The Effect of the Disability Insurance Application Decision on the Employment of Denied Applicants

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Abstract

Social Security Disability Insurance (SSDI) affects the labor supply of applicants through its work discouragement and through human capital deterioration regardless of the ultimate acceptance or denial of the claim. The existing literature is primarily focused on estimation of the benefit receipt effect of SSDI using the denied applicants as a comparison group. Instead, this paper provides an estimate of the causal effect of SSDI application on denied applicants using non-applicants as a comparison group. I find that SSDI causes a 36 percentage point reduction in employment for the denied applicants in the short-run. I exploit the differential incentives for SSDI application across birth-cohorts due to the increase in the Full Retirement Age and variance in the SSDI allowance rates across states to exogenously identify the SSDI application decision of denied applicants. The IV estimates suggest that the existing literature does not fully capture the negative labor supply effects of SSDI on the applicants. The findings of this paper will facilitate policymakers to re-think reforms to reduce the work disincentives while applying and waiting for SSDI determination and to make more resources available to smooth the transition of denied SSDI applicants back into the labor force, especially for older workers close to retirement.

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1. Introduction

In pursuit of explaining the persistent decline of labor force participation (LFP) rates among prime-aged individuals in the United States in the last few decades, a substantial body of research has focused on the interactions of social insurance programs and LFP. Much of this literature analyzes the causal effect of benefits receipt of the Social Security Disability Insurance (SSDI). In these studies, denied applicants are of interest mostly as a control group. Bound (1989) pioneers the empirical approach of using the labor supply of the denied SSDI applicants to estimate an upper bound on the potential labor supply of accepted applicants. Although Parsons (1991) raises questions on the validity of this comparison, the approach of Bound (1989) of comparing accepted and rejected SSDI applicants has been widely used to date (see for example, von Wachter et al., 2011). Chen and van der Klaauw (2008), Maestas et al. (2013), French and Song (2014), and Autor et al. (2015) have used this approach, along with various sources of exogenous variation inherent to the SSDI's application and evaluation process, to estimate the causal effect of receiving SSDI benefits on employment and earnings.

Implicit in the analytical approach of comparing for example, the employment of accepted and denied SSDI applicants is the assumption that SSDI affects employment through a single causal pathway: whether the applicant ultimately receives benefits. If the decision to go through the process of application itself affects the applicants - both the awarded and the denied – similarly, then the comparison between these two groups is still valid. However, the negative effect of application on denied applicants is unaccounted for in such analysis, despite the fact that initially denied applicants make up two-thirds of applicants – a total of 1.8 million individuals in 2013 alone. In this paper, I estimate the causal effect of the SSDI application on the labor supply of denied SSDI applicants.

SSDI affects the labor supply of applicants through the application and determination process itself. Denied applicants do not receive benefits, yet still face the same cost of applying as applicants who are ultimately allowed onto the program. Bound (1989, 1991a) and Parsons (1991) discuss three ways the SSDI application process can influence the labor-market activity of denied applicants in the post-application period: 1) they may be out as they plan to reapply; 2) applicants who appeal their initial denial decision may be out of the labor force while awaiting the decision of appeal to make their case stronger; or 3) once the process is over, they may face increased difficulty to get back to work due to human capital deterioration because they were out of the labor force for so long. The first two channels involve employment disincentives while individuals are still in the process of SSDI application, appeal, and reapplications. The third channel suggests that human capital deterioration while staying out of the labor market during this process can cause substantial loss in potential employment after denial.

In this paper, I estimate the causal effect of SSDI on employment of the denied applicants (combining all of these channels) over the short-run. Comparing the labor supply of the eligible non-applicants of SSDI who are similar in observable characteristics to those of the denied SSDI applicants, I examine how the application process hurts the post-application employment of denied applicants. I find that the employment of denied applicants at ages 50-58 is as much as 49 percentage points lower two to three years after the application. The causal effect is somewhat smaller: a 36 percentage point reduction estimated using an instrumental variable approach that exploits the differential incentives for SSDI application across birth-cohorts and states.

An important decision like applying for SSDI involves a set of characteristics unobserved by econometricians, which are correlated to most of the economic decisions that individuals make. Unobservable characteristics like relatively low opportunity costs of applying for SSDI affect labor supply as well. Econometricians need to take into account the endogeneity of decision to apply for SSDI while estimating its effect on labor supply. The data in this paper allow me to exploit the exogenous variation across birth cohorts in the Full Retirement Age (FRA) – the age at which claimants receive the full Social Security retirement benefit (their Primary Insurance Amount, or PIA). The FRA has increased from 65 for individuals born before 1937 to 66 for those born in 1943-1954, effectively lowering their benefit at any claiming age. The lower benefit increases the attractiveness of the SSDI application decision, but should have no direct effect on labor supply before turning age 62.

Moreover, I use data on allowance rates[1] into SSDI to capture differences across individuals in their likelihood of successfully obtaining benefits based on the state in which they live. The Social Security Act and the regulations implementing it set up universal criteria to determine the disability status of someone who applies for SSDI benefits. However, historically the Disability Determination Services (DDS) offices across states in the U.S. have awarded SSDI benefits to applicants at differential rates with significant variation not only across states but also over time within each state (McVicar, 2006; Bound and Burkhauser, 1999; Rupp and Stapleton, 1998; Parsons, 1991a). The DDS office that evaluates an application depends on which state the applicant resides. The DDS allowance rate does not endogenously affect the application decision of denied applicants. However, the allowance rate affects the outcome of the application. In this paper, I exploit the variation of the aggregate allowance rates across location and over time that is exogenous to the labor supply of individuals but influences the outcome of SSDI application. Hence, I can use both the FRA and a component of the aggregate allowance rate to instrument for the SSDI application decision of the denied applicants to control for the endogeneity problem that arises while estimating its causal effect on labor supply.

The employment and earnings trajectories of denied applicants before and after the application decision has been well analyzed in the literature, but only in the context of understanding the effects of SSDI on the awarded applicants. Very few papers have focused on the importance of the effects the SSDI application process have on the denied applicants. As the number of denied applicants has been growing over the years, understanding these effects on them is becoming more and more important and relevant for policy considerations. While analyzing the trends in employment and income of SSDI applicants, von Wachter et al. (2011) compared the employment and earnings of the rejected SSDI applicants to non-applicants using matching in observable pre-application characteristics; they find sizeable negative effects on employment rate of the rejected applicants. However, they cannot claim these findings to be causal as unobservable characteristics may affect their results. In a recent paper, Autor et al. (2015) explores the human capital

[1] The allowance rate is the ratio of number of SSDI applicants awarded benefits over the total number of applicants.

deterioration effects on labor supply of the denied SSDI applicants to find a significant causal adverse effect of waiting time on employment and earnings in the long run. However, they only capture a part of the total negative effects that SSDI application process has on the rejected applicants, because their model misses the effect of work disincentives while applications are pending.

In this paper, I make a unique contribution to the literature by providing the full causal effect of SSDI application process on the labor supply of denied applicants in the short run. To the best of my knowledge this is the first paper to measure the negative causal effect of the SSDI application decision on employment of denied applicants using non-applicants as a control group. Most of the papers in this literature estimating the negative effect of SSDI benefit receipt use administrative disability insurance data to exploit the exogenous institutional variations for identification. This type of administrative data typically does not have information on non-applicants. The data I use in this paper has detailed information on applicants and non-applicants in their 50s and 60s, which allow me to identify a comparison group of non-applicants for the denied SSDI applicants.

The rest of this paper is organized as follows. The next section provides a background of the Old Age, Survivor, and Disability Insurance (OASDI) program and the Social Security Amendments of 1983 to understand the institutional setup relevant for this paper. Section 3 provides the description of the data I use in this paper and highlights important sample characteristics. Section 4 outlines my identification strategy. Section 5 presents the estimates of the labor supply effects of SSDI application decision of denied applicants. This is followed by a sensitivity analysis of the main finding of this paper in section 6. I conclude in section 7 with a discussion of the policy implications of my findings.

2. Background on OASDI program and 1983 amendments

2.1 The Disability Program

The SSDI program is part of the Old Age, Survivors, and Disability Insurance (OASDI) program of Social Security Administration and is funded mainly through payroll taxes. It is a social insurance program for disabled workers with eligibility conditioned on previous sufficient employment in jobs covered by Social Security[2]. The SSDI program defines disability as the "inability to engage in substantial gainful activity (SGA) by reason of any medically determinable physical or mental impairment(s) which can be expected to result in death or which has lasted or can be expected to last for a continuous period of not less than 12 months." Activity is considered "substantial" if it involves significant physical and/or mental exertion and it is considered "gainful" if it is performed for pay or profit (although realization of profit is not binding). SSA implements this definition by setting an earnings threshold - $1130 per month for non-blind and $1820 per month for blind in 2016 for example, which is adjusted over time - over which individuals are said to be engaging in SGA and are therefore disqualified from participating in the SSDI program.

While SSDI is a federal program with a uniform national standard, the initial disability determinations are made at state SSDI offices, on the basis of medical criteria. Individuals apply for DI benefits at their local field office, which screens out those who are not currently insured or who are engaging in SGA. These are labeled "technical denials" and do not receive further review. The remaining applications are forwarded to a state Disability Determination Services (DDS) office, where cases are assigned to disability examiners for review. The rejected applicants at the DDS level are then entitled to a series of appeals, first to the state SSDI agency, then to the Administrative Law Judge (ALJ), then to an Appeals Council, and finally to the Federal court system.

Autor et al. (2015) present statistics on fraction of SSDI applicants appearing in different stages of determination and how long an individual on average waits in each stage of determination in 2005.[3] Approximately two-thirds of the applicants are denied at the DDS level with determinations made on

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[2] To qualify for SSDI benefits, an individual must have sufficient employment subject to Social Security contributions. The amount of required labor force attachment depends on the age of disability application. Generally, an individual needs to have worked 10 years, five of which needs to be during the 10 years preceding the year of DI application. Relatively younger workers may qualify with less work experience than the general rule.

[3] Although this statistics differ from the SSA official statistics, I prefer these for the following reasons: Autor et al. (2015) exclude all technical denial; they drop people who died within two years of initial decision; they also drop people who previously applied for or received SSDI or SSI benefits. These three groups of people are excluded from the analysis in this paper as well, making the statistics provided in Autor et al. (2015) much more relevant for this paper.

average in about three months. Just over a quarter of applicants go to the reconsideration stage, which adds another five months on average to the determination period. Just under one-third of applicants take their case to the ALJ level, which adds more than two years to the average total waiting time for determination. Very few applicants who are denied at the ALJ level move their case further into appeal system. However, applicants who do so have to wait more than a year on average to learn about the final outcome of the appeal.

Clearly, there is a significant amount of time that the applicants are out of the labor force, which varies across individuals according to their selection onto reconsideration and appeals of initial decision on DI application. In addition to the processing time, as the determination requires that an individual was not engaged in SGA five months prior to application, many applicants were out of the labor force even before filing application for SSDI. The SSDI application can keep an applicant out of the labor force for a significant amount of time, significant enough for deterioration of human capital and labor market attachment. This is particularly important for the eventually denied applicants who then need to return to the labor force, especially for people who are well below the early retirement age set by the Social Security.

