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The Effect of Disability Insurance Receipt on Labor Supply

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By Eric French and Jae Song[1]

Abstract

This paper estimates the effect of the Disability Insurance program on labor supply. We find that 30% of denied applicants and 15% of allowed applicants work several years after a disability determination decision. The earnings elasticity with respect to the after tax wage is 0.8. However, the labor supply of those over age 55, college graduates, and those with mental illness is not sensitive to allowance of benefits.

1. Introduction

This paper presents new evidence on the effect of the Disability Insurance (DI) Program on labor supply. We compare the earnings patterns of individuals who applied for and received disability insurance benefits with the earnings patterns of those who applied for benefits but were denied.

Relative to Bound's (1989) classic study on earnings of rejected DI applicants, we make the following improvements. First, we use better data. Second, we address the fact that those who are denied benefits are potentially different than those who are allowed. We use plausibly exogenous variation in allowance rates to identify the effect of disability insurance on labor supply. Specifically, we exploit the assignment of DI cases to judges, which is essentially random.

We find that DI applicants who are denied benefits earn more than those who are allowed, but the effect is modest. For example, being allowed benefits reduces labor earnings by about $3000 per year in the years following a disability decision and reduces labor force participation by 15 percentage points. Moreover, participation of rejected DI applicants remains low, about 30%, even 5 years after they were denied. However, this implies a high labor supply elasticity with

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respect to the after tax wage. The earnings and participation elasticities are 0.8 and 0.6, respectively.

Furthermore, we estimate labor supply responses for different subgroups of the population. We identify many subgroups of the population whose labor supply is not sensitive to benefit receipt, such as those over age 55, college graduates, and those with mental illness. Because we have the population of DI applicants, we obtain precise estimates of the labor supply responses, even for these narrow subgroups of the population.

2. Literature Review

Disability insurance is one of America's largest social insurance programs. In 2005, 4.1% of men ages 25-64 were receiving disability insurance benefits. The total cost of the program was $85.4 billion, making it more costly than unemployment insurance. Furthermore, after 2 years on the disability rolls, individuals are eligible for Medicare benefits. The total cost of Medicare payments to DI beneficiaries was $49 billion in 2005 (Autor and Duggan 2006).

Disability insurance has often been cited as one of the main causes of the fall in labor supply of American men aged 55-64. In order to better understand the labor supply effects of DI, Bound (1989) compared earnings patterns of individuals who applied for and received DI benefits to those who applied for benefits but were denied. He found that those who were allowed benefits were less likely to work than those who were rejected, but the effect was modest. Even those who were denied benefits had participation rates of less than 50% after denial of benefits. Thus, Bound inferred that at most 50% of rejected male applicants during the 1970s would have worked were it not for the availability of disability benefits.

However, there are three key criticisms of Bound's approach. First, those who are denied benefits are different than those who are allowed benefits. Bound's claim was that this should lead to an overstatement of the effect of disability on labor supply, because those who are denied are on average healthier than those who are allowed. However, Lahiri et al. (2008) found that those who are denied benefits tend to have very intermittent work histories. Those who are allowed benefits are more likely to work and have higher earnings before applying for benefits.

Thus it is not clear whether those who are denied are more or less likely to work in the absence of benefits.

It is this problem that our study addresses. Our identification approach matches those who are denied benefits to those who are otherwise similar but are allowed benefits. Our approach compliments the approach of Chen and Van der Klaauw (2008) who exploit the vocational grid. They use the fact that in many cases, an individual aged 54 applying for benefits would be denied, although the same individual at age 55 would be allowed. Our estimated labor supply effects are similar to Chen and Van der Klaauw (2008). However, we add to their analysis by providing larger sample sizes. This allows for more precise estimates. It also allows us to document how the responsiveness of labor supply varies with demographics, because we can obtain precise estimates for narrow subgroups.

However, our approach does not address the following two criticisms brought up by Parsons (1991). First, many individuals who are denied continue to appeal the denial. On order to be deemed eligible for benefits, the individual cannot work while appealing the initial denial. Thus, many of those who are denied do not work in order to increase the chances of successful appeal. If the option to appeal had not existed, more of these individuals might have returned to the labor force.[2]

Second, in order to apply for benefits, the individual must be out of the labor force for a period of time. For example, the individual can only work a very limited amount in the 5 months before applying for benefits. During that period human capital may depreciate. Thus the individual may not be able to return to her previous job, even if she is healthy. In other words, the very act of applying for benefits reduces ability to work.

3. The Disability Insurance System

3.1 Why Getting DI Affects Labor Supply

Individuals who are allowed benefits are given a benefit that depends on previous labor earnings. Disabled worker benefits averaged $1,004 per month for DI beneficiaries in 2007 (Social Security

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[2] In the future we plan to measure the fraction of denied disability applicants who appeal the decision, or file a new DI claim.

Administration, 2008). Because the benefit schedule is progressive, disability benefits replace over 60% of labor income for those at the 10th percentile of the earnings distribution (Autor and Duggan 2006). Those receiving benefits can earn up to the Substantial Gainful Activity level (SGA) of $500 per month (in current dollars) during the 1990s and was $900 per month in 2007. Those earning more than this amount for more than a 9 month Trial Work Period will lose their benefits.

Thus both income effects (through the high replacement rate) and substitution effects (beneficiaries will loose benefits if they earn above the Substantial Gainful Activity amount) indicate that DI should reduce labor supply. Furthermore, getting DI benefits makes the individual eligible for Medicare after a 2 year waiting period. Medicare eligibility may affect labor supply if individuals work not only for the labor income from work, but also for the employer provided health insurance benefit. Medicare largely eliminates that value of employer provided health insurance, and eliminates an important work incentive (French and Jones, 2009).

Individuals with weaker earnings histories and low asset levels who are disabled are eligible for a related program called Supplemental Security Income (SSI). SSI benefits are not a function of previous labor income. The Federal Maximum SSI benefit level was $386 per month in 1990, rising to $623 in 2007 although some states supplement this benefit. Benefits are reduced by 50 cents for every dollar of labor income. Individuals drawing SSI may also be eligible for Medicaid, the government provided health insurance program for the poor. Many people draw both DI and SSI benefits concurrently.

Relatively few people lose disability benefits for reasons other than death.[3] For example, of 7.1 million individuals (SSDI worker beneficiaries) drawing DI benefits in 2007, 33,381 had benefits terminated because they earned above the Substantial Gainful Activity level for an extended period of time in 2007. Furthermore, 20,592 had benefits terminated because they were deemed medically able to work after a continuing disability review, which is a periodic review of the health of DI beneficiaries (Social Security Administration, 2007).

The disability allowance decision is high stakes. If the individual is allowed benefits, that individual is typically given disability benefits until the normal retirement age (age 65 during the

[3] DI benefits are converted into retiree benefits once the beneficiary turns the normal retirement age. The statistics above are for DI benefits before the conversion to retiree benefits.

1990s and now 66), when these benefits are converted into Social Security benefits. Thus an individual age 51 who receives $10,000 in disability benefits a year will likely receive these benefits for 15 years, meaning that she will receive $150,000 in transfers. Furthermore, 2 years after receiving benefits, she will receive Medicare benefits, which are worth about $50,000. Thus, being allowed benefits is worth on average $200,000 over her lifetime.

3.2 Determining Eligibility for DI benefits

An individual is deemed eligible for benefits if they have met certain work requirements and if they are deemed medically disabled. Although the exact algorithm is complex (see Hu et al. 2001 for details), one of two conditions must be met for the individual to be deemed disabled.

The first condition is "listed impairment". Individuals that meet one of over 100 specific listed impairments are given immediate benefits. Examples include statutory blindness (i.e., corrected vision of 20/200 or worse in the better eye) and multiple sclerosis.

The second condition is inability to perform either past work or other work. This condition involves a combination of medical impairment and vocational factors such as education, work experience, and age. These cases can be especially difficult to evaluate. Myers (1993), a former Social Security Administration Deputy Commissioner, points out that "if a worker has a disability so severe that he or she can do only sedentary work, then disability is presumed in the case where the person is aged 55 and older, has less than a high school education, and has worked only in unskilled jobs, but this is not so presumed in the case of a similar young worker. Clearly, borderline cases arise frequently and are difficult to adjudicate in an equitable manner!"

The disability determination process is multi-step process. The share of applicants who were allowed at different steps is shown in Figure 2A. Figure 2A shows allowance rates for our initial sample (described in detail in Section 4 and Appendix A). After an initial waiting period of 5 months, DI applicants have their case reviewed by a disability determination service review board. Figure 2A shows that 39% of applicants are allowed and 61% are denied at this stage. At this stage the most clear cut cases are allowed, such as those that have a listed impairment. Cases that are more difficult to judge (such as mental and musculoskeletal problems) are usually denied at this stage. About half of all applicants denied for medical reasons appeal at the disability determination service reconsideration stage, and about 10% of those that appeal are given benefits at this stage (Social Security Administration, 2008). Figure 2A shows that another 5% of all cases are allowed at this stage. 60 days after disability determination service decision, a DI appeal can be requested. DI appeals are reviewed in court by Administrative Law Judges (ALJs) after a delay of about 1 year.[4] 14% of all initial claims and 59% of all claims that are appealed at the ALJ level are allowed.[5] If the case is denied at the ALJ level, the applicant can then appeal the Appeals Council level. If the applicant is denied at this level, she can appeal after 60 days at the Federal Court level. However, Figure 2A shows that appeals at the higher levels are rarely successful. Figure 2A shows that less than 2% of all initial claimants receive benefits at the Appeals Council or Federal Court level. Lastly, denied applicants can also re-apply for benefits. The last line on Figure 2A includes those who re-apply for benefits. Another 7% of all initial claimants are eventually allowed benefits through a re-application. In short, a large share of all individuals are allowed benefits at the ALJ stage, and relatively smaller share receive benefits thereafter.

Figure 2B shows the status of all these cases. Figure 2b shows the total share allowed, the share who are still in the process of appealing or re-applying for benefits, and the share who were not allowed and no longer applying for benefits. Ten years after the initial filing, 67% of all claimants were allowed benefits, 27% were denied and the process ended, and 6% were still in the process of applying for benefits. Together, Figures 2a and 2b emphasize the fact that re-applications and appeals are important for understanding the DI system.

Because we identify the causal effect of DI on labor supply using variation at the ALJ level, we are estimating the effect only for marginal cases. The least healthy individuals such as those with listed impairments are allowed at the Disability Determination Service stage. The healthiest individuals will be denied by every judge, and will be denied on every appeal. Thus our results may not be fully generalizable to all DI applicants. However, these marginal cases are of great interest, because these are the individuals most likely to be affected by changes in the leniency of the appeals level of the DI system.

3.3 Assignment of DI cases to judges

[4] Judges can make one of three decisions: allowed, denied, or remand. A "remand" is a request for more information from the disability determination service. Our measure of "allowed" is the final determination at the ALJ stage, and thus includes the final decision on remands.
[5] The full allowance rate at this stage is slightly higher than 59%. Our 59% allowance rate is for our estimation sample, which drops pre-reviewed cases that have higher allowance rates. See footnote 7.

Administrative Law Judge (ALJs) are assigned to appeals cases on a rotational basis, with the oldest cases receiving priority at each hearing office.[6] Thus, the oldest case is given to the judge who most recently finished a case. Therefore, conditional on applying at a given office at a given point in time, the initial assignment of cases to judges is "essentially random" (Social Security Advisory Board, 2006). Judges do not get to pick the cases they handle. Judges are not assigned cases based on the expertise of the judge. Furthermore, an individual cannot choose an alternate judge after being assigned a judge.

The initially assigned judge is the same as the deciding judge in 96% of all cases. Although the deciding judge is not necessarily randomly assigned, the initially assigned judge is.[7] We use the initial assignment to a judge as our source of exogenous variation.

