Biases in the Disability Insurance Application Process: A Mechanism Design Approach *

Richard W. Evans
Department of Economics
University of Texas at Austin
evans@eco.utexas.edu

DRAFT
January 2007

Abstract

It is well documented that individuals tend to over-report disability levels when applying for government disability insurance. One might also expect that a disability program administration could have an incentive to "under-accept" disability claims due possibly to an objective of cost minimization or an asymmetric information problem. This study seeks to understand how individual and administrative characteristics influence the propensity for individuals to over-report their disability level (reporting bias) and the propensity for a disability program administration to under-accept reported disability levels on applications for disability benefits (acceptance bias). I use a mechanism design framework in to structurally model optimal choices by individuals in their personal disability claims and by an administration in its acceptance of disability claims. I then estimate the effects of the individual and administrative characteristics on the reporting and acceptance biases, respectively, using the Union Army dataset of Civil War veterans. I find that older Southern veterans tend to overreport their disabilities more often, but that administrations award more benefits to older, married veterans who have fought in more battles.

keywords: Mechanism Design; Asymmetric Information; Disability Insurance; U.S. Economic History Pre-1913

JEL classification: C72; D82; J14; N31; H53

*I am grateful to Sven Wilson at Brigham Young University for getting me started on this project, as well as to Noelle Yoetter and Sharon Nielsen at the CPE Washington, D.C. office for their guidance, many helpful comments, and time spent at the National Archives pulling original records. The comments and suggestions of Dan Hamermesh at the University of Texas were also instrumental in the more advanced stages of the project. This work was funded by a grant from the Center for Population Economics (CPE) at the University of Chicago Graduate School of Business and the National Bureau of Economic Research (NBER), a subgrant of National Institutes of Health (NIH) grant number P01 AG10120.

1 Introduction

In 2005, the Social Security Administration (SSA) of the United States processed 2.6 million applications for disability benefits.[1] U.S. government expenditures in fiscal year 2005 for its two main disability programs—Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI)—were expected to be approximately $127 billion or nearly 5 percent of the Federal budget. This percent was estimated to remain the same during both 2006 and 2007.[2] Applications by individuals for these disability programs involve detailed personal claims, medical evaluations, and final administrative approval. However, until recently, no available dataset has contained information on all three stages of the application process (personal, medical, and administrative) for specific individuals.

The motivation for this paper grows out of the documented phenomenon that individuals tend to over-report disability claims. One might also expect that a disability program administration could have an incentive to "under-accept" disability claims. Potential sources of this adverse incentive of the administration include an objective of cost minimization or an asymmetric information problem.

This study seeks to understand how individual and administrative characteristics influence the propensity for individuals to over-report their disability level (reporting bias) and the propensity for a disability program administration to under-accept disability levels on applications for disability benefits (acceptance bias). I use a game theoretic framework, similar to those used in the conventional arbitration literature, to model optimal choices by individuals in their personal disability claims and choices by an administration in its acceptance of disability claims. I then estimate the effects of the individual and administrative characteristics on the reporting and acceptance biases, respectively, using standard econometric methods.

Most personal disability datasets only have information on either personal dis-

[1] See Office of Management and Budget (2006a, p. 289).

[2] See Office of Management and Budget (2006a, p. 313) and Office of Management and Budget (2006b, pp. 1102, 1105). Total Federal outlays for SSDI and SSI in fiscal year 2005 were $86.5 billion and $40.9 billion, respectively, and total Federal outlays were about $2.5 trillion. Total outlays for SSDI and SSI in fiscal year 2007 were estimated to be $100.5 billion and $40.0 billion, respectively, and total outlays were estimated to be about $2.8 trillion.

ability claims or administrative disability evaluations—not both together. Even more elusive are data with medical evaluations of individuals' disabilities. One benefit of learning more about the respective reporting and acceptance biases would be to shed light on which data are more accurate. For example, if a question arises about disability policy, does the policy maker use administrative disability data or personal claims disability data? And once a data type is chosen, how might that data be expected to differ from the true disability level?