2.2 Calculation of the OASI and SSDI Benefits

The progressive nature of Social Security benefits calculation makes the SSDI benefits fairly generous compared to OASI benefits. Workers are eligible for OASI benefits after accumulating at least forty quarters in employment subject to Social Security contributions and may collect benefits starting at age 62. Both OASI and SSDI benefits are based on workers' earnings history. The first step for either program is calculating the Average Indexed Monthly Earnings (AIME). For OASI benefits, the AIME is the average of the top 35 years of earnings indexed to the year of age 60 using the Average Wage Index (AWI), divided by 12. For SSDI, the Social Security averages earnings from the year a worker turned 21 to the year that worker became disabled and index the earnings to the year of disability onset. If a disabled worker has over 35 years of indexed earrings, the Social Security only averages 35 highest years of earnings.

The next step to calculate benefits in both programs is determining the Primary Insurance Amount (PIA), based on a progressive benefit formula. The formula for calculating PIA is the same for both OASI and SSDI. The lower income workers receive a higher return on their Social Security taxes than the higher income workers. This is achieved by breaking the AIME into three parts and weighting each part[4]. The main difference between OASI and SSDI benefit calculation is in the actuarial adjustment factors applicable to earlier or later than FRA OASI claiming. However, the FRA does not play any role on the benefit calculation of the disabled workers.

Disability beneficiaries receive their full PIA regardless of the age at which they first receive benefits. OASI beneficiaries, however, have their benefits adjusted to account for their age at claiming relative to their FRA. Retired workers' benefits are exactly equal to their full PIA only if they first claim the benefits at their FRA. Otherwise, OASI benefits are actuarially adjusted, which is designed to yield equal expected lifetime benefits no matter when they are first received. The earliest age for OASI claiming is 62 and it has the largest actuarial adjustment factor associated with it. If retirees choose to receive benefits early, their benefits are adjusted downward by more for each month that the claim was earlier than the FRA.[5] Claiming after the FRA yields larger benefits than the PIA.

Individuals may apply for SSDI benefits up to their FRA, and the fact that SSDI benefits – unlike OASI benefits – are not subject to actuarial reduction makes SSDI application quite valuable to individuals who think they are too unhealthy to keep working and disabled enough to get enrolled into SSDI. Although, the SSDI benefits are fairly generous in replacing the earning of the beneficiaries, however, the applicants need to put in considerable amount of effort to arrange necessary documentations to prove the disability status. In practice, the SSDI application rate falls off quickly after retirement benefits become available at age 62,

[4] The breakpoints in AIME to calculate PIA are adjusted annually based on changes in national average wages. However, the weighting scheme remains the same. For example, for a worker with 62nd birthday in 2016 the PIA is equal to 90 percent of the worker's first \$856 of AIME, plus 32 percent of the AIME between \$856 and \$5,157, plus 15 percent of the remaining AIME.

[5] Benefits are reduced by 5/9 of one percent times the number of months between claiming and the FRA, if claiming was no more than 36 months early; if benefits were claimed more than 36 months early, benefits are reduced by 5/12 of one percent per month up to where the 36-month period begins.

which suggests that the "pecuniary" and "non-pecuniary" costs of disability application substantially exceed the (minimal) costs of claiming retirement benefits (Rutledge, 2012).

2.3 The Social Security Amendments of 1983

The Social Security Amendments of 1983 included a number of significant changes to social security, including an increase in the payroll tax rate, an expansion in the number of individuals covered by the program, and an increase in the actuarial adjustment factors beyond the FRA. Perhaps the most significant change of all, which plays an instrumental role in this paper, was a maximum of two-year increase in the full retirement age and a corresponding increase from 20 to 30 percent in the penalty for claiming OASI benefits at the early retirement age of 62.

These reductions in the generosity of Social Security OASI benefits were phased in gradually and occurred in two main stages. Individuals born in 1937 or earlier were unaffected by the change. The full retirement age then increased in two-month increments by subsequent birth cohort until reaching 66 for those born in 1943. For individuals born between 1943 and 1954 (inclusive) the FRA remains at 66 years until again increasing in two-month increments from the 1955 to 1960 cohorts. Along with this change, the fraction of full benefits that individuals could receive at the early retirement age of 62 fell from 80 percent for those born in 1937, to 75 percent for those born between 1943 and 1954, and to 70 percent for those born in 1960 or later.[6] Most importantly, for the purpose of this paper, these amendments do not change the benefits of SSDI across birth-cohorts.

3. Data and Sample Characteristics

In this paper I use data from the *Health and Retirement Study* (HRS), a nationally representative longitudinal household survey of older Americans. The original sample of 12,561 comprised individuals

[6] This policy also changed the actuarial adjustment factors beyond the age of 62 from 5/9 of a percentage point per month to 5/12 of a percentage point per month. This converted back to 5/9 of a percentage point 36 months before the full retirement age. Thus a person born in 1943 could receive 75 percent of his or her PIA at the age of 62, 80 percent at the age of 63, 86.67 percent at the age of 64, 93.33 percent at the age of 65, and 100 percent at age 66.

who were born 1931-41 or were the spouse of a participant in that birth cohort; individuals born 1942-47, 1948-53, and 1954-59 were added in 1998, 2004, and 2010. Participants are interviewed every two years. This paper uses eleven waves of data from 1992 to 2012 and detailed information on both SSDI applicants and the non-applicants in panel form. The HRS has detailed self-reported information on SSDI application, award, reapplication, and appeal as well as a whole array of information on health, wealth, demographic and socio-economic characteristics, and employment.

I merge the HRS to the Social Security Administration (SSA) administrative geographic identification data in order determinate the state of residence in US of individuals from age 50 and older as long as they are observed in the HRS. This allows me to match the DDS level SSDI allowance rate data to individuals at a given age. The SSA provided me with aggregate data on the number of applications, the number of awards, and the number of denials at the DDS level of determination by gender, age-groups defined as 45-49, 50-54, 55-59, and 60-64, and US state for each year from 1992 to 2013[7]. Each individual in my sample is then matched to the appropriate allowance rate by geographic location, gender, and age.

In this paper I estimate the labor supply model of workers age 50 to 58 two to three years from every integer age. For example, for a worker who is at 50, I estimate the probability of being employed of the worker at 52 or 53. The HRS interviews people every two years. Depending on the month of interview in two consecutive HRS waves an individual can be observed more or less than two years apart, but always less than three years apart between waves.

I am particularly interested in estimating post-application employment of SSDI denied individuals. The application to SSDI can happen in the year when HRS interview happens or in between two consecutive interviews. If the application was filed during the HRS interview year, then for that individual the post-application employment is observed roughly two years from the application. If the application was filed in a year in between HRS waves, then I observe the labor supply of that individual in the second wave of HRS

[7] I do not have access to the Social Security "831 files" data to use in this paper.

after the application. I do not take the wave immediately after the application as it makes the post-application labor supply within 1 year of application. I want to observe the employment of the denied applicants after their initial denial for SSDI. Hence, I skip the immediate wave of HRS post-application and instead observe the employment for those individuals around 3 years after the application.

If I had a control group of individuals who are very similar to the people who file an unsuccessful application for SSDI, then I could compare the average labor supply of the two groups at a given age to measure the loss of employment potential of the SSDI denied applicants. However, to interpret the difference to be causal, the treatment and control status need to be assigned randomly. One might create such plausible treatment and control groups in a randomized control experiment, but not in survey data. Using survey data merged with administrative Social Security earnings data, Bound (1989) uses the labor supply of the denied SSDI applicants – who, he argues, is a "natural" control group for the awardees – to measure the potential labor supply of accepted applicants had they not received the benefit. As the denied applicants are healthier and more capable to work than the awarded applicants, he argues the difference in employment is an upper bound of the employment potential of awarded applicants.

In this paper the treatment group is the SSDI denied applicants who go through the SSDI application process with eventually unsuccessful in getting onto the program. Because these unsuccessful applicants were denied due to health reasons, the administration views them as capable of SGA like other non-applicants in the labor force. Thus, all the eligible non-applicants can be thought of as a control group to compare with the treatment group of SSDI applicants denied at the DDS level. However, some individuals with health shocks that may make them eligible for SSDI benefits may not apply for it due to the "hassle cost" and "stigma cost" associated with the social insurance programs (Benıtez-Silva et al., 1999; Haveman et al., 1991).

I identify a subset of all eligible non-applicants for SSDI who I argue to have only slightly higher "hassle cost" and "stigma cost" at a given age than the denied SSDI applicants at that age. Along the line of argument in Bound (1989), I argue that this subset of non-applicants is a "natural" control group for the denied applicants. As the individuals in the control group have slightly higher opportunity costs of application and most likely are in better health than the denied applicants, the labor supply of the control group can be thought of as an upper bound of the employment potential of the denied applicants. Obviously, there are unobserved factors associated with the treatment and control groups, which are likely to be correlated with the labor supply of the individuals. Thus, the difference in labor supply between the denied applicants and the control group cannot be interpreted as the causal effect of the SSDI application decision.

In this paper the control group for the denied SSDI applicants filing application at a given age between 50 and 58 (inclusive) comprises the individuals observed to be non-applicants between the age of 50 and 58 (inclusive), but who later filed SSDI applications for the first time on or after age 60. This set of individuals in the control group have a “hassle cost” and “stigma cost” that is at least a little bit higher in their 50s, but not so high that application is never worthwhile, seeing as they applied in their 60s. This is because workers who eventually apply in their 60s are likely to have their health deteriorating in their 50s. Researchers have shown that the employment and income of SSDI applicants start to decline as many as four to six years before SSDI application (see for example, von Watcher et al., 2011). The rest of the non-applicants who never apply for SSDI at any age must have experienced no significant work-limiting health shocks or may have had adverse health shocks, but they must have a much higher threshold of “hassle cost” and “stigma cost” in their 50s than the denied SSDI applicants around that age (assuming all else the same). This group of people who never applied for SSDI is much less comparable than those who apply in their 60s to the denied applicants at a given age between 50 and 58 when the denied applicants file SSDI application.

The sample in this paper includes all individuals whose labor supply is observed in HRS between age 50 and 61 (inclusive). I observe the non-applicants until they reach their FRA in HRS to define the control group for analysis. The reference ages of analysis are between 50 and 58 (inclusive). Because, I am estimating the employment after two to three years from the reference age and I do not want to observe labor supply at 62 or later, which is the Social Security early retirement age. In this way I am excluding the potential confounding effect of OASI benefits in the analysis.

Table 1 presents the economic, health, and demographic characteristics of the denied SSDI applicants, the control group, the other non-applicants who are not in the control group, and SSDI beneficiaries. In the sample, there are 322 individuals who applied to SSDI for the first time at any age of 50 to 58 and did not eventually receive benefits. The control group consists of 347 individuals who filed SSDI application for the first time only in their 60s. The sample includes the denied SSDI applicants only once at the age of their application and observes their employment two to three years from that age. The individuals in the control group are observed multiple times starting from the first time they are interviewed in HRS on or after age 50 and then in two years interval as they grow older. The primary sample of analysis has a total of 1231 observations.

I define the denied SSDI applicants as the treatment group and the control group is defined above. In an ideal scenario, the treatment and the control groups would have very similar characteristics. In Table 1, columns 2 and 3 provide the average sample characteristics of the treatment and control groups, respectively. Demographic characteristics show that the treatment group has a slightly higher fraction of female, non-white, school-dropouts and single individuals than the control group. The average age of treatment and control groups are roughly 55 years and there is no statistical difference in the fraction of high school graduates and college educated individuals between the two groups. These two groups have very similar educational profiles. The control group appears to be somewhat healthier than the treatment group. For example, compared to the control group in treatment group faction of individuals reporting poor or fair health is 28 percentage points higher, fraction reporting mobility problems is 25 percentage points higher, fraction with large muscle problems is 17 percentage points higher, and fraction reporting back pain is 16 percentage points higher. A higher fraction of individuals with doctor diagnosed diseases like high blood pressure, stroke, psychiatric problems, and arthritis are in the treatment group than in the control group.