4. Data

Our initial sample is the universe of individuals who appealed either a DI or SSI benefit denial, and were assigned to an ALJ during the years 1990-2006. Using Social Security Numbers, we match together data from the SSA 831 file, the Office of Hearings and Appeals Case Control System (OHACCS), the Hearing Office Tracking System (HOTS), the Appeals Council Automated Processing System (ACAPS), the Litigation Overview Tracking System (LOTS), the

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[6] Title 5, Part III, Subpart B, Chapter 31, Subchapter I, Section 3105 of the US Code states that "Administrative law judges shall be assigned to cases in rotation so far as practicable" (United States, 2007). The Social Security Administration's Hearings, Appeals and Litigation Law Manual (HALLEX) Volume I Chapter 2 Section 1-55 states that "the Hearing Office Chief Administrative Law Judge generally assigns cases to ALJs from the master docket on a rotational basis, with the earliest (i.e., oldest) Request for Hearing receiving priority." (Social Security Administration, 2009). HALLEX gives 11 exceptions to this rule. For example, the exceptions include "critical cases", such as individuals with terminal conditions and military service personnel, as well as remand cases. These cases are expedited and reviewed by Senior Attorneys. If there is a clear cut decision to be made, then the Senior Attorney will make the decision without a hearing. If the case is not clear cut, then the case is put back in the master docket and is assigned to a judge in rotation. Fortunately we can identify cases that were decided without a hearing and we delete them from our sample. Our analysis focuses on the remaining cases where there was a hearing.

[7] The initially assigned judge is not necessarily the judge who handles the case. This fact can potentially be exploited by DI claimants. For example, if an individual misses her court case, she may be reassigned to a different judge. Another possibility is that for some cases in remote areas, cases are held via video conference where the judge and claimant are not in the same room. Claimants can demand that the judge be present at a hearing, and thus the judge must travel to the claimant. Some judges refuse to travel, and thus another judge will be reassigned to the case. In this way, an individual can potentially reject a judge.

Master Earnings file (MEF), and the Numerical Identification file (NUMIDENT). These data are described in greater detail in the appendix. To the best of our knowledge, neither the OHACCS, HOTS, ACAPS, nor the LOTS datasets have been used for research purposes before.

Table 1 presents information on the age, race, and earnings histories of individuals in our estimation sample, which is a sample of those assigned to an ALJ 1990-1999. It disaggregates the data into those who were allowed benefits and those who were denied benefits. Table 1 shows that applicants age 60 and older comprise 8.9% of all allowed individuals and 4.9% of all denied individuals. Thus people aged 60-64 are more likely to be allowed benefits than other people. Table 1 also shows that allowed individuals earn on average $17,118 per year (in 2006 dollars) whereas denied individuals only earn $12,564 in the 10 years prior to the date of assignment.

Figure 3 shows annual earnings for those who are allowed and those who are denied DI benefits both before and after the date of assignment to a judge. Those who are allowed benefits have higher earnings than denied individuals prior to assignment. By the year of assignment earnings fall to $2479 and $2,302 per year on average for allowed and denied individuals, respectively. In the 5 years after assignment earnings of those allowed benefits average $1600 whereas those denied benefits have earnings of $3937. The difference in earnings between those allowed and denied following assignment is thus $2,337. Given that virtually all cases are decided within one year following assignment to a judge, it is perhaps unsurprising that the differences in earnings between those allowed and denied emerge rapidly, and are very stable at $2,337 per year between years 2-5 after assignment to a judge.

Consistent with the evidence on earnings, Figure 4 shows that those who are allowed benefits have participation rates that are 7 percentage points higher than those denied prior to assignment. After the date of assignment, those who are allowed benefits have participation rates that are 16 percentage points lower than those who are denied. Again, the differences between the two groups are stable two years after assignment. Standard errors on these estimated earnings levels and participation rates are tiny and so we do not present them.

5. Methods

In order to estimate the effect of DI allowance on earnings and labor force participation, we use a two step procedure. In the first step we generate an instrumental variable that is correlated with the probability of allowance, but is uncorrelated with health, ability, or preferences for work. In the second step we use instrumental variables procedures to estimate the effect of DI on earnings and participation.

Step 1: Using the full sample of data for 2001-2006 we estimate the equation

(1) $A(i)= j(i)\alpha_1 + h(i)\alpha_2 + t(i)\alpha_3 + e(i)$

where A(i) is a 0-1 indicator which is equal to 1 if case i was allowed, j(i) is a full set of 0-1 indicators equal to 1 if case i was heard by judge j, h(i) is a full set of 0-1 indicators equal to 1 if case i was heard at hearing office h, t(i) is a full set of 0-1 indicators equal to 1 if case i was heard in year t, and the α_1, α_2, and α_3 parameters are to be estimated. Our interest is in identifying the parameter vector α_1. Because judges are randomly assigned conditional on time and hearing office, we include hearing office and time indicators to better identify α_1. As a normalization, we assume the judge effects (i.e., α_1 vector) are the difference between the average judge allowance rate and the average allowance rate at that judge's hearing office, conditional on time.[8] Judges who heard over 50 cases and had an estimated value of α_1 that was in the top 20% of the α_1 distribution are considered "high" allowance judges. All cases assigned to "high" judges are "high" allowance cases. For these cases we denote H(i)=1.

[8] We estimate equation (1) in two stages. Because most judges work at a single office, hearing office effects and judge effects are tenuously identified from each other. If judges never moved offices, judge effects and office effects would not be separately identified. Thus we define the judge effect as the judge specific deviation from the average allowance rate at a given hearing office at a given point in time. Thus we estimate

(1') $A(i)= h(i)\alpha_2 + t(i)\alpha_3 + e^*(i)$

We take the estimated residuals $\hat{e}^*(i) = A(i) - (h(i)\hat{\alpha}_2 + t(i)\ \hat{\alpha}_3)$ from equation (1') and regress the residuals on a full set of judge indicator variables

(1'') $\hat{e}^*(i) = j(i)\alpha_1 + e(i)$

This gives us an estimate of α_1, the vector of judge specific allowance rates.

Step 2: We use the 1990-1999 data to identify the effect of DI allowance on labor supply using standard IV techniques. Recall that H(i) is randomly assigned, conditional on hearing office and time. We use both matching and regression procedures to control for hearing office and time.

The matching procedure is as follows. Each case where H(i)=1 is matched to case that was assigned on the same day at the same office, but is a low allowance case, H(i)=0 (i.e., it was not heard by a high allowance judge). The Appendix has more details of our matching algorithm. We then estimate the equations:

(2) $A(i)= \beta_0 + H(i)\,\beta_1 + u^*(i)$

(3) $y(i)= \gamma_0 + \hat{A}(i)\ \gamma_1 + \varepsilon^*(i)$

where $\beta_0, \beta_1, \gamma_0, \gamma_1$ are parameters to be estimated, y(i) is either earnings or participation of individual i, and $\hat{A}(i)$ is the predicted value of A(i) that we obtain from estimating equation (2).

The instrument H(i) is uncorrelated with $\varepsilon^*(i)$. Recall that we match "high" and "low" cases that occur at the same hearing office, and usually on the same day. Assignment of cases to judges on a given day is random. Thus, assignment should be uncorrelated with both preferences for work and labor market opportunities that is subsumed in $\varepsilon^*(i)$. Even if a given case where H(i)=1 has a high value of $\varepsilon^*(i)$ because it comes from an office where the applicants are healthy, that case will be matched to another case where H(i)=0 but also has a high value of $\varepsilon^*(i)$ because it is drawn from the same office on the same day. Thus the matching procedure eliminates any concerns that our controls are not sufficient to capture any unobserved variables.[9]

The regression procedure uses the full sample of data 1990-1999 and adds a full set of hearing office and time dummies to equations (2) and (3).[10]

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[9] We have experimented with estimating equation (2) and (3) by hearing office and year, then taking a weighted average of the estimates. These gave virtually identical results to results when we pool all hearing offices together with no weighting. We report only pooled results in the paper.

[10] If there is heterogeneity in the responsiveness of earnings and participation to DI allowance, then we are identifying a Local Average Treatment Effect. Given that judge assignment likely satisfies the

Both the regression and matching procedures eliminate the issue of small sample bias in IV estimators when the number of instruments and the number of observations is large (Wouterstein et al. (2009)). We use data from 2001-2006 to identify the high allowance judges, and 1990-1999 for the estimation procedure. For the estimation sample, we reduce the number of instruments (the number of judges) to just one instrument, whether the case was high or low.

6. Results

6.1 Establishing the validity of the randomization

In previous sections we claimed that assignment of cases to judges and thus cases to the instrument H(i) is random. Thus high (i.e., H(i)=1) and low (i.e., H(i)=0) allowance cases should be the same prior to assignment. If high and low allowance cases are the same, then the observable characteristics of the two groups should be the same prior to assignment.

Table 2 presents tests of this hypothesis. It shows differences between high and low allowance cases for a number of observable factors. Column 1 shows characteristics of high allowance cases. Column 2 shows characteristics of low allowance cases. Column 3 takes the difference and column 4 gives the t-statistic of the difference. Recall from Table 1 that there are large differences in observable characteristics between those allowed and denied. However, the observable characteristics of high versus low allowance cases prior to assignment are similar. Table 2 shows that differences between high versus low allowance cases are small when considering factors such as sex, health conditions, whether the individual is a SSI or DI applicant, and whether the case is represented by a lawyer.

There are a few statistically significant differences between the high and low allowance groups. Those aged 35-44 comprise 35.8% of all high allowance cases and 36.2% of all how allowance cases. The t-statistic of the difference between the groups is 3.0. If individuals were randomly assigned to the two groups, then only 5% of all the differences in means between the two groups should have t-statistics greater than 2. Table 2 shows that more than 5% of all differences have t-

independence and exclusion restriction assumptions, and as we show below seems to satisfy the first stage and monotonicity assumptions.

statistics greater than 2.[11] Nevertheless, these differences are small, especially in comparison to the differences between the allowed and denied groups.

6.2 First Stage Estimates

Column 1 of Table 3 shows allowance rates by demographic group. Those who are allowed benefits are older, whiter, have stronger work histories, and are less educated than those denied benefits. In terms of health conditions, those with musculoskeletal disorders such as back pain, and problems of the circulatory system such as heart disease are more likely to be allowed than those with other health conditions.

The other columns of Table 3 show that our first stage regression has power. Column 2 shows that allowance cases are allowed 68.1% of the time.[12] Column 3 shows that "low" allowance cases are allowed 48.9% of the time. Column 4 shows that the difference is 19.2%. High allowance cases are more likely to be allowed benefits, regardless of the applicant's race, age, sex, or prior earnings. Column 5 shows the standard error of the difference. Column 6 gives the t-statistic of the difference. The overall difference in allowance rates has a t-statistic of 141.3. The F-statistic is the square of the t-statistic when there is only one right hand side variable. Thus the F-statistic of 19971 far exceeds conventional statistical thresholds. Column 6 shows that even for narrow subgroups, there is a statistically significant difference between high and low allowance cases.

6.3 Estimates of the Effect of Disability Recipiency on Labor Supply

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[11] Furthermore, we regressed of H(i) on all the variables shown in table 2. The F-statistic of the hypotheses that all coefficients are 0 (meaning that none of the right hand side variables can predict whether H(i)=1) is 4.7. The associated p-value is 0.00: thus the hypothesis that all coefficients are 0 is rejected. However, the F-statistic is 945 for the hypothesis that all coefficients are 0 on the regression of the variable A(i) on all the same variables. Thus our IV procedure eliminates most of the selectivity concerns when considering the effect of DI allowance on labor supply.

[12] The allowance rate of high allowance and low allowance cases are estimates of $\beta_0 + \beta_1$ and β_0, respectively, from the first stage regression in equation (2). Thus the difference is the estimate of β_1.

Table 4 presents estimates of the effect of disability recipiency on earnings and labor force participation using both OLS and IV estimators.[13] It presents estimates both using the full sample of cases as well as for the matched sample, where each high allowance case is matched to a low allowance case. It also shows estimates with covariates and without. Parameter estimates are remarkably similar whether using IV or OLS, the full or matched sample, and whether using additional covariates or not.

Our preferred results are the IV estimates using the matched data, but with no covariates. These estimates suggest that those who are allowed benefits earn on average $1655 per year in the five years following assignment to a judge. Those who are denied allowed earn on average $3,858, or $2203 more than their allowed counterparts. Participation rates for allowed individuals are 15.2%. Those that are denied benefits have participation rates that are 13.7% higher, or 28.9%. Adding covaraites to this specification has only a modest effect on the estimates. Recall that using matching should deliver consistent estimates, with or without covariates. Thus the fact that adding covariates does not change the estimates is reassuring.

Figures 5 and 6 show IV estimates of earnings and labor force participation of allowed and denied individuals both before and after assignment to a judge.[14] Earnings and participation of the two groups are virtually identical before assignment to a judge, which is unsurprising given that our instrument is uncorrelated with earnings prior to assignment. However, after assignment, earnings and participation of allowed individuals are lower. Figure 5 shows that two years after the time of assignment the difference in earnings between the two groups is $2,023. By 5 years after assignment, the gap grows slightly to $2,474. Similarly, figure 6 shows that two years after assignment the difference in participation between the two groups is 14.1%, and does not change much over the next five years. The standard errors are tiny and thus we do not show them. One standard error on the effect of allowance on earnings averages $260 and one standard error on the effect of allowance on participation averages 1.1%.