Many studies trying to answer the questions above are found in the literature, but they all either look at only the relationship of administrative disability evaluations to medical evaluations or they only compare personal disabilities claims to medical evaluations. Durbin and Kish (1998) look at permanent partial disability (PPD) ratings and investigate the differences between the medical disability evaluations and final administrative evaluations. They find that a variety of factors other than the medically determined disability level of the applicant account for a large part of the final administrative disability rating.

The literature on self-reported disability claims is more extensive. Bound and Waidmann (1992) estimate that the bias in self-reported disability claims is smaller than one would expect. Another study with similar results is that of Parsons (1991). He finds that, because disability insurance administrations have eligibility-determination mechanisms which impose costs on disability benefit applicants, the self-reporting bias in disability claims is countered by decreased application rates due to screening costs. These costs might be related to the probability that an applicant's claimed disability level will differ from the medically or administratively evaluated disability level. Kreider (1998) looks at a similar question.

Lastly, Kreider (1999) tries to estimate the true disability of individuals using a simultaneous model of work participation, reported disability, and income flows. This is analogous to estimating the medically evaluated level of disability in this study.

One can find studies examining the personal, medical, and administrative perspectives of disability insurance policy separately, or at most, in tandem with one of the other perspectives. But what is lacking is research using all three perspectives together. The goal of this study is to fill the void.

2 Theoretical Model

Some institutional background on disability pension applications for Civil War veterans will give some intuition for the model that will be used in this paper.[3] Pension applications were a three-stage process. First, the veteran would make a detailed application to the Federal government claiming whatever disabilities he wished to be compensated for. Then he would be evaluated by a certified physician. Lastly, an administrative panel would examine the application containing both the personal claims and the medical evaluation and make a final decision as to how much compensation to give the applicant for his disabilities.

Because of the three-stage process of the disability benefits application process, it is effectively modeled as a sequential game. The intuition of this model is that the applicant is a biased party who knows the truth (potentially with some error, so his knowledge is at least unbiased) and the examining physician is an impartial judge who can be slightly biased by the reporting behavior and the applicant. The problem of the administration is that they only know the reported level of disability from the doctor and the reported level from the applicant. The administration must set up a rule that recognizes a disability level as close to the true disability level as possible. This is a problem of mechanism design.

What we see in practice (equilibrium) is that small differences between reported disability level and medically evaluated disability level can be due to noise, so an administration is acting optimally to take into account both reported values. But when the deviation is large, something is wrong with the application, and (in practice) it probably gets sent back. In the model, the administration just gives a large penalty to big deviations and a small penalty for small deviations.

The problem of the disability applicant is to maximize his expected accepted level

[3] Detailed information on the pension process during the mid-to-late 1800s, as well as on the Union Army Dataset (UAD), can be found in Fogel (2000).

of disability by the administration $E\left[d_i^a\right]$ given his knowledge of how the level of disability he reports d_i^r will affect the expected accepted level. I assume that the applicant knows his true level of disability with some noise $\tilde{d}_i$:

$$\tilde{d}_i = d_i + \nu_i \quad \text{where} \quad \nu_i \sim \text{i.i.d.}(0, \sigma_\nu^2) \tag{1}$$

where d_i is the true level of disability and the expected value of the applicants knowledge of the disability equals the true disability level $E\left[\tilde{d}_i\right] = d_i$. Therefore, the applicant knows that his perception of disability $\tilde{d}_i$ will be correct on average, but he does not know the decomposition of either the true value d_i or the error term ν_i. In deciding what level of disability to report d_i^r to maximize expected accepted level of disability $E\left[d_i^a\right]$, the applicant knows how his reported disability level d_i^r will influence the physician's evaluated disability level d_i^m in equation (2), but he again does not know his true disability level d_i and he cannot predict the error ε_i in the examining physician's evaluation. The applicant also understands how his reported disability level d_i^r will influence the administratively accepted level in (3). That is, the applicant knows the parameter values of α and β as well as how his reported disability level d_i^r and the medically diagnosed level d_i^r enter into (3).

