp 2012; Schimmel Hyde et al. 2021; Schmidt and Sevak, 2017; Schwabish 2017; Sevak et al. 2018).

Using area-level factors that have previously been tested in the literature, we sought to understand the demographic, social and economic factors that might explain variation in the share of awards by impairment group. We find evidence that demographic factors such as age, gender, and race, are associated with awards by impairment group, which may in part reflect differences in health conditions across those groups. Additionally, socioeconomic factors including veteran status, educational attainment, and, to a lesser extent, local industry composition are associated with certain award types. We find that many observable characteristics often thought to explain benefit awards and receipt are not strongly predictive of award shares across impairment groups. We discuss the types of factors not accounted for in our model, describe the ways in which they might affect award shares, and offer suggestions that might help SSA understand the impairments faced by new applicants in the future.

Why Might We Observe Local-Level Variation in Awards by Impairment Group?

Before considering why there may be local-level concentrations within impairment groups, it is helpful to consider the individual disability determination process. The decision to apply for disability benefits depends on one's knowledge of the program, his or her health status, and the availability of jobs that can accommodate the person's disability (including transit to and from work). After deciding to apply, the SSDI applicant must provide information on their health and functioning, and information on their past work activity. SSA disability examiners base their award decisions on the impairments reported in the application, the strength of medical documentation, and SSA's medical-vocational factors that take into account the applicant's residual functional capacity and past relevant work if the applicant is age 55 and older (SSA 2012, SSA 2015). The strength of one's application—initially and on appeal—depends on detailed knowledge of the required steps and information, and often applicants are more likely to receive an award if they have legal representation assisting with their application (see Luca and Ben-Shalom, 2021 and Hoynes, Maestas and Strand, 2016).

Given the process at the individual level, we might expect that the share of awards in a particular impairment group in an area to be a function of four primary categories:

Prevalence and Incidence of Chronic Health Conditions. The prevalence and incidence of chronic health conditions varies quite a bit across the country, both within large geographic regions (e.g., prevalence in the south differs from that in the north), but also locally—with differences across counties and in urban versus rural areas. To highlight one example, the model-based prevalence of arthritis has been found to vary at the county-level, with a higher concentration among counties in the Appalachian region, but substantial within-state variation in other areas of the country such as the pacific Northwest and northern New England (Barbour et al. 2018). There is also above-average mortality in Appalachia from chronic obstructive pulmonary disorder with the highest rates found in West Virginia and eastern Kentucky with other spots of high rates in Tennessee. The variation suggests the importance of local-level determinants in addition to state and regional factors. (Dwyer-Lindgren et al. 2017).

The prevalence of chronic conditions and overall health status in a given area likely reflects a host of other factors that vary locally, including health behaviors (such as obesity, smoking, or substance use disorders),[2] environmental factors (such as air and quality, lead exposure, or the nature of the predominant industries and occupations in the area),[3] and the characteristics of the area (such as walkability, the availability of public transit, or access to healthy food).[4] These factors may be both recent (such as the opening of a new bus route) or the result of longer-term exposure (such as structural racism, water quality, or obesity since childhood).

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[2] See for example, Dywer-Lindregn et al. (2014), Guettabi and Munasib (2014), Fingar et al. (2018), and Slack et al. (2014).
[3] The United States Environmental Protection Agency's (EPA) Environmental Quality Index documents substantial local-level variation in environmental quality, reflecting numerous factors (EPA, 2020).
[4] See for example, Conderino et al (2021) and Cooksey-Stowers et al. (2014).

Local Economic Conditions. Local-level variation in economic climates could lead to differential disability claiming pattern. Applications to federal disability programs increase during economic downturns (Nichols et al. 2017; Maestas et al. 2019), with changes in the composition of applicants over the business cycle that vary based on capacity for work (Lindner et al. 2017). Disability applications are also weakly responsive to changes in the minimum wage and unemployment insurance (Duggan and Goda, 2020; Mueller et al. 2016; Lindner, 2012; Rutledge, 2012). It is therefore possible that the local economic conditions such as the availability of jobs—which could affect the health and functioning of potential applicants as well as the attractiveness of the disability program relative to employment—could ultimately influence the share of awards in different impairment groups.

Other local area economic factors such as population density, availability of public transit, and the cost of housing among others may also correlate to the ability of applicants to find employment suited to their disabling conditions and the relative desirability of income from SSDI. For example, an applicant with a new musculoskeletal condition may be more likely to apply for SSDI if they can only find work in manual industries or would have to take public transit, relative to living in an area with more sedentary occupations or where commuting to work via personal vehicle was the norm.

Social Networks. Attitudes toward disability benefit receipt, employer attitudes toward hiring workers with disabilities, and knowledge of the disability determination process can all affect the decision to apply for benefits and the strength of one's application. Work by Armour (2018) highlighted the importance of information in the decision to apply for benefits and though that example used official mailings from SSA, it is likely that informal knowledge may be similarly important. Other work has considered the influence of average waiting times in the state on the timing between disability onset and application, with mixed findings (Burkhauser, Butler, and Weathers, (2001/2002; Lahiri, Song, and Wixon, 2008). To the extent social networks share health characteristics (e.g., applicants from the same employer, from the same racial background, or residing in the same area), social networks may affect the alleged impairments and the likelihood of an award.

The Disability Determination Process. Having assistance from an advocate or a legal representative may increase the likelihood of a successful claim for federal disability benefits (Hoynes, Maestas and Strand, 2016; Government Accountability Office, 2017). Individuals who live in areas where such representation can be easily accessed or where particularly prominent representation advertises may be more successful in receiving an award, and this might vary across disabling condition types, particularly for conditions that are harder to verify. Online SSDI applications appear to vary with local-level high-speed internet accessibility (Foote et al., 2019) and the ability to apply for benefits online may vary by the type of disabling condition, which could subsequently affect the share of awards for particular conditions in the area.

While disability eligibility criteria are the same across the country, there are reasons to think that award rates and the share of awards in given impairment groups may vary locally and over time based on the individuals reviewing the claims. Evidence has shown that disability examiners vary in their stringency (Maestas et al., 2013) and that, at least for SSI, field office closures result in reductions in applications concentrated in disadvantaged groups (Deshpande and Li, 2019). Beyond initial claims processing, other work has found variation in allowance rates among Administrative Law Judges, even after holding constant characteristics of claimants, judges, hearing offices, and other factors (Warshawsky and Marchand, 2015; U.S. Government Accountability Office, 2018).

Categorizing SSDI Awardees by PUMA and Primary Impairment

We used SSA's Disability Analysis File (DAF) to identify new adult SSDI awardees (aged 18 to full retirement age on January 1 in the calendar year) in each calendar year from 2005 through 2018. The DAF version we used contained information on all disability beneficiaries with at least one month of SSDI or SSI benefits from March 1996 through December 2018. The DAF Awardee Data Mart identifies the earliest award that occurred in or after 1996. As a result, our data include fewer awards than official statistics from SSA, which publishes awards across multiple periods of entitlement (Table 1; see also Mathematica 2021).

We used the latest ZIP code available during the year that a benefit award was made, populating zip code based on an individual's SSI record if it was available, or the SSDI record if it was not.[5] The likelihood that SSA has outdated geographic information for disability program beneficiaries has grown as the agency has moved away from paper checks for benefits. This is

[5] The DAF contains the ZIP code of each beneficiary based on the information that beneficiaries provide to SSA via the SSI or SSDI program. Because SSI benefits change more frequently in response to other income than SSDI benefits, SSI beneficiaries are in more frequent contact with SSA, and thus the ZIP code data maintained on the SSI files is more likely to be updated.

unlikely to be a substantial concern in our case, however, given that we are using information from new awardees, who are likely more inclined to keep SSA updated with current address information while awaiting a decision.

Mapping ZIP Codes to PUMAs

Using the GeoCorr concordance from the University of Missouri, we mapped zip codes to Census Bureau PUMAs.[6] PUMAs are areas that the Census Bureau defines within states so that no PUMA has fewer than 100,000 people. This allows the routine release of geographic statistics that are reliable, without concerns over small sample size. There are 2,351 PUMAs in the United States based on the 2010 Census. About half of ZIP codes are split across multiple PUMAs. In those cases, we used allocation factors to randomly assign awardees to PUMAs in a way that was proportional to the zip code's population split across PUMAs.

Table 1 shows that we are able to identify a PUMA for virtually all new beneficiaries in the DAF. Of the few beneficiaries identified in the DAF as new awardees that we cannot map to a PUMA, more than 90 percent were missing ZIP code data altogether. The remainder of unmapped beneficiaries had a ZIP code that was not mapped to a PUMA based on our concordance; this could happen due to data entry error or in locations that are not part of a PUMA classification, such as a military installation or post office box.

[6] We used the 2010 definition to map zip code to PUMAs consistently across the years of our analysis, even before the 2010 Census definitions were introduced in 2012.

Table 1. *SSDI Awardees by Year, Based on SSA's DAF*

	Number in SSA published statistics	Number in DAF Awardee Data Mart	Number mapped to PUMA	Percent of DAF-documented awardees mapped to PUMA
2005	909,681	781,026	773,639	99.1
2006	885,876	764,858	756,521	98.9
2007	901,114	778,784	769,276	98.8
2008	987,525	864,499	853,508	98.7
2009	1,081,983	968,713	956,465	98.7
2010	1,141,928	1,015,638	1,002,775	98.7
2011	1,114,057	1,002,242	988,848	98.7
2012	1,063,045	953,738	940,738	98.6
2013	965,190	878,473	865,540	98.5
2014	869,371	795,123	782,365	98.4
2015	839,429	762,526	750,148	98.4
2016	799,330	725,820	714,112	98.4
2017	812,019	718,249	708,969	98.7
2018	785,106	668,659	664,372	99.4

Source: The number of awardees in SSA's published statistics and in the DAF Awardee Data Mart were taken from Mathematica (2021). Other statistics are the authors' calculations using the DAF as described in the text.

Categorizing Impairment Groups Among New Awardees

We grouped SSDI awardees into five impairment groups based on primary disabling condition categories recorded by SSA at the time a benefit award was made. These represent aggregations of the 22 categories that SSA uses in its published statistics and have been found to be associated with different patterns in employment and earnings (Mann et al. 2015):

1. **Mental disorders.** These include mood disorders; organic mental disorders; schizophrenic and other psychotic disorders; other mental disorders; autistic disorders; developmental disorders; childhood and adolescent disorders not elsewhere classified; and intellectual disabilities.

2. **Musculoskeletal disorders.** This category includes musculoskeletal system and connective tissue disorders such as tendinitis, rheumatoid arthritis, and fibromyalgia.

3. **Neoplasms, infectious diseases, and injuries.** This includes cancers and skin disorders like bullous disease and dermatitis.

4. **Systems diseases.** These diseases include blood and blood-forming organs; digestive system; genitourinary system; nervous system and sense organs; skin and subcutaneous tissue disorders; and endocrine, nutritional, and metabolic diseases. This would include Parkinson's disease, blindness, deafness, and epilepsy.

5. **Circulatory and respiratory disorders.** Diseases in this category include the cardiovascular conditions including heart failure and other circulatory conditions, as well as chronic respiratory diseases including asthma, asbestosis, and pneumoconiosis (commonly known as black lung).

For each beneficiary, we identified the latest available primary impairment in the year of award, using the "best" information available in the DAF.[7] We made the decision to aggregate to minimize small cells that would have limited the data that SSA could have provided, combining diagnoses into as similar of categories as possible.[8,9] A sixth category that we do not analyze aggregates diagnoses that are missing, unknown, or did not map from four-digit diagnosis codes into one of SSA's categories. It is important to note that we use the *primary* impairment information even though people can and do receive SSDI benefits for multiple impairments that cross multiple categories.