[13] The estimates are from equation (3), where our estimates for denied individuals are γ_0 and out estimate for allowed individuals is $\gamma_0 + \gamma_1$. The OLS estimates use the actual value of A(i). The IV estimates use equation (2) to predict the probability of being allowed.

[14] In order to obtain these IV estimates, we estimate the first stage equation equation (2) as before, then estimate a modified version of equation (3) using the distributed lag model

y(it)= $\sum_{\tau=-10}^{5}[1\{\tau=t\}\times(\gamma_{0\tau}+\hat{A}(i)\gamma_{1\tau})]$. Figures 5 and 6 plot the $\gamma_{0\tau}$ and $\gamma_{1\tau}$ coefficients.

Table 5 disaggregates the earnings responses by demographics, earnings, and health conditions. Column 1 reports estimated earnings for denied individuals and column 2 the associated standard error. Column 3 reports the effect of being allowed benefits and column 4 the standard error. For all groups, being allowed benefits reduces earnings. When pooling all groups together we see that being allowed benefits causes earnings to fall on average from $3858 to $1,655, a difference of $2,203. But some of the groups have relatively small drops, suggesting that their labor supply is relatively insensitive to economic incentives. For example, those with neoplasms (most often cancer), mental disorders, mental retardation, and problems with the nervous and respiratory system all have relatively small earnings declines in response to receipt of DI benefits. For example, those with mental disorders have earnings of $2971 when denied and $1605 when allowed, a difference of $1366.

The low responsiveness of labor supply of those with mental illness is particularly surprising. Mental health is more difficult to monitor than many other health conditions. As a result, some analysts believe that many who claim mental illness are those who are healthy and would have worked in the absence of benefit allowance (Bound and Burkhauser, 1999). This turns out not to be the case.

Table 6 disaggregates the participation responses by demographics, earnings, and health conditions. Table 6 shows that the effect of DI allowance on participation is smaller for college graduates than high school drop outs, and is smaller for mental disorders, mental retardation, and problems of the nervous and circulatory system than for musculoskeletal conditions and injuries. For example, DI allowance reduces participation of college graduates from 39.3% to 27.2%, a decline of 12.1 percentage points. For high school graduates, DI allowance reduces participation from 31.8% to 16.7%, a reduction of 15.2 percentage points.

Figure 7 presents IV estimates of the distribution earnings 5 years after assignment to an ALJ.[15] It shows the CDF of earnings both for the group that was allowed benefits and for the group that was denied benefits. Allowed individuals have lower earnings at all percentiles of the distribution. It shows that the 90th percentile of the distribution of allowed individuals is $4,000,

[15] The instrumental variables procedures used are described in the Appendix. However, we also tried more standard quantile IV procedures which produced similar estimates.

whereas for denied individuals it is $13,000. Surprisingly, we see little evidence of bunching at the Substantial Gainful Activity level of $9,000 for those allowed benefits.[16]

Figure 8 presents IV estimates of the distribution of earnings for those with positive earnings. Those who are allowed are less likely to earn above the Substantial Gainful Activity level. 60% of workers who are allowed earn less than $9,000, whereas 50% of denied workers earn less than $9,000. Thus, not only do those allowed benefits have lower participation, they have lower earnings, conditional on participation.

6.4 Elasticity of Labor Supply with Respect to the After Tax Wage

In this section we present estimates of the effect of DI on the implicit tax on work and thus the after tax wage, as well as the earnings and participation elasticity with respect to the after tax wage. In this section we focus on the work incentives Figure 1 shows the static budget set faced by an individual drawing DI benefits.

Table 6 shows participation and earnings elasticities with respect to the after tax wage, which we calculate as follows:

$$(4)\quad \varepsilon_{y,w} = \frac{(y(A=0) - y(A=1))/(y(A=0) + y(A=1))}{(w(A=0) - w(A=1))/(w(A=0) + w(A=1))}$$

where y(A=0) is the outcome variable (either mean earnings or participation) of denied individuals and y(A=1) is the outcome variable for allowed individuals. w(A=0) is the after tax wage for denied individuals and w(A=1) is the after tax wage for allowed individuals.

The after tax wage is defined as the income gain from wage earnings plus DI benefits (net of federal, state and payroll taxes) when working. We first predict the distribution of pre-tax wages

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[16] The Substantial Gainful Activity limit for non-blind individuals was $6,000 per year in current dollars from 1990 to mid 1999, which averages to $7,600 in 2006 dollars. The limit increased to $8,400 in 1999, then was indexed afterwards to rise with national wages, which averages to $9,800. We take the average of these two numbers, $8,700, for the average limit. For blind individuals, the limit is on average 60% higher than for non-blind individuals.

and DI benefits for everyone in the sample. Because working when allowed benefits often causes the loss of DI benefits, the after tax wage for this group w(A=1) is small.[17]

The first row of table 6 shows that the average pre-tax wage of workers in our sample is $12,620. The second row shows that the average predicted DI/SSI benefit in our sample is $7,569. The third row shows the average after tax wage, defined as the difference between after tax earnings plus DI/SSI benefit if work and average DI/SSI benefit it not working. The after tax wage is $10,419 on average for those who are denied benefits. Because most people who are working earn above the Substantial Gainful Activity level, most people who are allowed benefits will lose their DI benefit if they work. The average post-tax wage for those allowed benefits is thus $4,542. Thus, most of the gain from working is lost when the individual has been allowed DI benefits. We take estimates of earnings and participation if allowed versus denied (i.e., y(A=0) and y(A=1)) from table 4.[18] Table 6 shows that the implied earnings elasticity is 1.02 and participation elasticity is 1.02. Thus, while our estimates suggest that most people who are allowed benefits would not have worked even if they were denied benefits, labor supply is elastic for this group of individuals.

7. Appeals and Reapplications

[17] We estimate wages for denied and allowed applicants, w(A=0) and w(A=1), as follows. First, we estimate the distribution of wages facing DI applicants by estimating wage equations (using selection models to account for non-participation) and estimating the distribution of residuals. Second, we predict the distribution of pre-tax wages for every individual in the data. We take one draw from this distribution for every individual in the data. Third, we calculate the DI/SSI benefit for everyone in the sample. Because we have Social Security earnings histories for these people, we can calculate their DI benefits accurately. We impute SSI benefits for those drawing SSI benefits. Fourth, we predict the distribution of post-tax wages plus DI benefits (i.e., the difference between income if working and income if not working) for everyone in our data using the federal, state, and local tax schedule shown in French and Jones (2009). Those who are allowed benefits will have DI benefits if predicted income if working is below the Substantial Gainful Activity limit of $9,000. If income is above $9,000, then the individual will lose benefits. If the individual is denied benefits, then there are no DI benefits to be lost when working. We assume that SSI benefits are reduced 50 cents for each dollar earnings. Fifth, we take the sample average after tax wage if denied and allowed, which is our measure of w(A=0) and w(A=1). Our main limitation on these measurements is that ideally we should know family structure and all sources of income to calculate taxes. Unfortunately, we do not have this information, so we assume that the individual can claim no dependants for the DI benefit and is not pushed into a higher marginal tax bracket from spousal or other non-labor income.

[18] Equation (3) shows that y(A=1)= $\gamma_0 + \gamma_1$ and y(A=0)= γ_0.

Denied applicants have the option to appeal denials or reapply for benefits. Thus it seems plausible that a large number of denied applicants would subsequently appeal the denial or reapply for benefits. In order to appeal or reapply for benefits, individuals must keep their earnings below the substantial gainful activity level. Thus the low earnings level of denied applicants may not be caused by the poor health of denied applicants. Instead, the low earnings may be caused by the incentives to appeal or to reapply for benefits.

This section shows the share of individuals denied at the ALJ stage who appeal, reapply, and are subsequently allowed benefits.[19] Thus we can address many of the key issues presented in the exchange between Parsons (1991) and Bound (1989, 1991).

Figure 9 shows the share of denied (at the ALJ stage) individuals who are reapplying/appealing, allowed, and no longer replying/appealing relative to when they are assigned to a judge.[20] A large number of initially denied applicants are subsequently allowed benefits. Figure 9 shows that 37% of all applicants denied at the ALJ stage were allowed benefits within five years of assignment to a judge and 51% are allowed benefits within 10 years. Figure 9 also shows that many initially denied individuals continue to reapply or appeal for many years after their initial denial. For example, 5 years after assignment to an ALJ, 27% of all initially denied individuals are still in the process of appealing or reapplying for benefits.

Figure 10 shows the share of initially denied individuals who are allowed benefits, are still in the process of reapplying/appealing, or have given up applying for benefits relative to when they are assigned to a judge, where the shares are instrumented using judges. Thus the difference between Figure 9 and 10 is that Figure 9 uses OLS and Figure 10 uses IV, where initial denial is instrumented using judge assignment. Those affected by the instrument are likely the marginal cases who have better chances of final allowance than for average denials. For this reason we might think that subsequent allowance rates of those initially denied would be higher when instrumented. In fact, this is the case, although the OLS estimates in Figure 9 and the IV estimates in Figure 10 are surprisingly similar. Figure 10 shows that for those initially denied

[19] We use data from ACAPS and LOTS to identify denied applicants who successfully appealed at either the Appeals Council or the Federal Court level. We use data from SSA 831 files, MBR (Master Beneficiary Record), and SSR (Supplemental Security Record) to identify denied applicants to reapplied for benefits and were allowed at either the DDS, Reconsideration, ALJ, Appeals, or Federal Court level stage.

benefits, the IV estimate of allowance is 40% five years after assignment and 54% ten years after assignment (versus 37% and 51% from the OLS estimates).

In short, over 19% of all applicants denied by an ALJ are subsequently allowed DI benefits within 5 years. For this reason our estimates in Section 6 understate the true causal effect of disability benefits on subsequent labor supply decisions, as many of those who we count as denied subsequently receive benefits.

8. Conclusion

We find that DI has a work disincentive effect, but the effect is modest.

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Appendix A: Data

We use the universe of all DI appeals heard by ALJs, 1990-2006. We use data from the Office of Hearings and Appeals Case Control System (OHACCS), the Hearing Office Tracking System (HOTS), the Appeals Council Automated Processing System (ACAPS), the Litigation Overview Tracking System (LOTS), the SSA 831 file, SSA Master Earnings file (MEF), and the SSA Numerical Identification (NUMIDENT) file.

The OHACCS data contain the high quality data on the details of Social Security DI and SSI cases adjudicated at the ALJ level (and also contain limited information on cases heard at the

Appeals Council, Federal or Supreme Court). In addition to SSI and DI, they include cases involving Retirement and Survivors Insurance as well as Medicare Hospital insurance. We keep only the SSI and DI cases. The OHACCS data are used for administering DI and SSI cases, and are thus very accurate. The OHACCS data include information on the judge assigned to the case, the hearing office, the date of assignment, and the outcome of the case (such as allowed or denied). It also has data on the claimant's Social Security number, and type of claim (DI versus SSI). The data include all cases filed in 1982 to present. Because our earnings data go back to 1980, and we use earnings data 10 years prior to assignment, we use OHACCS data 1990-2006.

Until 2004, individual hearing offices maintained their own data, called the Hearing Office Tracking System (HOTS). These data were then uploaded to the OHACCS system. We found some missing cases in the OHACCS system. These are apparently the result of HOTS data not being properly uploaded. The problem occurs in about 1% of all cases. For these cases we augment the OHACCS data with HOTS. After 2004 all uploading of data is automatic, and thus there are no problems with missing data.

OHACCS also contains Appeals Council records. However, data on Appeals Council decisions are sometimes missing from OHACCS. Thus we use the Appeals Council Automated Processing System (ACAPS) data to track actions on cases heard at the Appeals Council level. ACAPS is the Appeals Council's data for administration of cases.

The Litigation Overview Tracking System (LOTS) data are used for administration of cases that are heard at the Federal or Supreme Court level. These data provide information on which cases that were denied at the Appeals Council level were appealed at the Federal Court level. We combine the LOTS data with information provided by the Federal Court to determine whether the cases was eventually allowed or denied.

