Long-Run Determinants and Idiosyncratic Factors of Social Security Disability Insurance Benefit Rates*

Lynn Bergeland Morgan
The University of Texas at Dallas

February 12, 2024

Abstract

Despite general improvements in health, advances in medical technology, and legislation designed to facilitate labor force participation for Americans with disabilities, the percentage of working-age adults receiving Social Security Disability Insurance (SSDI) increased nearly 150% from 1986 to 2013. In 2013, nearly one in twenty working-age adults was out of the labor force and receiving SSDI. After 2013, however, the increasing trend reversed, and the number of SSDI recipients has been persistently falling since. I find that the percentage of the population between the ages of 55 and 59 is what drives the long-run trend in the percent of working-age adults receiving SSDI. Additionally, states and counties experience the same common trend in SSDI rates over time, but there is a large degree of variation between states and counties. In 2013, state SSDI rates ranged from 2.75% to 8.6%, and county rates ranged from 0.64% to 21.28%. My results show real median household income, age profiles, and application rates explain 84.5% of the variation in SSDI between states. Finally, I show that labor market opportunities contribute to county-level variation in SSDI rates. Specifically, exposure to negative employment shocks at the county level lead to growth in county SSDI rates two to five years later, indicating SSDI not only explicitly insures workers against disability, but also implicitly insures workers, particularly lower skilled workers, against employment loss.

1 Introduction

Social Security Disability Insurance (SSDI), one of the largest social insurance programs in the United States, insures working Americans under the age of 65 against the risk of losing all of their income due to a work-prohibiting disability by providing monthly cash benefits and Medicare

*Email: Lynn.Morgan@utdallas.edu

to individuals who are no longer able to work due to disability.[1] In 2020, the Social Security Administration (SSA) paid more than $143.6 billion in SSDI cash benefits, and an additional $140.7 billion in Medicare expenditures for the 7.5 million disabled Americans who could no longer work.[2]

The protective benefit of SSDI receipt is substantial; it often prevents financial ruin as it is intended to (Deshpande et al. (2021)). The requirement that beneficiaries are too disabled to work in order to receive SSDI, however, also creates an adverse incentive for marginally disabled workers to prematurely exit the labor force. Prior literature suggests that the employment rate of marginally disabled workers would be 26-28% higher in the absence of SSDI receipt (French and Song (2014), Maestas et al. (2013)). SSDI benefits are modest; the average annual benefit in 2022 was $16,296, roughly equal to the earnings of a full-time worker earning minimum wage. The marginally disabled individuals who have the highest incentive to apply for SSDI, therefore, are those with the lowest earnings potential, as the opportunity cost for a marginally disabled high-income individual is much higher. This is empirically evident in the fact that SSDI recipients with less severe medical conditions are more likely to have experienced a mass layoff, bankruptcy, foreclosure, and eviction in the three years prior to SSDI award than SSDI recipients with severe medical conditions (Deshpande and Lockwood (2022)). Future earnings potential is an explicit consideration in the disability determination process. By design, individuals with less education and fewer vocational options have less stringent medical impairment requirements in the medical review process. SSDI receipt, therefore, is not solely a function of health, but also reflects an individual's potential labor market outcomes and employability.

Despite advances in medical technology, overall improvements in health, and the 1990 passage of the Americans with Disabilities Act (ADA), which made it easier for disabled individuals to engage in the work force, the percent of working-age adults receiving SSDI benefits (PAD) increased nearly 150% from the mid-1980s to 2013. Roughly one in fifty working-age adults received SSDI in 1986, and thus was out of the labor force. By 2013 that ratio had increased to nearly one in twenty working-age adults. This increase amounts to an additional three out of every 100 working-age adults exiting the labor force due to disability during this time period. This has ramifications not only for the individuals who are having to exit the labor force, but also has broader economic consequences for the level, and possibly growth rate of GDP, the tax base, and the solvency of the SSDI trust fund. In 2013, the Social Security Administration (SSA) projected the SSDI trust fund would be depleted within three years, by 2016.[3]

After peaking in 2013, the percent of working-age adults receiving SSDI reversed course and

[1] The SSA also has a separate disability program, Supplemental Security Income (SSI), which is a means tested program for low-income disabled Americans. This program does not require a work history, and thus is not a type of insurance for lost wages due to disability.

[2] MEDPAC (2023)

[3] Social Security Administration (2013)

started to decline year after year through 2021. In 2014, the percent of working-age adults receiving SSDI decreased for the first time in over 25 years. This reversal in trend occurred absent any policy changes in SSDI, and had large implications for the depletion of the SSDI trust fund. The fund that in 2013 was expected to be depleted by 2016, was projected to be fully funded for the next 75 years (as far out as the SSA projects), by 2022.

In this paper I explore the key mechanism that drives the long-run trend in PAD from 1986-2021. There is a sizable body of literature that examines factors that may account for some of the increase in PAD over differing portions of the period from 1986-2013 (Liebman (2015), Social Security Administration (2019), Duggan et al. (2007)), but literature examining why the increasing trend reversed in 2013 is sparse (Liu and Quinby (2023)). More importantly, none have determined the root cause, if one exists, that drives the long-run trend in PAD from 1986-2021. I test for a stable, long-run relationship between the trends in the numerous proposed causes and the trend in PAD. I find that the percentage of the US population between the ages of 55 and 59 is the key determinant in the long-run trend in PAD, and that a one percentage point increase in the percentage of the population in this age range leads to a 0.9 percentage point increase in PAD, from the means. It could be that disability incidence is more likely at more advanced ages. It could also be that it is more difficult to find new employment at the tail end of one's working age years, and thus more people apply for disability at more advanced ages due to a lack of other vocational options.

Another striking feature in disability receipt is the degree of variation in PAD by state and county. West Virginia had the highest PAD in 2013, with nearly one in ten working age adults (8.60%) receiving SSDI, up from 3.27% in 1986. In contrast, the PAD in Hawaii at its peak in 2013 was less than a third of that of West Virginia, with 2.75% of working-age adults receiving SSDI that year. Variation in the PAD at the county level was even more pronounced. More than one in five working-age adults (21.28%) in Dickenson County, Virginia, received SSDI benefits in 2013, more than a 250% increase from the 6.06% who received it in that county in 1986. Pitkin County, Colorado, however, a county with roughly the same size population as Dickenson County, had 0.64% of working age adults receiving SSDI in 2013, up from 0.23% in 1986. Importantly, as Figure 2 displays, the counties with the highest PAD are not equally distributed across the United States but are instead clustered in three relatively small geographic areas, namely, a portion of Appalachia, the southern Ozarks, and Alabama/Mississippi. Three small geographic zones contain almost all of the alarmingly high rates of disability, which has substantial consequences for the labor force participation and productivity in these areas.

Additionally, I investigate the idiosyncratic determinants of variation in PAD between states, or the time-varying state determinants that are independent of the overall national trend. Others have examined state-level variation in SSDI application rates, and how state policies impact application rates, but application rates do not account for the flows in and out of SSDI, and the non-stationarity of application rates is not addressed (Coe et al. (2011), Burkhauser et al. (2002)). I detrend state PAD by including the common factor that drives the national trend, namely, the percent of the national population between the ages of 55 and 59. Including this common factor addresses the nonstationarity problem with PAD, allowing for valid statistical inference. I find that 84.5% of the state-level variation in SSDI rates is explained by three variables: real median household income, the difference in the percentage of the state population ages 55-59 and the US population ages 55-59, and state application rates.

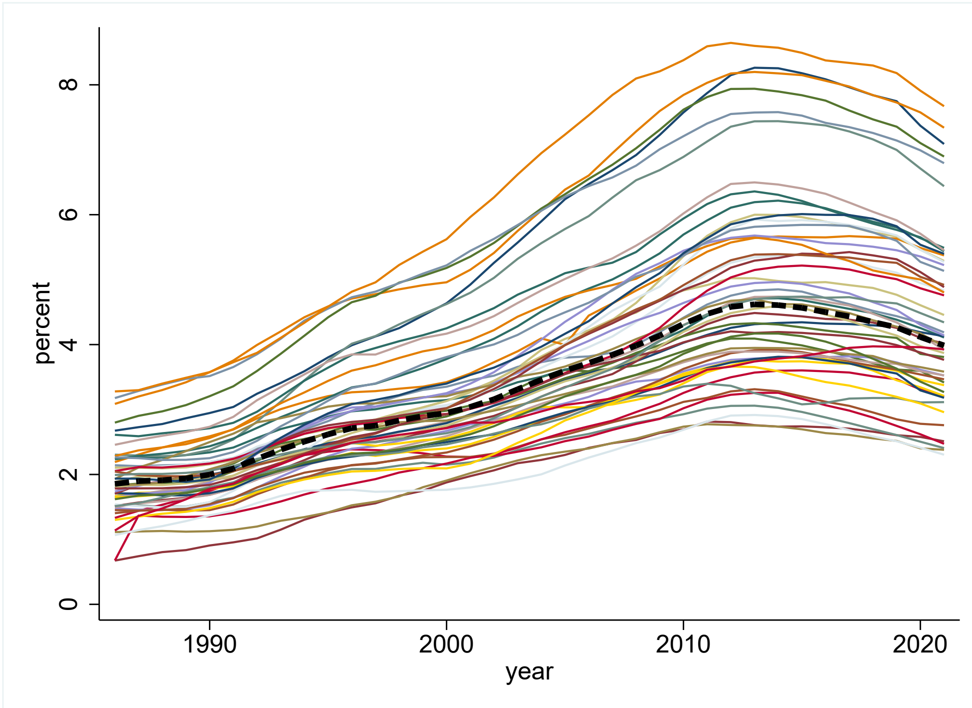
Finally, I examine whether some of the extreme variation in county disability rates is attributable to labor market conditions. Specifically, I test whether negative employment shocks contribute to growth in county disability rates. The relationship between local labor market conditions and county PAD may suffer from reverse causality. A county with increasingly larger shares of the working-age population who are disabled will see a reduction in labor supply. This reduction will lead to a reduction in total employment, ceteris paribus. It could also be the case that counties experience negative employment shocks due to a reduction in labor demand due to the closure or relocation of a major employer in the county. This reduction in labor demand may lead to some workers who are marginally disabled, but would have kept working in the absence of job loss, to apply for SSDI. Additionally, there may be confounding county-level factors that impact both employment growth and PAD growth such as opioid use, county norms toward work, and county stigma toward disability. To overcome potential reverse causality and control for other confounding variables, I use a Bartik-like instrumental variable to extract the exogenous impact of employment shocks on county PAD growth. I find a strong and negative relationship between employment growth and PAD growth at the county level, where the results indicate a 10% decrease in the employment growth rate leads to a 10.5% increase in PAD growth 2 years later.

The remainder of the paper is as follows. Section 2 provides a background of the SSDI program and its application and appeals processes, as well as trends in applications and appeals over time. Section 3 presents the explanations proposed by prior literature for the increasing national PAD through 2013, and the variance in PAD by state. Section 4 summarizes the data sources used and Section 5 explains the methodology I implement to explore the underlying cause of the national PAD trend, state-level variation, and the impact of county-level employment shocks on PAD. Section 6 contains the results and Section 7 uses those results to forecast future PAD at the national and state level. Finally, Section 8 concludes with a discussion of what the findings may mean to society.

2 Institutional Background and SSDI Trends

The application process for SSDI is quite involved, and in many cases can take over a year for a final decision to be rendered. If the initial application is denied, there is a process through which an individual can appeal the initial decision. An initial application is filed with the Social Security

Figure 1: State and National PAD 1986-2021

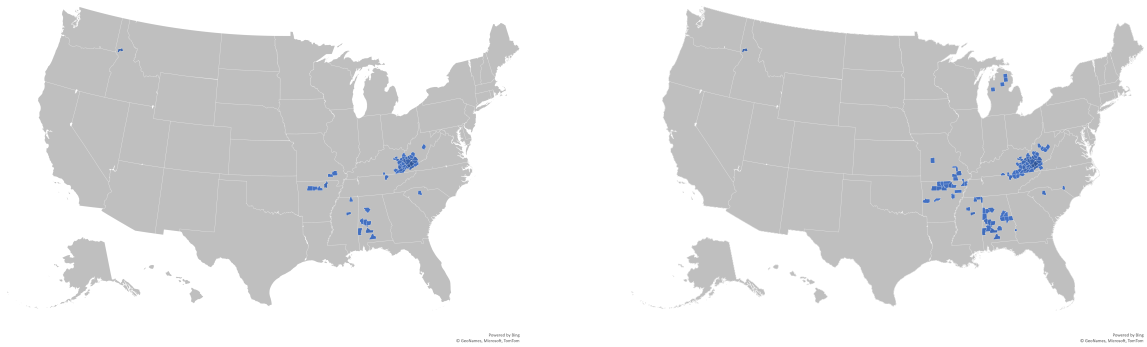


Notes: The solid lines are the percentage of working-age adults receiving SSDI benefits (PAD) for each of the 50 states plus the District of Columbia. The national PAD is represented by the bold dashed line. The mountain shaped trend that the PAD has followed from 1986-2021 is apparent at both the state and the federal levels. Although all of the states follow the same general time trend, there is a significant degree of variation in disability rates between states, and there appear to be six states that break away from the rest with PADs nearly double the national average. The six states are Alabama, Arkansas, Kentucky, Maine, Mississippi, and West Virginia.

field office where a determination will be made as to whether the person "technically qualifies", i.e. whether they have sufficient work history to be insured by SSDI.[4] If the person qualifies technically, the field office does a financial screen, which is the first step in a five-step sequential determination process to determine if the person is currently engaged in "substantial gainful activity" (SGA), or if the person is currently working and earning wages greater than the designated SGA value ($1,470 a month in 2023). If the person is currently working, their application will be denied on the grounds that SSDI is for those who are disabled to the point of being unable to work. If the applicant passes the financial screen, the application is sent to a state Disability Determination Service (DDS) agency where it is assigned to a disability examiner. In the second step, the examiner evaluates whether the disabling condition is severe enough to prevent the person from working, and if the condition is expected to last at least a year. Once again, if the criteria are not met, the application is denied.

[4]Typically, one needs to have earned 40 credits, 20 of which are from the past 10 years. In 2023 a person earned one credit for every $1,640 they earned that year, with a maximum of four credits per year.

Figure 2: Counties with the highest disability rates in 2010



(a) Highest 50 Counties (b) Highest 100 Counties

Notes: The 50 counties with the highest percent of working-age adults receiving SSDI in 2010 are clustered in three geographic areas: a portion of Appalachia, the lower Ozark region, and Alabama/Mississippi. SSDI rates range from 12.9% to 21.7% of the working-age population in the highest 50 counties. The top 100 counties in 2010 are clustered in the same three areas, plus North Central Michigan. In the top 100 counties PAD rates range from 11.6% to 21.7%.

If the criteria are met, the adjudicator goes to the third step. For the third step, SSA has a list of imparements that are so severe that a person automatically qualifies for SSDI by having an impairment that is on a list of severe conditions or is equal in severity to impairements on the list. If an individual's disability does not meet or equal the impairments on the list, the adjudicator goes to the fourth step which is to determine whether the person can perform their past relevant work. If so, the application is denied, and if not, in the fifth step the adjudicator will determine whether the person can perform any other type of work. For this step, age, education, and work experience are all considered in the evaluation. Individuals who are older, have less education, and/or less skilled work experience, all else equal, are more likely be awarded SSDI in this stage due to the increased difficulty in such individuals being able to perform other types of work.

In 2020, two out of every five workers filing their initial SSDI application were denied for technical reasons, a rate that has grown steadily since 1992. Of the remaining 60% of worker applicants who have sufficient work history to qualify technically, roughly 60% are denied for medical reasons at the initial examiner level, a rate that has remained fairly constant over time. Taking both technical and medical denials together, approximately 75% of initial worker applications are denied. If the initial application is denied, the individual can appeal for reconsideration, in which case a different disability examiner will review the application using the same five step sequential process. About half of applicants who are medically denied at the initial level appeal for reconsideration

(Strand and Messel (2019)). The vast majority of appeals are denied at the reconsideration stage; only between 10%-15% of worker applicants will be awarded SSDI in the reconsideration stage. After the second denial, an applicant may request a hearing with an administrative law judge (ALJ) where they will be able to present their case in person before an administrative judge. Roughly 40% of applicants who are denied at the initial level end up requesting a hearing with an ALJ. If an applicant is denied at the hearing level they may ask for a review by the Appeals Council, and finally, may appeal to a Federal District Court, although this is quite rare.[5] Award rates at the ALJ hearing level or higher are substantially higher than at the initial or reconsideration stage. Award rates hovered around 80% at the hearing level or higher until 2007 when they began to decline. In more recent years, award rates at this stage are closer to 60%.[6] Figure 3 depicts the percentage of denials at the various stages of the application and appeals process.