Individuals in the treatment group on average worked 4.6 years less than the control group, are less likely to have retiree health insurance from the employer than the control group, and have similar tenure in their longest jobs. In terms of wealth, the treatment group has a higher fraction of individuals in the bottom quintile and a lower fraction in the top quintile than the control group. Worse health conditions compared to the control group might have induced the treatment group to apply for SSDI; however, I cannot rule out unobserved factors like job loss or intensity of the taste for work as additional causes of application of the denied applicants. I argue that the severity of the health shocks of the individuals in the treatment group, which is unobserved in this paper, is marginally higher than the severity of the shocks of the control group as the rejected applicants are denied benefits at the DDS level for not being disabled enough.

A comparison of the treatment group with the all other never applicants for SSDI and the SSDI benefit recipients reveals that the applicants who apply in their 60s are, as I claimed, a “natural” control group when they are in their 50s for the denied SSDI applicants. In almost all the characteristics the difference between the treatment and the never applicants are much more pronounced than the difference between the treatment and the control group. For instance, the fraction of college educated in treatment group is 21 percentage points lower than the never applicants, whereas, the difference between the treatment and control among the college educated is statistically insignificant. The fraction of school dropouts in treatment group is 19 percentage points higher than the never applicants, but only 7 percentage points higher than the control group.

Among all the health related variables both self-reported and medically diagnosed, the treatment group are much less healthy than the never applicants. The difference in health and wealth between the denied SSDI applicants and the never applicants are much broader than that of between denied applicants and the control group. The never applicants are more educated, more wealthy and much healthy than the control group and even more so than the treatment group. These differences in characteristics explains why the never applicants have much higher threshold of “hassle cost” and “stigma cost” than the control group and never apply for SSDI.

In Table 1, column 7 presents the average characteristics of SSDI awardees and column 8 presents the difference between awardees and denied SSDI applicants. It is evident that the awardees are much less healthy than the denied applicants. Observing this difference, Bound (1989) argue that the employment of the denied applicants provide a plausible upper bound of employment of the awarded applicants had they not received the SSDI benefits. The differences in health profile between the treatment and control group used in this literature estimating the benefit receipt effect of SSDI is very similar to the differences in treatment and control group used in this paper to evaluate a treatment effect different from the focus of this literature.

Using the Bound (1989) approach it can be argued that as the control group defined in this paper is healthier than the denied SSDI applicants, the labor supply of the control group is an approximation of the upper bound of employment potential of denied SSDI applicants. The control group is also wealthier than the denied applicants. So, the labor supply of the control group at most be an underestimation of the upper bound of employment potential of denied applicants. However, this difference in labor supply between the treatment and control group cannot be treated as causal as itself, because, there are unobserved differences between the two groups. For example, compared to the denied SSDI applicants there could be much stronger labor market attachment of the individuals in the control group or the severity of the health shocks could be much less for people in the control group. However, an exogenous variation of the SSDI application decision that is uncorrelated with the unobserved characteristics differences between the treatment and the control group would allow estimating the difference in labor supply between the two groups that is causal. The goal of this paper is to find this causal treatment effect of SSDI application decision on employment.

4. Identification Strategy

In this paper I estimate the causal effect of SSDI application on post-application employment of denied applicants aged 50 to 58. Let y_i be the measure of outcome, in this paper indicator for working for pay, and t_i be the indicator of denied SSDI application, where $t_i = 1$ if treatment was received and $t_i = 0$ if not. Define $y_i(1)$ as the outcome if the individual i is given treatment and $y_i(0)$ if untreated. It is not possible to observe an individual simultaneously as an applicant for DI and a non-applicant at a given age. What I observe is the following:

$$y_i = t_i y_i(1) + (1 - t_i) y_i(0) \tag{1}$$

The strategy in this paper to evaluate the effect of SSDI application denial on employment originated from the evaluation strategy of Bound (1989), where he evaluates the effect of SSDI benefits receipt on employment using the denied applicants as a comparison group. However, in this paper the denied applicants represent the treatment group and I need a comparison group for evaluation of the treatment effect. The comparison group I propose is an observably similar group of individuals who are eligible for SSDI application, but choose not to apply. This allows me to compare the labor supply of the comparison group with those who applied for SSDI, but eventually did not receive benefits, which is primarily for not being disabled enough.

To understand this approach, consider the evaluation of the average treatment effect on the treated $E[y_i(1) - y_i(0)|t_i = 1]$, which in this paper is the average effect on post-application employment of denied SSDI applicants. While I can use the employment of the denied applicants and non-applicants in our sample to estimate $E[y_i(1)|t_i = 1]$ and $E[y_i(0)|t_i = 0]$ respectively, I do not observe the percentage of denied SSDI applicants who would have worked in the absence of SSDI program to estimate $E[y_i(0)|t_i = 1]$. I argue that as the denied SSDI applicants are denied for health reasons, they are not very different from individuals in the control group selected in this paper in terms of significant work limiting health shocks. However, as the individuals in the comparison group are generally healthier and more capable of performing SGA than the denied SSDI applicants, that is $E[y_i(1)|t_i = 1] \leq E[y_i(1)|t_i = 0]$, one could treat the observed labor supply of the individuals in the comparison group as an upper bound on the missing counterfactual. That is, by restricting the sample to the eventual SSDI applicants, I am able to estimate an upper bound of the average treatment effect on the treated. This is because if $E[y_i(1)|t_i = 1] \leq E[y_i(1)|t_i = 0]$ is true, then

$$|E[y_i(1) - y_i(0)|t_i = 1]| \leq |\, E[y_i(1)|t_i = 1] - E[y_i(0)|t_i = 0] \tag{2}$$

Moreover, if the individuals in the comparison group would have worked more as denied SSDI applicants at post-application ages, i.e. $E[y_i(1)|t_i = 0] \geq E[y_i(1)|t_i = 1]$, then the estimate of the right hand side of equation (2) would represent an upper bound of the average treatment effect $E[y_i(1) - y_i(0)]$.

The comparison group approach used to identify the upper bound of the employment potential of the denied SSDI applicants rests on the assumption that the only difference between the control group and the denied applicants is that the former are on average in better health and have more capacity to work. Table 1 provides evidence supporting this assumption in the sample selected for analysis in this paper. It is evident from Table 1 that the two groups are different in other characteristics as well as in health. Individuals in the comparison group are less likely to be school dropouts, female, and non-white and more likely to be married than the denied SSDI applicants. Individuals in the comparison group are on average have more work experience and more likely to have retiree health insurance from employment. I assume all these differences in characteristics would lead to individuals in the comparison group to be more capable of working (all else equal) than the denied SSDI applicants. Therefore, these differences in characteristics would reinforce the argument that the average employment of the comparison group can be considered to be an upper bound of the employment potential of denied SSDI applicants.

There could be differences in other characteristics that could make the individuals in the comparison group less likely to work in post-application years had they applied for SSDI. For example, the comparison group is on average wealthier than the denied SSDI applicants, making them less likely to work as they age. Factors like these may cause potential problems in identification of upper bound using the comparison group approach depending on the relative magnitude and importance of these factors.

Although, the employment comparison between the denied applicants and the appropriate control group gives a good measure of loss of employment potential of the denied applicants due to SSDI application, however, it does not necessarily give a causal estimate. Because, the treatment and control status was not assigned in a random way as it would have had it been a controlled experiment. There are unobservable characteristics – such as applicants having unobserved worse job prospects, lower taste for work, or higher severity of health issues than non-applicants – that may induce individuals to apply for SSDI and those characteristics most likely be correlated to labor supply making the SSDI application decision endogenous in any simple labor supply estimation function. As a result, I need to find an exogenous variation of SSDI application decision so that the estimate of employment difference of the denied SSDI applicants and non-applicants can be argued as causal effect of applying for, and being denied, SSDI benefits.

To identify exogenous variation in the application decision of the denied SSDI applications, I use the variation in FRA across different birth-cohorts brought about by the Social Security Amendments of 1983 and DDS level allowance rate of SSDI applicants for different age groups. The earliest claiming age for OASI benefits is 62. The OASI benefits at 62 depend on FRA along with other characteristics such as income history. The higher is the FRA the higher is the Social Security reduction factor applied to the PIA to reduce the benefits at 62. However, SSDI can be claimed at any age if you are insured for it and if awarded then the benefit amount is equal to the PIA calculated at the disability onset date using a different formula than that of calculating PIA for OASI benefits if SSDI is claimed before 62.

The actuarial reduction factor associated with OASI makes SSDI relatively more generous. This relative generosity provides greater incentives to apply for SSDI if insured than for OASI on or after 62. This incentive is proportionately greater for workers of different birth-cohorts as their FRA grows. Because, the actuarial reduction factors grows in a defined way as FRA grows. The change in FRA creates the relative generosity of SSDI to vary across birth-cohorts identified with the FRA. As a result, the incentive to apply for SSDI is proportionately greater for workers with higher FRA even before age 62.

Duggan et al. (2007), Li and Maestas (2008), and Coe and Haverstick (2010) find that the SSDI application rate is significantly higher for birth cohorts with later FRAs of men and women between the ages of 45 and 64, which suggests that the change in FRA is a sufficiently strong instrument for SSDI application decision in this paper. The crucial identifying assumption to satisfy the exclusion restriction of FRA in labor supply estimation is that the differences in employment of the different cohorts associated with different FRAs are only due to their heterogeneous incentives to apply for SSDI.

These heterogeneous incentives across cohorts for SSDI application are exogenously created by the Social Security Act of 1983 by changing the FRA across cohorts. It is well documented that these changes in OASI benefits across cohorts result into differences in LFP across cohorts identified by the FRA from age 62 onwards (see for example, Behaghel and Blau, 2012; Coe et al., 2013). These changes in OASI benefits, however, do not create any direct incentives to change the LFP before age 62, except through SSDI application, because workers cannot obtain retirement benefits until 62. In this paper I estimate the labor supply before age 62, so that I can exploit this exogenous variation in cohort differences identified with FRA that affect the employment only through the differential incentives to apply for SSDI.

Figure 1 presents the unconditional employment over ages 51 to 61, separately for the denied SSDI applicants and the non-applicants, of three different cohorts identified by FRA. For both denied applicants and non-applicants average employment declines with age; the trend for the denied applicants is steeper than for the non-applicants. The gap between the non-applicants and denied applicants shows not only the denied applicants have lower employment rate on average at all ages but also that the employment falls more as denied applicants grow older. It is important to note from Figure 1 that the employment of different cohorts of the non-applicants are essentially lying on top of each other, implying that the FRA increase, which only affected later cohorts, had no effect on employment by age for non-applicants.

The employment for the denied applicants across cohorts are also similar, but not as much as for the non-applicants, which is expected as different cohorts have different propensity to apply for SSDI. However, across cohorts there are no strong systematic differences in employment between the denied applicants and the non-applicants. A prominent systematic difference in unconditional employment between the two groups across cohorts would cast doubt on the assumption behind the exclusion restriction that the cohort differences do not affect labor supply directly. The pattern of employment of the denied applicants across cohorts suggests that the indirect effect of cohort differences on unconditional employment is a moderate one. However, this does not raise any concern over using the cohort differences identified with FRA as an instrument for the SSDI application decision of denied applicants. While analyzing employment trends over time researchers have shown educational and demographic composition across cohorts plays a role in explaining the trend (Banerjee and Blau, 2016). The regression model controls for education and demographic characteristics to account for these differences.