The SSA 831 data have information on the details of the DI application received at the Disability Determination Service. The data include information on the type of application (whether DI or SSI or concurrent) and whether the claim is on one's own earnings history or on the history of a spouse or parent. It also has all the information relevant for determining whether the application should be allowed, either through a medical listing or the vocational grid. Thus we have detailed medical information, such as the health condition of the individual. Because of the vocational grid, we have information on age, education, industry and occupation. We also have some other demographic information such as sex. Since a new 831 record is established whenever a new application is filed and adjudicated, we use information in the 831 file to identify those who reapplied for benefits.

The Master Earning File (MEF) includes annual longitudinal earnings data for the US population. It includes not only individuals' annual Social Security covered earnings from 1951 to the present (which we use to calculate the Primary Insurance Amount for DI benefits), but also individuals' annual wages directly taken from the W-2 starting from 1978. Because of data quality issues, we do not use data from 1978 and 1980. Wage earnings are not top-coded, but self-employment earnings are top coded until 1992. Our earnings measure is the sum of wage earnings and self employment earnings, which we topcode at $200,000 per year.

Lastly, we use the SSA NUMIDENT for information on date of death. The NUMIDENT file includes information from the Social Security Number application form such as name, date of birth and Social Security number. Once the individual dies, the date of death is placed on the file.

For Figure 2A and 2B we use all cases filed 1989-1999. We make no sample restrictions for these cases. For all other figures and tables, we make the following sample restrictions, described in Table A1:

1. We drop all Medicare cases. These Medicare cases are typically disputes over whether Medicare will pay for certain medical treatments.
2. We drop all remand cases (cases sent to Appeals Council, then sent back to the hearing office). We drop these because this would lead to double counting of cases, as a remand is a case that was already heard by an ALJ.
3. We drop cases with a missing Social Security number. This leaves us with 3,525,787 cases for 1990-1999 and 2,464,262 for 2000-2006.
4. We drop all cases younger than 35 or older than 64. For individuals in this age range, we keep all SSI, DI and concurrent cases where the individual is claiming against his own earnings history. Thus for DI and concurrent cases we drop records where the claim is against the earnings record of a spouse or parent.
5. We drop cases with missing judge or hearing office information.
6. We drop cases that were previewed prior to being assigned to a judge, approximately 1/3 of total. These cases are extremely likely to be critical cases that are reviewed by at senior attorney.

7. We drop cases that were dismissed. This leaves us with 1,842,960 cases for 1990-1999 and 1,698,340 cases for 2000-2006.
8. Of the 1,842,960 cases for 1990-1999, 504,324 were cases assigned to a high allowance judge, and matched to a non-high allowance judge.

Appendix B: Additional Results

Judges

Table A1 has some additional information on judges. For 2000-2006, there were 1,411 judges, of which 1,377 heard over 50 cases. The 274 judges with the highest allowance rates during the 2000-2006 period are our high allowance judges. Over the 1990-1999 period, these 274 judges heard 257,781 cases (of which 252,162 where matched to case heard by other judges during a window of plus or minus 15 days at the same hearing office).

Figure A1 shows the distribution of the judge-specific allowance rates in the sample period. As can be seen in the graph, many judges with high allowance rates during the 2000-2006 period have low allowance rates during the estimation (1990-1999) period, and many judges with low allowance rates during the 2000-2006 period have high allowance rates during the estimation period. Nevertheless, on average, those with high allowance rates during the 2000-2006 period are 19% more likely to allow a case during the estimation period.

Robustness Checks

Table A2 shows estimates of some robustness checks. Row 1 shows the basic estimates, row 2 shows estimates when we drop people who attrit from the sample, rows 3 and 4 changes the threshold for treatment judge changes from .2 to .1 and .3 respectively, and rows 4 and 5 show estimates when limited to 1994-1995 and 1996-1997 respectively. Table 7 shows that our estimates are little affected by making any of these changes.

Appendix C: IV Estimator of the Distribution of Responses

This appendix shows how we estimate the CDF of income for allowed versus denied applicants, instrumenting for the endogeneity of allowance. Consider individual i drawn randomly from the distribution of unobservable preferences and abilities X who is applying for DI benefits. We are interested in two objects. First, we are interested in the probability that earnings y(i) are less than a threshold level y^*, given that the individual was denied D, which is $P(y(i)<y^*|X, D)$, and if the individual is allowed it is $P(y(i)<y^*|X, A)$. Second, we are interested in the probability that earnings y(i) are less than y^*, given that the individual was allowed A, which is $P(y(i)<y^*|X, A)$. Define the probability that y(i) is less than y^*, given that they are randomly drawn from the distribution X and that the individual is assigned to a low allowance judge as $P(y(i)<y^*|X, H(i)=0)$, and for high allowance judges H(i)=1 it is $P(y(i)<y^*|X, H(i)=1)$. If assignment to high versus low allowance judges is truly random, then the distribution of preferences for the two groups should be the same, and should have the same distribution X.

By the law of total probability,

(A1) $P(y(i)<y^*|X, H(i)=0)= P(y(i)<y^*|X, D, H(i)=0)\, P(D|X, H(i)=0) + P(y(i)<y^*|X, A, H(i)=0)\, P(A|X, H(i)=0)$

and

(A2) $P(y(i)<y^*|X, H(i)=1)= P(y(i)<y^*|X, D, H(i)=1)\, P(D|X, H(i)=1) + P(y(i)<y^*|X, A, H(i)=1)\, P(A|X, H(i)=1)$.

Because assignment to high versus low allowance judges is irrelevant beyond its effect on its effect on the probability of being allowed, then

(A3) $P(y(i)<y^*|X, D, H(i)=0)= P(y(i)<y^*|X, D, H(i)=1) = P(y(i)<y^*|X, D)$

and

(A4) $P(y(i)<y^*|X, A, H(i)=0)= P(y(i)<y^*|X, A, H(i)=1) = P(y(i)<y^*|X, A)$

Inserting equation (A3) and (A4) into (A1) and (A2) yields

(A1') $P(y(i)<y^*|X, H(i)=0)= P(y(i)<y^*|X, D)\, P(D|X, H(i)=0) + P(y(i)<y^*|X, A)\, P(A|X, H(i)=0)$

and

(A2') $P(y(i)<y^*|X, H(i)=1)= P(y(i)<y^*|X, D)\, P(D|X, H(i)=1) + P(y(i)<y^*|X, A)\, P(A|X, H(i)=1)$

Equations (A1) and (A2') are two equations. We must solve for the two unknowns $P(y(i)<y^*|X, D)$ and $P(y(i)<y^*|X, A)$. In those equations we can measure $P(y(i)<y^*|X, H(i)=0)$, $P(y(i)<y^*|X,$

H(i)=1), P(D|X, H(i)=0), (P(A|X, H(i)=0)=1- P(D|X, H(i)=0)), P(D|X, H(i)=1), (P(A|X, H(i)=1)=1- P(D|X, H(i)=1)).

Solving for these two unknowns yields:

(A4) P(y(i)<y*|X, A)= [(P(y(i)<y*|X, H(i)=0)-G P(y(i)<y*|X, H(i)=1)]/[(P(A|X, H(i)=0)-G P(A|X, H(i)=1)]

and

(A5) P(y(i)<y*|X, D)= G[(P(y(i)<y*|X, H(i)=1)-H P(y(i)<y*|X, H(i)=0)]/[(1-G*H]

where

G=[P(D|X, H(i)=0) / P(D|X, H(i)=1)], H= [P(A|X, H(i)=1) / P(A|X, H(i)=0)].

Appendix D: Identifying the extent of endogeneity of the IV Estimator

This appendix shows how we estimate the extent of endogeneity of our instrument of high allowance judge. Recall the first stage and second stage equations.

(B1) A(i)= β_0 + H(i) β_1 + u*(i)

(B2) y(i)= γ_0 + $A(i)$ γ_1 + ε*(i)

Suppose that H(i) is uncorrelated with ε*(i) but we do not measure H(i), but instead measure H*(i), where

(B2a) H*(i)= $\begin{cases} A(i) with prob\ p \\ H(i) with prob\ 1-p \end{cases}$

If p=1 then our IV estimates will be identical to OLS. If p=0 then we will be able to estimate the true causal effect of DI allowance with our instrument.

Suppose the projection of ε*(i) on u*(i) yields

(B3) ε*(i) $= \varsigma(i) + \theta u*(i)$

where ς (i) is white noise and θ is a parameter. The OLS estimator of γ_1 when estimating equation (B2) converges to

(B4) $\gamma_{1OLS} = \gamma_1 + \theta \frac{Var[u^*]}{Var[A]}$

IV estimates of γ_1 using H as an instrument converge to γ_1, but using equations (B2), (B2a), and (B3) we can show that IV estimates using H* as an instrument converge to

(B5) $\gamma_{1IV} = \frac{Cov[y, H^*]}{Cov[A, H^*]}$

$$= \frac{Cov[\gamma_1 A, H^*] + Cov[\varepsilon^*, H^*]}{Cov[A, H^*]}$$

$$= \gamma_1 + p\theta \frac{Var[u^*]}{Cov[A, H^*]}$$

Using equations (B4) and (B5) we can derive

(B6) γ_1 = (γ_{1IV} - (pVar[A]/Cov[A, H*]) γ_{1OLS})/(1-(pVar[A]/Cov[A, H*])).

Thus we can identify the true causal effect of disability on labor supply using the OLS and IV estimates of γ_1 and Cov[A, H*]/Var[A] if we know p. We discuss OLS and IV estimates of γ_1 in the text. We identify Cov[A, H*]/Var[A] by OLS regression of H* on A. Thus all that remains is to identify p.

Our approach to identifying p is to use the observable variables, such as age, race, education and health conditions. Recall that if H* were truly randomly assigned, H* would be uncorrelated with the observable variables. Thus we can use the correlation of H* with the observables to identify the extent to which H* is not randomly assigned. Suppose we have K observable variables. Define x(k) as the kth observable (e.g., the 0-1 indicator for age<45) and define ε (k)= (x(k)-E(x(k))). The projection of ε (k) on u* is

(B7) ε (k) = $\varsigma(k) + \theta(k) u^*$

for all K observable variables ε(k), as well as ε(K+1), which is unobservable. Recall that u* is the residual in the first stage regression. Thus $\theta(k)$ parameterizes the correlation between the ε(k) and u*. By construction, $\varsigma(k)$ is uncorrelated with u*. The least squares projection coefficients of a regression of ε* on ε(1), …, ε(K-1) are

(B8) $\varepsilon * = \sum_{k=1}^{K+1} \phi(k)\varepsilon(k) = \sum_{k=1}^{K+1} \phi(k)(\varsigma(k) + \theta(k)u^*) = \varsigma + \theta u^*$

Where the $\phi(k)$ parameters are coefficients in the regression, $\sum_{k=1}^{K+1} \phi(k)\varsigma(k) = \varsigma$ and $\sum_{k=1}^{K+1} \phi(k)\theta(k) = \theta$. Note that this is the projection formula in equation (B3) and thus will produce the OLS and IV estimates in equation (B4) and (B5).

Now we identify p. From the Law of Total Expectations

E[ε(k)| H*]= E[ε(k)| H*, H*=A]prob[H*=A|H*] + E[ε(k)| H*, H*=H]prob[H*=H|H*]
= E[ε(k)| A]prob[H*=A|H*]
= E[ε(k)| A]p

Thus

(B9) p(k)= E[ε(k)| H*]/ E[ε(k)| A]

Equation (B8) can be used to estimate p a total of K times, so we have K estimates. Our final estimate of p is the average of the K estimates of p(k), or the weighted average, where the weights are the inverse variance of our estimate of E[ε(k)| H*]/ E[ε(k)| A]. Define a= E[ε(k)| H] and b = E[ε(k)| A]. We estimate the variance of this using the delta method: V(a/b)=(1/E(b))^2 * V(a) + (E(a)/E(b))^2 V(b) -2 (E(a)/E(b)) Cov(a,b)]. We need to get the covariance term from Jae. We have everything else. Our preliminary estimates that ignore the covariance term suggest p=.02, so our instrument is for all practical purposes randomly assigned.