3 Theoretical Explanations for Long-Run Trend in the Percent of Adults Receiving SSDI and State Variation

There are multiple possible reasons as to why the percentage of working-age adults receiving disability benefits increased from 1986-2013, after which point it has persistently declined. PAD is a flow variable because at any given time there are new awardees increasing PAD, but there are simultaneously SSDI recipients who are exiting the program due to death, reaching full retirement age (FRA), medical recovery, or employment with wages above the specified SGA level. In addition, the change in the population ages 20-64 relative to the change in the number of SSDI beneficiaries will also alter PAD. The equation below displays the flows in and out of PAD at the end of time t, where $w.a.\, population$ is the working-age population between the ages of 20 and 65.

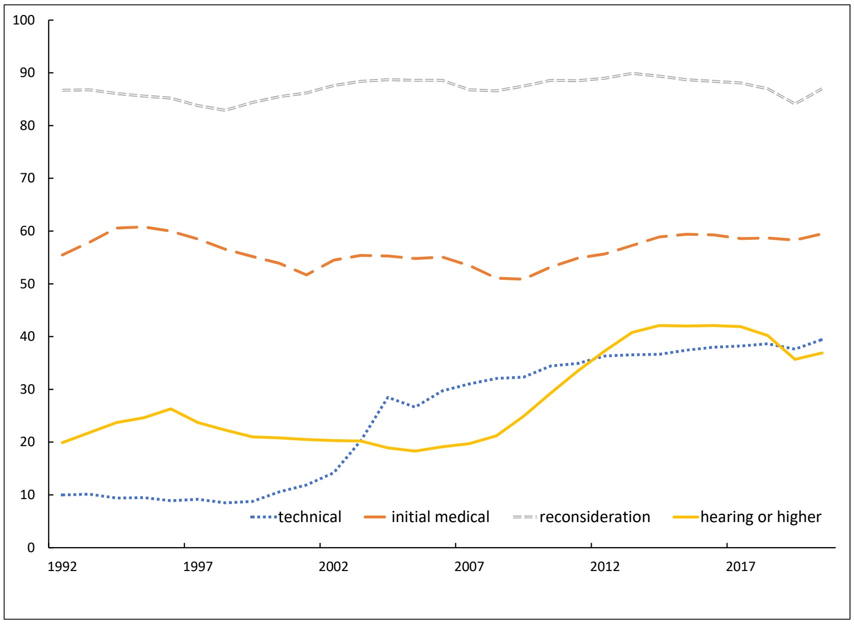
$$PAD_t = \frac{beneficiaries_t}{w.a.\, population_t} = \frac{beneficiaries_{t-1} + awards_t - deaths_t - FRA_t - recovery_t - work_t}{w.a.\, population_t}$$

3.1 Changes in the Number of New Awards

All else equal, something that changes the number of new awards will change PAD in the same direction. Holding the number of individuals leaving SSDI each year constant, something that caused the number of SSDI awards to increase steadily from 1986-2013, then peak and begin to decline, could be the cause of the long-run trend in PAD. There are numerous things that would

[5] See Wixon and Strand (2013) for a comprehensive description of the SSDI determination process.
[6] Social Security Administration (2021)

Figure 3: Percent of SSDI Denials by Stage



Notes: Denials at the initial medical examiner and reconsideration stages have remained relatively stable over time. Very few applicants are awarded benefits at the reconsideration stage, as is seen in the denial rate that hovers around 85%. Prior to 2007, the denial rate at the hearing level or higher was quite low, meaning the large majority (around 80%) of cases that went to the hearing level were awarded benefits. After 2007, this denial rate at the hearing level or higher nearly doubled over the next few years. The number of technical denials for insufficient work history also saw a dramatic increase, starting around 2000, and continuing to increase through 2021.

alter the number of SSDI awards granted, many of which have been the topics of interest in prior literature.

1. The Number of Disabled Individuals

   If there were national physical and/or mental health trends that changed over time, the number of disabled individuals would change accordingly. Changes in the access to health care, in obesity, diabetes, arthritis, smoking trends, non-fatal car accidents, or changes in industry composition toward or away from more inherently dangerous industries could all impact the number of disabled persons in the United States, and impact the PAD through the awards channel.

2. Economic Conditions

   It has been well documented that SSDI recipients are worse off financially than non-applicants prior to application, and that economic conditions such as the unemployment rate, the labor force participation rate, income inequality, and poverty are all correlated with SSDI application and award rates (Autor and Duggan (2003), Maestas et al. (2015), Deshpande and Lockwood (2022), von Wachter et al. (2011), Duggan and Imberman (2009)). There are three main channels through which these variables would impact the number of SSDI awards. 1) Unemployed workers have a lower opportunity cost of applying for SSDI, and thus applications increase during times of high unemployment. 2) A transformation of the economy away from low-skilled work, which led to an exit of low-skilled workers from the labor force due to a lack of opportunity. In 1992, 24.3% of SSDI awards were granted for a combination of medical and vocational reasons. By 2020, the number of allowances where the lack of vocational opportunities was partially responsible for SSDI award nearly doubled to 48.4%. 3) Trends in income inequality that cause changes in the replacement ratio, the ratio of one's benefits to their prior wages. When income inequality increases, the replacement ratio increases for the workers with the lowest wages prior to disability. A higher replacement ratio increases demand for SSDI benefits among the lowest skilled workers.[7]

3. Policy Changes Impacting Examiner or ALJ Leniency
   Policy changes that impact the propensity for disability examiners or ALJs to award SSDI will also impact PAD via the new awards channel. The 1984 Disability Reform Act, which made it easier for people with hard-to-verify conditions such as musculoskeletal and mental impairments to be awarded SSDI (Autor and Duggan (2006)), and a 1996 Act that terminated benefits for individuals whose primary impairment was drug addiction or alcoholism, and prohibited future applicants from being awarded on the basis of these two impairments could both impact the number of new awards granted each year.[8] There were also changes at the hearing level that could alter the propensity for ALJs to award SSDI. In 2007 wait times for an ALJ hearing were over 270 days in 50% of appeals (Astrue (2011)). In response, the SSA announced expectations that ALJs increase their caseloads, and also opened National Hearings Centers that heard cases from all over the country in order to alleviate local hearings offices. Since National Hearings Centers are often times not located near the applicant who is having his/her case heard, the hearings are held virtually. Finally, from 2007-2011, the SSA more than doubled the total number of ALJs from 685 to 1407.[9] New ALJs, increased

[7]SSDI benefits are determined by a worker's prior earnings, adjusted each year for average wage growth in the economy. If economic inequality is increasing, the average wage growth may be increasing, while the lowest wage workers see stagnant or even decreasing real wages. Therefore, calculating benefits by adjusting for the average wage growth in the economy increases the ratio of the benefit to one's prior wages if their wages did not grow at the same rate as wages in the economy as a whole. For a detailed discussion, see Autor and Duggan (2003).

[8]Waid and Barber (2001)

[9]Astrue (2011)

case loads, and virtual hearings could all impact the leniency of ALJ decisions. As Figure 3 shows, ALJ denials did increase significantly starting in 2007.

4. Number of Appeals and the Use of Representation
   The SSDI application process is complex and can be tough to navigate for many applicants. SSDI applicants are entitled to appoint a "qualified individual" (most often a lawyer) to represent them during any or all stages of their application process. Over time an increasing number of applicants have chosen to use representation at the initial stage of the application process rather than waiting until a hearing with an ALJ (Hoynes et al. (2022)). In addition, the percent of initial applicants that appealed at the hearing level increased steadily from 1992-2013 growing from approximately 42% in 1992 to 49% in 2013, impacting the total number of awards.[10]

5. Female Labor Force Participation
   As previously noted, individuals are eligible for SSDI if they worked a sufficient period prior to disability. Reno and Ekman (2012) attribute a portion of the increasing SSDI rolls from 1995-2011 to an increase in the number of individuals who were eligible for SSDI due to the large increase in the number of women entering the labor force in the 1970s and 1980s. Changes in female labor force participation could increase awards due to a larger percent of the working-age population that is insured by SSDI.

6. Aging of the Baby Boomer Generation
   The vast majority of new applicants to SSDI are in the later portion of their working years. As previously noted, examiners use vocational grids to determine eligibility in the fifth step of the sequential determination process. The grid gives more leniency to applicants who are 50-54 years old and is even more lenient still for applicants who are 55 and older (Maestas et al. (2023)). At the age of 55, workers are no longer expected to satisfy the fifth step of the five-step sequential process to determine SSDI eligibility, meaning they are not expected to adapt to new work if they are no longer able to perform their previous work. Strand and Messel (2019) show that this rule causes roughly a 33% increase in allowances for 55 year olds relative to 54 year olds. The baby boomer generation, the generation with the most births in US history, consists of individuals born between 1946 and 1964. In 2013, at the peak of PAD, baby boomers were between the ages of 49 and 67 years old, meaning a large fraction of the working age population at the older, more disability prone portion of their working years. Some estimates attribute 21% of the increase in PAD from 1985-2007 to the aging of the baby boomer population (Liebman (2015)).

[10] Social Security Administration (2021) based on author's calculations $decisions_{ALJ}/(medical\ decisions_{initial} - awards_{initial} - pending)$, by year of application

3.2 Changes in the Number of Beneficiaries Leaving SSDI

The previous subsection proposed theoretical explanations for how the long-run trend in the PAD may be impacted by changes in the number of new awards over time. It is also possible that the number of awards remained roughly constant, but the number of individuals leaving the SSDI rolls due to death, retirement, improved health, or return to work were the mechanism driving the long-run trend in PAD. The following would impact PAD by altering the number of SSDI beneficiaries leaving the rolls.

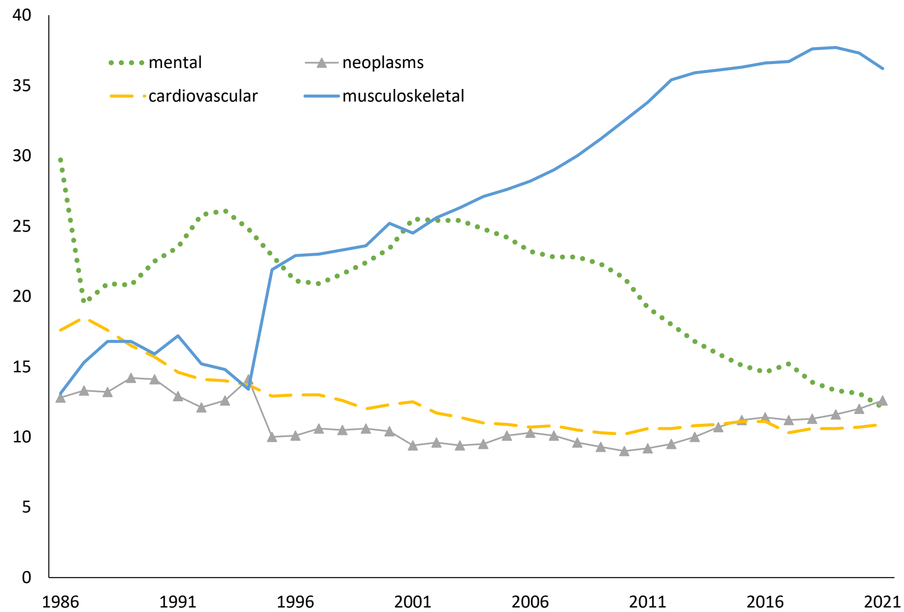
1. Increased Retirement Age
   In 1983 Congress passed a law increasing the retirement age from 65-67. The increase takes effect gradually, over 22 years. Individuals born in 1960 will be the first cohort to have the FRA of 67 years old. From 1986-2004 SSDI recipients about to transition from SSDI to Social Security retirement benefits had a FRA of 65. After 2004, beneficiaries about to transition from disability to retirement benefits had increasingly older FRAs. By 2021, the very oldest beneficiaries had FRAs just slightly less than 67 years old. The increased FRA led to individuals remaining on SSDI for more time before transitioning to SSA retirement benefits. Duggan et al. (2007) estimate that from 1983 - 2005 SSDI enrollment was 0.58 percentage points higher among men, and 0.89 percent higher among women ages 45-64 than it would have been absent the increased FRA.

2. Less Deadly Disabling Conditions
   From 1991-2014 there was a steady decline in the mortality rate of SSDI beneficiaries, causing a decrease in the rate at which beneficiaries left SSDI due to death. In 1991, 4.47% of beneficiaries died annually. Twenty-three years later, in 2014, the number of beneficiaries leaving SSDI rolls due to death was cut in half to an annual death rate of 2.15%.[11] Much of this decrease was due to an increasing percentage of awards granted for less deadly medical conditions, such as musculoskeletal impairments (typically back pain and arthritis) and mental impairments (primarily depressive and bipolar disorders). In 1987, musculoskeletal and mental disorders comprised a combined 35% of all SSDI awards. Since 2000, roughly 50% of new awards are granted for musculoskeletal or mental impairments each year, although as Figure 4 shows, that percentage is increasingly dominated by musculoskeletal awards. By 2019, nearly two out of every five awards was granted for musculoskeletal disorders.

3. Workers Receiving Benefits at Younger Ages
   The average age of SSDI recipients steadily declined from 1986 through 1992, when it hit a record low of 47.8 years. This meant that many beneficiaries would receive benefits for nearly two decades, reducing the rate at which recipients left the program due to retirement. Since

[11] Zayatz (2015)

Figure 4: Percentage of SSDI Awards for the Top 4 Medical Impairments



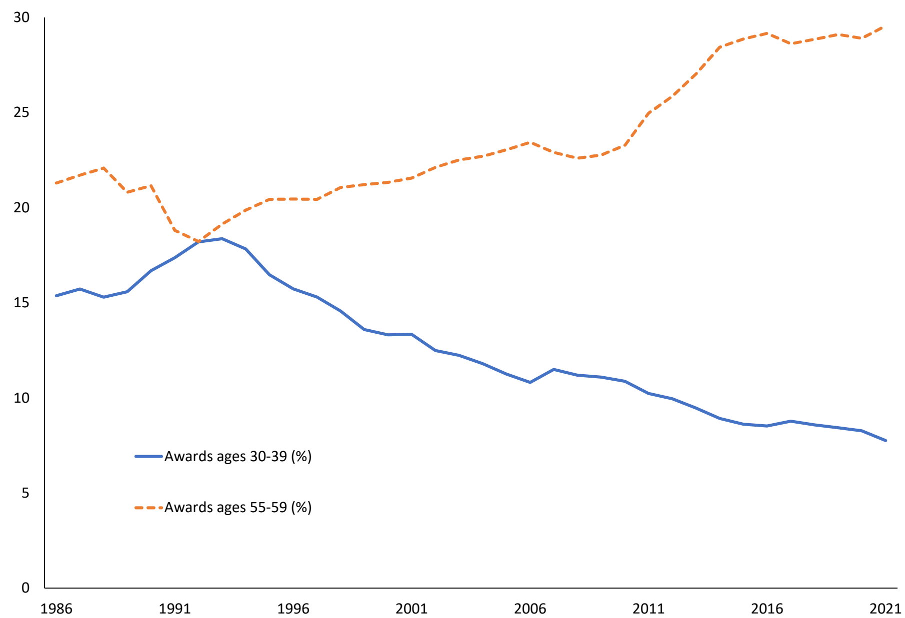
Notes: Roughly 70% of all SSDI awards are granted for mental, neoplasms, cardiovascular, or musculoskeletal impairments. The percentage of awards granted for cardiovascular impairments has slowly declined over time, falling from roughly 18% of all awards in 1986 to approximately 11% of awards in 2021. The distribution of awards for neoplasms (cancers) dropped precipitously in 1995, after which point is was relatively stable until 2018 when it started slowly increasing. The distribution of awards granted for mental impairments has oscillated over time, peaking in 1993 and 2001, after which point mental impairments have comprised a decreasing percentage of SSDI awards. The percentage of awards granted for musculoskeletal impairments has increased dramatically since 1994 when such impairments comprised 13% of awards. By 2019 the percentage of awards granted for musculoskeletal impairments has increased nearly three-fold, so that nearly two of every five awards was granted for a musculoskeletal impairment. Musculoskeletal impairments are most often arthritis or back pain and are less deadly conditions than most other SSDI medical impairments.

its low in 1992, the average age of beneficiaries has increased each year, reaching 55.3 years in 2021, with only 22% of those recipients under the age of 50.[12] Figure 5 provides visual evidence of this period in the early to mid-1990s when increasingly younger workers were awarded SSDI. As the figure displays, from 1986 - 1997, the percentage of new awards granted to individuals aged 39 and younger exceeded the percentage of awards granted to individuals ages 55-59. Since 1998, however, the proportion of new awards granted to individuals ages 55-59 has exceeded those granted to individuals 39 and younger, and the gap has widened

[12] Social Security Administration (2021)

over time.

Figure 5: Percentage Distribution of SSDI Awards by Select Age Categories



Notes: The dashed line displays the percent of total SSDI annual awards that were awarded to individuals between the ages of 30 and 39. The solid line shows the percentage distribution to individuals ages 55-59. For a brief period in the late 1980 to early 1990s the distributions of the two age groups were converging: in 1992, 18.2 percent of all SSDI awards were granted to individuals ages 30-39; the same percentage that were awarded to individuals ages 55-59. Since 1992, however, the distribution of awards to these two age groups has diverged. By 2021, over 20% more of the total awards were awarded to individuals ages 55-59 than ages 30-39.