In this paper I use aggregate data from the Social Security administration providing information on number of SSDI applicants, awards and denials at the DDS level by gender and age groups for almost all the states in US from 1992 to 2013. I calculate the DDS level allowance rate, which is defined as the number of awards or successful applications as a percentage of number of applications in a given year. Figure 2 presents three different US maps by states for men age 50 to 54 for year 1992, 2000, and 2010, each one plots the same five different categories of generosity levels of the SSDI allowance rate. In cross section of states the color composition reveals that there are significant variations in SSDI allowance rates across states. The changing color pattern of the three maps for three different years reflects that there is significant variation of this allowance rate over time within a state. Figure 3 presents US maps by states for women aging 50 to 54 for year 1992, 2000, and 2010, each one plots the same five different categories of generosity levels of the SSDI allowance rate similar to Figure 2. For women as well the SSDI allowance rate has significant variation across states and over time.

Figure 4 presents two sets of scatter plots for men age 50-54 and 55-59 of SSDI allowance rate, number of application per year, number of awards per year, and number of denials per year against calendar year of 1992 to 2013 for selected states. For either age group of men the number of applicants rises over time with a small spike after the 2001 recession and a big spike around the great recession. However, the allowance rate over time does not show any systematic pattern. This pattern of SSDI application and allowance rates suggest that although the application behavior closely follow the overall macroeconomic outlook of the economy, the allowance rate depends on state specific factors other than the macroeconomic conditions. The same conclusion can be drawn from Figure 5, which presents the same data for women age 50-54 and 55-59.

Much of the variation in allowance rates across DDS offices can be explained by economic, health, and demographic factors (Gruber and Kubik, 1997; Strand, 2002; Duggan and Imberman, 2009; Coe et al., 2011). Researchers attribute the remaining unexplained variation to factors like interpretation and application of the universal disability determination criterion differently by the DDS offices, variation in administrative efficiency across DDS offices, budgetary consideration of the states, and state level politics and policy making (Strand, 2002; Iyengar and Mastrobuoni, 2014; Coe et al., 2011). Factors like administrative efficiency of DDS, apparent differential interpretation of federal disability determination criterion, and state level politics are exogenous to the labor supply decision of individuals.

In a given cross-section of states the allowance rates reflect a number of factors as argued above, like average health composition of the applicant pool. Within a state the variation over time in allowance rates reflect factors like changing economic environment. As a result this variation in allowance rates as itself is not meaningful in identifying the effect of SSDI application decision on labor supply. Gruber and Kubik (1997) use a dramatic rise in state denial rates in late 1970s, due to federal funding crisis of SSDI, as an exogenous variation of SSDI policy to measure its effect on labor supply.

The data and time period that I explore in this paper do not allow me to exploit such policy shocks to allowance rate like in Gruber and Kubik (1997). Instead I propose a measure to identify state's level of generosity towards awarding SSDI benefits to applicants in a way that is independent of economic, health, and demographic factors. I calculate allowance rate for age groups 45-49, 50-54, 55-59, and 60-64 for each state from 1992 to 2013. For each age group in a given state I compare the allowance rate for a given year to the allowance rate of that age group in the same state in next year. For example, I compare the allowance rate of 45-49 in Massachusetts in 1992 to the allowance rate of 45-49 in Massachusetts in 1993. I define a state to be more generous in a given year only if the allowance rate of all four age groups in the following year is strictly higher than the allowance rate of the corresponding age group for that state in the base year.

This measure of categorizing the states according to its generosity inherently controls for change in application rates over time due to changing economic environment. Demography at the state level is slow to change making it less of a concern as we are considering change over only a year. The reason I choose all four age groups is to control for the unknown average health composition of underlying applicant pool. It would be highly unlikely to have the allowance rates for a given state in a given year to be higher compared to the previous year among all age groups due to health differences. Rather it reflects change in the level of overall generosity of the state in awarding SSDI benefits to applicants.

I assume that people do not choose their state of residence on the basis of allowance rate of the DDS office of that state, which is a fairly reasonable assumption. Then controlling for state level observables I argue that the measure of generosity across states and over time within state exogenously determines the outcome of SSDI application. The more generous the state's DDS office is the lower the probability that an applicant would be denied benefits (all else equal).

The goal of this paper is to estimate a causal model of labor supply using SSDI applicants and eligible non-applicants of age 50 to 58 of the following form:

$$y_i = X_i\beta + \gamma DI_i + \nu_i$$

where y_i is the employment status of individual i measured two to three years after a reference age, X_i denotes observable characteristics at the reference age and changes in time-varying attributes in two to three years after the reference age that may influence labor supply at the point of measurement, $DI_i = 1$ if individual i applied SSDI first time at the reference age and never received benefits, and ν_i is an error term. The causal parameter of interest in this paper is γ which measures of effect of SSDI on employment of the denied applicants two to three years after the decision to apply for SSDI. This parameter represents the average effect of SSDI application on post-denial employment rates over application ages 50 to 58. Inference is hindered if some unobserved factors such as severity of health shock or low opportunity cost of SSDI application due to lack of labor force attachment affect both labor supply and SSDI application decision. Then essentially what I have is the following:

$$y_i = X_i\beta + \gamma DI_i - s_i + \varepsilon_i$$

where s_i represents unobserved factors, which are uncorrelated with any remaining idiosyncratic element ε_i. If $E[s_i|DI_i] \neq 0$, then in the regression of labor supply on observed factors and $\nu_i = -s_i + \varepsilon_i$ with ordinary least squares (OLS) gives a biased estimate of the average treatment effect of γ. In particular, the OLS estimate can be written as $\gamma - \left[E[s_i|DI_i = 1] - E[s_i|DI_i = 0]\right]$. If $\gamma < 0$ and if the unobserved characteristics are positively correlated with the SSDI application decision, then OLS overestimates the magnitude of the coefficient on DI_i and provides an upper bound of the potential labor supply loss of the denied SSDI applicants.

Exogenous variation of the SSDI application decision that is uncorrelated with the unobserved characteristics differences between the denied SSDI applicants and the control group would allow estimating the difference in employment between the two groups that is causal. I provide evidence above to show that birth-cohorts identified with differences in FRA and relative generosity of states in awarding SSDI benefits exogenously determine the SSDI application decision of the denied applicants. Using these set of variables we can instrument the indicator variable of the denied SSDI application in the labor supply equation and estimate the model using two-stage least squares (2SLS) technique. The first stage of the two stage instrumental variable (IV) model can be written as:

$$DI_i = \lambda X_i + \delta Z_i + \eta_i$$

where Z_i includes the indicators for FRA between 65 and 66, FRA equal to or higher than 66, and FRA equal to 65 the omitted category. Z_i also includes an indicator variable for individuals living and applying for SSDI in the most generous states in terms of awarding the benefit to the SSDI applicants at the age of application. η_i is an idiosyncratic error term. The literature provides evidence on the existence of this first stage (see for example, Dugan et al. 2007; Li and Maestas 2008) and the exclusion restriction assumes that the change in FRA and relative generosity of states in SSDI award rate affect the employment only through the channel of SSDI application decision and its outcome. As I have more instruments than the endogenous variable I can test for the validity of the overidentification restriction while estimating the 2SLS model.

I estimate the upper bound of loss of employment two to three years after a reference age of 50 to 58 of the denied SSDI applicants using OLS and the causal estimate of the loss of employment using 2SLS for three different specifications. The specification (i) includes all the individual specific controls and age fixed effect and national unemployment rate for the US to control for the macroeconomic conditions. Specification (ii) includes all the controls included in (i) and adds unemployment rate of the state of residence of the individuals to capture the local macroeconomic environment. Finally, specification (iii) adds individuals' state of residence fixed effects to all the controls in (ii). Specification (iii) is the preferred specification in this paper.

The individual specific controls include demographic information like race, gender, marital status, and indicator for school dropouts and college education leaving the high school graduates as the omitted category. Individuals' taste for work is measured by three different variables: number of years worked till the reference age; indicator for having at least one job with more than 5 years in tenure; and indicator for having retiree health insurance from employer. Higher degrees polynomial of number of years worked is included in the labor supply equation. Indicators for different wealth quintile are incorporated in the labor supply equation with the first quintile as the omitted option. Previous research finds that care-giving for parents is an important factor in determining the labor supply of older workers. So, I include indicator whether an individual is a care giver for parents or not in the labor supply equation.

A variety of self-reported and medically diagnosed indicator variables for health outcome are included to control for the health status of the workers. Previous research on health and labor supply argues that self-assessed health status has contemporaneous reverse causality in labor supply equation (see for example, Bound, 1991b; Gruber and Kubik, 1997). However, medically diagnosed health outcomes are unlikely to have such problems. I include all medically diagnosed medical condition at the reference age and at the age when the labor supply is measured. I included the self-assessed health status in the reference age, which is well before the labor supply is measured. These self-assessed health status variables are strong predictor of the decision to apply for SSDI (Li and Maestas, 2008).

Researchers have documented a strong U-shaped relationship between the Body Mass Index[8] (BMI) and both self-assessed health status and mortality, controlling for other demographic factors (Kushner, 1993; Gruber and Kubik, 1997). Gruber and Kubik (1997) argue that being underweight for one's height is associated with increased risk of respiratory diseases and being overweight for one's height is associated with increased risk of cardiovascular disease, diabetes, and colon cancer. These diseases are most common among the SSDI applicants (Social Security Administration, various years). Instead of self-assessed health measures at the age when labor supply is measured I use the BMI to control for health status at that age in the labor supply equation. Figure 6 presents the relationship BMI, self-reported poor or fair health, and employment. Considering the non-linear relationship between BMI and employment, I include a quadratic form of BMI at the reference age into the labor supply equation. Gruber and Kubik (1997) define most severe case of disability by BMI less than 20 and greater than 34. Using this definition of disability I also include transition in health indicator by moving in and out of this disability measure from the reference age to the age at which the labor supply is measured.

5. Empirical Results

Table 2 presents the average employment of the SSDI denied applicants, the control group of non-applicants, the awarded applicants, and the never-applicants. The table provides the average employment at a reference age between 50 and 58 (inclusive); two to three years before the reference age; and two to three years after that same reference age. For the denied SSDI applicants in this paper the reference age is the age of application. Column 4 of this table presents the average unconditional difference in employment between the denied SSDI applicants and the control group. It shows that the unconditional employment of the denied applicants are 18 percentage points lower than a comparison group of non-applicants two to

[8] BMI = (Body mass in kilograms)/ (Height in meters)^2. Gruber and Kubik (1997) argue that BMI is an objective anthropometric measure of disability status.

three years before the application. This pattern of employment of the rejected applicants before the application is consistent with the findings of other papers in this literature (see for example, von Wachter et al., 2011).

Table 2 also shows that the denied SSDI applicants are on average 56 percentage points less likely to be working during the period of application and are on average 54 percentage points less likely to be working two to three years after the application compared to the comparison group of non-applicants, though this comparison does not control for the observable differences between these groups. The employment of the denied applicants falls significantly during the time of SSDI application and remains at that low level two to three years from that time period.

Table 3 presents the regression estimates of the instrumental variables from the first stage of the 2SLS model for labor supply. All the estimates are fairly stable over all three specifications. The estimates in the preferred specification (iii) show that compared to the birth-cohorts with FRA equal to 65, the cohorts with FRA more than 65 and less than 66 are 3 percentage points more likely to be denied SSDI applicants, although the parameter is not statistically significant. Compared to the omitted category, cohorts with FRA equal or higher than 66 are 17 percentage points more like to be denied SSDI applicants and this parameter is significant at 1 percent level. The parameter of the indicator for relatively more generous states in terms SSDI allowance rate over time is -0.02, which has the expected negative sign. However, this parameter is not statistically significant. The first stage is fairly strong with 28 percent of the variation of the indicator of denied SSDI application explained by the model. The results of the weak identification test show that the preferred specification rejects the null that the first stage is weakly identified at 10 percent level.