TABLE 1: SAMPLE MEANS, ALLOWED VERSUS DENIED

Dependent Variable	Allowed Mean (1)	Denied Mean (2)	Difference (1)-(2) (3)	Std. Error of difference (4)	T-ratio of difference (5)
		Sex			
Male	0.493	0.500	-0.008	0.001	-5.3
Female	0.507	0.500	0.008	0.001	5.3
		Age			
44 or younger	0.317	0.425	-0.108	0.001	-78.6
45 to 54	0.426	0.430	-0.004	0.001	-2.9
55 to 59	0.168	0.096	0.072	0.001	76.8
60 or older	0.089	0.049	0.040	0.001	56.8
		Race			
White	0.662	0.586	0.075	0.001	54.4
Black	0.223	0.277	-0.053	0.001	-43.0
Other (non-black, non-white) or unknown	0.115	0.137	-0.022	0.001	-23.0
		Labor force participation and income			
Average participation rate, years -11 to -2	0.691	0.620	0.071	0.001	76.7
Average earnings, years -11 to -2 ($2006)	17,118	12,564	4554.724	56.546	80.5
		Represented by lawyer			
Represented by lawyer	0.693	0.600	0.093	0.001	67.7
		Application type			
SSDI	0.407	0.325	0.082	0.001	59.9
SSI	0.224	0.307	-0.083	0.001	-65.4
Concurrent (both SSDI and SSI)	0.369	0.368	0.001	0.001	0.7
		Education			
Less than high school	0.074	0.050	0.024	0.001	35.2
High school graduate, no college	0.376	0.378	-0.002	0.001	-1.8
Some college	0.406	0.415	-0.009	0.001	-6.6
College graduate	0.099	0.116	-0.017	0.001	-19.3
Unknown	0.045	0.040	0.005	0.001	8.7
		Health conditions (by diagnosis group)			
Neoplasms (e.g., cancer)	0.020	0.019	0.001	0.000	2.6
Mental disorders	0.138	0.175	-0.036	0.001	-34.8
Mental retardation	0.016	0.019	-0.003	0.000	-8.0
Nervous system	0.058	0.054	0.004	0.001	5.6
Circulatory system (e.g., heart disease)	0.114	0.099	0.015	0.001	16.8
Musculoskeletal disorders (e.g., back pain)	0.363	0.343	0.021	0.001	15.2
Respiratory system	0.040	0.043	-0.003	0.001	-4.6
Injuries	0.065	0.064	0.002	0.001	2.5
Endocrine system (e.g., diabetes)	0.051	0.047	0.004	0.001	5.9
All other	0.134	0.138	-0.004	0.001	-3.6
		Year assigned to judge			
1990	0.046	0.037	0.009	0.001	16.5
1991	0.061	0.043	0.018	0.001	28.6
1992	0.084	0.059	0.024	0.001	33.5
1993	0.090	0.070	0.020	0.001	26.4
1994	0.112	0.098	0.014	0.001	15.7
1995	0.113	0.120	-0.007	0.001	-7.1
1996	0.109	0.136	-0.027	0.001	-28.8
1997	0.121	0.149	-0.028	0.001	-28.3
1998	0.135	0.152	-0.017	0.001	-17.0
1999	0.128	0.135	-0.007	0.001	-7.0
N	295,062	209,262			

TABLE 2: TESTS FOR VALIDITY OF RANDOMIZATION

Dependent Variable	High (1)	Low (2)	Difference (1) - (2) (3)	Std. Error of difference (4)	T-ratio of difference (5)
Sex					
Male	0.497	0.496	0.000	0.001	0.2
Female	0.503	0.504	0.000	0.001	-0.2
Age					
44 or younger	0.358	0.362	-0.004	0.001	-3.0
45 to 54	0.429	0.427	0.002	0.001	1.7
55 to 59	0.139	0.138	0.001	0.001	0.7
60 or older	0.074	0.073	0.001	0.001	1.5
Race					
White	0.630	0.624	0.005	0.001	3.8
Black	0.241	0.244	-0.002	0.001	-1.8
Other (non-black, non-white) or unknown	0.129	0.132	-0.003	0.001	-3.2
Labor force participation and income					
Average participation rate, years -11 to -2	0.662	0.660	0.002	0.009	0.2
Average earnings, years -11 to -2 ($2006)	15243.4	15266.8	-23.4	57.747	-0.4
Represented by lawyer					
Represented by lawyer	0.643	0.643	0.000	0.001	-0.1
Application type					
SSDI	0.373	0.372	0.001	0.001	0.7
SSI	0.258	0.262	-0.004	0.001	-3.4
Concurrent (both SSDI and SSI)	0.369	0.366	0.003	0.001	2.4
Education					
Less than high school	0.059	0.064	-0.005	0.001	-7.3
High school graduate, no college	0.379	0.375	0.004	0.001	3.1
Some college	0.409	0.410	-0.001	0.001	-0.5
College graduate	0.109	0.106	0.003	0.001	3.1
Unknown	0.044	0.045	-0.001	0.001	-1.9
Health conditions (by diagnosis group)					
Neoplasms (e.g., cancer)	0.020	0.019	0.001	0.000	2.0
Mental disorders	0.156	0.152	0.004	0.001	3.8
Mental retardation	0.016	0.017	0.000	0.000	-0.8
Nervous system (e.g., blindness)	0.056	0.057	-0.001	0.001	-1.2
Circulatory system (e.g., heart disease)	0.109	0.107	0.001	0.001	1.7
Musculoskeletal disorders (e.g., back pain)	0.352	0.353	-0.001	0.001	-0.7
Respiratory system (e.g., asthma)	0.041	0.041	0.001	0.001	1.1
Injuries	0.064	0.067	-0.002	0.001	-3.5
Endocrine system (e.g., diabetes)	0.050	0.049	0.000	0.001	0.7
All other	0.136	0.139	-0.003	0.001	-2.7
Year assigned to judge					
1990	0.042	0.043	-0.001	0.001	-1.2
1991	0.054	0.054	0.000	0.001	0.3
1992	0.075	0.073	0.002	0.001	2.9
1993	0.082	0.081	0.001	0.001	1.0
1994	0.106	0.106	-0.001	0.001	-1.1
1995	0.116	0.117	-0.001	0.001	-1.2
1996	0.121	0.120	0.001	0.001	0.6
1997	0.132	0.133	-0.001	0.001	-1.3
1998	0.143	0.142	0.001	0.001	0.6
1999	0.131	0.131	0.000	0.001	-0.3
N	252162	252162			

Robust standard errors reported in column (4)

TABLE 3: ALLOWANCE RATES, BY DEMOGRAPHICS

	Allowance rate Average (1)	Allowance rate High group (2)	Allowance rate Low group (3)	Difference (3) - (2) (4)	Std. Error of difference (5)	T-ratio of difference (6)
		All groups				
All groups	0.585	0.681	0.489	-0.192	0.001	-141.3
		Sex				
Male	0.581	0.674	0.489	-0.185	0.002	-95.4
Female	0.589	0.688	0.489	-0.199	0.002	-104.4
		Age				
44 or younger	0.512	0.616	0.408	-0.208	0.002	-91.0
45 to 54	0.583	0.684	0.482	-0.203	0.002	-97.7
55 to 59	0.712	0.787	0.637	-0.150	0.003	-44.3
60 or older	0.719	0.787	0.653	-0.134	0.005	-28.8
		Race				
White	0.614	0.709	0.518	-0.191	0.002	-112.8
Black	0.532	0.625	0.441	-0.183	0.003	-65.8
Other (non-black, non-white) or unknown	0.542	0.649	0.437	-0.212	0.004	-54.6
		Labor force participation and income				
Average participation rate, years -11 to -2<70%	0.521	0.618	0.424	-0.194	0.002	-87.9
Average participation rate, years -11 to -2≥70%	0.626	0.721	0.531	-0.191	0.002	-111.5
Average earnings, years -11 to -2 ($2006)<$10	0.525	0.624	0.426	-0.198	0.002	-103.5
Average earnings, years -11 to -2 ($2006)≥$10	0.650	0.742	0.557	-0.186	0.002	-97.7
		Represented by lawyer				
Represented by lawyer	0.619	0.718	0.521	-0.197	0.002	-119.2
		Application type				
SSDI	0.638	0.734	0.542	-0.191	0.002	-88.0
SSI	0.507	0.602	0.414	-0.188	0.003	-68.9
Concurrent (both SSDI and SSI)	0.586	0.683	0.488	-0.195	0.002	-87.1
		Education				
Less than high school	0.675	0.755	0.590	-0.166	0.005	-32.1
High school graduate, no college	0.583	0.679	0.489	-0.189	0.002	-85.3
Some college	0.580	0.676	0.482	-0.194	0.002	-91.1
College graduate	0.546	0.651	0.442	-0.209	0.004	-49.7
Unknown	0.613	0.706	0.519	-0.187	0.006	-28.9
		Health conditions (by diagnosis group)				
Neoplasms (e.g., cancer)	0.598	0.680	0.520	-0.161	0.010	-16.5
Mental disorders	0.527	0.635	0.422	-0.212	0.004	-60.5
Mental retardation	0.542	0.630	0.450	-0.180	0.011	-16.9
Nervous system	0.601	0.698	0.501	-0.197	0.006	-34.7
Circulatory system (e.g., heart disease)	0.618	0.703	0.535	-0.167	0.004	-40.8
Musculoskeletal disorders (e.g., back pain)	0.599	0.699	0.499	-0.199	0.002	-87.9
Respiratory system	0.570	0.657	0.483	-0.174	0.007	-25.8
Injuries	0.592	0.686	0.494	-0.191	0.005	-35.8
Endocrine system (e.g., diabetes)	0.603	0.695	0.512	-0.183	0.006	-30.2
All other	0.579	0.670	0.487	-0.183	0.004	-49.3
		Year assigned to judge				
1990	0.638	0.710	0.567	-0.143	0.006	-22.1
1991	0.666	0.747	0.585	-0.162	0.006	-28.7
1992	0.665	0.745	0.583	-0.162	0.005	-33.5
1993	0.645	0.732	0.558	-0.174	0.005	-37.5
1994	0.616	0.705	0.529	-0.176	0.004	-42.6
1995	0.571	0.667	0.477	-0.190	0.004	-47.3
1996	0.530	0.632	0.428	-0.204	0.004	-51.4
1997	0.534	0.631	0.438	-0.193	0.004	-51.0
1998	0.556	0.664	0.448	-0.216	0.004	-59.6
1999	0.573	0.685	0.460	-0.225	0.004	-60.1
N	504324	252162	252162			

TABLE 4: ESTIMATED EFFECT OF DI RECIPIENCY ON LABOR SUPPLY

Estimation procedure	matched sample?	Allowed	Denied	Without Coviates: Difference	Without Coviates: Std. Error	With Covariates: Difference	With Covariates: Std. Error
				Dependent Variable: Earnings			
OLS	yes	1600	3937	-2337	22	-2495	28
OLS	no	1566	3934	-2368	15	-2583	52
IV	yes	1655	3858	-2203	126	-2277	120
IV	no	1481	4101	-2620	98	-2158	97
				Dependent Variable: Participation			
OLS	yes	0.141	0.305	-0.164	0.001	-0.163	0.001
OLS	no	0.139	0.304	-0.166	0.001	-0.164	0.001
IV	yes	0.152	0.289	-0.137	0.005	-0.138	0.005
IV	no	0.146	0.304	-0.158	0.004	-0.132	0.004

Covariates include all variables described in Table 1 as well as hearing office
Matched sample: N=504,324. Full sample: N=1,842,960.
Left hand side variable is either average earnings or participation, 2-5 years after assignment to a judge

TABLE 5: ESTIMATED EFFECT OF DI RECIPIENCY ON EARNINGS DISAGGREGATED BY DEMOGRAPHICS, INCOME, TYPE OF CLAIM; IV ESTIMATES

	Earnings			
	Allowed	Denied	Difference	Std. Error
All groups				
All groups	1655	3858	-2203	126
Sex				
Male	1872	4720	-2848	220
Female	1418	3034	-1617	134
Age				
45 or younger	2314	5227	-2912	230
45 to 54	1412	3481	-2069	174
55 to 59	900	2239	-1339	311
60 to 64	259	1067	-174	361
Race				
Black	1528	3570	-2042	231
White	1768	4075	-2307	168
Other (non-black, non-white) or unknown	1331	3427	-2097	325
Labor force participation and income				
Average participation rate, years -11 to -2<70%	364	2048	-1684	300
Average participation rate, years -11 to -2≥70%	2323	5088	-2765	192
Average earnings, years -11 to -2 ($2006)<$10000	816	2148	-1332	89
Average earnings, years -11 to -2 ($2006)≥$10000	2637	5891	-3254	249
Represented by lawyer				
Represented by lawyer	1523	4009	-2486	148
Application type				
SSDI	715	1871	-1156	143
SSI	2482	5575	-3093	272
Concurrent (both SSDI and SSI)	1529	3690	-2161	175
Education				
Unknown	1913	4776	-2863	738
Less than high school	811	2560	-1749	139
High school graduate, no college	1660	4405	-2744	201
Some college	3064	4828	-1764	428
College graduate	4800	6957	-2157	1077
Health conditions (by diagnosis group)				
Neoplasms (e.g., cancer)	2727	4089	-1361	1115
Mental disorders	1605	2971	-1366	264
Mental retardation	830	1526	-696	574
Nervous system	2006	3350	-1344	522
Circulatory system (e.g., heart disease)	1240	3421	-2181	373
Musculoskeletal disorders (e.g., back pain)	1731	4570	-2840	219
Respiratory system	1363	2427	-1064	502
Injuries	2210	6080	-3870	619
Endocrine system (e.g., diabetes)	1023	2174	-1151	368
All other	1716	3981	-2265	397
Year assigned to judge				
1990	975	2522	-1547	549
1991	1176	2841	-1664	523
1992	1354	3171	-1818	469
1993	1280	3875	-2595	451
1994	1547	3990	-2443	377
1995	2025	3995	-1970	402
1996	1865	4503	-2638	374
1997	1950	4034	-2084	379
1998	1534	4373	-2839	314
1999	1873	3409	-1536	314