4. Changes in Number of Continuing Disability Reviews

   The number of people leaving the SSDI rolls due to recovery is directly related to the number of continuing disability reviews (CDRs) performed by the SSA each year. CDRs reassess if SSDI beneficiaries continue to be too severely disabled to work, or if their health condition has improved. The total number of CDRs conducted significantly fluctuates year to year, based on the SSA's budget, legislation, and the size of the disability backlogs (Hemmeter and Stegman Bailey (2016)).[13] In the late 1990s as many as 30% of beneficiaries received CDRs. Since 2013 the percent of recipients receiving CDRs hovers around 12%, although the percent

[13] Social Security Administration (2011)

fluctuates by up to 5% over short periods of time.[14]

3.3 Variation Between States

Sections 3.1 and 3.2 outline numerous reasons that have been proposed to account for the long run trend in the PAD. The possible explanations, however, are looking to explain a national trend, which will not explain interstate variation in the PAD. As previously noted, in 2013, the PAD in West Virginia was 8.6%, whereas in Hawaii that same year it was 2.75%. Understanding why over three times as many working age adults are receiving SSDI in one state than another is critically important. Many of the hypotheses in the literature as to the factors that could be driving the long-run trend in SSDI could also be factors that impact the variation at the state level. Education levels and economic variables such as median household income, poverty rates, and unemployment rates all impact SSDI application and awards, as previously discussed, and there is a significant degree of variation in each between states. Health variables such as obesity and smoking rates also vary by state.

Industry may also play a role in state-level variation in PAD levels, in one of two ways. First, industries that are more inherently dangerous, such as manufacturing, could be concentrated in certain states, leading those states to have higher levels of disability. Industry composition could also indirectly lead to increased disability in some states through the vocational mechanism. Autor et al. (2013) document the decline in manufacturing in the United States from 1990-2007 due to Chinese imports and how it impacted local labor markets. A key finding is that individuals did not leave local labor markets after losing manufacturing jobs, nor did they obtain non-manufacturing employment, but rather most become unemployed or leave the labor force. As mentioned in Section 3.1, SSDI applications increase when unemployment increases, and increasing awards have been granted for vocational reasons as manufacturing has declined.

There is also a growing literature on opioid use among SSDI beneficiaries. As previously noted, nearly 40% of current SSDI awards are granted for musculoskeletal disorders such as arthritis and back pain, disorders that may lead to opioid use. According to Peters et al. (2018), in 2013 24.5% of individuals under the age of 65 who were hospitalized for opioid overdose were SSDI recipients. Additionally, SSDI beneficiaries accounted for 80.8% of opioid overdose deaths among Medicare enrollees, even though they only comprise 14.9% of the Medicare population (Kuo et al. (2019)). Maestas et al. (2023) find that opioid use declined among SSDI recipients from 2013-2018, although there was substantial variability in the decreases by geography. State-level opioid dispensing rates may explain some of the state-level variation in PAD.

There is also the posibility that some of the variation stems from individuals moving to lower cost of living states once they receive SSDI benefits. The benefits formula does not take into account

[14] https://www.ssa.gov/open/data/Periodic-Continuing-Disability-Reviews.html#cdrProcessed

the cost of living of a particular area, so a person will receive the same benefit payment whether they are in a high cost of living state or a low cost of living state. If beneficiaries move to a lower cost of living state in order to increase the purchasing power of their benefits, this will also lead to variability in PAD by state.

Finally, SSA implemented a pilot program from 1999-2019 that altered the appeals process in nine states and a portion of a tenth. In the pilot program states, the reconsideration phase of the appeals process was eliminated, so an individual who wished to appeal their initial decision went straight to the hearing level. The contrast between the very low award rate at the reconsideration stage, and the high award rate at the hearing stage may have created variability in that there was lower opportunity cost to get to the high award rate hearing phase in the pilot states.

4 Data

To test the various hypotheses in Section 3, and to ascertain the underlying cause of the long-run trend in PAD over the last several decades, I compile a dataset from a variety of data sources. The state and national PAD data comes from the SSA's annual publication *OASDI Beneficiaries by State and County* for the years 1986-2021, all the years for which state-level data is publicly available. Each annual publication contains state-level data for that year only, so I combine the data for all 36 years to create a panel. I construct the national PAD variable by aggregating the state and District of Columbia data for each year. County-level PAD data is from the same publication, but the digital data is only available for the year 2000 and later, so the county dataset spans the years 2000-2021. The data is broken down by the total number of SSDI beneficiaries by category: disabled workers, spouses of disabled workers, and disabled children of insured workers. I use only the data for disabled workers, which make up the vast majority (over 85% in 2021) of SSDI beneficiaries.

I use four data sources to examine whether trends in the prevalence of disability in the United States drive the PAD trend. First, I use the Centers for Disease Control and Prevention (CDC) *Behavioral Risk Factor Surveillance System* (BRFSS) for self-reported poor health data, as well as numerous other health variables such as diabetes, obesity, arthritis, smoking, cardiovascular disease, and high blood pressure. The poor health question asks respondents how many of the past 30 days poor physical or mental health has kept them from doing their regular activities. I compute the overall average of this variable, as well as the average for anyone reporting greater than zero poor health days, to examine poor health on the intensive margin. The BRFSS data contains a state indicator, so I also use this data to examine differences in self-reported health status and health conditions across states.[15] In addition, I use data from the National Highway Traffic Safety

[15]The BRFSS has a fixed core of questions that are asked in all states every year, a rotating core of questions which are questions that are asked every other year, and modules, which are optional questions

Administration (NHTSA) for data on national trends in non-fatal traffic injuries from 1990-2021, all the years for which the data is available. I also use data from the CDCs *Wide-ranging Online Data for Epidemiologic Research* (WONDER) data, which contains annual cause of death data at the state-level. This data contains level data on the number of deaths by cause, as well as crude rates for the number of deaths per 100,000 people by cause. I use the level data on cause of death and divide by total annual deaths to construct a percent of total deaths variable that captures trends in the distribution of deaths by cause. To examine trends in the percent of workers working in more inherently dangerous industries, I use the Bureau of Labor Statistics (BLS) *Quarterly Census of Employment and Wages* (QCEW) to track changes in the raw number and percent of people employed nationally in various industries from 1986-2021. The QCEW also contains county-level employment data by industry. I use the three-digit North American Industry Classification Code System (NAICS) to construct county-level industry shares, as well as national industry growth rates for my Bartik instrument. There are a total of 99 three digit NAICS codes. For state-level industry data I use the Census Bureau's *Statistics of US Businesses* (SUSB) and use the two-digit NAICS codes.

To examine the long-run impact of economic trends such as poverty, childhood poverty, real median household income, income inequality, unemployment, educational attainment, female labor force participation and overall labor force participation, I use federal-level data from a variety of sources. Poverty and child poverty data are from the Census Bureau's *Small Area Income and Poverty Estimates* (SAIPE), female and overall labor force participation data is from the Bureau of Labor Statistics (BLS) *Employment Situation*, income inequality is measured using the World Bank's *World Development Indicators* Gini Index, real median household income data is from the Census Bureau's *Income and Poverty in the United States*, and educational attainment data is from the Census Bureau's *American Community Survey* (ACS). State-level economic data also comes from multiple sources. State unemployment and labor force data is from the Bureau of Labor Statistics *Employment and Earnings Survey*, and state poverty and median household income data is from the Census Bureau's SAIPE. State education data is also from the Census Bureau's ACS.

The SSA's *2021 Annual Statistical Report on the Social Security Disability Insurance Program* provides the necessary data for me to test the hypotheses of trends in examiner and ALJ leniency, the increased FRA, beneficiaries with less deadly medical conditions, or beneficiaries receiving benefits at younger ages being the mechanism behind the long-run trend in PAD. The report provides federal-level application, award, and termination data. More specifically, it contains the total number of annual applications for SSDI, the number of awards and allowances granted, the

---

from which states choose those which they feel are most pertinent to their populations. Not all states participated in the survey until 1993. In addition, since the data goes back to 1986, there are questions that were originally asked that were later modified, and questions that were not added to the survey until after 1986. For these reasons, both the number of states and the number of time periods vary by question in the BRFSS data.

total number of applications and awards broken down by adjudicative levels, and for those who are given a medical allowance, the percent that were granted their allowance at each stage of the determination process.[16] This data is available from 1992-2020. The report also includes annual time-series data on the distribution of beneficiaries by age, the average age of beneficiaries, the distribution of awards by age, average age when awarded benefits, the number and precentage of awards that are granted by diagnostic category, and the number of benefits terminated.[17] All of this data is available for my full sample period 1986-2021. Using this data, I construct variables for application rates (per 10,000 adults ages 20-64), award rates, and appeals rates at the different adjudicative levels.[18] I also calculate termination rates, rates for the percentage of beneficiaries awarded partially for a combination of vocational and medical reasons, and the percentage of beneficiaries who are impacted by the increased FRA, those over 65 years old after 2003.[19]

To explore state level variation in application and allowance rates to SSDI, I used the SSA's *State Agency Monthly Workload (MOWL)* data which spans from 2000-2022 and contains data on the number of applications and awards at the initial and reconsideration levels by state. The MOWL data also contains data on the number of Continuing Disability Reviews (CDRs) conducted and continuation rates by state. Table 51 of the SSA Annual Statistical Report contains the number and rate of terminations by state in 2020. To create a panel of this data, I compile the data from Table 51 from 2001-2020, all the years with available data.[20]

To examine trends in people leaving SSDI due to CDRs, I use data from Table B2 of Social Security Administration (2011) for data from 1993-2012, and SSAs *Periodic CDR Cases-Processed* dataset for data from 2013-2021. For data on the use of representation over time, I use SSA's *Statistics on Title II Direct Payments to Claimant Representatives* which contains data on the total

[16]Allowances are the number of cases given a medical allowance for SSDI. Some of these allowances end up being denied for non-medical reasons after the allowance has been granted. Awards are those who ultimately receive SSDI benefits.

[17]The data prior to 2000 is only available for men and women separately. I use the totals to create a male and female weights and then calculate the overall percentages as a weighted average.

[18]Both the award rates and appeals rates are as a fraction of the applicants that are not technically denied.

[19]The increased FRA did not impact workers until 2003, at which point it increased to 65 years and two months for workers born in 1938. It then increased by 2 months for each subsequent birth year cohort until 2007 when the FRA reached 66 years old and remained 66 years old for 11 years, impacting those born between 1943 and 1954. Then, beginning in 2020 it began to increase by 2 months annually again. Individuals born in 1960 will be the first cohort with a FRA of 67. The age distribution data does not contain an age bin for those over the age of 65, but instead has a bin for those 60-FRA. To construct the percent of beneficiaries over the age of 65, starting in 2003 when the FRA was 65 years and 2 months, I divided the total number of beneficiaries in the 60-FRA category by 62, the total number of months in the 60-FRA category at that time, to get the number of people in each monthly bin within the 60-FRA age group (the assumption being that there are roughly the same number of people who are the same age in months within that age bin). I then multiply that number by two since the FRA was 65 and two months, and then divide by the total number of SSDI recipients. I repeat this process, dividing and then multiplying by the corresponding number of months for each year the FRA increases.

[20]The table number varied in prior years, but the data it contained remained constant from 2001 on.

number of cases using representation as well as the total dollar amount spent on representation. This data is reported monthly from 2000-2021, so I aggregate it to yearly data. For data on the percent of the population by age I use the Census Bureau's *Annual Estimates of the Resident Population for Selected Age Groups by Sex* which contains national and state-level data on the percent of population by five-year age categories. This data is published by decade, so I combine several decades to get data that spans from 1986-2021. State-level opioid dispensing data comes from the CDC's *U.S. State Opioid Dispensing Rates* data, but is only available from 2006-2020.

I explore the hypothesis that SSDI recipients relocate to lower cost of living states by using the MOWL data. While I do not directly observe relocation in the data, the data does contain the number of initial applications by state. If people relocate after applying for SSDI there should be a disconnect between the number of applications and the PAD in a state. If people relocate prior to application, however, this will not be observed.

Finally, county-level control variables for age, gender, and race come from the Census Bureau's *County Intercensal Datasets* files, and county median household income is from the Census Bureau's SAIPE.

I take the natural log of all ratio variables, such as PAD, and all variables that grow exponentially over time.

4.1 State-Level Summary Statistics

Table 1 shows the state summary statistics in 2010 for the states in the top decile of the PAD distribution (West Virginia, Arkansas, Kentucky, Alabama, and Mississippi) and the five states in the bottom decile of the PAD distribution (Utah, Alaska, Hawaii, California, and Colorado), and the mean for 2010. The states in the top decile appear to have populations that are older, and have worse outcomes in terms of health, economic outcomes, education levels, and opioid dispensing rates. More specifically, populations in the high PAD states have many more deaths per 100,000 people, are more likely to die from diseases of the circulatory and respiratory systems, less likely to be employed, more likely to be in poverty, have significantly lower incomes, have worse self-reported health outcomes by every measure except the risk of heavy drinking, have higher application rates for SSDI, but lower allowance rates, and have more than double the percent of individuals employed in manufacturing than states in the bottom decile.

5 Methods

To determine the cause of the long-run trend in PAD, I test for a cointegrating relationship between the national PAD and each of the variables proposed in Section (3), since variables that are cointegrated share a stable, long-run relationship with one another. I first confirm that each of the

Table 1: 2010 State-Level Summary Statistics

	Highest 10%	Lowest 10%	Mean
PAD	7.7	2.8	4.6
Deaths per 100,000	1016.1	601.7	826.7
Opioid dispensing rate per 100 people	130.6	66.6	85.6
Level of education (by percent)			
9-12 education, no diploma	11.2	6.5	7.9
High school graduate, no college	34.5	24.4	29.5
Bachelor's degree or higher	19.8	30.64	27.9
Economic variables			
Unemployment rate	9.5	8.9	8.8
Employment to population ratio	53.5	61.2	59.8
Labor Force Participation Rate	59.1	67.2	65.5
Real Median Household Income	50,202	71,881	62,289
Poverty Rate	17.9	12.7	14.3
Percentage of population by age:			
0-9	12.9	14.6	13.0
10-19	13.6	14.1	13.6
20-29	13.3	15.1	13.9
30-39	12.7	13.6	12.7
40-49	13.6	13.5	13.9
50-59	13.9	13.2	13.9
60-69	10.4	8.6	9.8
70 plus	9.6	7.2	9.2
Health variables			
Poor mental health days if reporting > 0	13.1	9.7	11.0
Poor health days a month if reporting > 0	14.4	10.7	12.2
Percent with no exercise in past month	35.3	21.0	27.4
Percent with high blood pressure	47.3	32.8	39.0
Percent with diabetes	16.2	9.3	12.5
Percent obese	32.7	24.3	28.4
Percent current or former smokers	48.1	41.8	46.7
Percent at risk for heavy drinking	2.7	5.1	4.4
Percent with high cholesterol	46.8	40.9	43.5
Percent with heart disease	8.3	4.5	6.4
Percent had heart attack	8.2	4.5	6.4
Percent had stroke	5.9	3.3	4.4
Percent with artritis	43.5	30.9	37.1

Table 1 Continued...