The data show that from 2005 through 2018, the share of SSDI awardees with mental health conditions fell from 25.3 to 18.4 percent, while musculoskeletal impairments increased from 27.8 to 36.1 percent of all awardees over the same period (Figure 1). Over that period, the

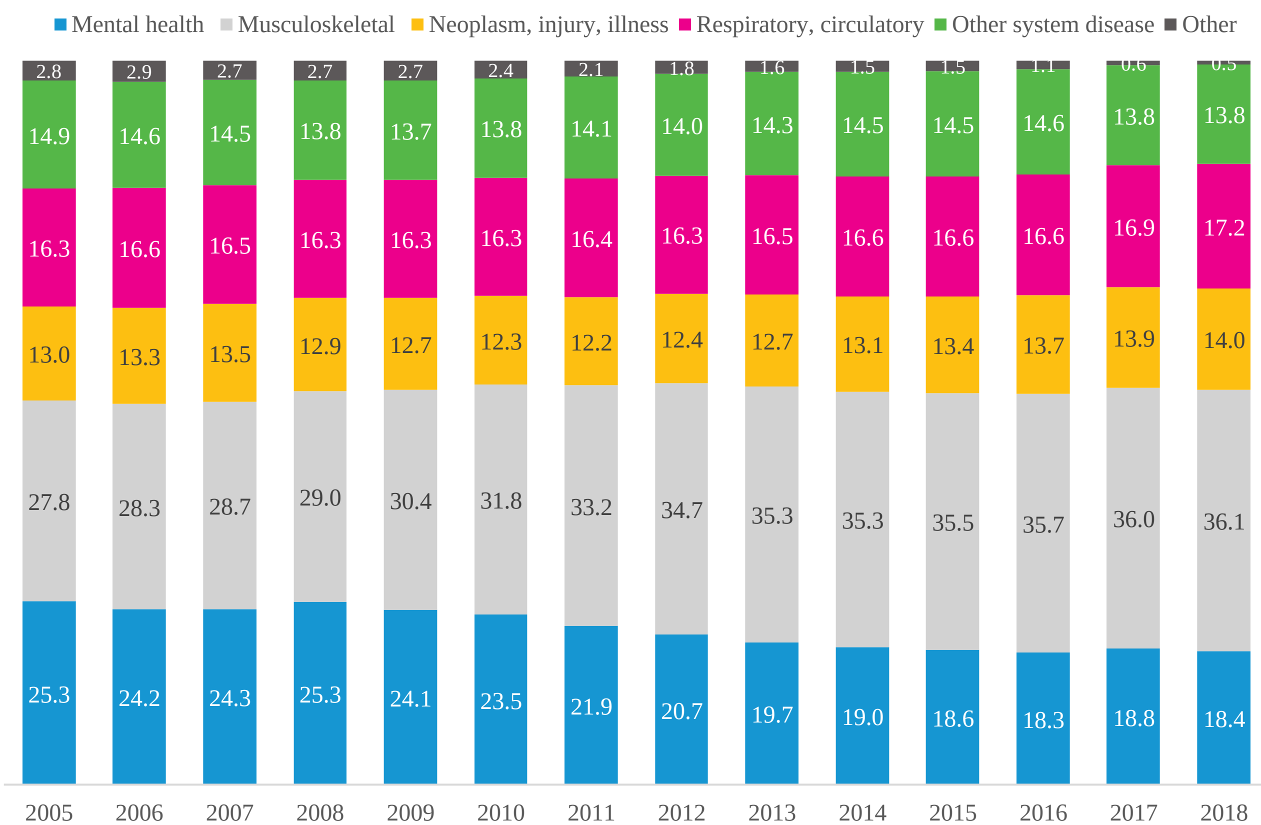
[7] The DXPRIBEST variable in the DAF is derived from information across several source files to identify the most accurate and updated information available to SSA about the beneficiary's primary disabling condition.

[8] The data provided for this project was initially developed as a subset of that used in Schimmel Hyde et al. (2021). The number of awards in each of these five categories will be made available via ssa.gov and data.gov with a wider set of PUMA-level statistics on SSDI and SSI award counts, as well as counts of beneficiaries overall and those with work activity, including suspense and termination of benefits for work.

[9] We were unable to transfer data from SSA in cases where a PUMA-impairment group summed to less than 10, based on SSA's disclosure rules. In those cases, we imputed awards randomly from 1-9 for purposes of having complete data; none of these cells represented hot spots given the small number of observations. We imputed the count of SSDI awards for: musculoskeletal conditions for four PUMAs, neoplasms for seven PUMAs, systems diseases for five PUMAs, and circulatory and respiratory disorders for 97 PUMAs.

two impairment groups together represented just over half of all SSDI awards. The share of impairments in the other groups was relatively steady over time, with 12-14 percent with neoplasms, injury or illness, 16-17 percent with respiratory or circulatory conditions, and 13-15 percent with other system diseases.

Figure 1. *Distribution of Primary Impairments Among New SSDI Awardees, 2005-2018*



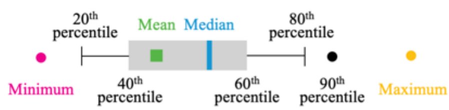
Source: Authors' calculations using the 2018 DAF Awardee Data Mart.

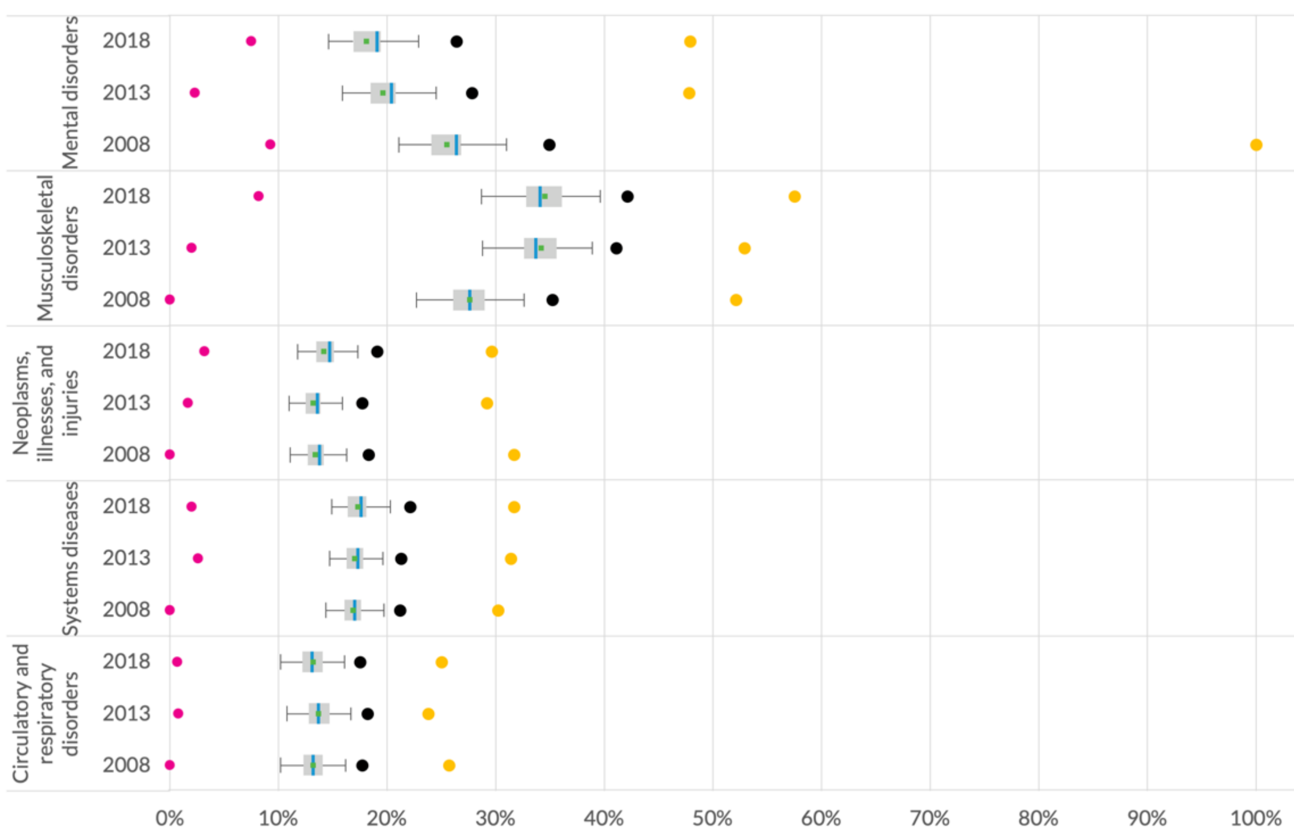
PUMA-Level Distributions of Primary Impairments Among 2018 SSDI Awardees

National statistics across impairment groups mask significant heterogeneity in the distribution of award shares across PUMAs. Figure 2 highlights the distribution of award shares in three years in our data, from most recent to earliest—2018, 2013, and 2008. Over time, we see the same chronological patterns as shown in Figure 2—growth in the share of awards for musculoskeletal and mental disorders, and about constant rates of award shares in the other impairment groups. Looking within a single year highlights the broad range of award shares across PUMAs. For example, in 2018, the 20th percentile PUMA for musculoskeletal and disorders had 28.7 percent of all awards in that group, while the 80th percentile PUMA had 39.9 percent of all awards in that group; across all PUMAs, the range spanned 7.5 to 47.9 percent of all awards. The share of awards for musculoskeletal disorders in the same year ranged from 8.2 to 57.5 percent of awards in the PUMA during the year, with similarly broad ranges across other conditions and years.

Figure 2. *Distribution of PUMA-Level Award Shares in Each Impairment Group*

Table legend:





Note: Appendix Table 1 contains a tabular version of the data in this figure. One PUMA in 2008 had all of its awards in mental disorders.
Source: Authors' calculations using the 2018 DAF Awardee Data Mart.

PUMA-Level "Hot Spots" in Impairment Group Shares

In addition to the impairment distribution of awards in each PUMA, we sought to identify PUMAs for which the share of awards was well above average. Based on our inspection of the data, we selected the top decile of award shares for each impairment group. This cutoff was high enough to identify PUMAs outside of the interquartile range but low enough to have sufficient mass to conclude that the cases were not simply outliers. The difference between the 80th and 90th percentiles in some impairment groups was narrower than others; for example, 20.3 and 22.1 percent (1.8 percentage points) for systems diseases compared with 22.9 and 26.4 percent (3.5 percentage points) among mental disorders.

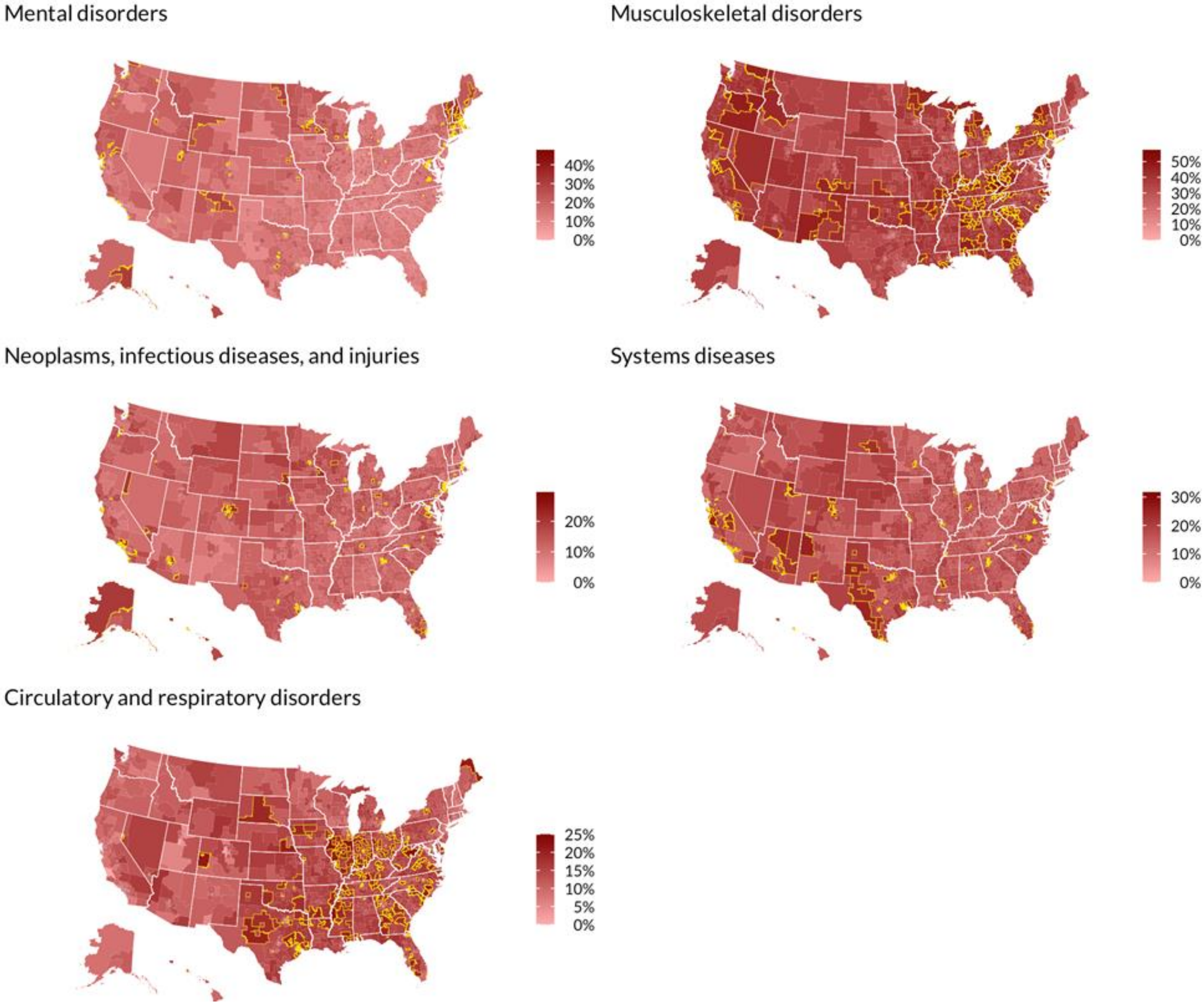
Our calculation of award shares uses *total awards* in the denominator, which we selected to mitigate large variation in SSDI awards across PUMAs, previously documented by Schimmel Hyde et al. (2021). By design, within a given PUMA, the shares across impairment groups sum to 100%. This means, however, that a single PUMA is not often a hot spot in more than one impairment group—having an exceptionally high impairment share in one group generally, though not always, means a low share in the other groups. In 2018, of 2,351 PUMAs (where for each impairment group, 235 are categorized as a hot spot), 124 PUMAs were hot spots in two impairment groups, while only 10 were hot spots in three groups.