TABLE 6: ESTIMATED EFFECT OF DI RECIPIENCY ON PARTICIPATION DISAGGREGATED BY DEMOGRAPHICS, INCOME, TYPE OF CLAIM; IV ESTIMATES

	Participation			
	Allowed	Denied	Difference	Std. Error
All groups				
All groups	0.152	0.289	-0.137	0.005
Sex				
Male	0.153	0.303	-0.149	0.008
Female	0.150	0.276	-0.126	0.007
Age				
45 or younger	0.202	0.373	-0.171	0.009
45 to 54	0.130	0.260	-0.130	0.007
55 to 59	0.100	0.205	-0.106	0.015
60 to 64	0.112	0.144	-0.032	0.022
Race				
Black	0.175	0.305	-0.130	0.011
White	0.149	0.289	-0.140	0.007
Other (non-black, non-white) or unknown	0.120	0.257	-0.137	0.013
Labor force participation and income				
Average participation rate, years -11 to -2<7(	0.084	0.201	-0.117	0.007
Average participation rate, years -11 to -2≥7(	0.196	0.348	-0.152	0.007
Average earnings, years -11 to -2 ($2006)<$	0.112	0.235	-0.123	0.006
Average earnings, years -11 to -2 ($2006)≥$1	0.195	0.351	-0.155	0.008
Represented by lawyer				
Represented by lawyer	0.146	0.291	-0.145	0.006
Application type				
SSDI	0.094	0.212	-0.118	0.009
SSI	0.190	0.342	-0.151	0.009
Concurrent (both SSDI and SSI)	0.152	0.295	-0.143	0.008
Education				
Unknown	0.134	0.308	-0.175	0.023
Less than high school	0.098	0.224	-0.126	0.007
High school graduate, no college	0.167	0.318	-0.152	0.008
Some college	0.242	0.362	-0.121	0.016
College graduate	0.272	0.393	-0.121	0.030
Health conditions (by diagnosis group)				
Neoplasms (e.g., cancer)	0.184	0.317	-0.133	0.047
Mental disorders	0.172	0.266	-0.094	0.012
Mental retardation	0.120	0.187	-0.067	0.036
Nervous system	0.167	0.282	-0.115	0.022
Circulatory system (e.g., heart disease)	0.135	0.252	-0.117	0.017
Musculoskeletal disorders (e.g., back pain)	0.152	0.320	-0.168	0.009
Respiratory system	0.121	0.239	-0.118	0.026
Injuries	0.171	0.377	-0.207	0.022
Endocrine system (e.g., diabetes)	0.101	0.228	-0.127	0.021
All other	0.156	0.278	-0.121	0.015
Year assigned to judge				
1990	0.100	0.237	-0.138	0.030
1991	0.124	0.227	-0.103	0.024
1992	0.133	0.265	-0.132	0.021
1993	0.142	0.285	-0.142	0.019
1994	0.154	0.312	-0.159	0.018
1995	0.167	0.312	-0.144	0.016
1996	0.165	0.319	-0.154	0.015
1997	0.162	0.299	-0.137	0.015
1998	0.150	0.299	-0.149	0.012
1999	0.159	0.260	-0.101	0.012

TABLE 7: EARNINGS AND PARTICIPATION ELASTICITIES

	Means		Percent	
	Allowed	Denied	Change	Elasticity
Pre Tax Wage	12,620	12,620		
DI benefit if Allowed	7,569	-		
After Tax Wage	3,283	10,419	1.04	
Earnings	1,655	3,858	0.80	0.77
Participation	0.152	0.289	0.62	0.60

Notes: Earnings and Participation estimates are from Table 4
Elasticity is an arc elasticity: see equation (4)

TABLE A1: SAMPLE SELECTION

	Sample size	
	1990-1999	2001-2006
Original sample	3,525,787	2,464,262
Number of drops		
(1): Age at assignment <35 or >64	792,939	518208
(2): Missing judge or hearing office information	174	118
(3): case is pre-viewed	825,302	541869
(4): DI Child case	30,221	8,113
(5): Survivor case	3,564	3966
(6): dismissal	30,627	36000
total number of sample dropped (sum of drops 1-6)	1,682,827	1108274
Remaining sample	1,842,960	1,698,340
number of judges 2001-2006:		1411
number of judges who had 50 or more cases per year in 2001-2006		1377
number of high allowance judges	274	274
Number of cases assigned to high allowance judges	257781	
total matched to low allowance judges	252162	
total low allowance cases	252162	
Number of cases heard by either high or low allowance judge	504,324	
Fraction of remaining sample assigned to high allowance judges	0.13987336	
Fraction of remaining sample assigned to high or low allowance judge:	0.27364891	

TABLE A2: ROBUSTNESS CHECKS

	Earnings of allowed		Earnings of denied	
	Estimate	Std. Error	Estimate	Std. Error
Basic Specification				
Basic Specification	3858	75	-2203	126
*Exclude Attriters**				
Exclude Attriters*	4246	87	-2264	151
Change Threshold for High Allowance				
0.1	3753	86	-2019	152
0.3	3770	70	-2080	114
Treat dismissals as denials				
Include dismissals	4119	64	-2649	98
Change Sample Period				
1994-1995	3999	166	-2255	277
1996-1997	4227	143	-2301	262

*Attriters are individuals who die before sample period ends

All estimates are IV with no covariates

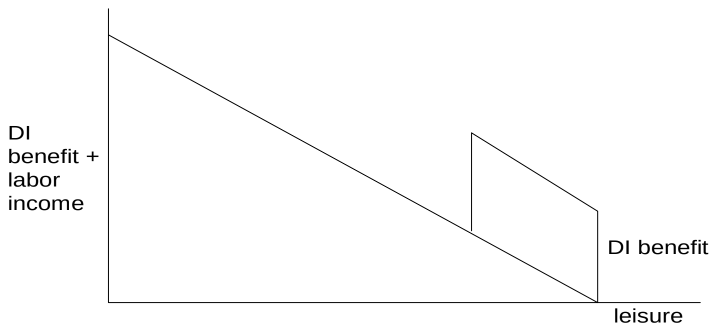

Figure 1: The Static DI Budget Set

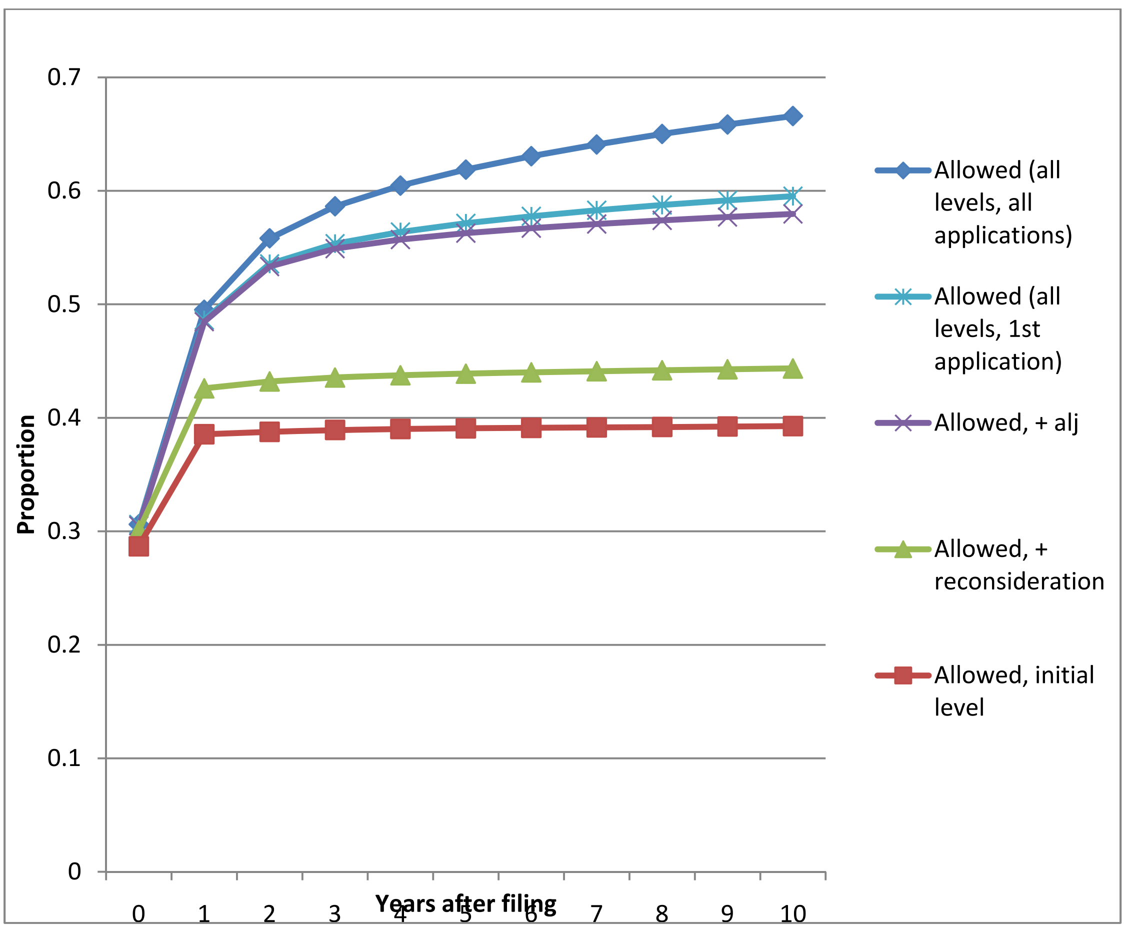

Figure 2A: Allowances at different stages of the applications and appeals process