	Highest 10%	Lowest 10%	Mean
Applications and allowances			
Allowance rate at initial stage	29.3	40.0	36.4
Allowance rate at reconsideration stage*	9.8	17.3	15.0
CDR continuation rate	90.9	87.4	90.2
Initial applications per 10,000 working age adults	175.6	75.2	109.3
Percent applying for reconsideration	58.1	46.2	53.5
Percent of receipts ending in determination	93.5	85.4	94.3
Allowance rate at initial or reconsideration	22.6	35.3	30.1
Percent of disability cases sent to CDR	3.3	2.5	2.2
Percentage employed by select industries			
Agriculture (11)	0.3	0.2	0.2
Mining, Quarrying, Oil and Gas Extraction (21)	1.8	1.3	1.0
Utilities (22)	0.9	0.5	0.5
Construction (23)	4.9	5.9	5.1
Manufacturing (31)	13.9	6.6	9.8
Professional, Scientific, and Technical Services (54)	4.4	7.3	6.4
Health Care and Social Assistance (62)	17.8	13.7	16.4
Percentage of total deaths from			
Neoplasms(CD)	22.7	23.3	23.7
Endocrine, nutritional and metabolic diseases (E)	4.2	4.0	4.1
Mental and Behavioral Disorders (F)	4.2	5.4	5.1
Diseases of the Nervous System (G)	5.2	5.8	5.8
Diseases of the Circulatory System (I)	32.1	28.8	30.8
Diseases of the Respiratory System (J)	10.5	9.3	9.8
Diseases of the Digestive System (K)	3.4	4.0	3.8
Diseases of the musculoskeletal system (M)	0.5	0.7	0.6
Diseases of the genitourinary system (N)	3.1	2.2	2.6
Injury	7.7	9.9	7.6
Drug related	1.7	2.2	1.6
Alcohol related	0.6	1.8	1.1

Notes: Highest 10% refers to the mean of the five states with the highest PAD in 2010, lowest 10% refers to the mean of the five states with the lowest levels of PAD in 2010, and mean is the national mean that year. The means are at the state level, not the population level so that each state's statistics are weighted equally. Allowance rates do not include applications that were denied for technical reasons in the denominator. Some of the more rare type of death categories are not included in the table under the the percentage of total deaths category, and injury, drug related, and alcohol ralated deaths are not mutually exclusive of the other categories. *Not all states had a reconsideration stage in 2010 due to the SSA's pilot program which eliminated the reconsideration phase in 9 states, and parts of a tenth.

potential determinants is non-stationary by running an augmented Dickey Fuller unit root test. I cannot reject the null of a unit root for any of the variables, providing strong evidence that each variable is non-stationary, and thus could potentially be causing the long-run trend in PAD. While each variable is non-stationary on its own, if it is cointegrated with PAD, there exists a parameter, or scaling factor, that when multiplied by the variable, results in the two series following the same path over time, so that the distance between the two variables is roughly constant over time. Importantly, this means that when PAD is regressed on the cointegrating variable, the residuals will be stationary, and thus valid statistical inference is possible (Engle and Granger (1987)).[21]

I use Stata's Engles Granger test, *egranger*, to test for cointegration between PAD and each proposed cause of the trend in PAD separately. The test first regresses:

$$y_t = a + \lambda g_t + \eta_t \tag{1}$$

where y_t is national-level PAD at time t, and g_t are the numerous potential explanatory variables from Section 3. The null hypothesis is that the residual is non-stationary, meaning the variables are not cointegrated. To test this, the Stata command then estimates p by regressing:

$$\Delta\hat{\eta}_t = p\hat{\eta}_{t-1} + \epsilon_t \tag{2}$$

The test statistic is the typical ordinary least squares (OLS) t-statistic for $\hat{p}$, but Engles Granger critical values are used to test for significance.[22]

In addition to the Engles-Granger test, I also run (1), obtained the residuals $\hat{\eta}_t$, and estimated the autoregressive coefficient, ρ by running

$$\hat{\eta}_t = \alpha + \rho\hat{\eta}_{t-1} + v_t \tag{3}$$

to examine how persistent $\hat{\rho}$ is for each of my candidate variables.

After obtaining any or all variables that share a common, long-run trend with the national PAD, I verify that whatever is driving national PAD is the common factor that also drives state trends. Since the state-level data is panel data, I test for the cointegrating relationship with the Kao, Pedroni, and Westerlund panel cointegration tests, using Stata's *xtcointtest* command. Similar to the Engles Granger test, the null hypothesis for all three panel cointegration tests is that the error term is non-stationary, and thus the variables are not cointegrated. Dissimilar to the Engles Granger test, the Kao, Pedroni, and Westerlund test statistics have limiting distributions that converge to standard normal, so standard critical values are used. For all three tests, state-level PAD for state j at time t, y_{jt}, is first regressed on any national-level variable found to be

[21] See appendix for a more on cointegration

[22] StataCorp (2023)

cointegrated with national PAD, g_t:

$$y_{jt} = a_j + \lambda g_t + \eta_{jt} \tag{4}$$

and the residuals are tested for stationarity.[23]

Next, I examine state-level variation in PAD. I first run the following two-way fixed effects regression:

$$\dot{y}_{jt} = \dot{x}'_{jt}\beta + \dot{v}_{jt} \tag{5}$$

where x_{jt} is a vector of the time-varying state-level variables discussed in Section (3.3), and $\dot{y}_{jt} = y_{jt} - \frac{1}{n}\sum_{j=1}^{n} y_{jt} - \frac{1}{T}\sum_{t=1}^{T} y_{jt} + \frac{1}{nT}\sum_{j=1}^{n}\sum_{t=1}^{T} y_{jt}$ and similar for $\dot{x}_{jt}$ and $\dot{v}_{jt}$. The two-way fixed effects regression eliminates individual and time fixed effects, so no bias arises from omitted time-invariant state characteristics, or homogeneous common time trends. There are two downsides to (5), however. First, the common factor that is driving the time trend in the dependent variable is eliminated when the time fixed effects are subtracted out, which eliminates the ability to forecast future state-level PAD. In addition, if the states follow heterogeneous trends, as it appears they do in Figure (1), where it appears six states break away for the rest of the states, two-way fixed effects using a dummy variable will not eliminate the trend component, but rather it will remain in the error term, meaning there will be autocorrelation in the error term, and the error term remains nonstationary.[24]

To get a stationary error term, I include the augmented factor, or the variable that is cointegrated with national PAD, rather than eliminating time-fixed effects with year dummy variables. I still subtract out individual fixed effects to eliminate the potential for bias due to omitted unobserved state characteristic variables in the following model, which is my preferred specification:

$$\tilde{y}_{jt} = \alpha + \lambda\tilde{g}_t + \beta(\tilde{g}_{jt} - \bar{\tilde{g}}_t) + (\tilde{x}_{jt} - \bar{\tilde{x}}_t)'\gamma + \tilde{v}_{jt} \tag{6}$$

where $\tilde{y}_{jt} = y_{jt} - \frac{1}{T}\sum_{t=1}^{T} y_{jt}$ and similarly for $\tilde{g}_t$ $\tilde{g}_{jt}$. $\bar{\tilde{g}}_t$, $\tilde{x}_{jt}$, $\bar{\tilde{x}}_{jt}$, and $\tilde{v}_{jt}$. The coefficient β measures the difference between an individual state's percentage of the population ages 55 to 59 and the national percentage in the age range, $(\tilde{g}_{jt} - \bar{\tilde{g}}_t)$. γ is a vector of coefficients measuring the impact of the de-factored independent variables, $(\tilde{x}_{jt} - \bar{\tilde{x}}_t)$, where $\bar{x}_t$ is a vector of the cross-sectional averages of the various x_{jt} variables.

To determine the impact of employment shocks on county-level variation in PAD, I use a Bartik, or shift-share instrumental variable to instrument for county employment growth rates (Bartik (1991)). The relationship between a county's employment growth rate and the growth of disabled

[23]See appendix for more on how the various tests test for stationarity.

[24]If the DGP is $y_{jt} = a_j + b_j\theta + \beta x_{jt} + \xi_{jt}$ and one runs (5) then it can be shown $\dot{v}_{jt} = (b_j - \frac{1}{n}\sum_{j=1}^{n} b_j)(t - \frac{1}{T}\sum_{t=1}^{T} t) + \dot{\xi}_{jt}$.

working-age adults in the county may suffer from reverse causality. It could be the case, for example, that the closing of a major employer in a county decreases labor demand and leads to an increase in SSDI applications from marginally disabled workers who would have continued working in the absence of job loss. It could also be the case, however, that an abundance of disabled working-age adults reduces labor supply, thus depressing employment growth in the county. Additionally, there may be confounding county-level factors that impact both employment growth and PAD growth that will invalidate any causal interpretation of employment shocks on disability growth. Counties with high opioid use, for example, could experience declining employment and increased disability rates, but the mechanism for the disability growth would not be the decline in employment, but rather the increased use of opioids, which also caused the decline in employment. County norms toward work and stigma toward disability could also be confounding factors if they vary over time. Using an instrumental variable allows me to impose a direction on the causality and control for confounding factors in order to measure the causal impact of employment shocks on PAD growth.

The Bartik instrument utilizes the accounting identity:

$$\mathcal{E}_{it} = \sum_{k=1}^{K} s_{itk} g_{itk} \tag{7}$$

which states that the employment growth rate, $\mathcal{E}_{ijt}$, for county i at time t is equal to the inner product of the share of a county's employment in each industry k and the growth rate of industry k in county i at time t, summed over industry.

Although I can control for individual and time fixed-effects in my regressions to account for time-varying common variables and time-invariant county and state characteristics, endogeneity will still exist if county-specific trends exist that impact both the county's industry shares at time t and contemporaneous PAD growth via some mechanism other than employment growth. Both components of the inner product of $\mathcal{E}_{it}$ may suffer from reverse causality and endogeneity, and as previously stated, will invalidate any causal interpretation of the relationship between employment growth and PAD growth. To add exogeneity, the Bartik instrument substitutes the national growth rate of each industry, g_{tk}, for the county-specific industry growth rate, g_{itk}.

While disability growth in a particular county may be the result of employment loss in the county, or may be the cause of declining employment in the county, national employment growth in an industry is most certainly not impacted by disability growth in any particular county. Therefore, substituting national employment growth by industry for county-specific industry employment growth ensures the direction of the relationship is employment shocks leading to disability growth and not the other way around. It also eliminates potential confounding factors, as national employment growth is not a function of the county specific trends in opioid use, disability stigma, etc.

The other component of $\mathcal{E}_{it}$, s_{itk}, may also suffer from endogeneity. There may be confounding variables that impact both the county-level trend in disability and the simultaneous trend in that county's industry composition. To account for this, the Bartik instrument substitutes either the initial county industry shares at time $t = 0$, s_{i0k}, or the average county industry shares for $t = 0...T$, $s_{i\bar{t}k}$, for the time-varying industry shares, s_{itk} (Goldsmith-Pinkham et al. (2020)). I create two separate instruments, one using s_{i0k}, and one using $s_{i\bar{t}k}$. My preferred instrument uses $s_{i\bar{t}k}$ because it is the more relevant of the two instrumental variables.

The key identifying assumption in substituting $s_{i\bar{t}k}$ for s_{itk} is that a county's average industry shares are independent of any county-specific trends that are driving contemporaneous PAD *growth* through any channel other than employment growth (or decline). One can imagine that the level of PAD would be impacted by average industry shares - a county with a large share of employment in an inherently dangerous industry will likely have higher disability rates. The average industry share, however, is constant, and thus cannot be responsible for *changes* in PAD.

I therefore use:

$$B_{it} = \sum_{k=1}^{K} \underbrace{(\frac{1}{T}\sum_{t=1}^{T}\frac{w_{itk}}{w_{it}})}_{s_{i\bar{t}k}} \underbrace{(\frac{(w_{tk} - w_{0k})}{w_{0k}})}_{g_{tk}} \tag{8}$$

to instrument for county employment growth, where w_{itk} is the number of employees in county i in industry k at time t, w_{it} is total employment in county i at time t, w_{tk} is the national number of individuals employed in industry k at time t, and w_{0k} is the national number of employees in industry k at time $t = 0$.[25] Since the Bartik instrument de-localizes g_{itk} by using the national growth rate, the instrument can be interpreted as measuring county exposure to exogenous employment shocks. For example, if there is a large decrease in oil and gas extraction nationally, counties with higher initial shares of oil and gas extraction will be more exposed to national employment shocks in oil and gas employment.

To examine the relationship between PAD growth and employment growth rates, I first run a simple OLS regression controlling for county and state fixed effects, and I include year dummy variables to account for time fixed effects. Since there is likely a lag between losing a job and SSDI award, I examine the impact of an employment shock on disability growth two, three, four, and five years after the shock. The lag in disability growth following an employment shock likely exists for a number of reasons. First, when there is a negative employment shock, there is likely an interim period between losing a job and applying for SSDI. Secondly, people who choose to apply for SSDI after losing a job are likely marginally disabled. These cases, therefore, are more likely to have to go through all five steps of the disability determination process, and are also more likely

[25] In the instrument that is constructed using initial industry shares rather than average industry shares, $s_{i0k} = \frac{w_{iok}}{w_{i0}}$ where w_{i0k} is total employment in county i in industry k at time $t = 0$, and w_{i0} is total employment in county i at time $t = 0$.

to be denied initially, and have to appeal. Moreover, if a large number of people within a county lose their jobs simultaneously, application rates increase, which can lead to increased backlogs and processing times (Kearney et al. (2021), Autor and Duggan (2003), Maestas et al. (2013)). Finally, French and Song (2014) find that the percent of initial applicants who are ultimately awarded SSDI increases steadily for the first four years after initial filing as applicants make their way through the appeals process or reapply. Lagging the employment growth data therefore accounts for the time between job loss and benefit award.

The OLS regression is therefore:

$$\frac{\Delta y_{it}}{y_{2000-\kappa}} = a_i + c_j + \beta \mathcal{E}_{it-\kappa} + \theta_t + x_{it}\gamma_1' + u_{it}, \ for\ \kappa = 2:5 \tag{9}$$

where $\frac{\Delta y_{it}}{y_{2000-\kappa}}$ is the growth rate in PAD for county i since the year $2000-\kappa$, at time t, κ is the number of lags, $\mathcal{E}_{it-\kappa}$ is the lagged county employment growth rate, and x_{it} is a vector of controls for gender, age, education, and real median household income. I then account for potential endogeneity by running a two-stage least squares regression using my Bartik instrument, B_{it}. I use both the instrument constructed using initial county industry shares, as is convention, and the instrument constructed using average county industry shares. Each regression includes controls for individual county and state fixed effects, and controls for time fixed effects by including year dummy variables. The first stage regression is:

$$\mathcal{E}_{it-\kappa} = \alpha_i + \zeta_j + \delta B_{it-\kappa} + \theta_t + x_{it}\gamma_2' + v_{it} \tag{10}$$

and in the second stage I regress county PAD growth rates on the estimated $\hat{\mathcal{E}}_{it-\kappa}$:

$$\frac{\Delta y_{it}}{y_{2000-\kappa}} = a_i + c_j + \beta_1 \hat{\mathcal{E}}_{it-\kappa} + \theta_t + x_{it}\gamma_3' + \epsilon_{it} \tag{11}$$

I also run each of the models above, but instead of including year dummy variables to account for time fixed effects, I include the augmented factor (the variable cointegrated with PAD) to account for the trend in PAD, and I detrend the employment growth rate and control data by subtracting out the cross-sectional mean of each variable, $\bar{x}_t$. This model is preferred to model (11) because the inclusion of the augmented factor guarantees stationarity of the dependent variable, PAD, and also retains the more information. In the instrumental variable model, the first stage is:

$$\mathcal{E}_{it-\kappa} = \alpha_i + \zeta_j + \delta(B_{ijt-\kappa} - \bar{B}_{t-\kappa}) + \lambda_1 g_t + \lambda_2(g_{it} - \bar{g}_t) + \lambda_3(g_{it} - \bar{g}_{jt}) + (x_{it} - \bar{x}_t)\gamma_4' + \eta_{it} \tag{12}$$

for county i in state j at time t. λ_2 and λ_3 capture the impact of county deviations from the national and state trends. The instrumental variable regression then becomes:

$$\frac{\Delta y_{it}}{y_{2000-\kappa}} = a_i + c_j + \beta_2(\hat{\mathcal{E}}_{it-\kappa} - \hat{\bar{\mathcal{E}}}_{t-\kappa}) + \lambda_4 g_t + \lambda_5(g_{it} - \bar{g}_t) + \lambda_6(g_{it} - \bar{g}_{jt}) + (x_{it} - \bar{x}_t)\gamma_5' + v_{it} \quad (13)$$

in all of the regressions, standard errors are clustered at the county level.

The main coefficient of interest in (13) is β_2. Theoretically, the sign on β_2 is ambiguous. If either 1) a loss of employment in a county with a large amount of employment in a dangerous industry, the negative employment shock could lead to a decrease in the disability growth rate, or 2) employment growth leads to a larger proportion of the working-age population eligible for SSDI, and thus an increase in disability growth, $\beta_2 > 0$. If, on the other hand, 1) a loss of employment induces SSDI application from the marginally disabled, or 2) employment loss causes able bodied individuals to exit the county, thus decreasing the working-age population, then $\beta_2 < 0$.

6 Results

The results for the national-level cointegration tests are displayed in Table 2. As previously noted, some of the data is not available for the full 1986-2021 time period, so the Engle-Granger critical values differ for some regressions. There are only four variables that are significant at the 95% confidence level or higher: the number of deaths from neoplasms (cancer) per 100,000 people, the labor force participation rate two years prior, the average number of poor health days each month for those reporting more than zero, and the percentage of the population aged 55-59.

The sign of the lagged labor force participation rate coefficient is negative. It isn't straight forward what the expected sign would be ex-ante; it could be a positive if a lower labor force participation rate leads to fewer people who are eligible for SSDI due to insufficient work history. The sign could be negative, however, if people become disabled and subsequently drop out of the labor force while they apply for SSDI. Additionally, discouraged workers with poor labor market prospects who exit the labor force and apply for SSDI would also cause the sign to be negative. The results therefore suggest the long-run relationship between PAD and labor force participation is driven by people dropping out of the labor force, and then receiving SSDI, and not by fewer SSDI recipients due to fewer insured workers, or vise versa.

Cancer deaths per 100,000 people also has a negative long-run relationship with PAD. Deaths from cancer peaked in 1991 after which point, they declined by 32% by 2019 due to reductions in smoking, and better early detection and treatment.[26] While deaths from cancer have steadily fallen since 1991, cancer incidence rates have not. Cancer incidence rates were steady for most of the 1990s and early 2000s, with a slight decrease beginning in the late 2000s.[27] With a decline in

[26] American Cancer Society (2022)
[27] National Cancer Institute (2023)

the overall cancer deathrate, but not incidence rate, the number of cancer survivors has increased. Cancer survivors have increased risk for other diseases in the future, and are also able to live longer, into their more disability prone years (Florido et al. (2022)). Additionally, new treatments have increased the life expectancy of those who will not ultimately survive their cancer. All of these things lead to a negative long-run relationship between PAD and the number of cancer deaths per 100,000 people.