The main findings of the paper are presented in Table 4. The OLS estimates represent the estimates of the upper bound of the effects on employment of SSDI application on denied applicants. Estimates from the preferred specification (iii) shows that the potential loss of employment of the denied SSDI applicants is at most 49 percentage points. This estimate is statistically the same across all three specifications. The IV (2SLS) estimates present the causal point estimate of the effect on employment of the application decision of the denied SSDI applicants. The IV estimates show that the SSDI application decision causes a 36-percentage-point decrease in the employment of the denied SSDI applicants of ages 50-58 two to three years after filing the application. Thus, adjusting for differences in the unobserved characteristics between the denied SSDI applicants and the comparison group through IV has a substantial impact on the estimated labor supply effect of SSDI.

Unobserved factors like lower opportunity cost of SSDI application or severity of health shocks are positively correlated to SSDI application decision. OLS overestimates the causal effect on employment of SSDI application on denied applicants due to these unobservables by 13 percentage points, relative to the IV estimate. As the OLS estimate represents the upper bound of the effect of SSDI application decision of the denied applicants, I argue that unobserved factors such as the severity of health shocks or low labor market opportunities of the denied applicants account for this 13-percentage-point reduction in employment rate for the denied applicants.

Table 4 also reports the p-value from the overidentification test. These values are fairly high for all the specifications implying that I cannot reject the null that the overidentification restrictions are valid. Although the overidentification test does not provide any sense of the validity of the instruments in term of the underlying identifying assumptions, failing to reject the null of this test validates the use of more than one instrument for the single endogenous variable in the model.

My estimate of a 36-percentage-point reduction in employment is in line with correlational estimate that other researchers have found in the literature. Using the matching in observable pre-application characteristics, von Wachter et al. (2011) find that in 1990s the employment rate of the denied SSDI applicants of age 45-64 is about 30 percentage points lower than the rate of the non-applicants two to three years after the application. Although they cannot claim this estimate to be causal as their identification strategy cannot isolate the effects of unobserved characteristics, they argue that this is a close approximation of the true effect. The causal estimate I find in this paper for the age group 50-58, which is a subset of the population analyzed by von Wachter and others, falls between their matching estimate and the OLS upper bound estimate that I find of the effect on labor supply for the denied SSDI applicants.

Autor et al. (2015) estimate that the effect of waiting time of denied SSDI applicants on employment reduction in the long-run is around 6 percentage points, which they interpret as the human capital deterioration effect. They do not provide the causal estimate for this human capital effect for the short-run. Although it is expected that the human capital effect is higher in the short-run than in the long-run, without knowing the changing pattern over time, it is hard to extrapolate the human capital effect for the short-run. However, the findings of Autor and others suggest that the total effect of SSDI that I find for denied applicants on employment in the short-run comprise a relatively larger fraction of work disincentive effect than the human capital deterioration effect. Hence, initiatives to reduce the work disincentives of the SSDI determination process would result into a significant first order improvement of labor supply of the denied applicants. The findings of this paper suggest that the existing literature does not fully capture the negative labor supply effects of SSDI on the applicants.

6. Sensitivity Analysis

I use self-reported survey data on SSDI application, award, and denial decision in this paper. These self-reported data always have this concern about under-reporting or misreporting the true outcome causing measurement error in the variable of interest. The indicator of denied SSDI application is the key explanatory variable in this paper, which is vulnerable to under reporting by the survey respondents. For example, if someone reports the application decision but fails to report the award decision, then I might incorrectly include that person into the denied SSDI applicant category. This person has larger negative effect on post-application labor supply compared to the rejected applicants due to being less healthy as well as for the negative effects of SSDI benefit receipt. If this misreporting is significant in the sample, then the estimated effect of SSDI application would be biased upward in absolute value. Similarly, if I misspecify a Supplemental Security Income (SSI) applicant as SSDI applicant, then the estimates would be biased upward, because, SSI applicants generally have very low labor market attachment to begin with.

The miss-specification of SSI as SSDI is not a big concern in HRS data. Khan et al. (2016), merging the HRS with the administrative SSA summary earnings data, find that the HRS reporting of SSDI and SSI status can be verified with job history data in HRS. Using the methodology in that paper I am able to isolate the SSI applicant from the analysis of this paper. The other concern of misreporting of SSDI beneficiary as SSDI denied applicant is hard to verify directly without the SSA disability record files. However, I can replicate the Bound (1989) approach of comparing the SSDI beneficiary and SSDI denied applicants. If the SSDI denied applicants have a misreporting problem in my sample, then I would get an underestimate of the upper bound of labor supply effect of the beneficiaries compared to what other researchers have found.

Column 8 of Table 1 presents the differences in characteristics between the SSDI beneficiaries and denied applicants. The groups have no statistically significant differences in demographic, wealth, and taste for work characteristics. However, the denied applicants are healthier than the SSDI beneficiaries both in terms of self-reported health status and medically diagnosed conditions. Bound (1989) also found similar differences in characteristics between two groups using a completely different sample of men in 1970s. Comparing the employment of these two groups Bound found that benefit receipt led to a 29 percent reduction in the employment rate of the beneficiaries. Using the much more recent Survey of Income and Program Participation (SIPP) from the 1990s, Chan and van der Klaauw (2008) replicated the Bound (1989) approach using administrative disability data that comes from SSA's "831 file". They found that the employment rate of awarded SSDI applicants is 19 percentage point lower than the denied applicants in 1990s for a sample that includes both men and women. The reduction in estimate compared to what Bound found is argued to be largely due to the increased generosity of SSDI policy and change in demographic composition of applicants from the 1970s to the 1990s.

Table 2 shows that the unconditional employment rate of the awarded SSDI applicants is 22 percent lower than the rate of denied applicants in the sample selected in this paper. Using specification (iii), the OLS estimates in my sample of SSDI beneficiaries and denied applicants show that the benefit receipt reduce employment rate of the awarded applicants by 21 percent[9]. As the replication of the Bound (1989) approach using the sample of denied SSDI applicants used in this paper produces a similar estimate of the one that Chan and van der Klaauw (2008) found in their paper using administrative data, I believe that the problem of misreporting is not a concern for the sample of denied SSDI applicants selected in this paper.

To make sure that my findings are not driven by any specific characteristics of the sample, I estimate the preferred specification of the model using both OLS and 2SLS for different subsamples identified for specific considerations. The results of this sensitivity analysis are presented in Table 5. During the great recession the SSA observed a big spike in SSDI applications and it was difficult for people to get back in to the labor market if they were out for any reason. Considering that these factors might influence the result, I dropped individuals who applied for SSDI around 2008. The OLS estimate of this subsample is a little higher than the full sample estimate; however, the IV estimates are the same. There are not a lot of individuals in the full sample who are observed during the great recession and the results in this paper clearly are not affected by the outcomes of the great recession.

Considering the demographic differences between the denied SSDI applicants and the comparison group, I create separate subsamples without widows, without singles, and without non-whites. Both the OLS and IV estimates using these three different subsamples are very similar to the estimates of the full sample. However, the IV estimates are not significant in subsamples without the singles and without the non-whites. The singles and the non-whites are 32 percent and 26 percent of the full sample. Thus, it is not surprising that dropping a large proportion of the small full sample to get to those subsamples of married and whites results into the IV estimates being imprecisely estimated. Over all, the sensitivity analysis presented in this section indicates that the findings of this paper are robust.

[9] The full set of this regression results is not reported in this paper, but is available upon request.

7. Conclusions

In this paper I identify the causal effect of the SSDI application process on the employment at ages 50-58 of denied applicants two to three years after filing the application. For the identification, I use a comparison group of non-applicants of age 50-58 whom I observe in the data eventually applying for SSDI in their 60s. I provide evidence that this group of late applicants represent a natural control group for SSDI denied applicants. Using the variation in FRAs as a result of the Social Security Act of 1983 and a measure of generosity of state SSDI allowance rate that exogenously determine the decision to apply for SSDI of the denied applicants, I find that the application process reduces the employment rate of the denied applicants by 36 percentage points. I interpret this effect as a loss of employment potential of the denied SSDI applicants *caused* by their decision to go through the process of SSDI application without successfully receiving benefits.

Although my estimates represent the short-run effect of SSDI on employment, there is evidence in recent literature that suggests that this effect persists even in the long-run, especially for older workers close to their end of their careers. The magnitude of the effect is expected to decline over time, because, in the long-run, the work disincentive effect disappears as the denied applicants are done with their appeal and reapplications. The only effect that remains in the long-run is through the human capital deterioration channel.

My findings also suggest that unobserved factors like severity of health condition or low labor market opportunities of the denied applicants account for another 13-percentage-point reduction in the employment rate. It is hard to disentangle the contribution of different factors into this 13-percentage-point reduction in employment of denied applicants, but this result suggests that some of the denied applicants are incapable of doing SGA. However, as these people are not disabled enough to receive SSDI, they are left out of the Social Security safety net. Further research is required to think about policy considerations to improve the work capacity and welfare of this group of people.

In United States the denial rate of SSDI applications, combining at all adjudicative levels, has risen from 45 percent in 2000 to 72 percent in 2013. The denial rate for medical reasons at the medical adjudicative level has also risen from 38 percent to 50 percent during this time period. In absolute terms, the number of applicants has doubled during that time period and about 1.8 million applicants were denied SSDI benefits in 2013.[10] More people than ever are applying for disability benefits, removing themselves from the labor market for months or even years, and then many are forced to re-enter when they are denied enrollment. The findings of this paper suggest that the process of SSDI application causes a substantial loss of employment potential to the denied applicants. The magnitude of the effect is so significant that it suggests that policymakers revisit the disability determination process to make it shorter and also make reforms to reduce the work disincentives while applying and waiting for SSDI determination. Moreover, these findings should facilitate policymakers to think about the importance of resources needed for smoothing the transition of denied SSDI applicants back into the labor force, especially for older workers close to retirement.

[10] Annual Statistical Report on the Social Security Disability Insurance Program, 2014.