Persistence in the Share of Awards by Impairment Group

The general patterns of award rates by impairment category shown in Figure 3 are persistent across time, with regions that have high award shares for a particular impairment group in 2018 usually having high award shares in that category in earlier years as well. (Additional maps that mirror those in Figure 3 spanning the 2005-2018 period are available at https://urbaninstitute.github.io/ssdi-hot-spots/analyses/maps.html.) Each of the panels in Figure 3 show a different impairment group with the yellow lines outlining those PUMAs that are hot spots during the 2018 sample period. We can see geographic distributions of some of these impairments across the country—for example, there are higher rates of musculoskeletal disorders in the Appalachia region and into the southeastern United States, and higher rates of mental disorders in the New England states, especially Vermont and New Hampshire. There are less obvious national patterns for the neoplasms, infectious diseases, and injuries, and systems diseases categories. For circulatory and respiratory disorders, we can see higher award rates in the Mississippi delta region and up along the Mississippi River to and through Illinois and Indiana.

Though broad patterns of award shares are persistent over time, the likelihood of a given PUMA being a hot spot is less so, with PUMAs moving in and out of the top 10th percentile hot spot definition routinely. Table 2 presents information about the hot spots identified in 2018 and the frequency that they were hot spots in the years before 2018. Just under half of PUMA hot spots for mental disorders were hot spots in the previous year, while 62 percent of musculoskeletal hot spots were also hot spots in 2017. Those conditions also had more years in the last five in which a 2018 PUMA was a hot spot. The other impairment groups had more variation in hot spots over time, as evidenced by fewer 2018 hot spots being 2017 hot spots, and a lower average number of years as a hot spot.

Figure 3. *Share of Total Awards in Each PUMA by Impairment Group, 2018*



Notes: The values shown are percentages, representing the share of awards in a particular PUMA within a given diagnosis during the year. The yellow lines outline PUMAs that are considered hot spots at any point in the 2005-2018 sample period. The majority of SSDI awards from 2018 could be categorized to one of the five impairment groups shown in this figure: we were unable to categorize 1.3 percent of all awards. Larger versions of these maps, along with separate annual maps spanning individual years during the period from 2005-2018 are available at https://urbaninstitute.github.io/ssdi-hot-spots/analyses/maps.html.
Source: Authors' calculations using SSA's DAF Awardee Data Mart.

Table 2. *Persistence of 2018 Hot Spots in Earlier Years*

	Number of hot spots in 2018[1]	Number of 2018 hot spots that were 2017 hot spots	Average number of years 2018 hot spots were hot spots from 2013-2017 (five years)
Mental disorders	235	109	2.9
Musculoskeletal disorders	235	145	2.2
Neoplasms, infectious diseases, and injuries	230	83	1.9
Systems diseases	233	74	1.6
Circulatory and respiratory disorders	232	71	1.7

Source: Authors' calculations using SSA's DAF Awardee Data Mart.

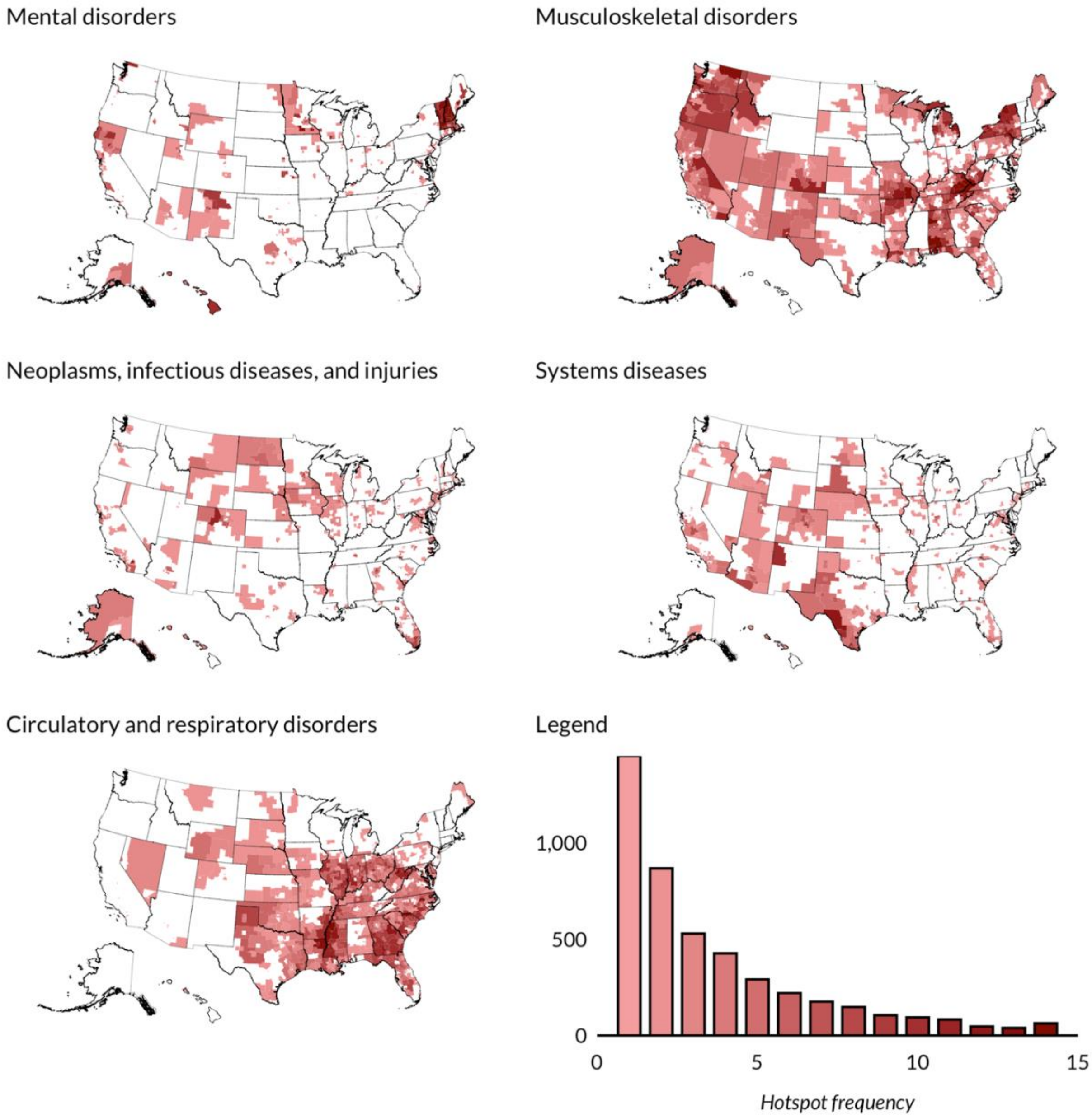
Geographic patterns in impairment category hot spots are perhaps more clearly seen in the maps presented in Figure 4a. Here, the geographic patterns are starker than in the maps in Figure 3. In these visuals, we shade each PUMA by the number of times it was identified as a hot spot during the 14-year sample period. The histogram at the bottom-right of the panel shows the overall distribution of hot spot frequency. Here, 1,449 PUMA-impairment group combinations are classified as a hot spot only once and more than 90 percent of all PUMA-impairment group combinations are classified as a hot spot fewer than 5 times (Figure 4b shows separate histograms for each impairment type).

There are exceptionally high rates of people receiving SSDI awards in the New England states, especially Massachusetts, New Hampshire, Vermont, and Rhode Island (also see Schwabish, 2017). In New Hampshire, for example, every PUMA in the state (there are ten) was classified as a hot spot all 14 years and the award rate for mental disorders in 2018 ranged from 35.7 percent to 45.7 percent. For musculoskeletal disorders, we find hot spots in Appalachia (southern West Virginia and eastern Kentucky) and in Alabama. Interestingly, while most PUMAs in Alabama have higher rates of musculoskeletal disorders relative to other PUMAs, only one PUMA in southern Mississippi was a hot spot at any time during the period for musculoskeletal disorders. These kinds of geographic patterns—one state that has markedly higher rates of an impairment while the neighboring state has relatively low rates of an impairment, despite populations that are similar on many dimensions—are one reason why we consider the local policy and local network effects to be potentially important and worthy of additional research and study.

Finally, we see more obvious geographic patterns among SSDI awardees with circulatory and respiratory disorders. PUMAs along the Mississippi River—especially in the southern part of the country—are identified as hot spots for multiple years. Dwyer-Lindgren et al. (2017) find that rates of asthma and other respiratory diseases are very high in this area, and Bell and Mazurek (2020) find that pneumoconiosis (black lung) mortality is high in coal-rich eastern West Virginia. Mirroring the finding for Alabama and Mississippi for musculoskeletal disorders, here, we find many PUMAs are hot spots for several years in Mississippi but only a few in Alabama and even those are infrequently hot spots. It is not entirely clear whether there are local policy or network effects at work or whether this somehow is an artifact of our measure of hot spots that is based on award shares that sum to 100 percent.