I model the examining physician as an impartial judge whose evaluation d_i^m of applicant i equals the true level of disability d_i on average when the applicant reports his true level of disability. But the physician's evaluation can be slightly biased when the applicant reports a disability level different from his true disability level.

$$\begin{aligned} d_i^m &= d_i + u_i \quad \text{where} \quad E\left[d_i^r u_i\right] > 0 \\ \text{let} \quad u_i\left(d_i^r\right) &= \theta\left(d_i^r - d_i\right) + \varepsilon_i, \quad \theta \in [0,1) \\ \Rightarrow \quad d_i^m &= d_i + \theta\left(d_i^r - d_i\right) + \varepsilon_i \end{aligned} \tag{2}$$

The physician, therefore, does not observe the true level of disability nor does he know the error ε_i in his diagnosis. The physician's information set at the time of the decision only contains the level of disability reported by the applicant d_i^r. The physician does not know that his decisions are biased. His belief is that he is diagnosing the true level of the applicant's disability.

The job of the disability administration is to set up an evaluation rule for the administratively accepted disability level d_i^a so as to minimize the expected difference between the accepted disability level and the true disability level, given the administrations knowledge of the optimal reported disability level of the applicant and how that level enters the medically diagnosed level. The problem thus becomes a mechanism design problem in which the administration tries to design a rule that induces the applicant to report in such a way as to minimize the expected difference in administratively accepted disability level and the true disability level. One candidate that represents a class of administrative evaluation rules is the following:

$$d_i^a = \alpha d_i^m + (1-\alpha)\, d_i^r - \beta \left(d_i^r - d_i^m\right)^2, \quad \alpha \in [0,1], \quad \beta \in [0,\infty) \tag{3}$$

This rule means that the administration accepts a disability level that is a convex combination of the individually reported level and the medically evaluated level minus a penalty for any deviation between the two. The problem of the applicant is then the following:

$$
\begin{aligned}
&\max_{d_i^r} E_r\left[d_i^a\right] \quad \Rightarrow \quad \max_{d_i^r} E_r\left[\alpha d_i^m + (1-\alpha)\, d_i^r - \beta\left(d_i^r - d_i^m\right)^2\right] \\
&\max_{d_i^r} E_r\left[\alpha\Big(d_i + \theta\left(d_i^r - d_i\right) + \varepsilon_i\Big) + (1-\alpha)\, d_i^r - \beta\Big(d_i^r - d_i - \theta\left(d_i^r - d_i\right) - \varepsilon_i\Big)^2\right] \\
&\max_{d_i^r} E_r\left[\alpha\Big(\tilde{d}_i + \theta\left(d_i^r - \tilde{d}_i\right) + \varepsilon_i\Big) + (1-\alpha)\, d_i^r - \beta\Big(d_i^r - \tilde{d}_i - \theta\left(d_i^r - \tilde{d}_i\right) - \varepsilon_i\Big)^2\right] \\
&\quad \max_{d_i^r} \quad \alpha\Big(\tilde{d}_i + \theta\left(d_i^r - \tilde{d}_i\right)\Big) + (1-\alpha)\, d_i^r - E_r\left[\beta\Big((1-\theta)d_i^r - (1-\theta)\tilde{d}_i - \varepsilon_i\Big)^2\right] \\
&\quad \max_{d_i^r} \quad \alpha\Big(\tilde{d}_i + \theta\left(d_i^r - \tilde{d}_i\right)\Big) + (1-\alpha)\, d_i^r \ldots \\
&\qquad\qquad - E_r\left[\beta\Big((1-\theta)^2\left(d_i^r\right)^2 - 2(1-\theta)^2 d_i^r \tilde{d}_i - 2(1-\theta)d_i^r\varepsilon_i + (1-\theta)^2\tilde{d}_i^2 + 2(1-\theta)\tilde{d}_i\varepsilon_i - \varepsilon_i^2\Big)\right] \\
&\quad \max_{d_i^r} \quad \alpha\Big(\tilde{d}_i + \theta(d_i^r - \tilde{d}_i)\Big) + (1-\alpha)\, d_i^r \ldots \\
&\qquad\qquad - \beta\Big((1-\theta)^2\left(d_i^r\right)^2 - 2(1-\theta)^2 d_i^r\tilde{d}_i + (1-\theta)^2(\tilde{d}_i)^2 + \sigma_\varepsilon^2\Big) \\
&\quad \Rightarrow \quad \alpha\theta + 1 - \alpha - 2\beta(1-\theta)^2 d_i^r + 2\beta(1-\theta)^2\tilde{d}_i = 0 \\
&\quad \hat{d_i^r} = \tilde{d}_i + \frac{\alpha(1-\theta)+1}{2\beta(1-\theta)^2} \\
&\quad \hat{d_i^r} = \tilde{d}_i + \frac{1}{2\beta(1-\theta)^2} - \frac{\alpha}{2\beta(1-\theta)}
\end{aligned} \tag{4}
$$