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Figure 1 - Labor Force Participation of Eligible Disability Insurance Denied Applicants and Non-applicants by FRA Cohort for Age 51-61

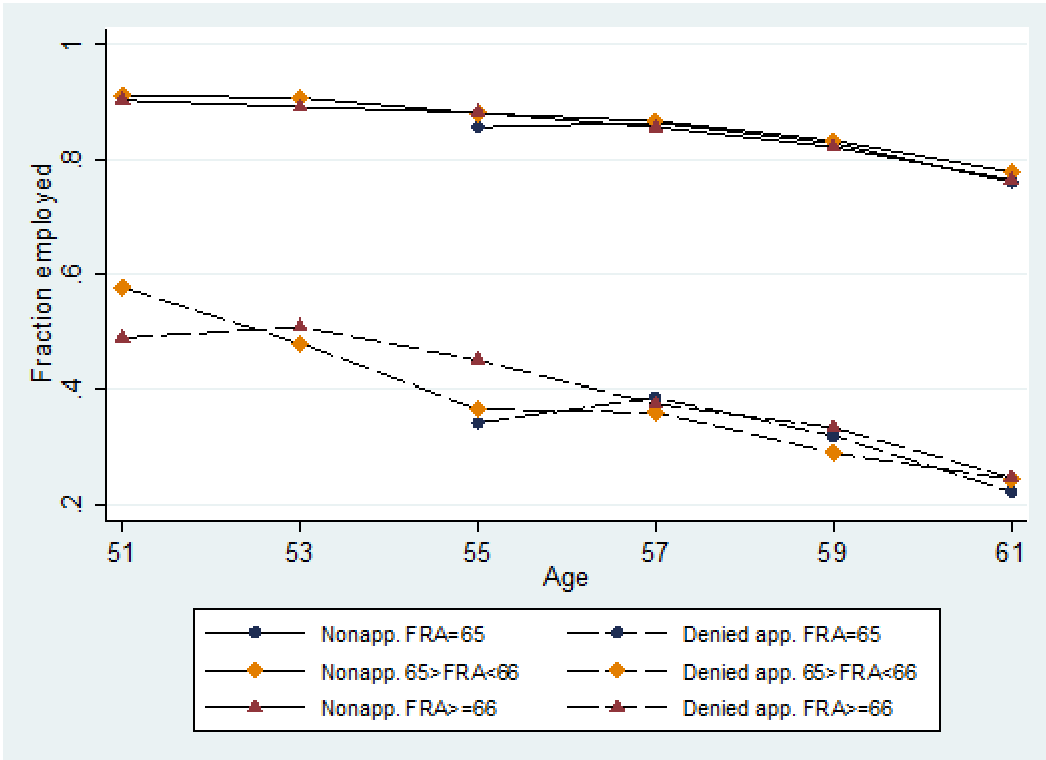
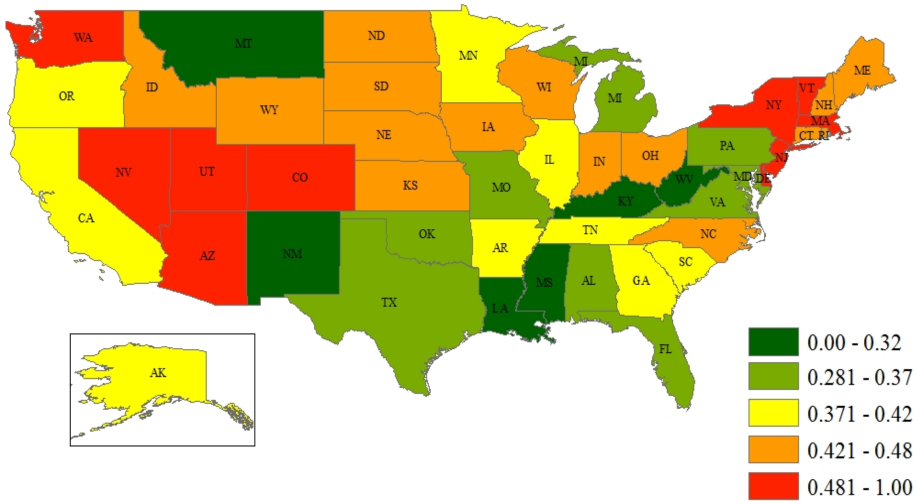
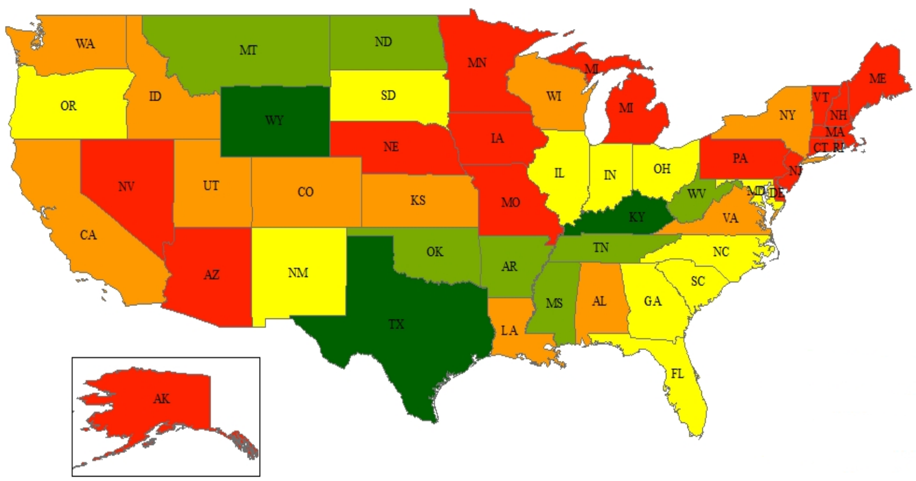


Figure 2 - SSDI Allowance Rate for Men Age 50-54

In Year 1992



In Year 2000



In Year 2010

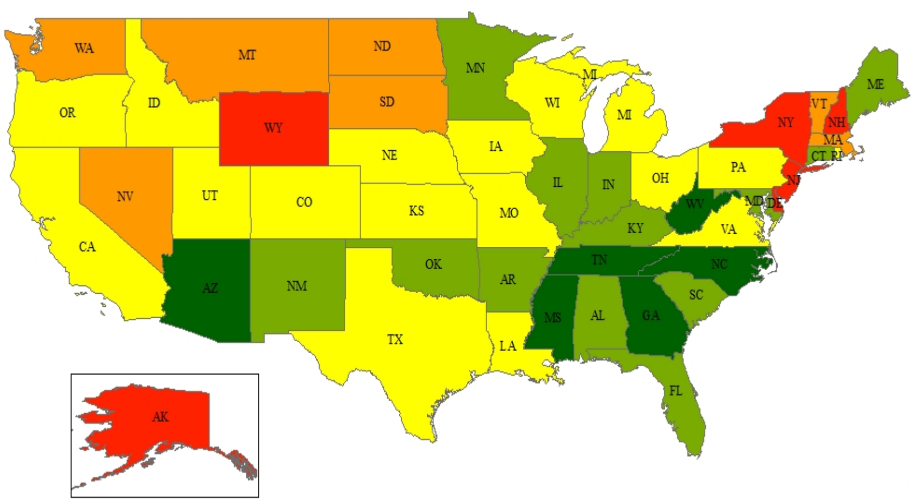


Figure 3 - SSDI Allowance Rate for Women Age 50-54

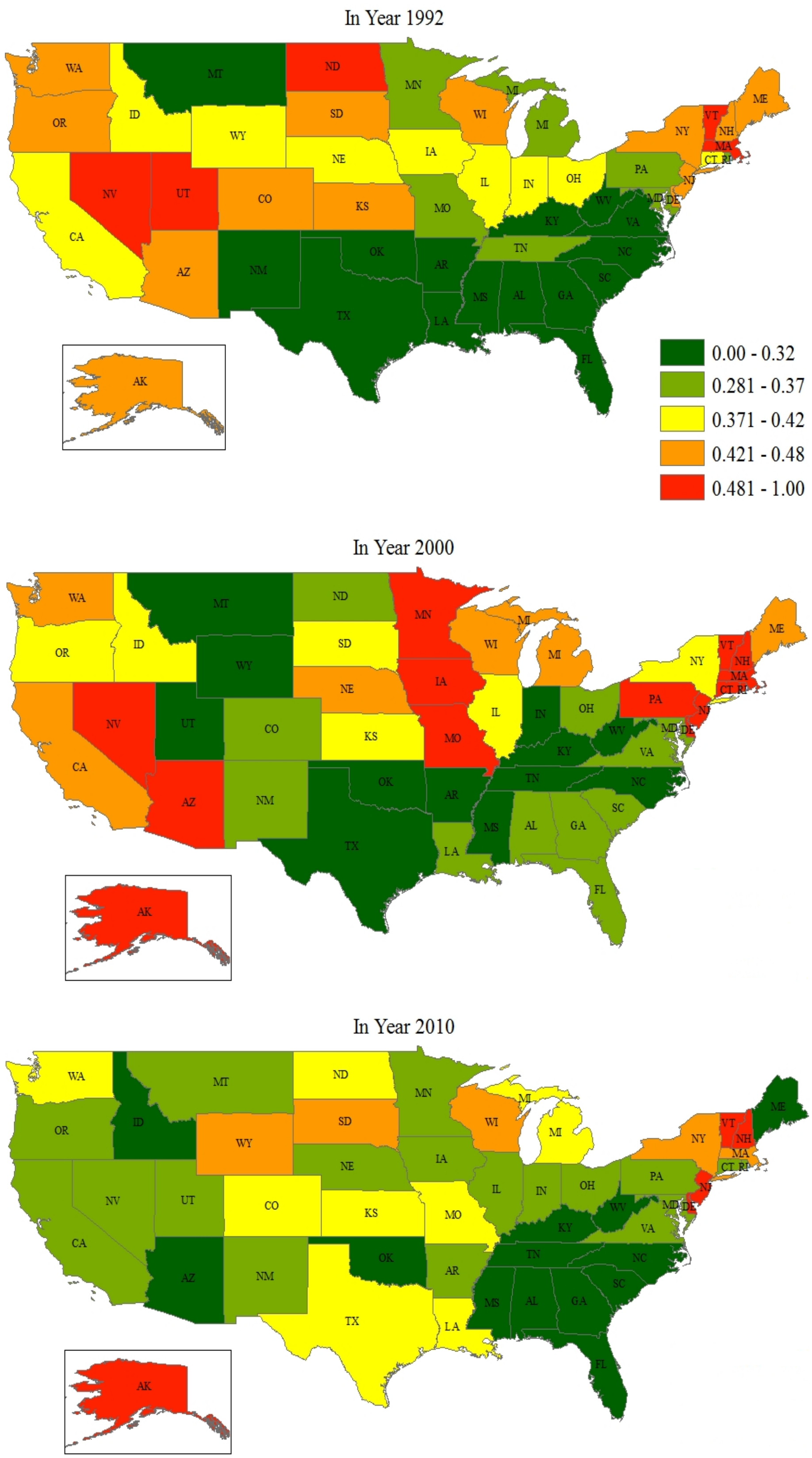


Figure 4 - Disability Insurance Application, Award, Denial, and Allowance Rate of Selected States in US for Men 1992 -2013