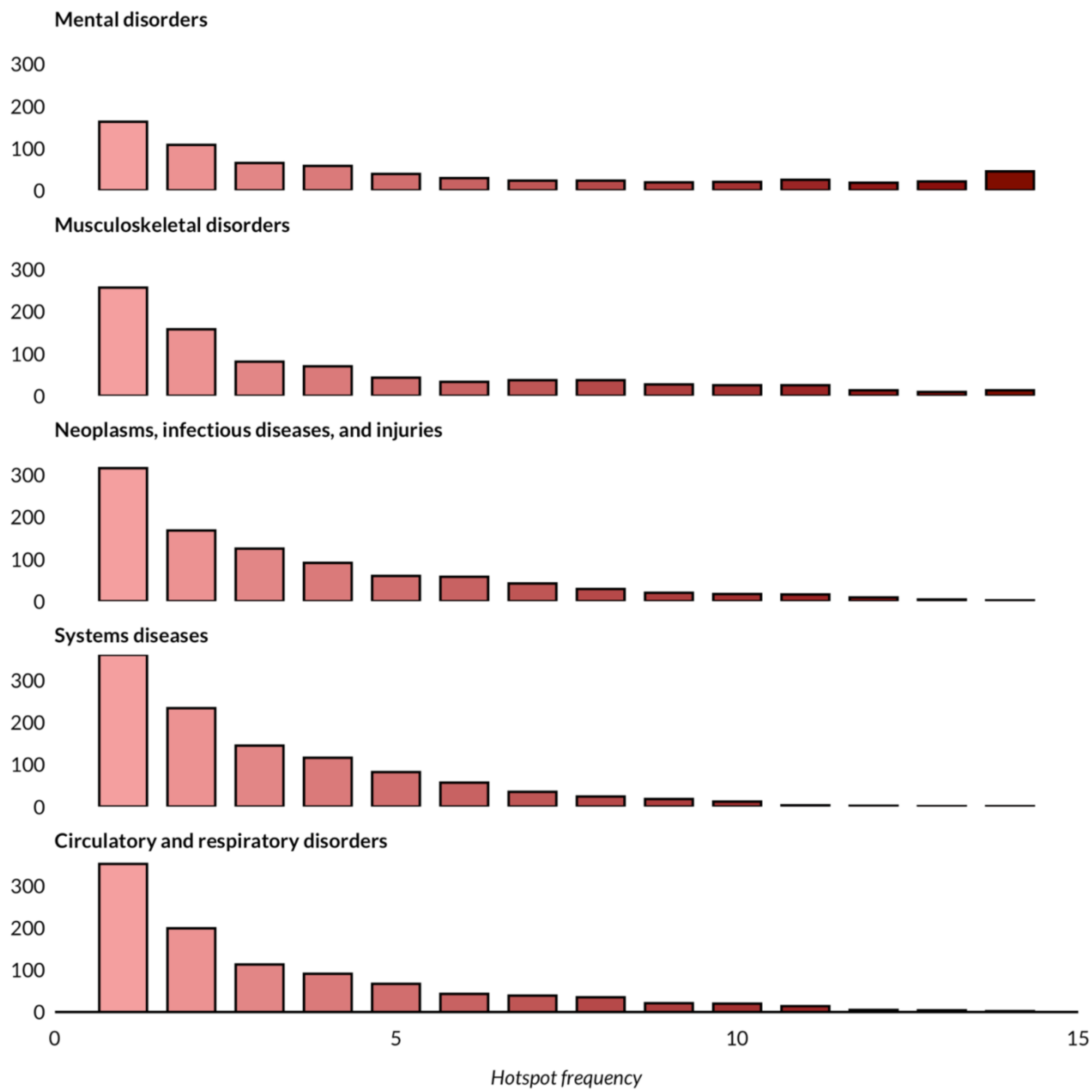
We do not observe obvious geographic patterns for the other impairment categories. For neoplasms, infectious diseases, and injuries, we see a cluster in Northern Virginia and around the Washington, DC metro area, in southern Florida around Miami, and in southern California around Los Angeles. We also find that the PUMA just west (but not including) Denver stands out and is a hot spot in 11 of the 14 years. It is possible that certain types of impairments are driving these patterns, but our data do not allow us to determine the reasons. We also see little obvious geographic patterns among the systems diseases category, though these diseases accounted for about 15 percent of all SSDI awards in 2019. We do see higher hot spot frequency along the southwestern Texas border and other parts of the southwest, and in parts of the Rocky Mountain states, but no obvious explanations for these patterns.

Figure 4a. *Hot Spot Frequency in Each PUMA by Impairment Group, 2005-2018*



Source: Authors' calculations using SSA's DAF Awardee Data Mart.

Figure 4b. *Distribution of Hot Spot Frequency for Each Impairment Group*



Note: Zeros are excluded from the legend for clarity.
Source: Authors' calculations using SSA's DAF Awardee Data Mart.

Factors that Contribute to Variation in Awards by Impairment Group

Earlier work has documented that factors such as local-level demographics, economic conditions, and health status are correlated with disability awards and beneficiary outcomes (Coe et al. 2011; Gettens et al., 2018; Nichols et al. 2017; Rupp 2012; Schimmel Hyde et al. 2021; Schmidt and Sevak, 2017; Schwabish 2017; Sevak et al. 2018). We sought to understand the extent to which similar factors explain the share of awards in each of our impairment groups. We are not ascribing a causal relationship between the independent and dependent variables in this model but instead are simply seeking to document associations that might be useful in identifying areas that may benefit from targeted supports or interventions. In what follows, we describe the estimated models and the covariates we considered, before highlighting the relationships we observed.

Empirical Framework

For each impairment group in 2018, we estimated a model of the following form:

$$ImpairmentShare_{djt} = \alpha + \beta_1 DEMOG_{jt} + \beta_2 SES_{jt} + \beta_3 OTHER_{jt} + \eta_j + \varepsilon_{jt}$$

where $ImpairmentShare_{djt}$ is a measure of the share of awards in the impairment group *d* in PUMA *j* in year *t*. $DEMOG_{jt}$, SES_{jt} and $OTHER_{jt}$ are vectors of demographic, socioeconomic, and other characteristics at the PUMA level in 2018, drawn from Schimmel Hyde et al. (2021) and the literature around factors that explain awards and beneficiary outcomes. State fixed effects, denoted by η_j, allow us to control for unobserved state-level factors that are the same across PUMAs within the state.

We estimated two versions of this model: one where the dependent variable was the award share (as percent of all SSDI awards in the PUMA/year), and another where the dependent variable was a binary indicator of the award share falling into the hot spot definition outlined above. In the version using award shares, we estimated the model using ordinary least squares regression. We regressed the natural log of the outcome measure on the natural log of all continuous regressors, allowing for the interpretation of the coefficients in the regression as elasticities, or the percentage change in the outcome associated with a one-percent change in the regressor. In the version using the hot spot indicator, we used a linear probability model, which allows for a simple interpretation of the coefficients though does not account for the binary nature of the dependent variable.[10] All of our models were estimated using Stata using robust standard errors.

In the models that use shares, it is important to interpret the coefficients for a particular impairment group keeping in mind that the award shares sum to 100 percent. The simplest version of this is to consider this with two dependent variables instead of five. For example, suppose we only had information on musculoskeletal disorders and mental disorders. If that were the case, the award share for musculoskeletal disorders would be 100 minus the award share for mental disorders. When considering the role of the covariates then, a covariate that was positively associated with the share of awards for musculoskeletal disorders would be negatively associated with the share of awards for mental health disorders. Extrapolating to the five impairment groups in our analysis, we therefore expect that the effect of each dependent variable will be approximately offsetting across the independent models.

Area-Level Predictors of Award Shares

As discussed previously, myriad factors likely are associated with local-level variation in award rates. Our paper is a first look at the topic and is narrowly focused on the relationship between award rates and demographic and socioeconomic factors, included those related to access to care (insurance and provider availability). We do not directly consider the role of health behaviors or environmental exposures, though recognize that those factors are highly correlated with other measures we have in our model. We also do not consider variation in Social Security disability determinations or other policies, recognizing that other studies have considered those factors in causal research designs (see, for example, Deshpande and Li, 2019).

To assess these area-level associations, we drew upon nationally representative data sources to incorporate into our regression model (Appendix Table 2 contains PUMA-level means in 2018 for each of the covariates we include in the regression model). First, we used PUMA-level statistics from the U.S. Census Bureau's American Community Survey (ACS):

[10] We considered using a logistic regression model to ensure predicted probabilities were within the [0,1] bounds of the dependent variable, but we could not include state fixed effects in that version because many states did not have a single hot spot which caused perfect prediction of the dependent variable. We thought that accounting for state-level unobserved factors was important enough—both theoretically and to facilitate comparison to the award share model—to opt for the linear probability model.

- **Demographic and socioeconomic factors:** age, sex, marital status, family composition, race, ethnicity, foreign-born status, veteran status, and educational attainment.
- **Area economic characteristics:** poverty rate, average home value, unemployment rate, share of workers working from home, share of people with disabilities who are employed, share of workers who are part-time (working 30 hours per week or less), and average wage and salary income.
- **Area geographic characteristics:** population density, whether the PUMA is classified as a metropolitan statistical area (MSA),[11] share of workers who take public transportation to work, and average commute times.
- **Area industry composition:** the share of workers in selected industries including trade, service, agriculture, mining, construction, manufacturing, transportation, and communication industries.
- **Health insurance coverage:** Share of the working-age population without health insurance and share of the working-age population with Medicaid.

Second, we used data from the Area Health Resource File (AHRF), collected by the U.S. Health Resources & Services Administration, to incorporate measures related to health care availability and utilization. These measures were available at the county-level, and we relied on the allocation factors available in GeoCorr to convert these to PUMA-level estimates. These factors include:

- **Number of physicians (MDs) per 10,000 residents**: a measure of access to primary health care in the area, which could reflect the demand for medical care in the area. It could also affect the likelihood that an individual is diagnosed with a condition that might qualify for disability benefits or a chronic condition and the extent to which individuals manage their chronic conditions to avoid or prolong disability
- **Share of non-federal MDs who are orthopedists**: this could be correlated with the share of musculoskeletal disorders among SSDI beneficiaries. A larger share of physicians available to treat musculoskeletal conditions could mean more medical documentation that could lead to a larger share of awards for musculoskeletal conditions. Conversely, more

[11] MSA is constant within PUMA from 2012-2018. From 2005-2011, MSA ranges from 0-100 percent because observations from earlier years that were categorized into 2000 Census PUMAs were mapped to 2010 Census PUMA definitions. For our cross-sectional models using 2018 data, MSA is a binary measure and for longitudinal models using data from 2005-2018, MSA is a continuous measure.

physicians to treat musculoskeletal conditions could mean more effective treatment to avoid conditions becoming disabling to the point of needing disability benefits.

- **Share of non-federal MDs who are in psychiatry**: this could be correlated with the share of mental health conditions among SSDI and SSI beneficiaries. The available measure considers psychiatry, not psychology or other types of mental health supports and therefore is only a proxy for a range of available services. This measure similarly has a theoretically ambiguous relationship on awards, for reasons similar to those described for musculoskeletal conditions.
- **Hospital beds per 10,000 residents:** this variable could signal the availability of acute healthcare in the PUMA
- **Total number of inpatient days per 10,000 residents:** this could signal the overall level of health in the PUMA and acute healthcare needs

When selecting predictors to include in the model, we recognized that the factors affecting impairment groups may differ—for example, the number of psychiatrists may be more strongly associated with mental disorders than respiratory and circulatory disorders, though the direction of the effect is theoretically ambiguous. We opted to include the same set of predictors across models to facilitate comparison and interpretation across conditions. We considered individual covariates in a stepwise approach to examine partial R-squared values and used least absolute shrinkage and selection operator (LASSO) to identify cases of multicollinearity between variables, but ultimately opted for a model similar to that used in recent work modeling awards with a full set of covariates (Schimmel et al. 2021). In general, we found that the addition of groups of covariates generally did not change the substance of our findings for core demographic factors that were the basis of our initial model.

Cross-Sectional Regression Results

We find that few PUMA-level demographic and socioeconomic factors in the models are consistently predictive of award shares across impairment groups in 2018. In fact, many of the predictors in our model have a very small and/or statistically insignificant association with award shares. Table 3 shows the regression results using award share in each impairment group as the outcome variable. Even the statistically significant coefficients show that award share is inelastic with respect to the PUMA-level characteristics in the model—that is, a one percent increase in the share of a PUMA's working-age population is associated with a change in the award share of less than one percent in absolute magnitude.

We find that demographic and socioeconomic factors are associated with the share of awards in particular impairment groups. We highlight just a few of the statistically significant associations here:

- Holding other factors constant, PUMAs with an older average age have larger shares of awards for mental disorders and neoplasms, and smaller shares for musculoskeletal and circulatory and respiratory disorders.
- PUMAs with a larger share of female residents have larger shares of awards for musculoskeletal, circulatory and respiratory disorders, but smaller shares of awards for neoplasms, infectious diseases and injuries.
- A higher proportion of the PUMA that identifies race as white is associated with an increased share of awards for mental disorders, but smaller shares of awards for neoplasms, infectious diseases, and injuries and for systems diseases.
- Education is strongly associated with the share of awards across impairment groups. PUMAs with a larger share of the population without a college degree have larger shares of awards in musculoskeletal disorders and circulatory and respiratory disorders, but smaller shares of awards in mental conditions and neoplasms, infectious diseases, and injuries.
- Areas with a larger share of veterans have higher award shares for musculoskeletal conditions but smaller shares for neoplasms, infectious diseases, and injuries and systems diseases, thought he magnitude of those effects are much smaller than for education.
- Other socioeconomic and economic characteristics do not show as consistent of associations as education.