The optimal individually reported disability level $\hat{d_i^r}$ has some very intuitive properties. The incentive to overreport decreases as the penalty β for deviations from the medical evaluation increases, and increases in the weight on the medical diagnosis α decrease the incentive to overreport. Also, as the degree to which the individual can influence the medical diagnosis θ rises, the incentive for the individual to overreport increases. But most interesting is the result that the disability administration cannot induce truth telling on the part of the individual if individual reporting levels can influence the medical diagnosis ($\theta > 0$). That is, even if the administration puts all of the weight on the medically reported disability level ($\alpha = 1$), the sum of the last two terms in (4) is always positive.

The objective of the disability administration is then to minimize the expected deviation of the administratively accepted disability level from the true disability level given the knowledge of the applicant's optimal reporting rule (4).

$$\begin{aligned} &\min_{\alpha,\beta} \left[E_a\left(d_i^a - d_i\right)\right]^2 \\ &\min_{\alpha,\beta} \left[E_a\Big(\alpha d_i^m + (1-\alpha)\, d_i^r - \beta\left(d_i^r - d_i^m\right)^2 - d_i\Big)\right]^2 \end{aligned} \tag{5}$$

- do the algebra for this and check all the cases and make sure the second derivatives are negative.
- use Matlab's symbolic math toolbox, or use mathematica on the computers at the UGL.
- write down equilibrium expressions for $\hat{d}_i^r$, $\hat{d}_i^m$, and $\hat{d}_i^a$, as well as the two respective biases $\hat{b}_i^a$ and $\hat{b}_i^a$.
- estimate the parameters from the structural model.
- it seems like α is the parameter that mostly governs the respective biases, so it would probably make sense to do something like making $\alpha = \gamma' \boldsymbol{x}$.

3 Data

Comparison of personal disability claims and administrative disability evaluation to medical disability evaluation for specific individuals and disability claims across time has recently been rendered possible using the Union Army Dataset (UAD)—a dataset of veterans of the Union Army who fought in the United States Civil War. Using a matching algorithm, Evans (2003) integrates two separate sections of the UAD to form a large panel dataset with information on all three stages of the disability insurance application process—personal, medical, and administrative. Using this historical dataset, I estimate how individual characteristics influence the reporting and acceptance biases, respectively.

Why use data from a century ago? First, if one is interested in history, the corresponding historical dataset is the correct population sample. Although this study will directly give insight into the effects of individual and administrative characteristics on reporting and accepting biases in the late nineteenth and early twentieth centuries, this is not my ultimate goal.