The sign on the percentage of the population between the ages of 55 and 59 is positive, as expected, since the probability of disability increases with age and the more lenient vocational standards for applicants who are 55 and older will both cause PAD to increase when a larger share of the population is age 55 to 59. The positive relationship between PAD and the number of poor health days is also likely reflective of the portion of the population that is in their advanced, disability prone working-age years.

Figure 6 shows the paths of the four variables that share a long-run relationship with PAD. Each shares the same mountain shaped trend with PAD, but as Panel (a) shows, the lagged labor force participation rate peaks roughly a decade before PAD, and the neoplasm death rate peaks roughly two decades prior to PAD, as displayed in Panel (b). Panel (c) shows that the percentage of the population between the ages of 55 and 59 also has a similar mountain shape to PAD, but its peak and subsequent decline occur simultaneously with PAD. The number of poor health days per month for people experiencing at least one also peaks around the same time as PAD, as demonstrated in Panel (d). There is more short-run variation between PAD and the number of poor health days, but they still both visually follow the same long-run trend.

While the results show the neoplasm death rate per 100,000 people, the average number of poor health days, and the lagged labor force participation rate all share a long-run relationship with PAD, none of these three variables is likely to be the causal force behind the long-run trend in PAD. New cancer treatments increasing the length of time cancer patients survive, and thus increasing the amount of time they can receive SSDI is unlikely to be driving the long-run trend in PAD because the percentage of SSDI beneficiaries receiving SSDI due to neoplasms is only roughly 10% of total beneficiaries at any given time, and this percentage has stayed relatively stable over time, as Figure 4 displays. There is also the possibility that cancer survivors develop long-term health effects from their cancer treatment and those lingering health effects are the primary diagnosis for disability (Miller et al. (2022), Mahumud et al. (2020)). This also is unlikely to be causing the long-run trend, however, because while the percentage of the population that are cancer survivors has increased steadily since 1986, the vast majority of cancer survivors are 65 years old or older, and thus likely to receive Social Security retirement benefits rather than SSDI. In 2022, 67% of all cancer survivors were 65 or older.[28]

Even though the lagged labor force participation rate shares a long-run stable relationship with

[28] Bluethmann et al. (2016)

Table 2: Engle-Granger Test Statistic and Autoregressive Parameter

	Coefficient	EG Test Stat	$\hat{\rho}$	T
Health				
Poor Health Days if > 0	0.208	-5.582***	.157	28
Diabetes	0.075	-2.401	.864	33
Obesity	0.039	0.968	1.01	35
Smoker	-0.068	0.010	1.00	35
ln(Motor Vehicle Injury Rate)	-1.09	-2.655	.670	32
ln(Deaths per 100,000)				35
Overall	-6.721	1.618	1.06	
Neoplasm	-8.308	-3.718**	.773	
Musculoskeletal	1.208	-1.159	.921	
Mental Disorders	0.527	-1.982	.729	
ln(Industry (%))				32
Manufacturing	-1.079	-1.172	.894	
Construction	0.249	-3.300*	.924	
Mining	-0.114	-3.072	.931	
Aggriculture	-3.872	-1.920	.828	
Economic Variables				36
ln(Median HH Income)	3.091	-1.367	.925	
ln(Poverty Rate)	0.984	-2.061	.867	
ln(Female LFPR$_{t-2}$)	3.049	-1.274	.973	
ln(LFPR$_{t-2}$)	-7.122	-3.721**	.890	
Gini Index	0.225	-2.422	.636	
Applications and Awards				29
ln(Application Rate)	0.799	-1.499	.891	
ln(Award Vocational)	1.162	-0.351	.953	
ln(Award Rate Initial Stage)	0.317	-2.790	.927	
ln(Award Rate Hearing or Higher)	-1.285	-2.184	.904	
ln(Award Rate Overall)	-1.400	-3.083	.835	36
ln(Awards per Insured Workers)	1.112	0.538	1.03	
Average Age at Award	0.177	-1.647	.895	

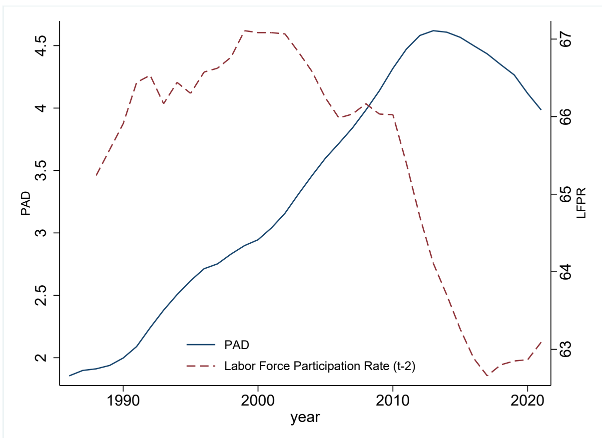
Table 2 Continued...

	Coefficient	EG Test Stat	$\hat{\rho}$	T
ln(% of Applicants Using Representation)	0.561	-3.179	.694	21
ln(Age Demographics (%))				36
50-59	1.708	-2.516	.852	
55-59	1.467	-3.832**	.827	
55-64	1.448	-3.419*	.879	
60-64	1.219	-3.091	.905	
60-69	1.189	-2.877	.924	
ln(% of Beneficiaries > 65 Years)	0.138	0.078	1.03	36
ln(Primary Diagnosis)				36
Neoplasm	-1.394	-1.076	.926	
Musculoskeletal	0.867	-2.877	.595	
Mental Disorders	-0.790	-1.019	.947	
Terminations				36
ln(Termination Rate)	-1.238	-0.223	.992	
Average Age of Beneficiaries	0.141	-2.730	.896	
ln(CDR Rate)	0.075	-0.910	.958	29

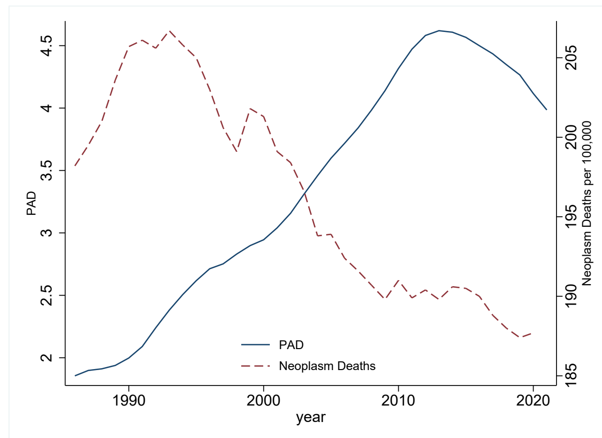
$^{***}p < .01$, $^{**}p < .05$, $^{*}p < .10$

Notes: The Engle-Granger critical values depend on the size of T, so the critical values are smaller (more negative) for data that is not available all 36 years from 1986-2021. $\hat{\rho}$ is the estimated autoregressive parameter obtained from equation 3. The health data comes from the BRFSS but has various size T because not all survey questions are asked annually, some are biannually, and some were not added to the survey until after 1986. The motor vehicle injury rate is the number of non-fatal motor vehicle injuries divided by the US population. The termination rate and average age of SSDI recipients data goes back to 1986, whereas the award data is only available from 1992 forward. The denominator of the award rate at the initial stage does not include those who were denied for technical reasons. Award Vocational refers to the fraction of total medical awards that were granted partially for vocational reasons. There are four variables that share a long-run relationship with PAD at a confidence level of 95% or greater: the average number of poor health days, the number of neoplasm (cancer) deaths per 100,000 people, the labor force participation rate from two years prior, and the percentage of the population that is between the ages of 55 and 59.

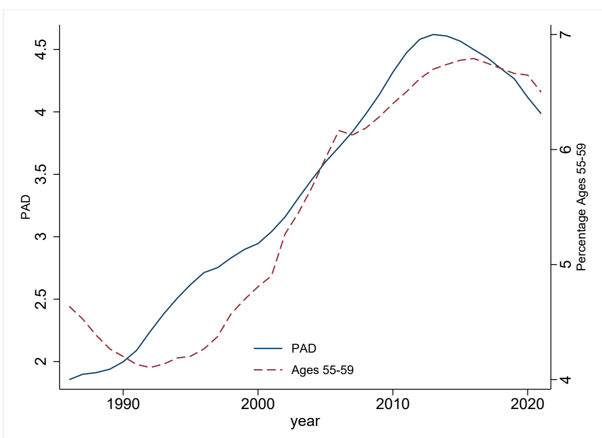
Figure 6: Long Run Relationships with PAD



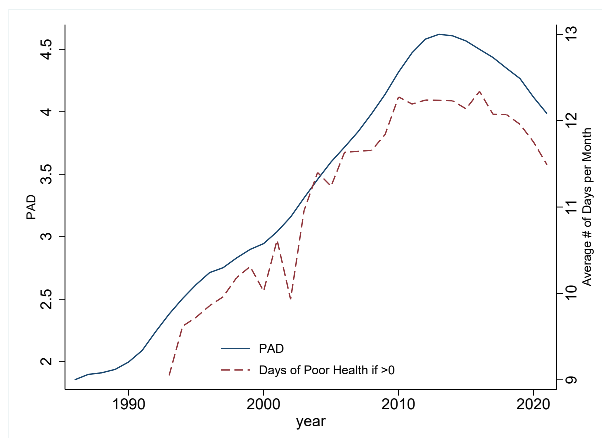
(a) PAD and Lagged Labor Force Participation Rate



(b) PAD and Neoplam Deaths per 100,000 People



(c) PAD and Percentage of Population Age 55-59



(d) PAD and the Number of Poor Health Days

Notes: Panel (a) displays the labor force participation rate alongside PAD from 1980-2021, panel (b) displays the number of neoplasm deaths per 100,000 people and PAD from 1986-2021, panel (c) displays PAD and the self-reported average number of poor health days in the past month for those reporting at least one day, and panel (d) displays the percent of the US population that is between the ages of 55 and 59 and PAD. Each variable shares a cointegrated, long-run relationship with PAD, which is visually evident in each panel through the similar mountain shaped trend over time.

PAD, it also is not likely to be the primary determinant driving the long-run path of the percent of working-age adults receiving SSDI because the labor force participation rate itself is driven by a common time trend. When the labor force participation rate is decomposed by age group, the vast majority of participants are ”prime-age”, or ages 25 to 54. From 1986-2021 the prime-age labor force participation rate oscillated around 82%. In contrast, the labor force participation rate for individuals aged 55 and older hovered around 30% from 1986 through 2000, after which point it increased through 2010, and has remained between 38 and 40% since. In other words, prime-age adults are more than two times more likely to participate in the labor force than adults age 55 and older. The aging of the baby boomer generation is therefore a confounding factor in the relationship between the labor force participation rate and PAD. The labor force participation rate peaked in the United States from 1997-2000, years where the baby boomers were at the tail end of their prime-age working years. In 2001, the first baby boomers turned 55, and after that point labor force participation begins to decline as a large share of the population enters ages with substantially lower labor force participation rates.[29]

The long-run relationship between the average number of poor health days each month and PAD is also likely impacted by the confounding factor of the fraction of the population that is more advanced in age. In general, as a people age, health declines. When a larger share of the population is in their more advanced years, we would expect to see an increase in the number of days individuals report poor health. There is therefore a common trend that both labor force participation and PAD share, and poor health and PAD share, and that common trend is tied to the percent of the population that is more advanced in age.

The final variable that showed evidence of a long-run relationship with PAD, the percentage of the population between the ages of 55 and 59, appears to best account for the common trend that we see in PAD, and explains the long-run relationships that exist between PAD and labor force participation and poor health. While previous literature has found a variety of things that impact PAD in the short-run, the primary driver of the long-run trend in PAD is the percentage of the population that is between the ages of 55 and 59. A one percent increase in the percentage of the population that is in this age group leads to a 1.47% increase in the percent of working age adults receiving SSDI. Put differently, a one percentage point increase in the population ages 55 to 59 from the mean of 5.48% leads to a 0.9 percentage point increase in PAD from the mean of 3.351%. This result aligns closely with the findings of Rutledge et al. (2016) who find that the substantial decrease in labor force participation among veterans receiving Veterans Affairs Disability Compensation from 1995-2014 was primarily a function of the aging of the disabled veteran population.

As previously mentioned, the disability determination process becomes more lenient at the age of 55, resulting in a large number of beneficiaries being granted benefits at the age of 55. As an increasing percentage of the population is between the ages of 55 and 59, such as when the baby

[29] Juhn and Potter (2006)

boomers entered this age range, we see PAD increase. As the baby boomers move out of the age range and into full retirement age, and a smaller percentage of the population is ages 55 to 59, PAD started to decline. Figures 7 and 8 provide graphical evidence of the importance of this age category on the percent of working-age adults receiving SSDI (PAD). Figure 7 displays the fraction of the working age population that is between the ages of 55 and 59 on the left in yellow, and PAD on the right in blue. Apart from 1986, it is clear that as the working-age population is more heavily distributed in the older working-age years, PAD correspondingly increases. Similarly, once the baby boomers retire and the working-population becomes less skewed toward the older years, PAD begins to fall. The year 1986 is an outlier with its relatively large portion of the workforce ages 55 to 59, and relatively small PAD. This is a result of 1980 SSA legislation that dramatically increased the number of continuing disability reviews, resulting in nearly 20% of SSDI recipients losing their benefits in the early 1980s (Kearney (2006)).[30]

Figure 8 displays the age distribution of PAD and the working-age population for four select years, 1986, 1991, 2006, and 2021. The light bars represent individuals born between 1957 and 1961, the five years in the baby boomer generation with the most births each year. When the baby boomers were at the beginning years of their working-age years in 1986 and 1991, a large fraction of the work force was young, and correspondingly, PAD was low. By 2016, however, the baby boomers were at the end of their working age years. Correspondingly, PAD is substantially higher in 2016. By 2021 baby boomers were between the ages of 57 and 75, so some were still at the end of their working-age years, but many had already reached FRA. With a smaller fraction of the population at the end of their working age years, PAD declines in 2021.

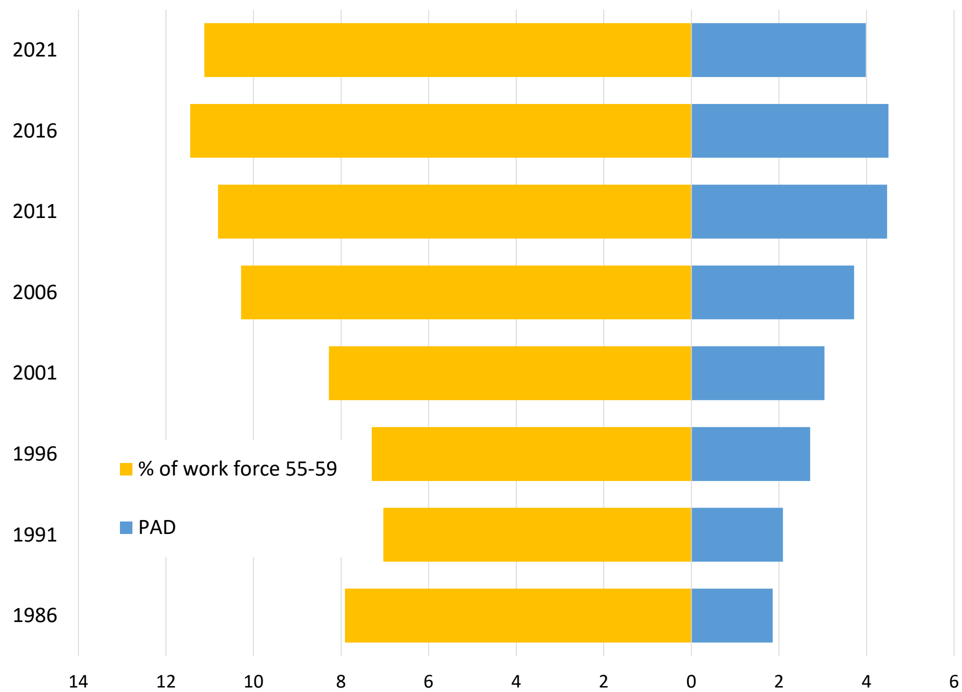
Perhaps as interesting as discovering that the percentage of the population age 55-59 has been driving the long run trend in PAD since 1986, is being able to rule out multiple hypothesis about other factors that have not caused the long-run trend such as increased female labor force participation and the increased FRA. These variables and others have certainly impacted PAD and caused temporary deviations in PAD from its long-run trend or level shifts, but they are not responsible for the long-run mountain shaped trend over time.

Table 3 shows the results of running (4) to verify that the percent of the population ages 55-59 held up as the common trend at the state level. All but one test statistic are highly significant, far beyond the .01% level. The remaining statistic is significant just above the .15% level, leading me to conclude that the percentage of adults age 55-59 is indeed the common factor driving PAD at the state level.

The results for the state-level variation in PAD are displayed in Table 4. Column (1) displays the results from the two-way fixed effects regression (5), and column (2) contains the results from model (6). Due to the non-stationary nature of PAD, Column (2) is the preferred specification.