The associations between PUMA-level geographic and local industry composition reveal complex patterns. More densely populated areas are associated with increased award shares for mental disorders, but decreased award shares for musculoskeletal disorders. Yet, the associations are in opposite directions for those conditions for PUMAs in within Metropolitan Statistical Areas. Holding all else constant, PUMAs with longer average travel times to work have lower award shares for mental disorders and systems diseases, and higher award shares for musculoskeletal disorders. Areas with larger shares using public transit to work also have higher award shares for musculoskeletal disorders while having lower award shares for neoplasms, infectious diseases, and injuries as well as for systems diseases. Patterns by industry are varied and do not reveal strong consistent patterns, though areas with a higher composition of the workforce in the service sector have significantly higher award shares for mental disorders, but lower for circulatory and respiratory disorders as well as musculoskeletal disorders.

Table 3. *Regression Models Predicting the Share of PUMA-Level Awards in Each Impairment Group, 2018*

	Mental disorders	Musculo-skeletal disorders	Neoplasms, infectious diseases and injuries	Systems diseases	Circulatory and respiratory disorders
Demographic and socioeconomic factors					
Average age (years)	**0.432*** *(0.131)***	**-0.626*** *(0.094)***	**0.607*** *(0.145)***	-0.181 *(0.122)*	**-0.515** *(0.211)***
Female (%)	-0.150 *(0.155)*	**0.197* *(0.105)***	**-0.341** *(0.169)***	0.223 *(0.137)*	**0.889*** *(0.295)***
Married (%)	**-0.349** *(0.164)***	0.082 *(0.113)*	-0.097 *(0.169)*	**0.307** *(0.144)***	0.119 *(0.250)*
Female and married (%)	0.088 *(0.156)*	0.039 *(0.107)*	0.071 *(0.156)*	-0.200 *(0.128)*	-0.069 *(0.228)*
Childless (%)	**-0.343*** *(0.129)***	**0.267*** *(0.090)***	-0.054 *(0.135)*	-0.045 *(0.112)*	0.298 *(0.237)*
White (%)	0.028 *(0.018)*	**0.052*** *(0.012)***	**-0.033* *(0.018)***	**-0.081*** *(0.015)***	-0.006 *(0.025)*
Hispanic (%)	0.002 *(0.010)*	0.003 *(0.007)*	0.002 *(0.010)*	**0.015* *(0.009)***	**-0.023* *(0.012)***
Born abroad (%)	**0.019* *(0.012)***	0.004 *(0.008)*	0.005 *(0.012)*	-0.008 *(0.011)*	-0.012 *(0.018)*
Veteran status (%)	0.01 *(0.015)*	**0.079*** *(0.011)***	**-0.069*** *(0.014)***	**-0.058*** *(0.011)***	0.026 *(0.020)*
No college degree among ages 25+ (%)	**-0.290*** *(0.049)***	**0.412*** *(0.044)***	**-0.211*** *(0.054)***	-0.046 *(0.051)*	**0.438*** *(0.105)***
Area economic characteristics					
Under federal poverty line (%)	0.029 *(0.024)*	-0.014 *(0.020)*	-0.022 *(0.025)*	-0.009 *(0.023)*	0.049 *(0.045)*
Average home value ($1,000)	-0.028 *(0.022)*	**0.035** *(0.016)***	0.009 *(0.027)*	**-0.041** *(0.020)***	-0.007 *(0.032)*
Unemployment rate (%)	-0.014 *(0.013)*	**0.026*** *(0.009)***	**-0.047*** *(0.013)***	-0.005 *(0.012)*	-0.009 *(0.019)*
Work from home (%)	0.005 *(0.009)*	0.008 *(0.008)*	-0.005 *(0.010)*	0.009 *(0.008)*	-0.014 *(0.013)*
	-0.009	-0.017	0.032	-0.019	-0.001

Employed, among people with any disability (%)	*(0.018)*	*(0.014)*	*(0.021)*	*(0.020)*	*(0.029)*
30 hours or less worked in a week (%)	0.004 *(0.025)*	**0.043**** ***(0.017)***	0.005 *(0.025)*	-0.015 *(0.022)*	-0.010 *(0.050)*
Average income ($1,000)	-0.001 *(0.041)*	**-0.062*** ***(0.032)***	**0.124***** ***(0.048)***	-0.020 *(0.037)*	0.085 *(0.076)*
Area geographic characteristics					
In Metropolitan Statistical Area (1=yes, 0=no)	**-0.041***** ***(0.015)***	**0.020**** ***(0.010)***	0.008 *(0.017)*	**0.050***** ***(0.014)***	-0.031 *(0.022)*
Population density (100 people per sq. mile)	**0.014**** ***(0.007)***	**-0.020***** ***(0.005)***	0.003 *(0.007)*	0.008 *(0.006)*	0.003 *(0.012)*
Average travel time to work (minutes)	**-0.062**** ***(0.030)***	**0.108***** ***(0.022)***	0.018 *(0.036)*	**-0.083***** ***(0.027)***	-0.058 *(0.045)*
Use of public transportation for work (%)	0.008 *(0.008)*	**0.012**** ***(0.005)***	**-0.025***** ***(0.008)***	**-0.013*** ***(0.007)***	-0.001 *(0.013)*
Area industry composition					
Trade (%)	0.046 *(0.031)*	**-0.053**** ***(0.024)***	**0.076**** ***(0.033)***	0.015 *(0.030)*	-0.009 *(0.060)*
Service industry (%)	**0.281***** ***(0.050)***	**-0.069**** ***(0.033)***	-0.070 *(0.052)*	0.037 *(0.045)*	**-0.168**** ***(0.072)***
Agriculture (%)	0.008 *(0.006)*	**-0.011***** ***(0.004)***	0.006 *(0.006)*	0.008 *(0.005)*	0.002 *(0.009)*
Mining (%)	0.001 *(0.002)*	-0.001 *(0.001)*	-0.003 *(0.002)*	0.002 *(0.002)*	0.000 *(0.003)*
Construction (%)	0.011 *(0.015)*	**-0.027**** ***(0.011)***	**0.033**** ***(0.017)***	0.016 *(0.014)*	**-0.047*** ***(0.027)***
Manufacturing (%)	0.013 *(0.013)*	-0.009 *(0.008)*	0.02 *(0.013)*	0.008 *(0.010)*	-0.011 *(0.023)*
Transportation (%)	-0.015 *(0.012)*	-0.015 *(0.009)*	**0.024*** ***(0.012)***	0.004 *(0.011)*	0.023 *(0.019)*
Communication (%)	0.005 *(0.004)*	0.002 *(0.003)*	-0.003 *(0.005)*	-0.003 *(0.004)*	-0.009 *(0.006)*
Health care access and utilization					
Uninsured (%)	-0.011 *(0.014)*	-0.011 *(0.011)*	0.006 *(0.015)*	0.016 *(0.014)*	0.026 *(0.026)*
Health insurance through Medicaid (%)	0.023 *(0.025)*	0.002 *(0.019)*	-0.013 *(0.026)*	**-0.061***** ***(0.023)***	-0.019 *(0.043)*
Number of non-federal MDs per 10,000 people	**0.034**** ***(0.014)***	**-0.023**** ***(0.009)***	-0.009 *(0.014)*	**0.026**** ***(0.012)***	0.021 *(0.017)*
Number of non-federal psychologists per 10,000 people	0.002 *(0.004)*	0.001 *(0.002)*	0.000 *(0.004)*	**-0.006*** ***(0.003)***	0.000 *(0.005)*
Number of non-federal orthopedist MDs per 10,000 people	-0.001 *(0.006)*	0.003 *(0.003)*	0.007 *(0.005)*	0.000 *(0.004)*	-0.008 *(0.006)*
Number of hospital beds per 10,000 people	-0.033 *(0.027)*	**0.060***** ***(0.018)***	**-0.059**** ***(0.028)***	-0.007 *(0.023)*	-0.018 *(0.038)*

Number of hospital-inpatient days per 10,000 people	0.027	**-0.042*** **	**0.041** **	0.004	0.008
	(0.020)	***(0.013)***	***(0.020)***	*(0.015)*	*(0.026)*

Note: Coefficients are shown on the same line as the variable name; standard errors are in parentheses on the next row. Bolded values are statistically significantly different from 0 (* p<0.10, **p<0.05, ***p<0.01); **bold black** are positive values and **bold red** are negative values. Models included state fixed effects. All regression models included 2,351 observations, where values for masked cells due to disclosure risk were imputed with a random number of awards from 1-9.
Source: Authors' calculations using data from the DAF, ACS, and AHRF.

We did not find strong associations between health care access and utilization and award shares. The share uninsured and the share with Medicaid were not strong predictors of award shares overall. We also did not find strong associations between the availability of healthcare providers and award shares, perhaps because the offsetting effects of better health care and more diagnosed medical conditions discussed above. The number of non-federal physicians in a PUMA is positively correlated with shares of awards in mental disorders and systems diseases but negatively associated with shares of awards in neoplasms, infectious diseases, and injuries. Interestingly, the coefficients on hospital beds and hospital-inpatient days were roughly offsetting in each award share; for example, a higher number of beds was associated with a larger award share in musculoskeletal conditions, but a higher number of inpatient hospital days was associated with a lower award share that was similar in magnitude to that of available beds.

As an alternative to modeling the share of awards, we considered a version of the model that predicted being a hot spot, with a share of awards within a given impairment group in the top decile across PUMAs in 2018 (Appendix Table 3). In this version of the model, the coefficients reflect a 1 unit increase in the independent variable on the likelihood of being in the top 10th percentile of award shares, so the coefficients are necessarily smaller. In general, the results modeling hot spots showed similar patterns in terms of the covariates with a significant association with the dependent variable—covariates with strong associations in award shares also tended to have strong associations with the likelihood of the PUMA being a hot spot. For only two coefficients was the direction of a statistically significant association different across the two models, to be expected with multiple comparison. There were, however, many times that covariates had statistically meaningful associations in the models of award shares, but not in the hot spot model, meaning that the factors likely were associated generally with the impairment group's award share, but not necessarily in a way to lead to the top 10th percentile of award shares.

Pooled Cross-Section Regression Results

We also estimated pooled cross-sectional models covering the period from 2005 through 2018. We estimated these models as described above for 2018, with repeated observations for each PUMA and the addition of year fixed effects as well as standard errors that accounted for repeated PUMA observations. Table 4 presents the results from this model using award shares, analogous to Table 3. The pooled multi-year results are similar to the results from the 2018 analysis and largely indicate that the share of awards in each impairment group is inelastic with respect to the PUMA-level characteristics that we included in the model (that is, the estimated coefficients are well below 1). Most of the significant associations between PUMA-level characteristics and award share found using data from 2018 hold when earlier years of data are included in the regression, indicating that these associations are relatively stable over time. Several associations between PUMA-level demographic and socioeconomic characteristics and award share became statistically significant when earlier years were added, but this might be due to increased statistical power from adding more years of data and not necessarily stronger relationships between PUMA-level characteristics and SSDI award shares. All estimated elasticities remain small, though the relationship between the share of working age residents who are uninsured and share of SSDI awards in all impairment groups became consistently stronger when earlier years were added to the regression. PUMAs with a larger share of working-age adults who are uninsured had smaller shares of SSDI awards for mental and musculoskeletal disorders and larger shares of awards in all other impairment groups while we find no significant association in the 2018 analysis.

Appendix Table 4 presents a version of the model that replaces the dependent variable of award shares with the measure based on the PUMA being a hot spot, in the top 10th percentile. We calculated the threshold for hot spot separately for each year, so that the cutoff for being a hot spot in 2017 might not be the same as in 2018. Results were consistent with those found using on data from 2018: estimated coefficients are small, but we find that coefficients are more often statistically significant in the multi-year models, which is likely due to the increased sample size relative to the 2018 analysis.