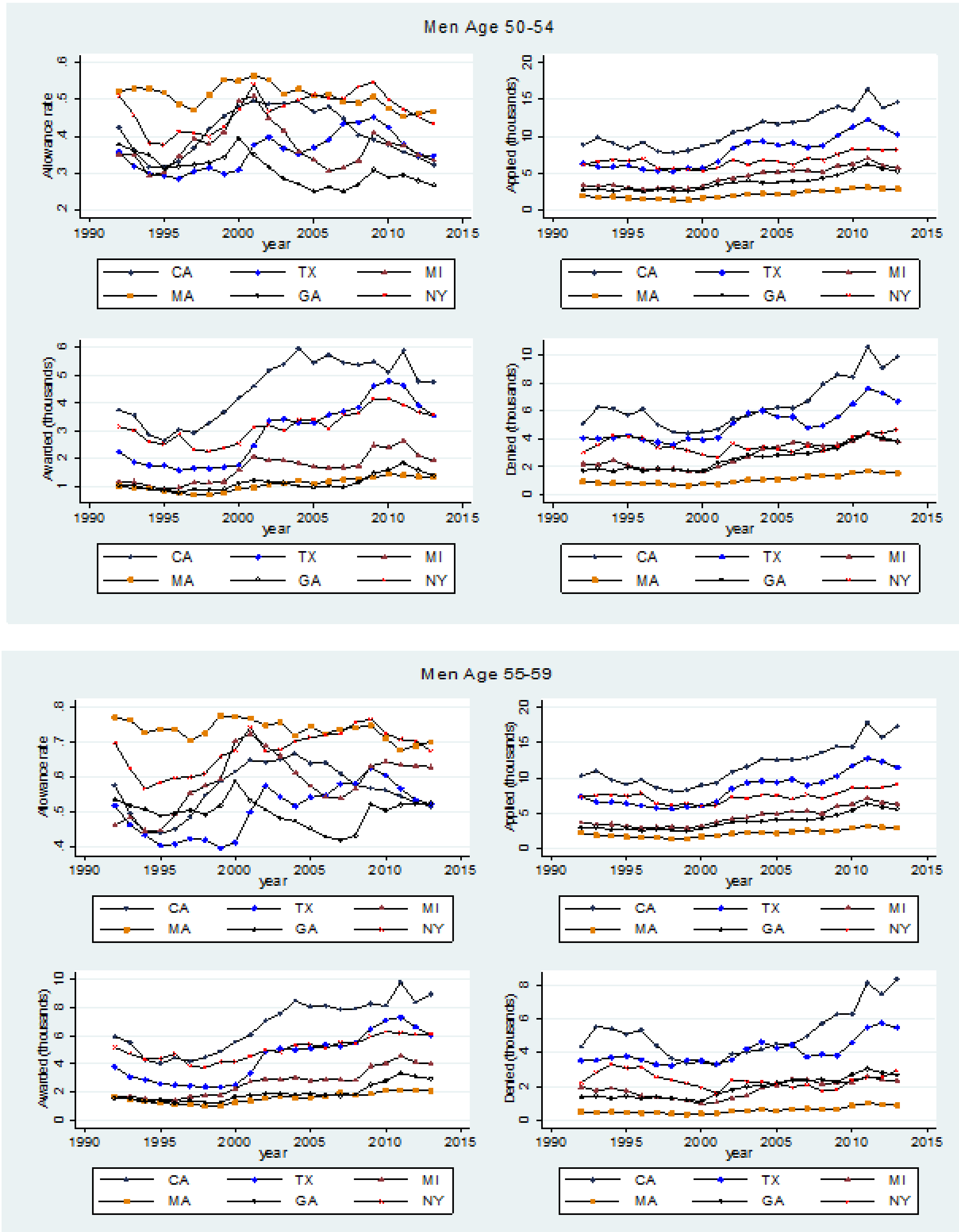
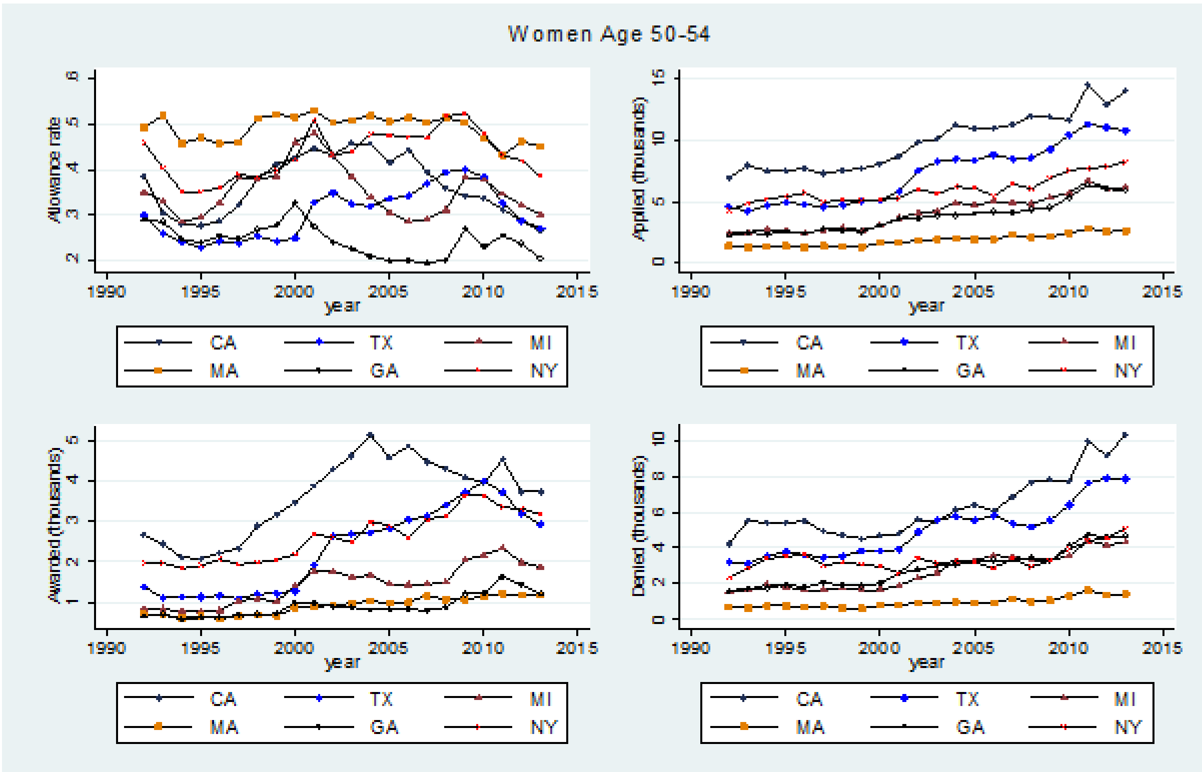


Figure 5 - Disability Insurance Application, Award, Denial, and Allowance Rate of Selected States in US for Women 1992 -2013



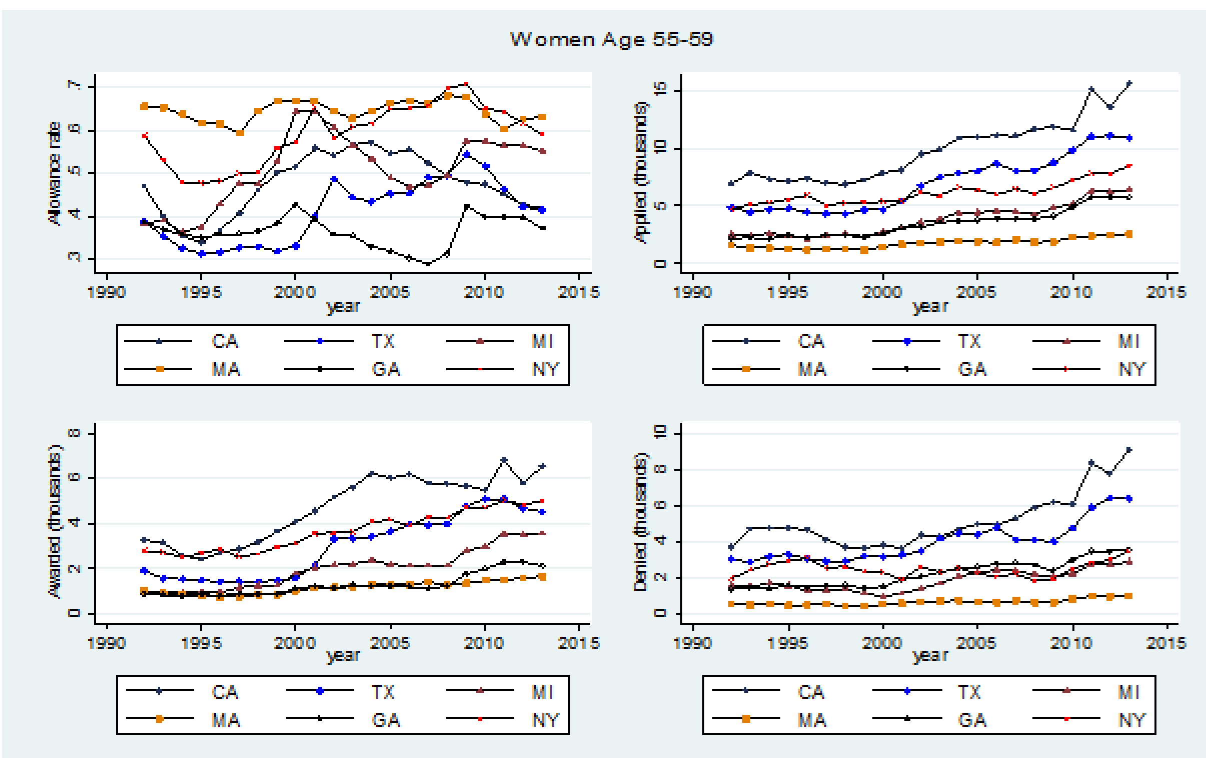


Figure 6 – The Relationship Between BMI, Self-reported Poor or Fair Health, and Employment

Table 1 – Sample Characteristics of Non-applicants, Denied, and Allowed SSDI Applicants and Comparison Between Groups

	Denied applicants T=1	Control group T=0	(T=1) - (T=0)	Never applied N=1	(T=1) - (N=1)	Allowed applicants B=1	(B=1) - T(=1)
Demographics							
Age	54.76	55.26	-0.51***	54.82	-0.06	55	0.24
	(2.28)	(2.21)	(0.15)	(2.34)	(0.13)	(2.20)	(0.16)
Fraction of female	0.57	0.5	0.07*	0.56	0.01	0.56	-0.01
	(0.50)	(0.50)	(0.03)	(0.50)	(0.03)	(0.50)	(0.04)
Fraction of non-white	0.33	0.23	0.10**	0.17	0.15***	0.32	0
	(0.47)	(0.42)	(0.03)	(0.38)	(0.03)	(0.47)	(0.03)
Fraction of school dropouts	0.31	0.24	0.07*	0.12	0.19***	0.28	-0.04
	(0.46)	(0.43)	(0.03)	(0.33)	(0.03)	(0.45)	(0.03)
Fraction of high school educated	0.40	0.38	-0.02	0.35	0.03	0.42	0.04
	(0.49)	(0.49)	(0.03)	(0.48)	(0.03)	(0.49)	(0.04)
Fraction of college educated	0.31	0.36	-0.05	0.52	-0.21***	0.31	0
	(0.46)	(0.48)	(0.03)	(0.50)	(0.03)	(0.46)	(0.03)
Fraction married	0.6	0.71	-0.10***	0.76	-0.16***	0.65	0.05
	(0.49)	(0.46)	(0.03)	(0.43)	(0.03)	(0.48)	(0.04)
Fraction widowed	0.03	0.07	0.04**	0.04	0.03*	0.06	-0.01
	(0.17)	(0.26)	(0.02)	(0.19)	(0.01)	(0.24)	(0.02)
Caregiver for parents	0.11	0.14	-0.03	0.17	-0.06***	0.15	0.04
	(0.32)	(0.35)	(0.02)	(0.38)	(0.02)	(0.36)	(0.02)
Caregiver in next wave	0.16	0.17	0	0.21	-0.05*	0.19	0.03
	(0.37)	(0.37)	(0.02)	(0.41)	(0.02)	(0.39)	(0.03)
Body Mass Index (BMI)	28.87	28.80	0.08	27.80	1.08***	30.10	1.22**
	(5.37)	(6.36)	(0.37)	(5.31)	(0.30)	(7.01)	(0.45)
Fraction with health conditions							
BMI return to normal range	0.03	0.03	0.00	0.03	0.00	0.05	0.02
	(0.17)	(0.18)	(0.01)	(0.16)	(0.01)	(0.22)	(0.01)
BMI move to abnormal range	0.07	0.05	0.02	0.03	0.03*	0.09	0.02
	(0.25)	(0.22)	(0.02)	(0.18)	(0.01)	(0.28)	(0.02)
Self-reported poor/fair health	0.53	0.25	0.28***	0.11	0.42***	0.69	0.16***
	(0.50)	(0.43)	(0.03)	(0.31)	(0.03)	(0.46)	(0.04)
Self-reported mobility problems	0.68	0.43	0.25***	0.28	0.40***	0.81	0.12***
	(0.47)	(0.50)	(0.03)	(0.45)	(0.03)	(0.39)	(0.03)
Self-reported Large muscle problems	0.76	0.59	0.17***	0.42	0.34***	0.83	0.06*
	(0.43)	(0.49)	(0.03)	(0.49)	(0.02)	(0.38)	(0.03)
Self-reported back problem	0.54	0.38	0.16***	0.29	0.26***	0.62	0.08*
	(0.50)	(0.49)	(0.03)	(0.45)	(0.03)	(0.48)	(0.04)
Health limits work previous wave	0.13	0.1	0.04	0.05	0.08***	0.23	0.10***
	(0.34)	(0.30)	(0.02)	(0.22)	(0.02)	(0.42)	(0.03)
High blood pressure (BP)	0.48	0.36	0.12***	0.31	0.17***	0.57	0.08*
	(0.50)	(0.48)	(0.03)	(0.46)	(0.03)	(0.50)	(0.04)
Onset of BP current wave	0.3	0.16	0.13***	0.15	0.15***	0.31	0.01
	(0.46)	(0.37)	(0.03)	(0.35)	(0.03)	(0.46)	(0.03)
Onset of BP next wave	0.07	0.05	0.01	0.04	0.02	0.05	-0.02
	(0.25)	(0.22)	(0.02)	(0.20)	(0.01)	(0.22)	(0.02)