[30]The 1980 Amendments were extremely unpopular politically, and by 1984 new Amendments reversed the strict continuing disability review standards mandated by the 1980 Amendments.

Figure 7: Fraction of Working Age Population Ages 55-59 and PAD Over Time



Notes: The bars on the left display the percent of the working-age population that is between the ages of 55 and 59, and the bars on the right show the percent of the working-age population that is receiving SSDI. With the exception of 1986, there is a strong relationship between the percent of the labor force that is age 55-59 and the percent of disabled working-age adults, as the two tend to grow and shrink together over time. The small PAD relative to the percent of the working-age population ages 55-59 in 1986 is likely due to strict legislation enacted by the SSA in 1980 that increased the number of continuing disability reveiws, and resulted in roughly 20% of recipients losing benefits.

Figure 8: Age Distribution of PAD and Population Ages 20-64

(a) 1986 (b) 1991

(c) 2016 (d) 2021

Notes: Each panel displays the distribution of the working age population by age in blue, and the distribution of PAD by age in yellow for various years. The lighter bars represent the cohort born between 1957 and 1961, the five years within the baby boomer generation with the highest number of births. In 1986 this cohort was aged 30 and younger, and in 1991 the cohort was 30-35. It is visibly apparent that in 1986 and 1991 a large share of the working age population was in the early portion of their working years, and a relatively small portion of the working-age population was more advanced in age. The corresponding PAD is relatively low during both years, consistent with the finding that the percent of the population age 55-59 drives PAD. Three decades later, in 2016 the 1957-1961 cohort was between the ages of 55 and 59, and the fraction of the working-age population in the advanced portion of their working years was significantly higher than in 1986 or 1991. This transition of a large share of the working-age population into their more advanced years causes PAD to increase dramatically, as can be seen by comparing the yellow right-side columns in 1986 and 2016. *Note:* The 60-FRA age bin is slightly larger in 2016 and 2021 due to the increased FRA.

Table 3: State-Level Cointegration Test Statistics

y_{jt}: ln(state PAD), g_t: ln(% age 55-59)

Cointegration Test	Test Statistic	p-value	T
Kao			34
Modified DF	-14.17	0.000	
DF	-14.71	0.000	
Augmented DF	-10.57	0.000	
Unadjusted Modified DF	-4.798	0.000	
Unadjusted DF	-15.86	0.000	
Pedroni			35
Modified Phillips-Perron	1.004	0.158	
Phillips-Perron	-11.67	0.000	
Augmented DF	-24.11	0.000	
Westerlund	-4.643	0.000	36

Notes: Stata has three different panel cointegration tests that calculate a total of nine test statistics. The null is that the error term is non-stationary, and thus the series is not cointegrated. I can reject the null with very high confidence with eight of the nine test statistics. One test statistic only allows me to reject the null at the 85% confidence level.

The magnitude of the impact of the U.S. population ages 55-59 on state SSDI rates is similar to the magnitude of the age group on national PAD, and remains highly significant, consistent with the findings in Table 3. The common trend is so strong at the state level that it alone explains 82.4% of the time-series variation within a state over time. There is no coefficient for the common trend that results from this age demographic in column (1) since all common trends are eliminated in the two-way fixed effects specification.

The variables in Column (2) of Table 4 account for 86% of the variation in SSDI rates between states, but only three variables have an impact on PAD that is statistically different from zero: the difference in the state and U.S. percentage of the population ages 55-59, the application rate, and real median household income. When these three variables alone are regressed on state PAD, they account for 84.5% of total variation between states. The coefficient of the difference between the state and U.S. population ages 55-59 is positive. A state with a higher-than-average percentage of its population between the ages of 55 and 59 will have higher PAD, as is to be expected, knowing the importance of this age demographic. The number of applications per working-age population is positive, indicating that states with higher application rates also have higher SSDI rates. The higher application rates in higher PAD states cannot be explained by time-invariant state characteristics, or by the age, health, education, economic, or industry variables that are controlled for in Table 4. The relationship that exists between application rates and state PAD is likely due to a network effect - as individuals encounter larger numbers of others within their networks receiving SSDI, they are more likely to apply themselves. Finally, the coefficient on real median household income is negative, as would be expected from the large literature detailing how SSDI recipients are worse off financially prior to disability onset (Autor et al. (2020)).

Interestingly, according to the model used for column (2), variation in health variables, the number of adults with a high school degree or more, and the percentage of people employed by industry do not explain differences in state-level PAD once the other variables are accounted for.[31] The prototype program that SSA implemented from 1999-2019 also had no distinguishable impact on the variation in PAD between states, regardless of the model. The lack of evidence of any impact from the prototype program is likely due to the small number of awards at the reconsideration stage, as displayed in Figure (3) which leads to most applicants who choose to appeal their initial ruling ending up at the hearing stage regardless of whether there is a reconsideration stage in the appeals process. Beyond that, a full 40% of applicants who are denied at the hearing level will reapply and be granted benefits within three years of initial application (French and Song (2014)). So, it is not surprising that the elimination of an appeals stage that is responsible for a very small number of awards had no impact on PAD. The prototype program likely did impact the length of time it took to get to the ALJ stage or to reapply for those who were initially denied, however, which could have real repercussions for applicants. The longer applicants are out of the labor force applying for SSDI, the more difficult it is to rejoin the labor force if benefits are ultimately denied (Autor et al. (2015)).

There was likely no detectable impact from unemployment rates and industry composition because the state-level is too high of a level to examine these variables. When Autor et al. (2013) look at labor market impacts due to the loss of manufacturing, they do so at the local labor market level. The closing of a manufacturing facility that is the major employer in a small town will have a negligible impact on the state as a whole but could have a devastating impact on that small town. State-level data is too delocalized to detect the impact of industry composition and unemployment rates over time. When the data is aggregated at the state level important variation within a state cannot be detected, which is one of the motivations for looking at the impact of county-level employment shocks.

Table 5 displays the results for the impact of county-level employment shocks on disability growth, using both employment growth rates themselves, and instrumenting for employment growth rates with the average shares Bartik instrument. Both models include two, three, four, and five year lagged employment shocks. (See Appendix E for results using the initial shares Bartik instrument.) The results for $(\frac{\Delta \dot{y}_{it}}{y_{it}})$ correspond to model 11 and the results for $(\frac{\Delta \tilde{y}_{it}}{y_{it}})$ correspond to model 13.

Panel A displays the results using actual employment growth, plus demographic control variables and individual and time fixed effects. Both model specifications produce similar results, regardless of the number of years employment shocks are lagged. All of the estimates in Panel A are negative, and highly significant, indicating that there is a high degree of confidence that employment shocks

[31] In an alternate specification I also included state opioid dispensing rates (see Appendix D), but the results are not included in Table 4 since the opioid dispensing data is only available from 2006 forward.

Table 4: Determinants of State-Level Variation in PAD

Dependent Variable:	$\dot{y}_{jt}$ (1)	$\tilde{y}_{jt}$ (2)
Age		
US 55-59		1.346***
State 55-59 - US 55-59	0.194	0.270**
Prototype State	-0.019	-0.012
Health		
Death rate	0.213	0.178
Diabetes	0.031	0.034
Smoker	0.090	0.096
Obese	0.026	0.025
Education		
HS degree or more	-0.199	-0.183
Application Trends		
Allowance rate, initial	0.045	0.042
Applications / w.a. pop	0.145***	0.146***
Economic		
Unemployment rate	-0.033**	-0.032
Median household income	-0.105**	-0.094**
Poverty rate	0.008	0.009
Labor force participation rate	-0.119	-0.141
Percent of employees by industry		
Mining & oil & gas extraction	-0.000	0.001
Construction	0.027	0.024
Manufacturing	0.001	-0.002
obs	1014	1014
R^2_{within}	0.949	0.905
$R^2_{between}$	0.862	0.860

Notes: With the exception of the prototype state indicator, the natural log of each variable is used, and thus coefficients are interpreted as elasticities. The health variables are from a survey that does not ask every health question every year, resulting in an unbalanced panel. Years where the four health questions are not asked are dropped. $\dot{y}_{jt}$ corresponds to model 5 and $\tilde{y}_{jt}$ refers to model 6. $\tilde{y}_{jt}$ is the preferred specification since its error term is known to be stationary. No coefficient is reported for US 55-59 in column since the common trend is eliminated in the two-way fixed effects regression. The allowance rate at the initial stage does not include technical denials. Once controlling for the other variables, only three variables explain the vast majority of the variation in PAD between states. The variables are the difference in the percentage of the state population and the U.S. population ages 55-59, the number of applications per working-age adults, and real median household income.

Table 5: County Employment Results by Model and Lag

Dependent Variable	$(\frac{\Delta \dot{y}_{it}}{y_{it}})$	$(\frac{\Delta \tilde{y}_{it}}{y_{it}})$
Panel A: OLS estimates		
2 year lag	-0.181***	-0.199***
3 year lag	-0.168***	-0.184***
4 year lag	-0.155***	-0.169***
5 year lag	-0.133***	-0.145***
Panel B: IV estimates $\mathcal{B}_{i\bar{t}}$		
2 year lag	-0.865***	-1.054***
3 year lag	-0.789***	-0.934***
4 year lag	-0.706***	-0.811***
5 year lag	-0.552***	-0.608***
First stage F-statistics		
2 year lag	154.13	94.70
3 year lag	245.69	253.02
4 year lag	358.41	358.79
5 year lag	481.48	478.21

$^{***}: p < .01, ^{**}: p < .05, ^{*}: p < .10$

Notes: $(\frac{\Delta \dot{y}_{it}}{y_{it}})$ corresponds to the augmented factor model, equation (13), and $(\frac{\Delta \tilde{y}_{it}}{y_{it}})$ corresponds to the two-way fixed effects model, equation (11). Panel A displays the OLS estimates and Panel B displays the instrumental variable estimates. Controls for age, gender, race, and household income and individual and time fixed effects are included in all regressions. Standard errors are clustered at the county level. Both the OLS and the IV results provide evidence of a negative relationship between employment shocks and disability growth rates. The OLS results are larger than the instrumental variable estimates, suggesting the OLS results contain an upward bias due to confounding factors. The F-statistics from the first stage instrumental variable regressions are all very large, indicating the Bartik instrument is a strong instrument.

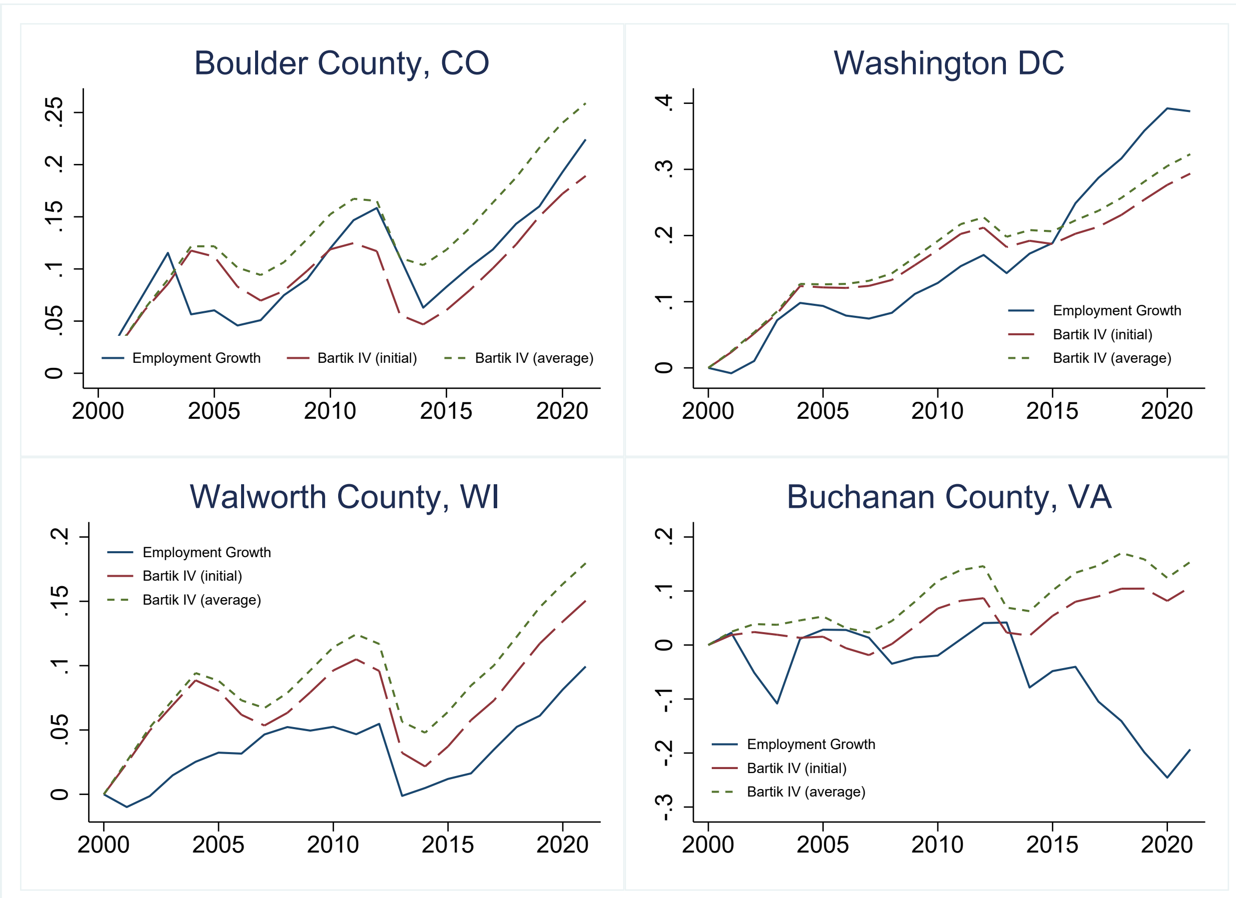
are negatively correlated with disability growth. The magnitude of the relationship decreases (gets less negative) as the number of lags increases, indicating that the relationship between employment shocks and disability growth is strongest two years after the initial employment shock.

The Panel B first stage F-statistics demonstrate that the Bartik instrument proves to be a strong instrument, highly correlated with actual employment growth, regardless of the specification. The high F-statistics for all model specifications and lags clearly demonstrate the Bartik instrument is relevant, which can also be seen visually in Figure 9. Figure 9 displays both the average shares and initial shares Bartik instruments alongside actual employment growth for three select counties and Washington DC. Both instruments follow the same general path over time as actual employment growth, for the most part. The instruments and actual employment growth do diverge for certain periods, however, indicating the exogeneity of the instruments. In Buchanan County, VA, for example, actual employment growth has declined rapidly since 2013, but the instruments slowly grew over the same time period. This deviation is likely due to a trend specific to Buchanan County that is not present in the instruments since they replace county employment growth by industry with national employment growth by industry.

The results for the average shares Bartik instrumental variable are displayed in Panel B. Like the OLS estimates, all of the instrumental variable estimates are negative and highly significant. The estimates also have the largest magnitude two years after an employment shock, and the magnitude decreases with additional lags. In my preferred specification I find that a 10% decrease in employment growth since 1998 increases the SSDI growth rate by 10.54%. Consistent with previous literature, the results suggest that employment loss in a local labor market causes an increase in disability growth (Maestas et al. (2021)).

As previously mentioned, there are two potential mechanisms through which employment shocks would lead to PAD growth. The first is via the marginally disabled mechanism, where workers who are marginally disabled apply for SSDI after losing a job, but they would not have applied in the absence of job loss. The second mechanism that could account for the negative impact of employment shocks on PAD growth is through able bodied individuals moving out of a county after job loss, thus decreasing the working-age population of the county. I believe the marginally disabled mechanism is what is responsible for this causal relationship for three reasons. First, prior literature finds no evidence that shocks in local manufacturing employment lead to substantial changes in population, and that mobility is lowest for non-college educated workers (Autor et al. (2013)). Secondly, not only do the percent of working-age adults who are disabled increase following an employment shock, but the number of SSDI applications increase as well, indicating the growth is not a function of a shrinking working-age population (Maestas et al. (2015)). Finally, the mean elasticity of the working-age population with respect to employment growth is 0.185, and the mean elasticity of the working age population with respect to employment growth since 1995 is 0.053,

Figure 9: Instrumenting for Employment Growth vs Actual Employment Growth



Notes: The instrumental variables used to instrument for employment growth are plotted alongside actual employment growth for three select counties and Washington DC. The Bartik IV (initial) instrument is constructed using the initial industry shares for each county at time $t = 0$, and the Bartik IV (average) instrument is constructed using each county's average industry shares over time. Both instruments follow roughly the same path over time as actual employment growth in Boulder County, CO and Walworth Couty, WI. In Washington DC actual employment growth has a steeper trend than the instruments from 2015 onward, and in Buchanan County, VA the instruments diverge from the steep decline the county experienced in employment decline since 2013.

indicating changes in the working-age population are highly inelastic to changes in employment.[32]

Consistent with the hypothesis that there could be confounding factors that are unaccounted for in the OLS regressions, the OLS results are larger (less negative) for all model and lag specifications, indicating the OLS estimates suffer from an upward bias. In other words, there is some county-level time-varying factor or factors that are unaccounted for that decrease employment growth and also decrease disability growth, but the decreasing disability growth is not a direct result of the changes to employment growth. It could be that the loss of jobs in a dangerous facility or industry in a county lead to lower disability rates in the future since people are no longer exposed to the risks of the facility or industry. It is also possible that county-level opioid use or attitudes toward work shift over time and lead to people exiting the labor force for reasons other than employment shocks. If this labor force exit leads to ineligibility for SSDI based on insufficient recent work history, PAD growth would decrease as well. Figure 3 suggests this may be true in some cases. As the figure illustrates, the number of technical denials, or applicants who are denied for insufficient work history, increased from approximately 10% in 1992 to roughly 40% in 2021. Without using an instrumental variable to identify the impact of employment shocks, the estimates would underestimate the impact that shocks to local labor markets have on disability growth due to confounding factors.