Table 4. *Pooled Cross-Sectional Regression Models Predicting the Share of PUMA-Level Awards in Each Impairment Group, 2005-2018*

	Mental disorders	**Musculo-skeletal disorders**	**Neoplasms, infectious diseases and injuries**	**Systems diseases**	**Circulatory and respiratory disorders**
Demographic and socioeconomic factors					
Average age (years)	**0.349*** *(0.082)***	**-0.500*** *(0.050)***	**0.412*** *(0.063)***	-0.057 *(0.054)*	**-0.300*** *(0.083)***
Female (%)	**-0.170** *(0.070)***	**0.161*** *(0.052)***	**-0.127** *(0.060)***	**0.177*** *(0.062)***	0.128 *(0.083)*
Married (%)	**-0.306*** *(0.052)***	**0.184*** *(0.040)***	-0.069 *(0.053)*	**0.139*** *(0.043)***	-0.025 *(0.066)*
Female and married (%)	**0.116*** *(0.042)***	**-0.061* *(0.032)***	0.024 *(0.042)*	**-0.096*** *(0.036)***	0.083 *(0.053)*
Childless (%)	**-0.112** *(0.053)***	**0.089** *(0.043)***	**-0.161*** *(0.051)***	**-0.071* *(0.039)***	**0.211*** *(0.074)***
White (%)	**0.057*** *(0.010)***	**0.047*** *(0.008)***	**-0.069*** *(0.009)***	**-0.080*** *(0.008)***	**-0.046*** *(0.011)***
Hispanic (%)	0.007 *(0.005)*	0.006 *(0.004)*	**-0.019*** *(0.004)***	**0.015*** *(0.004)***	**-0.022*** *(0.005)***
Born abroad (%)	**0.017*** *(0.006)***	**-0.021*** *(0.005)***	**0.028*** *(0.005)***	0.004 *(0.005)*	-0.005 *(0.007)*
Veteran status (%)	0.000 *(0.013)*	**0.054*** *(0.009)***	**-0.042*** *(0.007)***	**-0.025*** *(0.007)***	0.008 *(0.009)*
No college degree among ages 25+ (%)	**-0.220*** *(0.029)***	**0.371*** *(0.022)***	**-0.123*** *(0.023)***	**-0.087*** *(0.024)***	**0.322*** *(0.042)***
Area economic characteristics					
Under federal poverty line (%)	**0.041*** *(0.010)***	**-0.024** *(0.010)***	**-0.029*** *(0.011)***	**-0.037*** *(0.010)***	**0.058*** *(0.015)***
Average home value ($1,000)	-0.002 *(0.012)*	0.010 *(0.008)*	**0.060*** *(0.009)***	**-0.045*** *(0.008)***	**-0.047*** *(0.012)***
Unemployment rate (%)	-0.002 *(0.006)*	**0.015*** *(0.004)***	**-0.031*** *(0.005)***	**-0.009* *(0.005)***	**0.014* *(0.007)***
Work from home (%)	**0.020*** *(0.005)***	-0.003 *(0.003)*	**0.010*** *(0.003)***	**0.006* *(0.003)***	**-0.022*** *(0.004)***
Employed, among people with any disability (%)	**0.011* *(0.006)***	0.000 *(0.005)*	**0.012** *(0.006)***	0.003 *(0.006)*	**-0.014* *(0.008)***
30 hours or less worked in a week (%)	-0.007 *(0.010)*	**0.016** *(0.008)***	0.011 *(0.009)*	**0.026*** *(0.008)***	0.003 *(0.013)*
Average income ($1,000)	-0.002 *(0.023)*	**-0.109*** *(0.016)***	**0.133*** *(0.018)***	0.025 *(0.016)*	**0.123*** *(0.026)***

Area geographic characteristics					
In Metropolitan Statistical Area (1=yes, 0=no)	-0.002**	0.002***	-0.001	0.002***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population density (100 people per sq. mile)	0.018***	-0.021***	-0.001	0.011***	-0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Average travel time to work (minutes)	-0.037*	0.071***	-0.019	-0.078***	-0.013
	(0.019)	(0.013)	(0.013)	(0.013)	(0.018)
Use of public transportation for work (%)	0.007*	0.008**	-0.005	-0.012***	-0.006
	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)
Area industry composition					
Trade (%)	0.045***	-0.016	0.039***	-0.015	-0.039**
	(0.013)	(0.011)	(0.013)	(0.010)	(0.016)
Service industry (%)	0.248***	-0.026	-0.090***	-0.052***	-0.095***
	(0.026)	(0.018)	(0.019)	(0.018)	(0.025)
Agriculture (%)	0.000	-0.009***	0.002	0.010***	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Mining (%)	-0.001	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Construction (%)	0.014**	-0.029***	0.039***	0.005	0.000
	(0.007)	(0.005)	(0.006)	(0.005)	(0.008)
Manufacturing (%)	0.020**	-0.006	0.009*	-0.007	-0.003
	(0.008)	(0.005)	(0.006)	(0.005)	(0.007)
Transportation (%)	-0.018***	-0.010**	0.021***	0.004	0.032***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)
Communication (%)	0.005***	0.001	0.001	-0.004***	-0.007***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Health care access and utilization					
Uninsured (%)	-0.027***	-0.020***	0.022***	0.023***	0.030***
	(0.007)	(0.005)	(0.006)	(0.006)	(0.009)
Health insurance through Medicaid (%)	0.034***	0.001	-0.043***	-0.020**	0.008
	(0.010)	(0.008)	(0.009)	(0.008)	(0.013)
Number of non-federal MDs per 10,000 people	0.021***	-0.011*	0.009	0.016***	0.004
	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)
Number of non-federal psychologists per 10,000 people	0.005**	0.000	-0.003*	-0.004**	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of non-federal orthopedist MDs per 10,000 people	0.001	0.002	-0.001	0.000	-0.005*
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Number of hospital beds per 10,000 people	-0.034**	0.025**	-0.003	-0.027**	0.003
	(0.017)	(0.010)	(0.012)	(0.012)	(0.015)
Number of hospital-inpatient days per 10,000 people	0.024*	-0.017**	0.003	0.021**	-0.007
	(0.012)	(0.007)	(0.008)	(0.009)	(0.010)

Note: Coefficients are shown on the same line as the variable name; standard errors are in parentheses on the next row. Bolded values are statistically significantly different from 0 (* p<0.10, **p<0.05, ***p<0.01); **bold black** are positive values and **bold red** are negative values. Models included state and year fixed effects. All regression models included 2,351 observations, where values for masked cells due to disclosure risk were imputed with a random number of awards from 1-9.

Source: Authors' calculations using data from the DAF, ACS, and AHRF.

Discussion

As SSA seeks to project new SSDI awards, our results suggest that it may be important to consider the role of local-level determinants to improve precision. In this paper, we document that there is substantial variation in the share of awards across impairment categories at the local level in the United States, with both cross-state and within-state variation. Additionally, we find that there are some areas that we categorize as "hot spots"—in the top ten percent of award shares for a particular impairment group—and that some areas have been persistent hot spots over many years. Understanding the areas in which awards are concentrated within impairment groups may highlight the potential for targeted interventions that could assist workers with disabilities to stay in the labor force and refrain from or delay applying for disability benefits. SSA could also use this information to target post-entitlement supports or consider the need for targeted training for disability reviewers, to the extent that the patterns suggest the role of adjudicators in the outcomes.

Our multivariate analysis sheds light on some of the factors that may be correlated with those local-level patterns, with important caveats. *It is important to note that we ascribe a correlation interpretation to our results only; we cannot say that any of the factors in our model causally determine the outcomes we consider*. Our models incorporated predictors that were readily available from selected public data sources to align with the resources available to this project. It is also important to note that there are other factors not included in our model may be just as—and perhaps more—important to consider. These fall in three buckets: (1) factors that are measurable with existing local-level data including environmental factors such as air and water quality; health behaviors such as obesity, smoking, drinking, or substance use; and access to a healthy lifestyle including factors such as food desserts, food swamps, and walkability; (2) factors that are potentially measurable such as variation in outcomes by disability examiners or administrative law judges; applications with representation, including claims filed with assistance from local firms with proven track records in certain claims; and applications filed with documentation or assistance from medical providers (ranging from major medical centers to sole practitioners); and (3) factors that might be difficult to measure systematically, such as social networks and local attitudes toward work, working with a disability, and hiring workers with disabilities.

Multivariate modeling can help identify the relative importance of individual factors while holding others constant, but many of the determinants of awards within impairment groups are correlated. As such, it may be difficult to extend the type of model we considered to include an even broader range of additional covariates. More valuable may be a geographic analysis at an even finer geographic unit such as ZIP code or Census tract; we used PUMAs because it allowed for analysis without substantially masked data to minimize disclosure risk of SSA data. SSA collects data on beneficiaries including new awardees, however, at the 9-digit zip code level, and analysis of that data at a finer level of detail may be fruitful for identifying smaller geographic areas that might warrant qualitative exploration to identify the factors driving a high share of awards within a particular impairment group.

Conclusion

In addition to local-level variation in SSDI award shares previously documented in Schimmel Hyde et al. (2021), we find significant and persistent variation in the share of SSDI awards within certain impairment groups. Our models show that at least some of the observed variation is driven by observable factors available in publicly available data sources, and we hypothesize that other factors not included in our model may be important determinants of award rates. While some of those factors may be measurable with other data sources, we think that qualitative analyses to explore particularly persistent hot spots may be critical to understanding patterns we observe.

References

Armour, Philip. 2018. "The Role of Information in Disability Insurance Application: An Analysis of the Social Security Statement Phase-In." *American Economic Journal: Economic Policy* 10(3): 1-41.

Bell, Jessica L. and Jacek M. Mazurek. 2020. "Trends in Pneumoconiosis Deaths—United States, 1999–2018." *Morbidity and Mortality Weekly Report* 69(23): 693.

Burkhauser, Richard V., J. S. Butler, and Robert R. Weathers II. 2001/2002. "How Policy Variables Influence the Timing of Applications for Social Security Disability Insurance." *Social Security Bulletin* 64(1): 52-83.

Coe, Norma B., Kelly Haverstick, Alicia H. Munnell, and Anthony Webb. 2011. "What Explains State Variation in SSDI Application Rates?" Working Paper 2011-23. Chestnut Hill, MA: Center for Retirement Research at Boston College.

Conderino, Sarah E, Justin M. Feldman, Benjamin Spoer, Marc N. Gourevitch, and Lorna E. Thorpe. 2021. "Social and Economic Differences in Neighborhood Walkability Across 500 U.S. Cities." *American Journal of Preventive Medicine,* in press.

Cooksey-Stowers, Kristen, Marlene B. Schwartz, and Kelly D. Brownell. 2017. "Food Swamps Predict Obesity Rates Better Than Food Deserts in the United States," *International Journal of Environmental Research and Public Health* 14(11): 1366.

Deshpande, Manasi and Yue Li. 2019. "Who Is Screened Out? Application Costs and the Targeting of Disability Programs." *American Economic Journal: Economic Policy* 11(4): 213-248.

Duggan, Mark G. and Gopi Shah Goda. 2020. "The Minimum Wage and Social Security Disability Insurance." RDRC Working Paper 20-17. Cambridge, MA: National Bureau of Economic Research. Available at: https://www.nber.org/sites/default/files/2021-02/NB20-17%20Duggan%2C%20Goda.pdf

Dwyer-Lindgren, L., A. H. Mokdad, T. Srebotnjak, A. D. Flaxman, G. M. Hansen, and C. J. L. Murray. 2014. "Cigarette Smoking Prevalence in US Counties: 1996-2012." *Population Health Metrics* 12(1).

Dwyer-Lindgren, Laura, Amelia Bertozzi-Villa, Rebecca W. Stubbs, Chloe Morozoff, Shreya Shirude, Mohsen Naghavi, Ali H. Mokdad, and Christopher J. L. Murray. 2017. "Trends and Patterns of Differences in Chronic Respiratory Disease Mortality among US Counties, 1980-2014." *JAMA* 318(12): 1136-1149.

Fingar, Kathryn R., Halcyon Skinner, Jayne Johann, Natalia Coenen, William J. Freeman, Kevin C. Jeslin. 2018. "Geographic Variation in Substance-Related Inpatient Stays Across States and Counties in the United States, 2013-2015." Statistical Brief #245. Rockville, MD: Healthcare Cost and Utilization Project.

Foote, Andrew, Michel Grosz, and Stephanie Rennane. 2019. "The Effect of Lower Transaction Costs on Social Security Disability Insurance Application Rates and Participation." *Journal of Policy Analysis and Management* 38(1): 99-123.