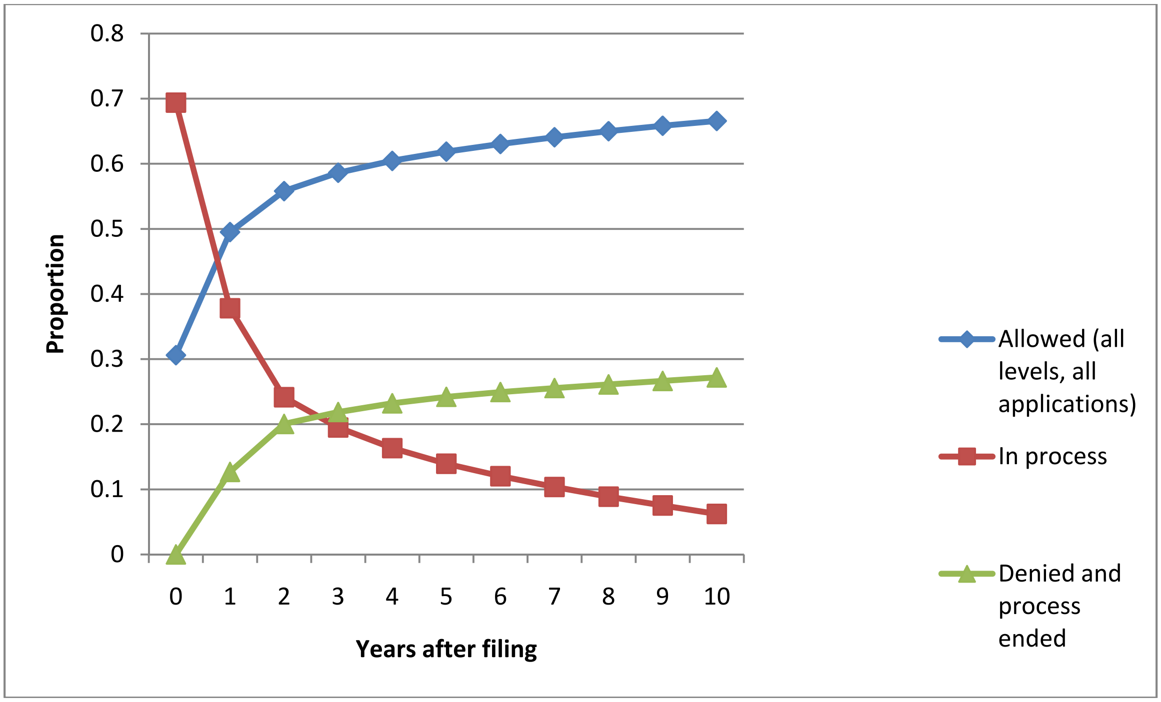

Figure 2B: outcomes of cases

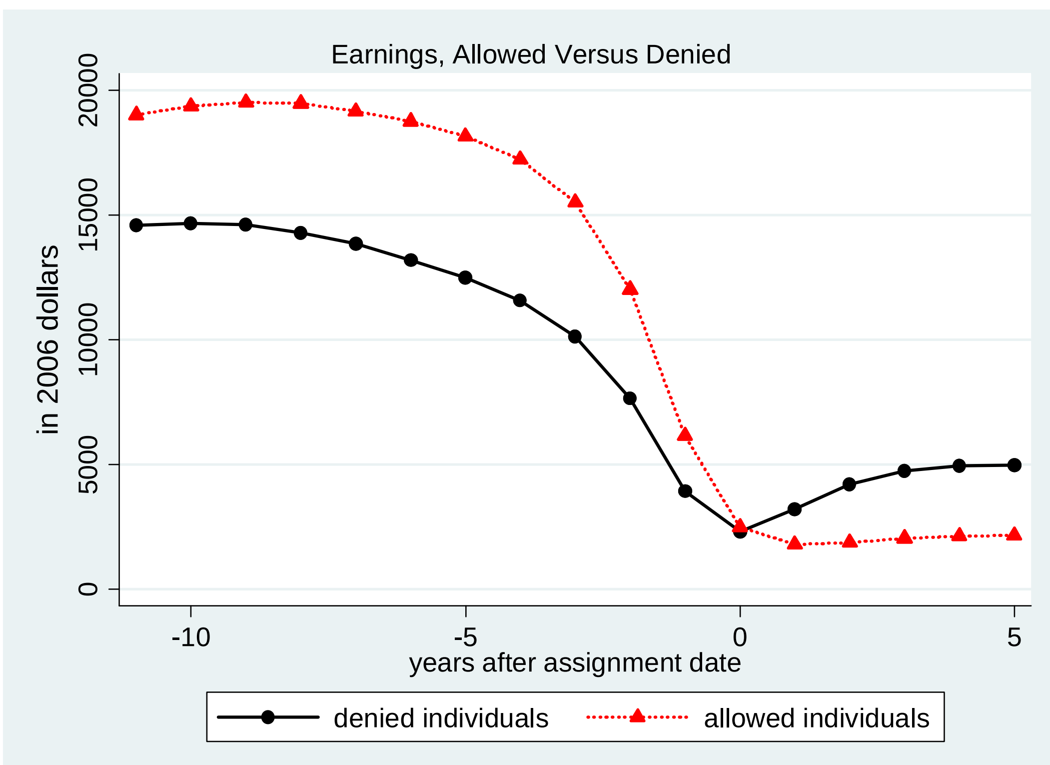

Figure 3

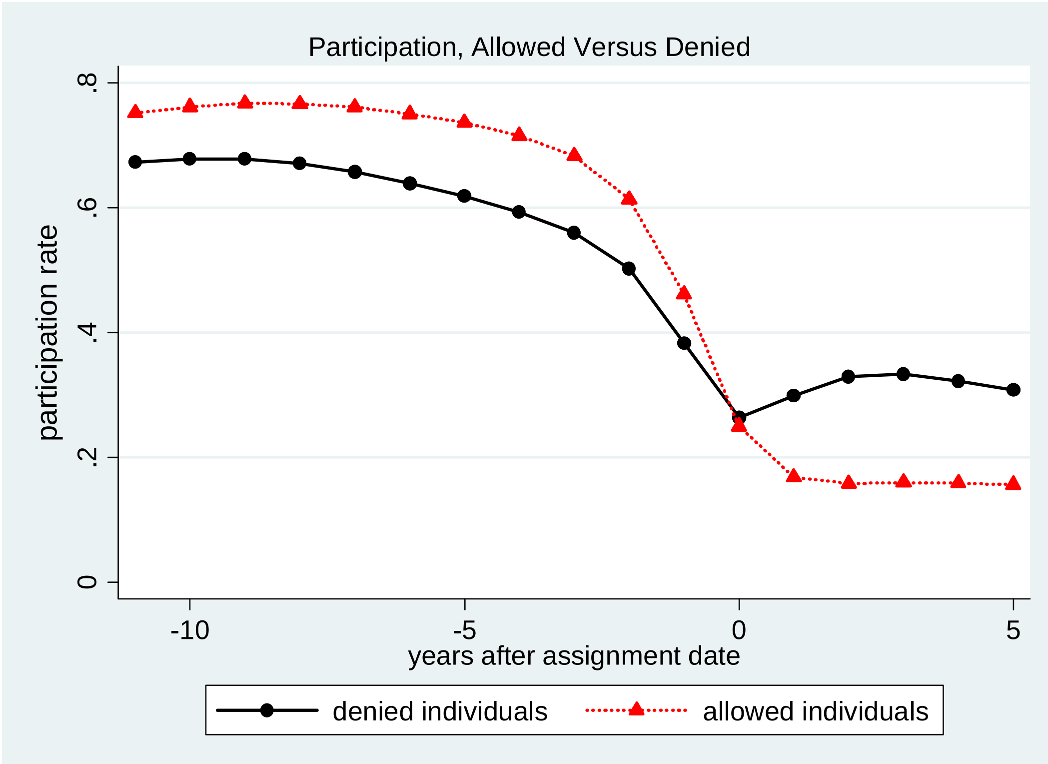

Figure 4

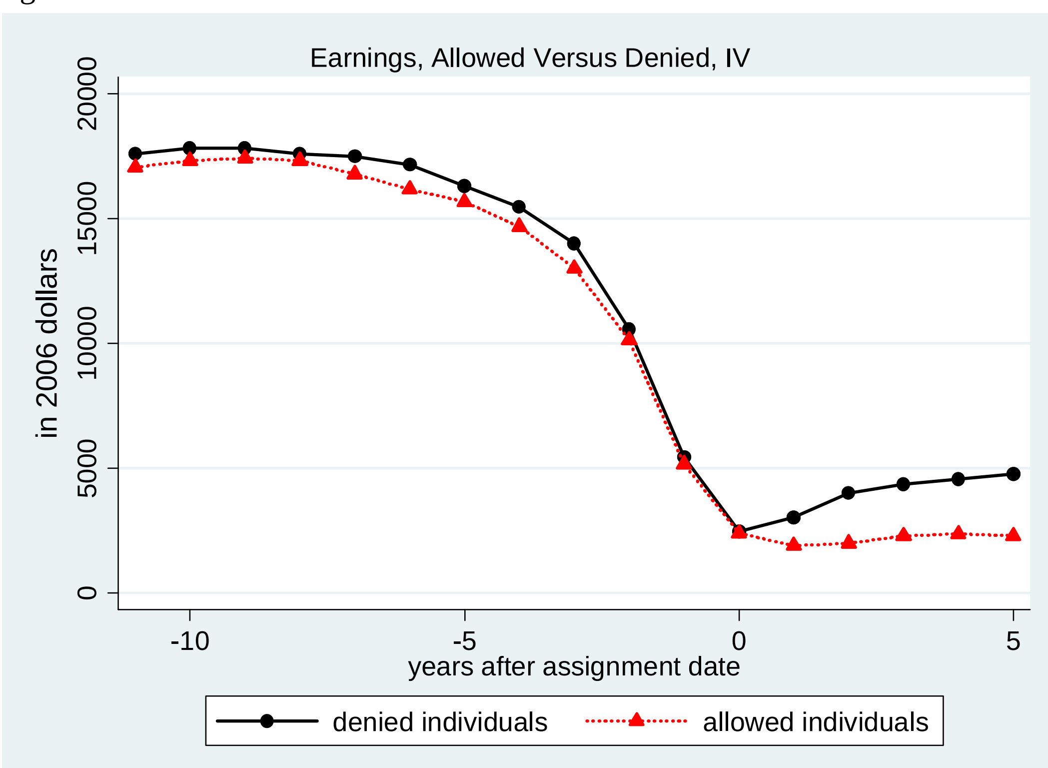

Figure 5

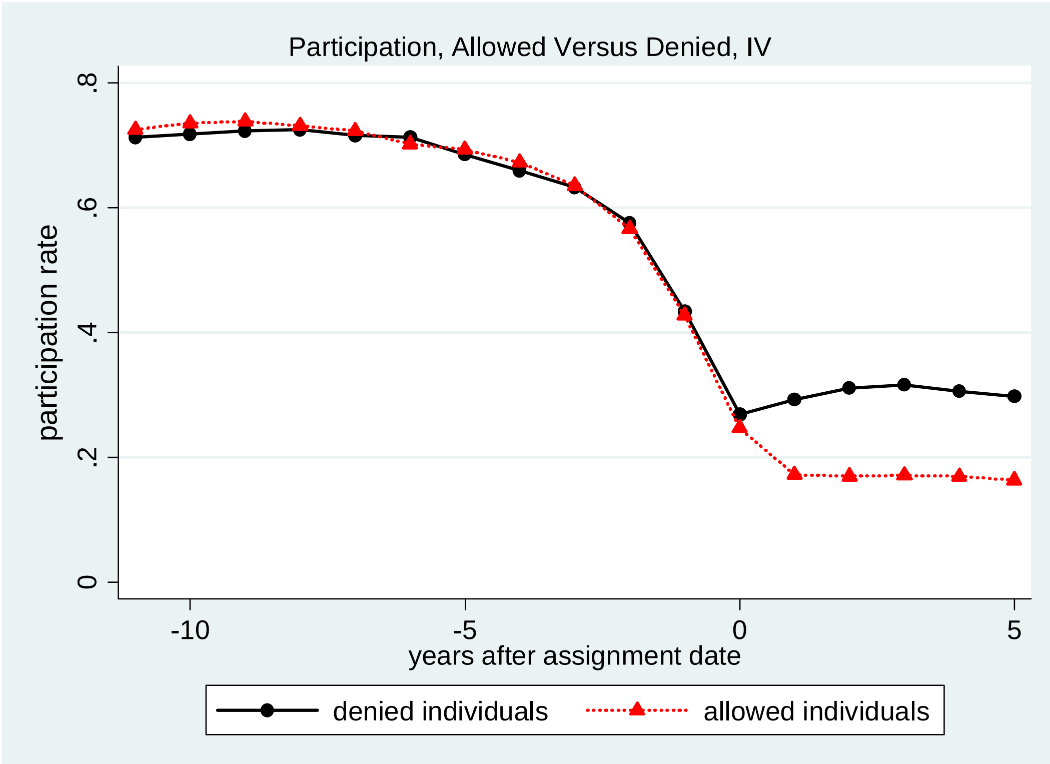

Figure 6

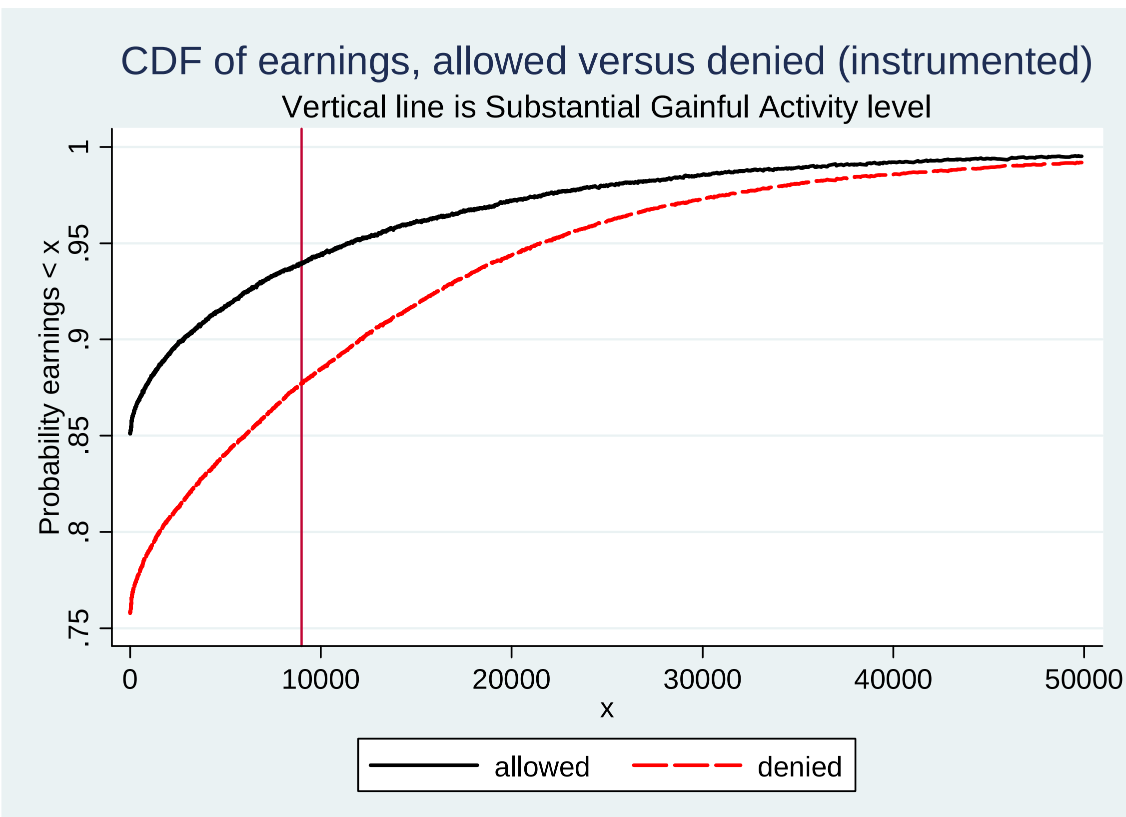

Figure 7