7 Forecasting

Knowing that the primary determinant of PAD over the past several decades was the percentage of the population that was between the ages of 55 and 59 allows me to forecast future levels of PAD, both at the national, and the state level. Clearly, the percentage of the population that is between the ages of 50 and 54 in 2021 will be transitioning to ages 55-59 over the next five years. I therefore use that age cohort to forecast the percent of people who will be ages 55-59 in the future. I did this by first regressing the natural log of the percent of the population ages 55-59 ($ln(g_{55})$) on the natural log of the five year lagged percent of the population ages 50-54 ($ln(g_{50})$).

$$ln(g_{55,t}) = \alpha + \delta ln(g_{50,t-5}) + u_t \tag{14}$$

After obtaining $\hat{\alpha}$ and $\hat{\delta}$, I calculated

$$\widehat{ln(g_{55,T+k})} = \hat{\alpha} + \hat{\delta} ln(g_{50,T-5+k}) \tag{15}$$

for $k = 1:5$. After obtaining my estimates for the percent of the population that will be ages 55-59 over the next five years, I use $\hat{a}$ and $\hat{\lambda}$ from 1 and $\widehat{ln(g_{55,T+5})}$ from 15 to calculate future ln(PAD),

[32] $\frac{1}{nT}\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{\%\Delta w.a.population}{\%\Delta employment}$

$\hat{y}_{T+k}$:

$$\hat{y}_{T+k} = \hat{a} + \hat{\lambda} ln(\widehat{g_{55,T+k}}) \tag{16}$$

I repeat the same process at the state level, estimating 14 for each state, i, resulting in 51 $\hat{\alpha}_i$ and $\hat{\delta}_i$. I then calculate the future percentage of the population ages 55-59 using the same procedure as 15, for each state individually, to obtain each $ln(\widehat{g_{55,iT+k}})$, and then estimate

$$\tilde{y}_{it} = \lambda \widetilde{ln(g_{55,t})} + \beta(\widetilde{ln(g_{55,it})} - \widetilde{ln(\bar{g}_t)}) + \tilde{e}_{it} \tag{17}$$

and use the resulting $\hat{\lambda}$ and $\hat{\beta}$ to calculate each state's constant:

$$\hat{a}_i = \frac{1}{T} \sum_{t=1}^{T} (y_{it} - \hat{\lambda} \widetilde{ln(g_{55,t})} - \hat{\beta}(\widetilde{ln(g_{55,it})} - \widetilde{ln(\bar{g}_t)})) \tag{18}$$

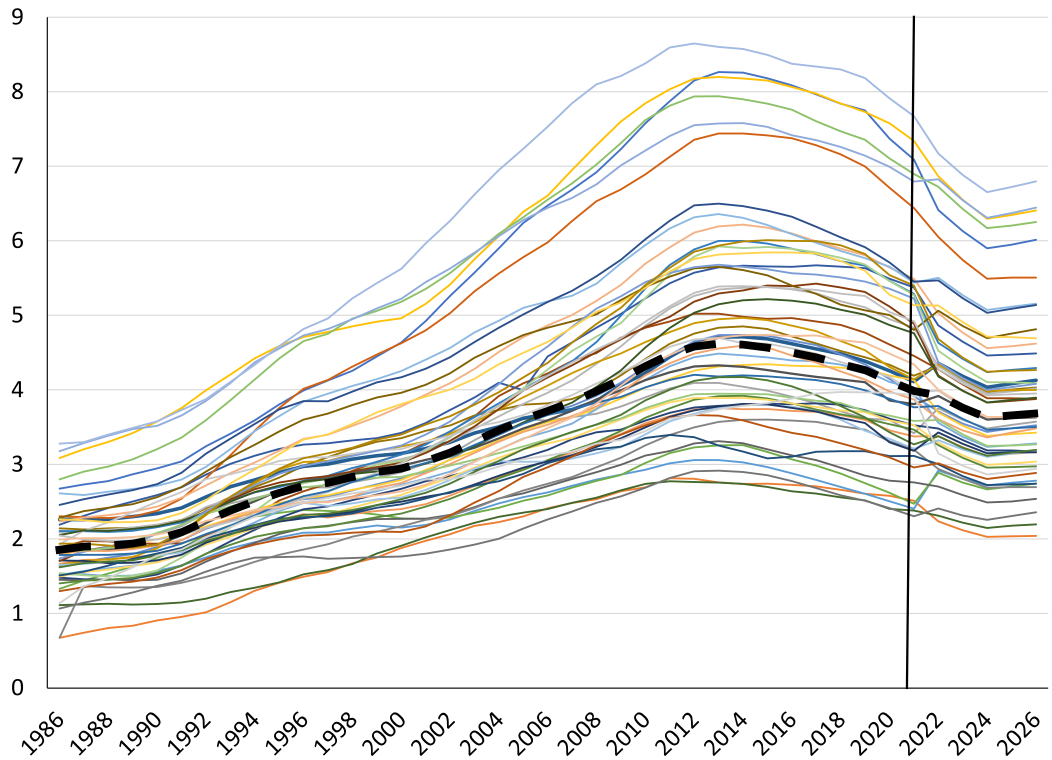
and finally, calculate future ln(PAD) for the next five years:

$$\hat{y}_{iT+k} = \hat{a}_i + \hat{\lambda} ln(\widehat{g_{55,iT+k}}) + \hat{\beta}(ln(\widehat{g_{55,iT+k}}) - ln(\widehat{\bar{g}_{55,iT+k}})) \tag{19}$$

Figure 10 displays the projected levels of state and national PAD, where the black dashed line represents national PAD. The projections show SSDI rates continuing to gradually decrease from 2021-2024, after which point they slightly increase for two years.[33] The projections follow the same pattern at the state-level, but importantly, there are a few states that I forecast to have PAD increase slightly before declining. The value of forecasting at the state-level is to create a baseline of where PAD is expected to go for each state. Deviations from projected PAD at the state-level could be due to imperfect forecasting but could also indicate something happening in disability rolls in the state that warrants more attention. Forecasting at the federal level is important for understanding future costs of SSDI.

[33]See Appendix C for forecasting robustness checks.

Figure 10: Projected State and National PAD 2022-2026



Notes: The black dashed line represents national SSDI rates, and each colored line corresponds to a state PAD. Actual SSDI rates are plotted from 1986-2021, and forecasted rates are plotted from 2022-2026. The horizontal line marks where the realized data ends and the forecast data begins. As the figure shows, national PAD is projected to continue to decrease through 2024, after which point it will increase slightly.

In order to estimate costs, I first convert ln(PAD) into the estimated raw number of workers on SSDI rolls for the next five years. This requires first estimating the working age population from 2022-2026. I predict this similarly to the way I predicted the future percent of the population between the ages of 55 and 59. I first regress the size of the population age 20 to 64 on the five year lagged population ages 15 to 59, obtain the estimated coefficients, and multiply them by the last five years (2016-2021) of data for the population ages 20-64.[34] I then take the exponential of ln(PAD), and multiply by the working age population divided by 100 to get the estimated number of people receiving SSDI from 2022-2026. The table below displays the estimates.

[34]I did not take the natural log of the working age population data since the working age population data is a level, not a ratio.

Year	Estimated Workers Receiving SSDI
2022	7,627,518
2023	7,302,711
2024	7,038,173
2025	7,157,538
2026	7,193,118

The trend in the of the number of worker SSDI beneficiaries peaked two years after PAD, in 2015, but it follows a very similar path to PAD. At its peak in 2015, there were 8,759,035 worker beneficiaries in the fifty states plus the District of Columbia. This means that over a ten-year time span, from 2015-2025, there will be an estimated 1,601,497 fewer recipients. This translates to roughly $2,375,020,051 (2023 $s) less spent in 2025 than in 2015. In 2015, the SSA projected the reserves in the SSDI trust fund would be depleted by 2016. Due to the reversal in the PAD trend and associated savings, however, the SSA now projects that the SSDI will be fully solvent for the entire projection period of 75 years. [35]

8 Discussion

A key finding of this paper is that the percentage of the population that is between the ages of 55 and 59 is what has driven the long-run trend in the percent of working-age adults receiving SSDI over the past 36 years, and it is the common factor driving state and county SSDI trends. This key demographic variable explains not only the long-run time-series trend, but is also responsible for variation in PAD between states. This age demographic is critically important to understanding PAD over time, and projecting future national and state PAD. This finding aligns with two facts regarding the intersection of disability and age. First, as people age, health declines and the likelihood of disability increases. Additionally, as discussed in Section 3, the SSDI eligibility determination process accounts for the fact that finding new work is more difficult at advanced ages and is thus more lenient by design for individuals 55 and older. Consequently, there is a health and a vocational explanation for why the percent of the population between the ages of 55 and 59 explains the long-run trend in PAD.

The policy relevant question, then, is how much of the of the long-run trend is driven by increased disability incidence that occurs as individuals age, and what portion is driven by vocational factors associated with difficulty finding work at more advanced ages?[36] It is important to first understand the heterogeneity in the percent of working-age adults receiving SSDI by education

[35] The Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds (2015 and 2023)

[36] In 2010, for example, more than half of unemployed workers aged 50-61 were long-term unemployed, or had been unemployed for more than 6 months (Johnson and Park (2011)).

and income, particularly at more advanced ages. By age 55, individuals from the lowest income group are 15 times more likely to enter the SSDI rolls each year than individuals in the highest income group (Manoli and Ramnath (2015)). Additionally, from 1992-2012, 16.9% of men ages 50-61 without a high school degree received SSDI, whereas 2.6% of men with a college degree in the same age category received SSDI (Poterba et al. (2017)). This striking difference may be a result of disabilities induced by jobs traditionally performed by less skilled labor, or the result of insufficient labor market opportunities for workers with less education. In future research I would like to decompose the relative importance of disability onset between the ages of 55 and 59, vs disability receipt due to a lack of vocational opportunities between the ages of 55 and 59. I would also like to examine the long-run relationship between the percent of the population aged 55-59 and the PAD for other OECD nations that provide their citizens disability insurance to see if the same stable, long-run relationship holds.

Another important finding of this paper is that apart from age demographics, median household income and application rates explain the vast majority of the variation in disability rates between states, emphasizing once again the strong connection between income and PAD, even though SSDI is not a means tested program. The importance of the application rate in explaining state-level variance is likely a result of an interaction between income and a network effect. Friedman et al. (2016) find that children from low-income families have stark differences in the probability of SSDI receipt, depending on where they grew up. No such locational variation exists, however, for children from high-income households. This network effect that appears to be present, particularly among the lowest income individuals, may be a result of increased information or decreased stigma as larger percentages of the population receive SSDI. In future work, I would also like to examine other disability outcomes that may have been impacted by the state-level prototype program. Although I find no evidence that the program impacted disability rates, it could have impacted the length of time it took to eventually be awarded SSDI, which has significant labor force implications (Autor et al. (2015)).

The county-level Bartik instrument results illuminate yet another way economic conditions and PAD interact. The results indicate that negative employment shocks in a local labor market will increase county PAD two to five years later, with the largest impact two years after the employment shock. Thus, county-level deviations from the long-run trend and the resulting county-level variation can be explained in part by exposure to employment shocks, demonstrating that SSDI is implicitly insuring against the loss of employment resulting from an employment shock to a local labor market. While this research does not examine the impact of employment shocks on individuals ages 55-59 specifically, the results are suggestive that some of the link between age and disability rates is structural in nature, or in other words due to the inability of older workers to find employment following an employment shock. This finding requires a rethinking of vocational opportunities available to the marginally disabled in the final portion of their working-age years. Maestas (2019) suggests allowing for partial disability. Allowing for partial disability would eliminate the binary decision workers face when deciding to drop out of the labor force to apply for SSDI or continue to work with their disability. With partial disability, workers could maintain some attachment to the labor force while also getting monetary help for any of their prior work that they are unable to perform due to their disability.

9 Appendix

9.1 Appendix A: Cointegration

Variables that are cointegrated share a long run relationship around a common trend. To see this, let the data generating process for y_t and x_t be:

$$y_t = a + \beta\theta_t + e_t$$
$$x_t = b + \theta_t + u_t$$

where y_t and x_t are both nonstationary, and $e_t \sim iid(0, \sigma_e)$, $u_t \sim iid(0, \sigma_u)$ and θ is a common time trend.

If y_t is cointegrated with x_t then there exists a cointegrating vector, $\boldsymbol{\beta} = [1, \beta]$ such that $\boldsymbol{\beta Y_t} = y_t - \beta x_t \sim \mathcal{I}(0)$, where $\boldsymbol{Y_t} = [y, x]'$, since:

$$\boldsymbol{\beta Y_t} = y_t - \beta x_t = \tag{20}$$

$$a + \beta\theta_t + e_t - \beta(b + \theta_t + u_t) =$$

$$(a - \beta b) + (e_t - \beta u_t) \sim \mathcal{I}(0)$$

If such a cointegrating vector does exist, then (20) can be rewritten as a standard OLS regression, $y_t = a + \beta x_t + e_t$, and the residuals, $\hat{e}_t$ will be stationary, and thus standard statistical inference is valid.

9.2 Appendix B: Panel Cointegration Tests

The Kao cointegration test produces five test statistics based off of the Dickey Fuller (DF) model:

$$\hat{\eta}_{it} = \rho\hat{\eta}_{i,t-1} + v_{it} \tag{21}$$

and the augmented DF Model:

$$\hat{\eta}_{it} = \rho\hat{\eta}_{i,t-1} + \sum_{j=1}^{p} p_j \Delta\hat{\eta}_{i,t-j} + v_{it} \tag{22}$$

where p is the number of lags. The DF tests test whether $\rho = 1$, whereas the modified DF tests whether $1 - \rho = 0$. The test statistics are calculated differently, based on differing assumptions about serial correlation in η.

The Pedroni test allows for heterogeneity among the autoregressive coefficients, ρ_i by estimating:

$$\hat{\eta}_{it} = \rho_i\hat{\eta}_{i,t-1} + v_{it} \tag{23}$$

and

$$\hat{\eta}_{it} = \rho_i\hat{\eta}_{i,t-1} + \sum_{j=1}^{p} p_j \Delta\hat{\eta}_{i,t-j} + v_{it} \tag{24}$$

and calculates the test statistics using panel specific test statistics. Finally, the Westerlund test also allows for heterogeneity in ρ by using (23), but uses variance ratios to calculate the test statistics. Additionally, the alternative hypothesis to this test is that some panels are cointegrated, not that all are cointegrated.

9.3 Appendix C: Testing Forecast Performance

To test my forecast model, I create out-of-sample comparisons between my model, and three other models. The first comparison model is the error correction model,

$$\Delta y = \alpha + \lambda(y_{t-1} - \beta x_{t-1}) + u_t \tag{25}$$

which can be rearranged and re-written as

$$y_t = \alpha + \gamma_1 y_{t-1} + \gamma_2 x_{t-1} + u_t \tag{26}$$

where y_t is the percent of working-age adults receiving SSDI benefits (PAD), and x_{t-1} is the percentage of the population between the ages of 55 and 59 one year prior. The error correction model is a natural model for comparison because the cointegrating relationship that exists between PAD and the percentage of the population ages 55-59 allows the right-hand side of the model to contain both the lagged dependent, and the lagged independent cointegrated variable. The lagged variables on the right-hand side lend the model to easily be used to forecast future PAD. Since my dependent variable is non-stationary, I also include a random walk model,

$$y_t = y_{t-1} + e_t \tag{27}$$

and a random walk with drift,

$$y_t = \alpha + y_{t-1} + v_t \tag{28}$$

Note that model (28) is nested in (26) and if no cointegrating relationship exists, $\gamma_2 = 0$ and equation (26) is equal to equation (28).

To test the accuracy of each model I use out-of-sample forecasting, using the first $21 - h$ observations to estimate the model, where h is the number of horizons, and predicting 16 observations for $t = 21...36$. I predict one through five horizons for each model using recursive sampling. To compare the forecast performance of each of the models, I then calculate the mean squared prediction error (MSPE) for each horizon of each model and perform a Clark-West test. The null hypothesis of the Clark-West test is that the MSPE of the alternative forecast model is less than or equal to the MSPE of my preferred model, model 19. The alternative hypothesis is that the MSPE of the alternative model is greater than my preferred model. The smaller the MSPE, the more accurate the model, so if the null hypothesis is rejected, the preferred model more accurately forecasts PAD.