Government Accountability Office. 2017. Additional Measures and Evaluation Needed to Enhance Accuracy and Consistency of Hearings Decisions. GAO-18-37. Washington, DC: U.S. Government Printing Office.

Government Accountability Office. 2018. "Social Security Disability, Additional Measures and Evaluation Needed to Enhance Accuracy and Consistency of Hearings Decisions." Washington, DC. Available at: https://www.gao.gov/products/gao-18-37

Gettens, Jack, Pei-Pei Lei, and Alexis Henry. 2018. "Accounting for Geographic Variation in Social Security Disability Program Participation." *Social Security Bulletin* 78(2): 29-47.

Guettabi, Mouhcine and Abdul Munasib. 2014. "'Space Obesity': The Effect of Remoteness on County Obesity." *Growth and Change* 45(4): 518-548.

Hoynes, H., N. Maestas, and A. Strand. 2016. "The Effect of Attorney and Non-Attorney Representation on the Initial Disability Determination Process." Working Paper DRC NB16-15. Cambridge, MA: National Bureau of Economic Research. Available at: https://www.nber.org/programs-projects/projects-and-centers/retirement-and-disability-research-center/center-papers/drc-nb16-15

Lahiri, Kajal, Jae Song, and Bernard Wixon. 2008. "A Model of Social Security Disability Insurance Using Matched SIPP/Administrative Data." *Journal of Econometrics* 145(1-2): 4-20.

Lindner, Stephan. 2016. "How Do Unemployment Insurance Benefits Affect the Decision to Apply for Social Security Disability Insurance?" *Journal of Human Resources* 51(1): 62-94.

Lindner, Stephan, Clark Burdick, and Javier Meseguer. 2017. "Characteristics and Employment of Applicants for Social Security Disability Insurance Over the Business Cycle." *The B. E. Journal of Economic Analysis and Policy* 17(1).

Luca, Dara Lee and Yonatan Ben-Shalom. 2021. "The Role of Nonattorney Representation in the SSDI Determination Process: A Case Study of One Prominent Intermediary." *Journal of Disability Policy Studies*, 32(2): 119-130.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. 2013. "Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt." *American Economic Review* 103(5): 1797-1829.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. 2015. "Disability Insurance and the Great Recession. *American Economic Review* 105(5): 177-182.

Mann, David R., Arif Mamun, and Jeffrey Hemmeter. 2015. "Employment, Earnings, and Primary Impairments Among Beneficiaries of Social Security Disability Programs." *Social Security Bulletin* 75(2): 19-40.

Mathematica. 2021 "Disability Analysis File 2019 (DAF19) Documentation: Data from January 1994 through December 2019." Washington, DC.

Mueller, A. I., J. Rothstein, and T. M. von Wachter. 2016. "Unemployment Insurance and Disability Insurance in the Great Recession." *Journal of Labor Economics* 34(Suppl), S445-S475.

Nichols, Austin, Lucie Schmidt, and Purvi Sevak. 2017. "Economic Conditions and Supplemental Security Income Application." *Social Security Bulletin* 77(4): 27-44.

Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 10.0. Minneapolis, MN: IPUMS. Available at https://doi.org/10.18128/D010.V10.0

Rutledge Matthew S. 2012. "The Impact of Unemployment Insurance Extensions on Disability Insurance Application and Allowance Rates." Working Paper 2011-17. Chestnut Hill, MA: Center for Retirement Research at Boston College.

Rupp, Kalman. 2012. "Factors Affecting Initial Disability Allowance Rates for the Disability Insurance and Supplemental Security Income Programs: The Role of the Demographic and Diagnostic Composition of Applicants and Local Labor Market Conditions." *Social Security Bulletin* 72(4): 11-35.

Schimmel Hyde, Jody, Jonathan Schwabish, Paul O'Leary and Dara Lee Luca. 2021. "Understanding the Local-Level Predictors of Disability Program Flows: New Adult Awards and Beneficiary Work Activity." Working Paper 2021-22. Chestnut Hill, MA: Center for Retirement Research at Boston College.

Schmidt, Lucie and Purvi Sevak. 2017. "Child Participation in Supplemental Security Income: Cross- and Within-State Determinants of Caseload Growth." *Journal of Disability Policy Studies* 28(3): 131-140.

Schwabish, Jonathan. 2017. "Geographic Patterns in Disability Insurance Receipt: Mental Disorders in New England." Research Report. Washington, DC: Urban Institute. Available at: https://www.urban.org/research/publication/geographic-patterns-disability-insurance-receipt

Sevak, Purvi, John O'Neill, Andrew Houtenville, and Debra Brucker. 2018. "State and Local Determinants of Employment Outcomes Among Individuals with Disabilities." *Journal of Disability Policy Studies* 29(2): 119-128.

Slack, Tim, Candice A. Myers, Corby K. Martin, and Steven B. Heymsfield. 2014. "The Geographic Concentration of Us Adult Obesity Prevalence and Associated Social, Economic, and Environmental Factors." *Obesity* 22(3): 868-874.

U.S. Environmental Protection Agency. 2020. "Environmental Quality Index - Technical Report (2006-2010)." Washington, DC. Available at: https://cfpub.epa.gov/ncea/risk/recordisplay.cfm?deid=350545

U.S. Social Security Administration. 2012. "Program Operations Manual System (POMS) DI 00115.015: Definitions of Disability." Washington, DC. Available at: https://secure.ssa.gov/apps10/poms.nsf/lnx/0400115015

U.S. Social Security Administration. 2015. "Program Operations Manual System (POMS) DI 25025.005: Using the Medical-Vocational Guidelines." Washington, DC. Available at: https://secure.ssa.gov/apps10/poms.nsf/lnx/0425025005

U.S. Social Security Administration. 2019. "Trends in Social Security Disability Insurance." Washington, DC. Available at: https://www.ssa.gov/policy/docs/briefing-papers/bp2019-01.html

Warshawsky, Mark J. and Ross A. Marchand. 2015. "Reforming Administrative Legal Review in Disability Insurance." *Tax Notes* 149(1): 139-147.

Appendix Table 1. *Distribution of PUMA-Level Award Shares in Each Impairment Group*

Impairment Group	Minimum	20th percentile	40th percentile	Median	60th percentile	80th percentile	90th percentile[1]	Maximum	Mean
Mental disorders									
2018	7.5	14.6	16.9	19.1	19.4	22.9	26.4	47.9	18.1
2013	2.3	15.9	18.5	20.4	20.8	24.5	27.8	47.8	19.6
2008	9.3	21.1	24.1	26.4	26.8	31.0	34.9	100.0	25.5
Musculoskeletal disorders									
2018	8.2	28.7	32.8	34.1	36.1	39.6	42.1	57.5	34.5
2013	2.0	28.8	32.6	33.7	35.6	38.9	41.1	52.9	34.2
2008	0.0	22.7	26.1	27.6	29.0	32.6	35.2	52.1	27.6
Neoplasms, illnesses, and injuries									
2018	3.2	11.8	13.5	14.7	15.1	17.3	19.1	29.6	14.2
2013	1.7	11.0	12.5	13.6	13.9	15.9	17.7	29.2	13.2
2008	0.0	11.1	12.7	13.8	14.2	16.3	18.3	31.7	13.4
Systems diseases									
2018	2.0	14.9	16.4	17.6	18.1	20.3	22.1	31.7	17.3
2013	2.6	14.7	16.3	17.3	17.8	19.6	21.3	31.4	17.0
2008	0.0	14.4	16.1	17.0	17.6	19.7	21.2	30.2	16.9
Circulatory and respiratory disorders									
2018	0.7	10.2	12.2	13.1	14.1	16.1	17.5	25.0	13.2
2013	0.8	10.8	12.8	13.7	14.7	16.7	18.2	23.8	13.7
2008	0.0	10.2	12.3	13.2	14.1	16.2	17.7	25.7	13.2

Source: Authors' calculations using SSA's DAF Awardee Data Mart.

Appendix Table 2. *PUMA-Level Means of Covariates in the Regression Models, 2018*

Characteristic	Mean (standard error)
Demographic and socioeconomic factors	
Average age	38.95 *(0.07)*
Female (%)	50.77 *(0.04)*
Married (%)	38.90 *(0.14)*
Female and married (%)	19.31 *(0.07)*
Childless (%)	74.89 *(0.11)*
White (%)	72.43 *(0.41)*
Hispanic (%)	18.21 *(0.41)*
Born abroad (%)	15.18 *(0.26)*
Veteran status (%)	6.91 *(0.06)*
No college degree among people aged 25 and over (%)	46.10 *(0.21)*
Area economic characteristics	
Under federal poverty line (%)	21.63 *(0.20)*
Average home value ($1,000)	348.32 *(5.90)*
Unemployment rate (%)	4.98 *(0.05)*
Work from home (%)	5.24 *(0.05)*
Employed, among people with any disability (%)	23.52 *(0.14)*
30 hours or less worked in a week (%)	7.02 *(0.04)*
Average income ($1,000)	31.05 *(0.26)*
Area geographic characteristics	
In Metropolitan Statistical Area (1=yes, 0=no)	79.71 *(0.83)*
Population density (100 people per sq. mile)	42.50 *(2.03)*
Average travel time to work (minutes)	27.02 *(0.12)*

Use of public transportation for work (%)	8.77 *(0.21)*
Area industry composition	
Trade (%)	12.22 *(0.04)*
Service industry (%)	30.76 *(0.139)*
Agriculture (%)	1.457 *(0.030)*
Mining (%)	0.29 *(0.016)*
Construction (%)	3.863 *(0.029)*
Manufacturing (%)	5.867 *(0.063)*
Transportation (%)	2.794 *(0.026)*
Communication (%)	0.599 *(0.010)*
Health care access and utilization	
Uninsured (%)	9.16 *(0.116)*
Health insurance through Medicaid (%)	20.72 *(0.20)*
Number of non-federal MDs per 10,000 people	54.28 *(0.72)*
Number of non-federal psychologists per 10,000 people	1.87 *(0.04)*
Number of non-federal orthopedist MDs per 10,000 people	1.34 *(0.02)*
Number of hospital beds per 10,000 people	46.3 *(0.51)*
Number of hospital-inpatient days per 10,000 people	11,143 *(140)*

Source: Authors’ calculations using data from the DAF, ACS, and AHRF.

Appendix Table 3. *Regression Models Predicting the Likelihood that a PUMA's Award Share Makes It a Hot Spot for the Impairment Group, 2018*

	Mental disorders	Musculo-skeletal disorders	Neoplasms, infectious diseases and injuries	Systems diseases	Circulatory and respiratory disorders
Demographic and socioeconomic factors					
Average age	**0.010**** ***(0.005)***	**-0.009*** ***(0.005)***	0.006 *(0.005)*	0.005 *(0.005)*	0.005 *(0.005)*
Female (%)	-0.006 *(0.004)*	-0.002 *(0.004)*	-0.006 *(0.004)*	0.000 *(0.005)*	**0.009**** ***(0.004)***
Married (%)	-0.006 *(0.006)*	0.009 *(0.006)*	0.001 *(0.006)*	0.002 *(0.007)*	-0.003 *(0.007)*
Female and married (%)	0.000 *(0.011)*	-0.002 *(0.012)*	-0.001 *(0.011)*	0.000 *(0.013)*	0.004 *(0.012)*
Childless (%)	-0.003 *(0.002)*	**0.005**** ***(0.002)***	0.003 *(0.003)*	0.000 *(0.003)*	-0.002 *(0.003)*
White (%)	**0.002***** ***(0.001)***	**0.002***** ***(0.001)***	0.001 *(0.001)*	**-0.002**** ***(0.001)***	-0.001 *(0.001)*
Hispanic (%)	0.000 *(0.001)*	0.000 *(0.001)*	**-0.002**** ***(0.001)***	**0.003***** ***(0.001)***	**-0.003***** ***(0.001)***
Born abroad (%)	**0.003**** ***(0.001)***	0.001 *(0.001)*	**0.007***** ***(0.001)***	-0.001 *(0.001)*	0.000 *(0.001)*
Veteran status (%)	0.005 *(0.004)*	0.003 *(0.004)*	**-0.008**** ***(0.003)***	**-0.013***** ***(0.003)***	**-0.007**** ***(0.003)***
No college degree among ages 25+ (%)	-0.003 *(0.002)*	**0.004*** ***(0.002)***	**-0.006***** ***(0.002)***	**-0.005*** ***(0.002)***	0.003 *(0.002)*
Area economic characteristics					
Under federal poverty line (%)	0.001 *(0.002)*	0.000 *(0.002)*	0.000 *(0.002)*	0.002 *(0.002)*	**0.004**** ***(0.002)***
Average home value ($1,000)	0.000 *(0.000)*	**-0.000*** ***(0.000)***	0.000 *(0.000)*	0.000 *(0.000)*	**0.000*** ***(0.000)***
Unemployment rate (%)	**-0.005*** ***(0.003)***	**0.008**** ***(0.004)***	**0.006**** ***(0.003)***	-0.002 *(0.004)*	0.000 *(0.004)*
Work from home (%)	0.003 *(0.003)*	-0.005 *(0.003)*	0.004 *(0.004)*	0.004 *(0.003)*	**-0.008**** ***(0.003)***
Employed, among people with any disability (%)	0.001 *(0.001)*	-0.001 *(0.001)*	0.000 *(0.001)*	0.001 *(0.001)*	0.000 *(0.001)*
30 hours or less worked in a week (%)	0.006 *(0.005)*	-0.004 *(0.005)*	-0.006 *(0.006)*	-0.008 *(0.006)*	-0.006 *(0.005)*
Average income ($1,000)	0.003 *(0.002)*	0.001 *(0.001)*	**0.005**** ***(0.002)***	0.001 *(0.002)*	0.001 *(0.002)*