Table 1 *continued …*

Cancer	0.08	0.06	0.02	0.05	0.04*	0.09	0.01
	(0.28)	(0.24)	(0.02)	(0.21)	(0.02)	(0.29)	(0.02)
Onset of cancer current wave	0.06	0.03	0.03	0.02	0.03**	0.06	0
	(0.23)	(0.17)	(0.01)	(0.15)	(0.01)	(0.23)	(0.02)
Onset of cancer next wave	0.02	0.01	0.01	0.01	0.01	0.04	0.02
	(0.15)	(0.12)	(0.01)	(0.10)	(0.01)	(0.20)	(0.01)
Lung disease	0.09	0.08	0.01	0.04	0.05**	0.16	0.07**
	(0.29)	(0.28)	(0.02)	(0.19)	(0.02)	(0.37)	(0.02)
Onset of lung disease current wave	0.07	0.04	0.02	0.02	0.05***	0.11	0.05*
	(0.25)	(0.20)	(0.02)	(0.14)	(0.01)	(0.31)	(0.02)
Onset of lung disease next wave	0.03	0.01	0.01	0.01	0.02*	0.05	0.02
	(0.17)	(0.12)	(0.01)	(0.09)	(0.01)	(0.21)	(0.01)
Heart disease	0.16	0.14	0.02	0.08	0.09***	0.28	0.11***
	(0.37)	(0.35)	(0.02)	(0.26)	(0.02)	(0.45)	(0.03)
Onset of heart disease current wave	0.11	0.07	0.04*	0.04	0.08***	0.17	0.05*
	(0.32)	(0.26)	(0.02)	(0.19)	(0.02)	(0.37)	(0.02)
Onset of heart disease next wave	0.06	0.03	0.03*	0.02	0.04**	0.05	-0.01
	(0.24)	(0.17)	(0.01)	(0.13)	(0.01)	(0.22)	(0.02)
Stroke	0.09	0.02	0.06***	0.01	0.08***	0.07	-0.02
	(0.28)	(0.15)	(0.02)	(0.10)	(0.02)	(0.25)	(0.02)
Onset of stroke current wave	0.06	0.01	0.05***	0.01	0.06***	0.06	0
	(0.24)	(0.11)	(0.01)	(0.08)	(0.01)	(0.23)	(0.02)
Onset of stroke next wave	0.03	0.01	0.02*	0	0.03**	0.04	0.01
	(0.18)	(0.10)	(0.01)	(0.06)	(0.01)	(0.21)	(0.01)
Psychiatric problems	0.24	0.15	0.10***	0.1	0.14***	0.29	0.05
	(0.43)	(0.35)	(0.03)	(0.31)	(0.02)	(0.45)	(0.03)
Onset of psychiatric event current wave	0.16	0.06	0.10***	0.04	0.11***	0.18	0.02
	(0.36)	(0.24)	(0.02)	(0.20)	(0.02)	(0.38)	(0.03)
Onset of psychiatric event next wave	0.07	0.03	0.04*	0.01	0.06***	0.06	-0.01
	(0.26)	(0.18)	(0.02)	(0.12)	(0.01)	(0.24)	(0.02)
Arthritis	0.46	0.4	0.06*	0.3	0.16***	0.57	0.11**
	(0.50)	(0.49)	(0.03)	(0.46)	(0.03)	(0.50)	(0.04)
Onset of arthritis current wave	0.3	0.19	0.10***	0.14	0.16***	0.31	0.02
	(0.46)	(0.39)	(0.03)	(0.34)	(0.03)	(0.46)	(0.03)
Onset of arthritis next wave	0.09	0.08	0	0.05	0.03*	0.08	-0.01
	(0.28)	(0.28)	(0.02)	(0.23)	(0.02)	(0.26)	(0.02)
Diabetes	0.2	0.15	0.05*	0.08	0.12***	0.2	0
	(0.40)	(0.36)	(0.03)	(0.27)	(0.02)	(0.40)	(0.03)
Onset of diabetes current wave	0.13	0.07	0.06**	0.04	0.09***	0.13	0
	(0.34)	(0.25)	(0.02)	(0.19)	(0.02)	(0.34)	(0.02)
Onset of diabetes next wave	0.03	0.03	0	0.02	0.01	0.04	0.01
	(0.17)	(0.17)	(0.01)	(0.14)	(0.01)	(0.19)	(0.01)
Taste for work							
Total years worked till reference age	27.9	32.53	-4.63***	31.5	-3.60***	29.11	1.21
	(10.73)	(9.14)	(0.67)	(8.54)	(0.60)	(10.10)	(0.76)
Fraction of at least one 5-year job tenure	0.87	0.92	-0.06**	0.94	-0.08***	0.88	0.02
	(0.34)	(0.27)	(0.02)	(0.23)	(0.02)	(0.32)	(0.02)
Fraction with retiree health insurance	0.29	0.41	-0.13***	0.43	-0.15***	0.33	0.04
	(0.45)	(0.49)	(0.03)	(0.50)	(0.03)	(0.47)	(0.03)

Table 1 *continued …*

Fraction in wealth quintile							
Lowest	0.35	0.22	0.13***	0.14	0.21***	0.32	-0.02
	(0.48)	(0.41)	(0.03)	(0.34)	(0.03)	(0.47)	(0.03)
Second	0.27	0.24	0.02	0.19	0.07**	0.29	0.03
	(0.44)	(0.43)	(0.03)	(0.40)	(0.02)	(0.46)	(0.03)
Third	0.19	0.23	-0.04	0.21	-0.02	0.19	-0.01
	(0.39)	(0.42)	(0.03)	(0.41)	(0.02)	(0.39)	(0.03)
Fourth	0.11	0.17	-0.05*	0.23	-0.11***	0.13	0.01
	(0.32)	(0.38)	(0.02)	(0.42)	(0.02)	(0.33)	(0.02)
Highest	0.08	0.14	-0.06**	0.23	-0.15***	0.07	-0.01
	(0.27)	(0.35)	(0.02)	(0.42)	(0.02)	(0.25)	(0.02)
Obs.	322	909	1231	21306	21628	453	775
Number of Individuals	322	347	669	8452	8774	453	775

Notes: Standard deviations are in parentheses. For the mean differences the standard errors are in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 2 – Employment Rate of Non-applicants, Denied, and Allowed SSDI Applicants

	Denied applicants T=1	Control group T=0	(T=1) - (T=0)	Never applied N=1	(T=1) - (N=1)	Allowed applicants B=1	(B=1) - T(=1)
Labor supply							
Fraction of working in previous wave	0.70	0.88	-0.18***	0.89	-0.19***	0.71	0
	(0.46)	(0.32)	(0.04)	(0.31)	(0.04)	(0.46)	(0.05)
Fraction of working in reference wave	0.31	0.87	-0.56***	0.88	-0.57***	0.34	0.03
	(0.46)	(0.34)	(0.03)	(0.33)	(0.03)	(0.47)	(0.03)
Fraction of working in next wave	0.28	0.82	-0.54***	0.85	-0.57***	0.06	-0.22***
	(0.45)	(0.38)	(0.03)	(0.36)	(0.03)	(0.23)	(0.03)
Obs.	322	909	1231	21306	21628	453	775
Number of individuals	322	347	669	8452	8774	453	775

Notes: Standard deviations are in parentheses. For the mean differences the standard errors are in parentheses.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 3 - First Stage Regressions Using different Specifications

	(i)	(ii)	(iii)
Indicator 65>FRA<66	0.04	0.04	0.03
	(0.05)	(0.04)	(0.05)
Indicator FRA>=66	0.19***	0.19***	0.17***
	(0.05)	(0.05)	(0.05)
More generous state		-0.03	-0.02
		(0.03)	(0.03)
Age fixed effects	Y	Y	Y
State level controls	N	Y	Y
State fixed effects	N	N	Y
Obs.		1231	
R^2	0.25	0.26	0.28
F-statistic of the weak identification test	17.34	11.81	9.84
Critical value for max 10% bias of the weak identification test	19.93	9.08	9.08

Note: Robust standard errors are in parentheses account for clustering at the individual level. The regressions include demographic, health, and economic controls into the three specifications as described in the paper.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 4 - Effect of SSDI Application Decision on Employment

	(i)		(ii)		(iii)	
	OLS	IV	OLS	IV	OLS	IV
Denied SSDI applicant	-0.49***	-0.37**	-0.50***	-0.38**	-0.49***	-0.36*
	(0.03)	(0.19)	(0.03)	(0.19)	(0.03)	(0.20)
Age fixed effects	Y	Y	Y	Y	Y	Y
State level controls	N	N	Y	Y	Y	Y
State fixed effects	N	N	N	N	Y	Y
Obs.				1231		
R^2	0.37	0.37	0.38	0.37	0.41	0.39
F stat.	14.08	7.05	14.51	6.94	11.73	6.47
P-value of the overidentification test		0.78		0.58		0.57

Note: Robust standard errors are in parentheses account for clustering at the individual level. The regressions include demographic, health, and economic controls into the three specifications as described in the paper.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 5 - Sensitivity Analysis of the Main Findings of the Paper

	Drop great recession years		Drop widows		Drop singles		Drop non-whites	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Denied SSDI applicant	-0.51***	-0.36*	-0.49***	-0.39**	-0.47***	-0.35	-0.47***	-0.34
	(0.03)	(0.22)	(0.03)	(0.21)	(0.04)	(0.26)	(0.04)	(0.29)
				First Stage of the 2SLS				
Indicator 65>FRA<66		0.03		0.002		-0.02		0.002
		(0.05)		(0.05)		(0.06)		(0.05)
Indicator FRA>=66		0.16***		0.15***		0.12**		0.11**
		(0.05)		(0.05)		(0.07)		(0.06)
More generous state		-0.02		-0.02		-0.01		-0.03
		(0.03)		(0.03)		(0.04)		(0.04)
Obs.	1191		1177		835		912	
P-value from the overidentification test		0.61		0.82		0.89		0.47

Notes: Robust standard errors are in parentheses account for clustering at the individual level. All the regressions are estimated using the specification (iii) described in the paper. Models also include age fixed effects and state fixed effects.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.