The results are displayed in Table 6. When two to five horizons are forecast, the null hypothesis is rejected with confidence in each of the competing models, leading to the conclusion that the preferred model more accurately forecasts PAD than the alternative models. When the forecasts only predict one horizon, the null is not rejected in the error correction model comparison, and the null hypothesis is only rejected at the 90% confidence level in the random walk with drift model. Taken together the results suggest that other models may perform similarly if they are only forecasting one period into the future, but the preferred model significantly outperforms the alternative models when forecasting more than one period into the future. Since I forecast PAD five years into the future, the Clark-West results suggest my preferred model is the most appropriate choice, and robust to other forecasting model specifications. These results also reinforce the importance of the percent of the population ages 55-59 in driving PAD, one of the key contributions of this paper.

Table 6: Clark-West Test for Forecasting Performance

	Horizon				
	1	2	3	4	5
Error Correction Model	0.646	2.152**	2.500***	2.510***	2.117**
Random Walk	3.000***	2.999***	3.008***	3.023***	3.027***
Random Walk with Drift	1.497*	2.915***	3.164***	3.370***	3.560***
Observations in Model	20	19	18	17	16
Observations Forecast	16	16	16	16	16

Notes: The out-of-sample forecasts of the three alternative models in the left-hand column are each compared to the out-of-sample forecasts from the preferred model 19. The null hypothesis is that the mean squared prediction error (MSPE) of the alternative model is less than or equal to the MSPE of the preferred model. The alternative hypothesis is that the MSPE of the alternative model is greater than the MSPE of the preferred model. The null is rejected with confidence for each of the three alternative models when the forecasts predict two to five horizons, meaning that the preferred model is more accurate than the alternative models. When only one horizon is forecast, the null is not rejected for the error correction model, and is only rejected at the 90% confidence interval for the random walk with drift model. ($^{***}p < 0.01,^{**} p < 0.05,^{*} p > 0.10$)

9.4 Appendix D: State Models Including Opioid Dispensing Rates

While opioid dispensing rates may impact the variation in PAD between states, the data is only available from 2006 forward. Therefore, including this data does not allow me to explain the variation in states that has occurred since 1986. The results for both the two-way fixed effects model and the augmented factor model including and excluding opioid dispensing are included in Table **??**. Columns (1) and (3) include opioid dispensing rates, and therefore have fewer observations than columns (2) and (4). Regardless of the model, opioid dispensing is not statistically significant, although in both models the sign is positive, as would be expected. Opioid dispensing rates likely didn't have any impact on PAD because the state-level is too high of a level to examine this variable. The impact of opioids varies greatly within states. Virginia, for example, has counties with some of the very highest dispensing rates in the nation, and other counties with some of the lowest. When the data is aggregated at the state level these important variations within a state cannot be detected.

Table 7: Determinants of State-Level Variation in PAD

Dependent Variable:	$\dot{y}_{jt}$ (1)	(2)	$\tilde{y}_{jt}$ (3)	(4)
Age				
US percent 55-59			1.689***	1.346***
State percent 55-59 - US percent 55-59	0.154	0.194	0.457***	0.270**
Prototype State	-0.006	-0.019	0.008	-0.012
Health				
Deathrate	0.211*	0.213**	0.115	0.178
Diabetes	0.009	0.031	0.017	0.034
Smoker	0.204**	0.090	0.227*	0.096
Obese	-0.053	0.026	-0.075	0.025
Opioids	0.035		0.055	
Education				
High school degree or more	-0.702***	-0.199	-0.593*	-0.183
Application Trends				
Allowance rate at initial stage	0.062**	0.045	0.051	0.042
Applications per working age adults	0.058**	0.145***	0.054*	0.146***
Economic				
Unemployment rate	-0.003	-0.033**	-0.012	-0.032
Median household income	-0.087**	-0.105**	0.058	-0.094**
Poverty rate	0.007	0.008	0.015	0.009
Labor force participation rate	-0.070	-0.119	-0.103	-0.141
Percent of employees by industry				
Mining & oil & gas extraction	0.003	0.000	0.006	0.001
Construction	0.031	0.027	0.035	0.024
Manufacturing	0.030	0.001	0.056	-0.002
obs	709	1014	708	1014
R^2_{within}	0.873	0.949	0.676	0.905
$R^2_{between}$	0.814	0.862	0.726	0.860

Notes: With the exception of the prototype state indicator, the natural log of each variable is used, and thus coefficients are interpreted as elasticities. The health variables are from a survey that does not ask every health question every year, resulting in an unbalanced panel. Years where the four health questions are not asked are dropped. $\dot{y}_{jt}$ corresponds to model 5 and $\tilde{y}_{jt}$ refers to model 6. No coefficient is reported for US 55-59 in column since the common trend is eliminated in the two-way fixed effects regression. Columns (1) and (2) are included for the sake of comparison, but should be interpreted with caution due to econometric issues that may arise using two-way fixed effects with a non-stationary dependent variable. The difference between columns (3) and (4) is the inclusion of an opioid dispensing variable in column (3). Due to data limitations, including this variable decreases the number of observations by about 300. The allowance rate at the initial stage does not include technical denials. In the preferred model, model (4), apart from the age demographic variables, only the application rate and median household income account for variation in state-level PAD when controlling for other factors.

9.5 Appendix E: Alternative Bartik Specification

Traditional Bartik instruments are constructed using either a county's initial industry shares at time $t = 0$, or a county's average industry shares over the entire period of study. The average industry shares instrument is used in the main body of the paper because the F-statistics show that it is a very strong instrument. The F-statistics for the initial shares instrument, however, do not provide confidence that the instrument is valid due to its lack of relevance, as displayed in Table 8. The initial shares instrument likely lacks a strong correlation with actual employment growth because the period of study spans 21 years, and industry shares many years prior may be very different from concurrent shares. Most literature that uses initial shares looks at growth rates over the span of only one decade. As Table 8 shows, the results using the initial shares instrument vary by model specification and by the number of lags. The noise in the results is likely due to the lack of relevance of the instrument.

Table 8: IV Estimates Using Initial Shares

Dependent Variable	$(\frac{\Delta \dot{y}_{it}}{y_{it}})$	$(\frac{\Delta \tilde{y}_{it}}{y_{it}})$
Panel A: OLS estimates		
2 year lag	-0.181***	-0.199***
3 year lag	-0.168***	-0.184***
4 year lag	-0.155***	-0.169***
5 year lag	-0.133***	-0.145***
Panel B: IV estimates $\mathcal{B}_{i0}$		
2 year lag	-1.894	-5.265***
3 year lag	-1.117**	-18.251
4 year lag	-0.705***	19.013
5 year lag	-0.521***	6.867
First stage F-statistics		
2 year lag	7.01	32.32
3 year lag	27.18	1.46
4 year lag	77.28	0.55
5 year lag	117.00	1.50

$^{***}p < 0.01, ^{**} p < 0.05, ^{*} p > 0.10$

Notes: $(\frac{\Delta \dot{y}_{it}}{y_{it}})$ corresponds to the augmented factor model, equation (13), and $(\frac{\Delta \tilde{y}_{it}}{y_{it}})$ corresponds to the two-way fixed effects model, equation (11). Panel A displays the OLS estimates and Panel B displays the instrumental variable estimates. Controls for age, gender, race, and household income and individual and time fixed effects are included in all regressions. Standard errors are clustered at the county level. The first stage F-statistics show that the initial shares Bartik instrument is not a strong instrument for employment growth rates, and the seeming inconsistent estimates in the IV results in Panel B is likely a direct results of the weak instrument.

References

American Cancer Society, “Cancer Facts and Figures,” 2022.

Astrue, Michael J., "Statement of Michael J. Astrue Commissioner, Social Security Administration before the House Committee on Ways and Means, Subcommittee on Social Security and the House Committee on the Judiciary Subcommittee on the Courts, Commercial and Adminisrative Law," 2011.

Autor, David H. and Mark G. Duggan, "The Rise in the Disability Rolls and the Decline in Unemployment," *The Quarterly Journal of Economics*, 2003, *118* (1), 157–206.

____ **and** ____ , "The Growth in the Social Security Disability Rolls: A Fiscal Crisis Unfolding," *Journal of Economic Perspectives*, 2006, *20* (3), 71–96.

____ **, David Dorn, and Gordon H. Hanson**, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168.

____ **, Nicole Maestas, Kathleen J. Mullen, and Alexander Strand**, "Does Delay Cause Decay? The Effect of Administrative Decision Time on the Labor Force Participation and Earnings of Disability Applicants," 2015.

Autor, David, Nicole Maestas, and Richard Woodbury, "Disability policy, program enrollment, work, and well-being among people with disabilities," *Soc. Sec. Bull.*, 2020, *80*, 57.

Bartik, Timothy J, "Who benefits from state and local economic development policies?," 1991.

Bluethmann, Shirley M, Angela B Mariotto, and Julia H Rowland, "Anticipating the "Silver Tsunami": Prevalence trajectories and co-morbidity burden among older cancer survivors in the United States," *Cancer Epidemiology, Biomarkers & Prevention*, 2016, *25* (7), 1029–1036.

Burkhauser, Richard V, J.S Butler, and Robert R Weathers II, "How policy variables influence the timing of applications for Social Security Disability Insurance. (Perspectives)," *Social security bulletin*, 2002, *64* (1), 52–.

Coe, Norma, Kelly Haverstick, Alicia H. Munnell, and Anthony Webb, "What Explains State Variation in SSDI Application Rates?," 2011.

Deshpande, Manasi and Lee M. Lockwood, "Beyond Health: Nonhealth Risk and the Value of Disability Insurance," *Econometrica*, 2022, *90* (4), 1781–1810.

____ **, Tal Gross, and Yalun Su**, "Disability and Distress: The Effect of Disability Programs on Financial Outcomes," *American Economic Journal: Applied Economics*, 2021, *13* (2), 151–178.

Duggan, Mark and Scott A. Imberman, "Why Are the Disability Rolls Skyrocketing? The

Contribution of Population Characteristics, Economic Conditions, and Program Generosity," in "Health at Older Ages: The Causes and Consequences of Declining Disability among the Elderly," University of Chicago Press, 2009, pp. 337–379.

———, **Perry Singleton, and Jae Song**, "Aching to Retire? The Rise in the Full Retirement Age and its Impact on the Social Security Disability Rolls," *Journal of Public Economics*, 2007, *91* (7-8), 1327–1350.

Engle, Robert F. and C. W. J. Granger, "Co-Integration and Error Correction: Representation, Estimation, and Testing," *Econometrica*, 1987, *55* (2), 251–276.

Florido, Roberta, Natalie R. Daya, Chiadi E. Ndumele, Silvia Koton, Stuart D. Russell, Anna Prizment, Roger S. Blumenthal, Kunihiro Matsushita, Yejin Mok, Ashley S. Felix, Josef Coresh, Corinne E. Joshu, Elizabeth A. Platz, and Elizabeth Selvin, "Cardiovascular Disease Risk Among Cancer Survivors: The Atherosclerosis Risk in Communities (ARIC) Study," *Journal of the American College of Cardiology*, 2022, *80* (1), 22–32.

French, Eric and Jae Song, "The Effect of Disability Insurance Receipt on Labor Supply," *American Economic Journal: Economic Policy*, 2014, *6* (2), 291–337.

Friedman, John N, Ithai Lurie, Magne Mogstad, and Raj Chetty, "Long-Run Drivers of Disability Insurance Rates," Technical Report, NBER DRC Working Paper No. NB16-01. Cambridge, MA: National Bureau of … 2016.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, August 2020, *110* (8), 2586–2624.

Hemmeter, Jeffrey and Michelle Stegman Bailey, "Earnings After DI: Evidence From Full Medical Continuing Disability Reviews," *IZA Journal of Labor Policy*, 2016, *5* (11).

Hoynes, Hilary W, Nicole Maestas, and Alexander Strand, "Legal Representation in Disability Claims," Working Paper 29871, National Bureau of Economic Research March 2022.

Johnson, Richard W and Janice S Park, "How did 50+ workers fare in 2010," *Washington, DC: The Urban Institute*, 2011.

Juhn, Chinhui and Simon Potter, "Changes in labor force participation in the United States," *Journal of Economic Perspectives*, 2006, *20* (3), 27–46.

Kearney, John R, "Social Security and the "D" in OASDI: the history of a federal program insuring earners against disability," *Social security bulletin*, 2006, *66* (3).

Kearney, Melissa S., Brendan M. Price, and Riley Wilson, "Disability Insurance in the Great Recession: Ease of Access, Program Enrollment, and Local Hysteresis," *AEA Papers* *and Proceedings*, May 2021, *111*, 486–90.

Kuo, Yong-Fang, Mukaila A. Raji, and James S. Goodwin, "Association of Disability with Mortality from Opioid Overdose Among US Medicare Adults," *JAMA Network Open*, 2019, *2* (11).

Liebman, Jeffrey B., "Understanding the Increase In Disability Insurance Benefit Receipt in the United States," *Journal of Economic Perspectives*, 2015, *29* (2), 123–150.

Liu, Siyan and Laura D. Quinby, "What Factors Explain the Drop in Disability Insurance Rolls From 2015-2019?," 2023.

Maestas, Nicole, "Identifying Work Capacity and Promoting Work: A Strategy for Modernizing the SSDI Program," *The ANNALS of the American Academy of Political and Social Science*, 2019, *686* (1), 93–120.

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

____, ____, and ____, "Disability Insurance and the Great Recession," *American Economic Review*, 2015, *105* (5), 177–182.

____, ____, and ____, "The effect of economic conditions on the disability insurance program: Evidence from the great recession," *Journal of Public Economics*, 2021, *199*, 104410.

____, Tisamarie B. Sherry, and Alexander Strand, "Opiod Use Among Social Security Disability Insurance Applicants, 2013-2018," *Journal of Disability Policy Studies*, 2023, pp. 1–11.

Mahumud, Rashidul Alam, Khorshed Alam, Jeff Dunn, and Jeff Gow, "The changing relationship between health burden and work disability of Australian cancer survivors, 2003–2017: evidence from a longitudinal survey," *BMC Public Health*, 2020, *20* (1), 1–14.

Manoli, Dayanand and Shanthi Ramnath, "Social Security Disability Insurance by Age, Income and Geography," Technical Report, NBER DRC Working Paper No. NB15-02. Cambridge, MA: National Bureau of ... 2015.

MEDPAC, "Health Care Spending and the Medicare Program," 2023.

Miller, Kimberly D, Leticia Nogueira, Theresa Devasia, Angela B Mariotto, K Robin Yabroff, Ahmedin Jemal, Joan Kramer, and Rebecca L Siegel, "Cancer treatment and survivorship statistics, 2022," *CA: a cancer journal for clinicians*, 2022, *72* (5), 409–436.

National Cancer Institute, "Cancer Stat Facts: Cancer of Any Site," `https://seer.cancer.gov/statfacts/html/all.html` 2023. Accessed: August 18, 2023.

Peters, Jillian L., Wesley M. Durand, Kristina A. Monteiro, Luba Dumenco, and Paul George, "Opioid Overdose Hospitalizations among Medicare-Disability Beneficiaries," *Journal of the American Board of Family Medicine*, 2018, *31* (6), 881–896.

Poterba, James M, Steven F Venti, and David A Wise, "The long reach of education: Health, wealth, and DI participation," Technical Report, National Bureau of Economic Research 2017.

Reno, Virginia P. and Lisa D. Ekman, "Social Security Disability Insurance: Essential Protection When Work Incapacity Strikes," *Journal of Policy Analysis and Management*, 2012, *31* (2), 461–469.

Rutledge, Matthew S, Geoffrey Sanzenbacher, and Caroline Crawford, "The labor supply of disabled veterans: 1995-2014," *CRR WP*, 2016, *8.*

Social Security Administration, "Annual Report on Continuing Disability Reviews," 2011.

——, "The 2013 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds," 2013.

——, "Trends in Social Security Disability Insurance," 2019.

——, "Annual Statistical Report on the Social Security Disability Insurance Program," 2021.

StataCorp, *Engle-Grander (EG) and Augmented Engle-Granger (AEG) Cointegration tests and 2-step ECM estimation* 2023.

Strand, Alexander and Matthew Messel, "The Ability of Older Workers with Impairments to Adapt to New Jobs: Changing the Age Criteria for Social Security Disability Insurance," *Journal of Policy Analysis and Management*, 2019, *38* (3), 764–786.

von Wachter, Till, Jae Song, and Joyce Manchester, "Trends in Employment and Earnings of Allowed and Rejected Applicants to the Social Security Disability Insurance Program," *American Economic Reveiw*, 2011, *101* (7), 3308–3329.

Waid, Mikki D. and Sherry L. Barber, "Follow-up of Former Drug Addict and Alcoholic Beneficiaries," 2001.

Wixon, Bernard and Alexander Strand, "Identifying SSA's Sequential Disability Determination Steps Using Administrative Data," 2013.

Zayatz, Tim, "Social Security Disability Insurance Program," 2015.