Area geographic characteristics					
In Metropolitan Statistical Area (1=yes, 0=no)	-0.010 *(0.014)*	-0.027 *(0.026)*	**-0.032**** ***(0.016)***	0.014 *(0.016)*	**-0.071***** ***(0.024)***
Population density (100 people per sq. mile)	**-0.001***** ***(0.000)***	0.000 *(0.000)*	0.000 *(0.000)*	0.000 *(0.000)*	0.000 *(0.000)*
Average travel time to work (minutes)	-0.001 *(0.002)*	**0.006***** ***(0.002)***	0.000 *(0.002)*	**-0.003*** ***(0.002)***	-0.002 *(0.002)*
Use of public transportation for work (%)	**0.004***** ***(0.001)***	0.002 *(0.001)*	**-0.003*** ***(0.002)***	**-0.003**** ***(0.001)***	-0.001 *(0.001)*
Area industry composition					
Trade (%)	-0.001 *(0.004)*	-0.002 *(0.004)*	-0.001 *(0.004)*	0.001 *(0.004)*	0.004 *(0.004)*
Service industry (%)	**0.006**** ***(0.002)***	-0.001 *(0.003)*	-0.002 *(0.003)*	-0.001 *(0.003)*	-0.001 *(0.003)*
Agriculture (%)	-0.007 *(0.004)*	-0.009 *(0.006)*	**-0.010**** ***(0.004)***	-0.007 *(0.007)*	**0.009*** ***(0.005)***
Mining (%)	-0.005 *(0.008)*	0.007 *(0.011)*	0.008 *(0.014)*	-0.010 *(0.013)*	0.001 *(0.011)*
Construction (%)	**-0.014***** ***(0.005)***	0.001 *(0.006)*	-0.003 *(0.006)*	-0.001 *(0.007)*	0.004 *(0.007)*
Manufacturing (%)	0.002 *(0.003)*	**-0.009***** ***(0.004)***	0.000 *(0.003)*	-0.003 *(0.003)*	-0.001 *(0.004)*
Transportation (%)	-0.005 *(0.005)*	0.000 *(0.006)*	0.001 *(0.006)*	-0.002 *(0.007)*	0.001 *(0.007)*
Communication (%)	**-0.038**** ***(0.016)***	**0.027**** ***(0.013)***	0.011 *(0.020)*	-0.010 *(0.020)*	-0.011 *(0.015)*
Health care access and utilization					
Uninsured (%)	0.000 *(0.002)*	-0.003 *(0.002)*	0.001 *(0.002)*	0.003 *(0.003)*	0.001 *(0.003)*
Health insurance through Medicaid (%)	**0.004**** ***(0.002)***	**0.004**** ***(0.002)***	0.001 *(0.002)*	-0.001 *(0.002)*	-0.003 *(0.002)*
Number of non-federal MDs per 10,000 people	**0.002**** ***(0.001)***	0.000 *(0.001)*	-0.001 *(0.001)*	-0.001 *(0.001)*	0.000 *(0.001)*
Number of non-federal psychologists per 10,000 people	0.001 *(0.010)*	-0.013 *(0.009)*	-0.002 *(0.008)*	-0.005 *(0.008)*	-0.009 *(0.006)*
Number of non-federal orthopedist MDs per 10,000 people	**-0.045***** ***(0.017)***	-0.014 *(0.015)*	0.005 *(0.015)*	0.017 *(0.016)*	-0.009 *(0.017)*
Number of hospital beds per 10,000 people	**-0.002*** ***(0.001)***	**0.003**** ***(0.001)***	-0.001 *(0.001)*	0.000 *(0.001)*	-0.001 *(0.001)*
Number of hospital-inpatient days per 10,000 people	0.000 *(0.000)*	**-0.000**** ***(0.000)***	0.000 *(0.000)*	0.000 *(0.000)*	0.000 *(0.000)*

Note: Coefficients are shown on the same line as the variable name; standard errors are in parentheses on the next row. Bolded values are statistically significantly different from 0 (* p<0.10, **p<0.05, ***p<0.01); bold black are positive values and bold red are negative values. Models included state fixed effects. All regression models included 2,351 observations, where values for masked cells were coded to not be hot spots.

Source: Authors' calculations using data from the DAF, ACS, and AHRF.

Appendix Table 4. *Pooled Cross-Sectional Regression Models Predicting the Likelihood that a PUMA's Award Share Makes It a Hot Spot for the Impairment Group, 2005-2018*

	Mental disorders	**Musculo-skeletal disorders**	**Neoplasms, infectious diseases and injuries**	**Systems diseases**	**Circulatory and respiratory disorders**
Demographic and socioeconomic factors					
Average age (years)	0.004 *(0.003)*	**-0.005**** ***(0.002)***	**0.010***** ***(0.002)***	**0.004*** ***(0.002)***	0.001 *(0.002)*
Female (%)	**-0.004**** ***(0.002)***	**-0.004***** ***(0.002)***	**-0.003*** ***(0.002)***	0.002 *(0.002)*	0.000 *(0.001)*
Married (%)	**-0.007***** ***(0.002)***	**0.007***** ***(0.002)***	-0.003 *(0.002)*	0.002 *(0.002)*	0.001 *(0.002)*
Female and married (%)	0.004 *(0.003)*	-0.003 *(0.003)*	0.003 *(0.003)*	0.001 *(0.003)*	-0.005 *(0.003)*
Childless (%)	0.002 *(0.001)*	**0.003***** ***(0.001)***	0.000 *(0.001)*	**-0.002**** ***(0.001)***	-0.001 *(0.001)*
White (%)	**0.003***** ***(0.000)***	**0.002***** ***(0.000)***	0.000 *(0.000)*	**-0.002***** ***(0.000)***	**-0.002***** ***(0.000)***
Hispanic (%)	**-0.001***** ***(0.000)***	0.000 *(0.000)*	**-0.001***** ***(0.000)***	**0.003***** ***(0.000)***	**-0.002***** ***(0.000)***
Born abroad (%)	**0.005***** ***(0.001)***	0.000 *(0.001)*	**0.006***** ***(0.001)***	-0.001 *(0.001)*	**-0.002***** ***(0.000)***
Veteran status (%)	0.002 *(0.002)*	0.001 *(0.002)*	**-0.004***** ***(0.001)***	**-0.007***** ***(0.001)***	**-0.006***** ***(0.001)***
No college degree among ages 25+ (%)	**-0.002**** ***(0.001)***	**0.004***** ***(0.001)***	**-0.004***** ***(0.001)***	**-0.005***** ***(0.001)***	**0.003***** ***(0.001)***
Area economic characteristics					
Under federal poverty line (%)	**0.002***** ***(0.001)***	**0.002***** ***(0.001)***	0.000 *(0.001)*	-0.001 *(0.001)*	**0.002***** ***(0.001)***
Average home value ($1,000)	0.000 *(0.000)*	**-0.000***** ***(0.000)***	**0.000***** ***(0.000)***	0.000 *(0.000)*	**0.000***** ***(0.000)***
Unemployment rate (%)	0.001 *(0.001)*	**0.004***** ***(0.001)***	**0.002***** ***(0.001)***	0.000 *(0.001)*	**0.003**** ***(0.001)***
Work from home (%)	**0.003**** ***(0.001)***	-0.002 *(0.001)*	**0.006***** ***(0.001)***	0.002 *(0.001)*	**-0.008***** ***(0.001)***
Employed, among people with any disability (%)	0.000 *(0.000)*	0.000 *(0.000)*	0.000 *(0.000)*	0.000 *(0.000)*	**-0.001***** ***(0.000)***
30 hours or less worked in a week (%)	0.001 *(0.002)*	-0.003 *(0.002)*	0.000 *(0.002)*	-0.002 *(0.002)*	0.000 *(0.002)*
Average income ($1,000)	**0.003**** ***(0.001)***	0.001 *(0.001)*	**0.007***** ***(0.001)***	**0.002**** ***(0.001)***	**0.002***** ***(0.001)***

Area geographic characteristics					
In Metropolitan Statistical Area (1=yes, 0=no)	0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)
Population density (100 people per sq. mile)	-0.000*** (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)
Average travel time to work (minutes)	-0.002** (0.001)	0.004*** (0.001)	-0.001** (0.001)	-0.003*** (0.001)	-0.002** (0.001)
Use of public transportation for work (%)	0.003*** (0.001)	0.000 (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	0.000 (0.000)
Area industry composition					
Trade (%)	-0.001 (0.001)	-0.004** (0.002)	0.000 (0.001)	0.000 (0.001)	-0.002 (0.001)
Service industry (%)	0.006*** (0.001)	-0.001 (0.001)	-0.005*** (0.001)	-0.002* (0.001)	-0.002** (0.001)
Agriculture (%)	-0.009*** (0.002)	-0.003 (0.003)	-0.004*** (0.002)	-0.007*** (0.003)	0.006*** (0.002)
Mining (%)	-0.010*** (0.004)	0.001 (0.005)	0.003 (0.003)	0.001 (0.005)	-0.005 (0.004)
Construction (%)	-0.005** (0.002)	-0.010*** (0.002)	0.000 (0.002)	-0.002 (0.002)	0.002 (0.002)
Manufacturing (%)	0.001 (0.001)	-0.005*** (0.002)	-0.003** (0.001)	-0.003** (0.001)	0.001 (0.001)
Transportation (%)	-0.003 (0.002)	0.000 (0.002)	-0.004* (0.002)	-0.001 (0.003)	0.008*** (0.003)
Communication (%)	0.000 (0.007)	0.012*** (0.005)	0.010 (0.006)	0.014** (0.006)	-0.014*** (0.005)
Health care access and utilization					
Uninsured (%)	-0.002** (0.001)	-0.001 (0.001)	0.000 (0.001)	0.004*** (0.001)	0.002** (0.001)
Health insurance through Medicaid (%)	0.003*** (0.001)	0.003*** (0.001)	0.000 (0.001)	0.000 (0.001)	-0.002*** (0.001)
Number of non-federal MDs per 10,000 people	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Number of non-federal psychologists per 10,000 people	0.006 (0.005)	-0.005 (0.004)	-0.006* (0.003)	-0.007** (0.003)	0.002 (0.003)
Number of non-federal orthopedist MDs per 10,000 people	-0.008 (0.009)	0.005 (0.009)	0.006 (0.008)	-0.002 (0.006)	-0.009 (0.008)
Number of hospital beds per 10,000 people	0.000 (0.000)	0.002** (0.001)	0.000 (0.000)	0.000 (0.000)	0.001 (0.001)
Number of hospital-inpatient days per 10,000 people	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)

Note: Coefficients are shown on the same line as the variable name; standard errors are in parentheses on the next row. Bolded values are statistically significantly different from 0 (* p<0.10, **p<0.05, ***p<0.01); bold black are positive values and bold red are negative values. Models included state and year fixed effects.

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