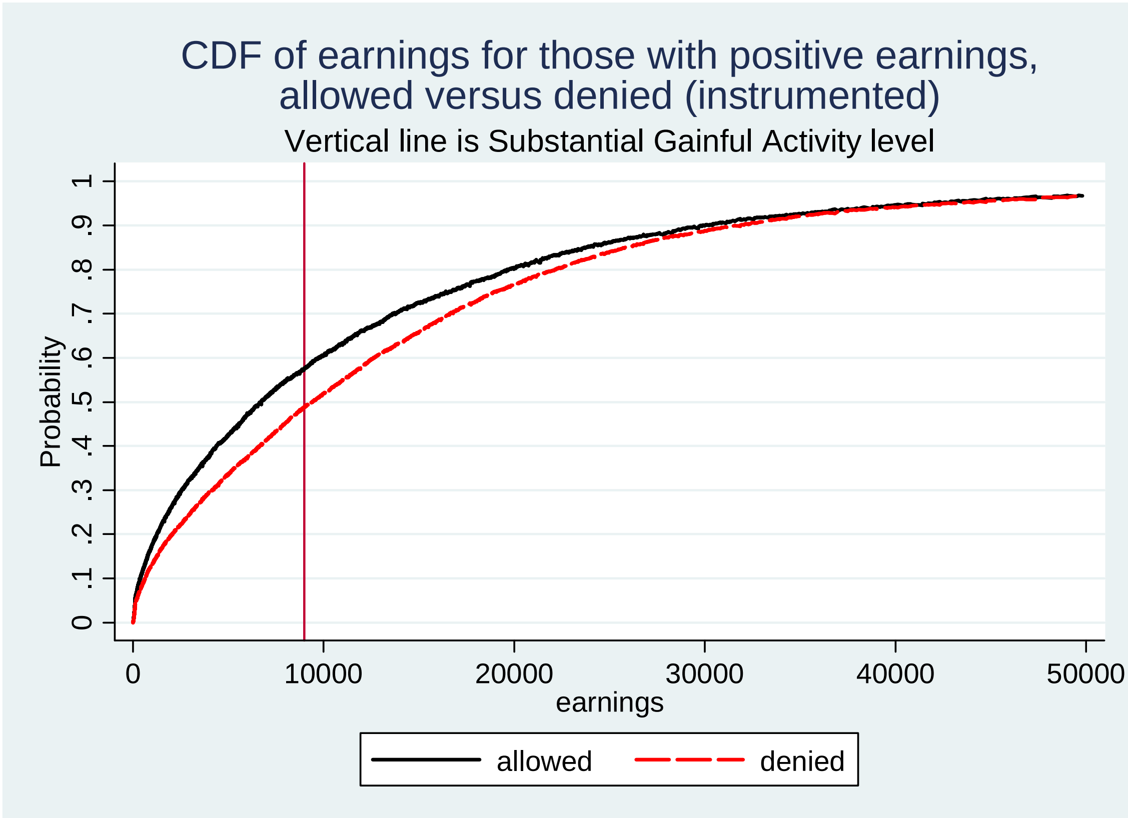

Figure 8

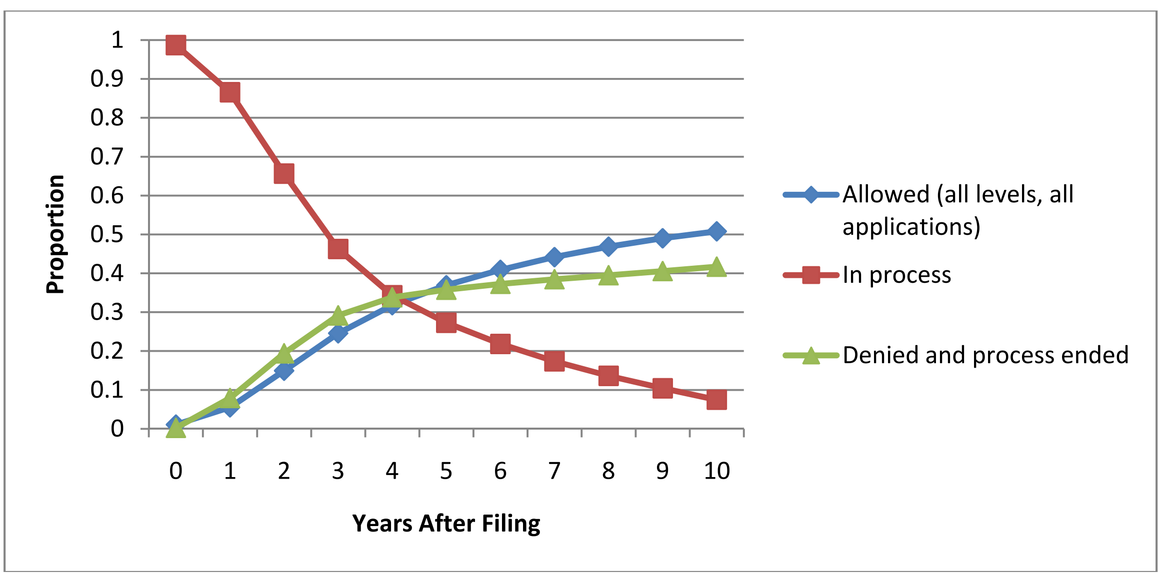

Figure 9: Appeals and reapplications of denied applicants, OLS estimates

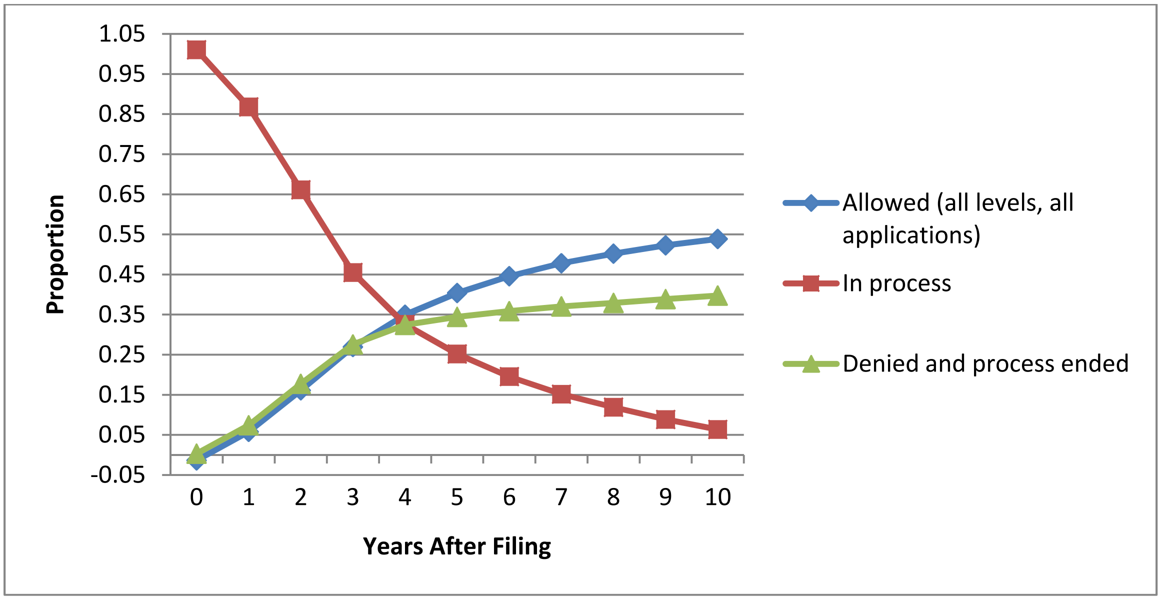

Figure 10: forthcoming

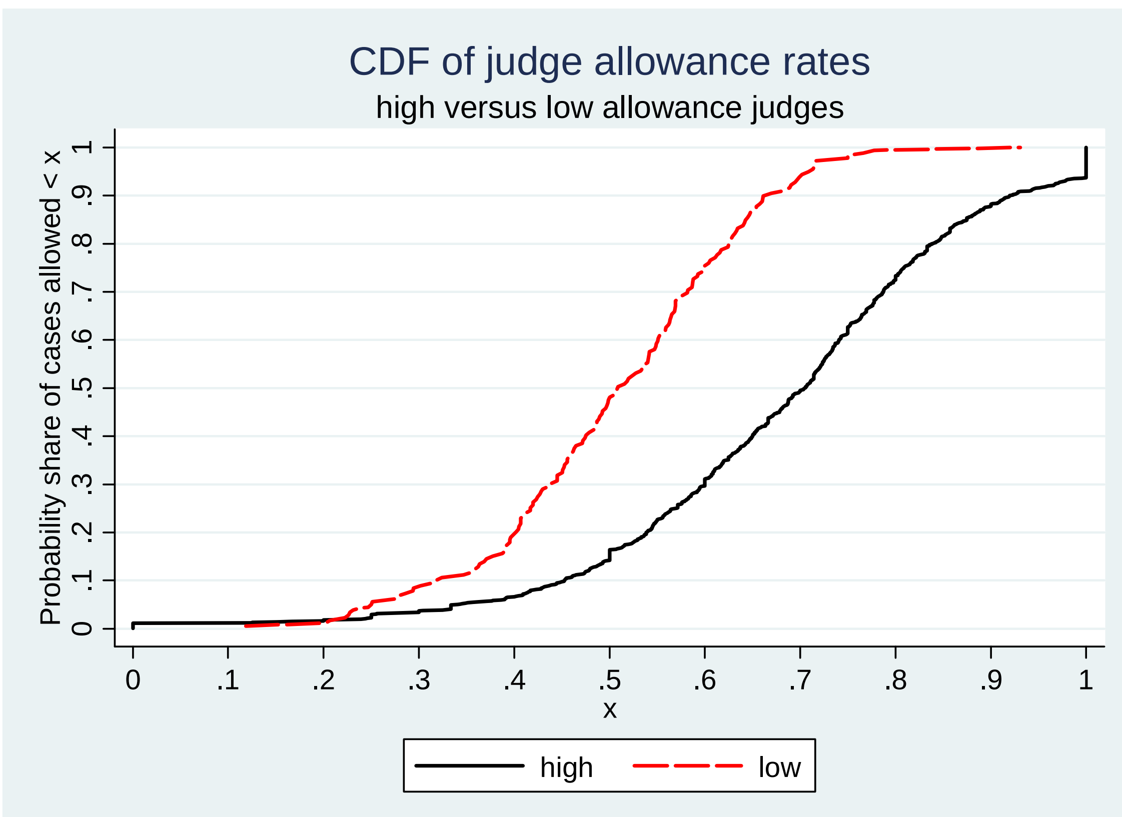

Figure A1

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