A second relevance for historical datasets is the case in which one can argue that the characteristics of the current population have not significantly changed over time. This is a very difficult argument to make when comparing today's disability policy to that of a century ago. Lastly, and most importantly for this study, a historical dataset is valuable if it is simply the best data available. In this case, the UAD with the newly integrated surgeon's certificates data is the only large longitudinal dataset with personal disability claims, medical disability evaluations, and administrative disability evaluations together. It is mainly upon this basis that I justify the use of the UAD to gain insight into current disability policy.

The sample in this study includes the first application for a disability pension by a veteran that has an associated surgeon's examination, a pension board ruling, and information on the individual characteristics controlled. I forego using the panel dimension of the dataset (multiple applications per veteran) for two reasons. First, repeat applications may differ from first applications in systematic ways. After an initial application, both the applicant and the ruling pension board have learned. The second reason is less theoretical and more practical. The SC dataset variable I use to determine the number of disabilities diagnosed by the examining physician in order to calculate d_i^m can only be confidently associated with the given application in the case of first applications because, otherwise, it refers to both the current examination and previous exams (see Appendix A-1).

The number of self-reported disabilities d_i^r and administratively accepted disabilities d_i^a are both clearly given in the MV dataset.[4] With the three disability count

[4]The MV dataset lists up to 12 self-reported disabilities for each application in the variables

values of d_i^r, d_i^m, and d_i^a, I can now calculate the reporting bias b_i^r and the acceptance bias b_i^a as shown in equations (**??**) and (**??**), respectively.

In the estimation, control variables for individual characteristics are taken from the veteran's application in the MV dataset. The variables used are the applicant's age, number of children, whether married, labor force participation rate (e.g., 100%, 75%, 25%, etc.), number of battles participated in, whether was ever a prisoner of war, and region of residence (see Appendix A-2 for description of regional categories). With the exception of whether the applicant was ever a prisoner of war, each of the individual characteristics controls represented the state of the applicant at the time of application. The variables are described in Table 1.

Table 1: Summary Statistics of Reporting Bias, Acceptance Bias, and Individual Characteristics ($N = 7,228$)

Variable	Mean	Std. Dev.	Min.	Max.
Reporting bias b_i^r	0.89	1.97	-12	11
Acceptance bias b_i^a	-0.19	1.92	-13	8
Reporting bias pct. $\widetilde{b_i^r}$	0.85	1.44	-0.91	11
Acceptance bias pct. $\widetilde{b_i^a}$	0.31	0.88	-0.92	8
Age	52.8	10.1	19	86
Number of children	2.7	2.9	0	15
Married	0.78	0.41	0	1
Number of battles	0.60	1.14	0	10
Whether POW	0.09	0.29	0	1
Residence in Northeast	0.32	0.47	0	1
Residence in South	0.05	0.22	0	1
Residence in Midwest	0.60	0.49	0	1
Residence in West	0.02	0.15	0	1

It is clear from Table 1 that most self-reported disabilities are greater than what the examining physician diagnosed (average reporting bias is positive) and that most administratively accepted disabilities are slightly less than what the physician diagnosed (average acceptance bias is negative). This is what would be expected and is an

a_sclm01 through *l_sclm20*. Administratively accepted disabilities are listed in the variables *a_bclm01* through *l_bclm20*. The number of medically diagnosed disabilities comes from the *a_ratfor* variable in the SC dataset.

indicator that the quality of the number of medically diagnosed disabilities is good.[5]

The rest of the variables in Table 1 are used as independent variables in the analyses of Section 4. The MV data provides information on the applicant's age, number of children, marital status, and residence at the time of each application. In the sample used here, the average age of disability pension applicant is about 53 years old. Just over 78 percent of the applicants were married at the time and had an average of almost three children.

Most of the applicants resided in the Midwest states (60 percent), with 32 percent residing in the Northeast, 5 percent in the South, and only 2 percent in the Western States (see Appendix A-2 for regional membership of states and representation of specific states). The application forms also contained information on when and whether the applicant was in any battles or was a prisoner of war. The average applicant was in either 1 battle or none, although some were in as many as 10 battles. Only 662 out of the 7,228 applicants were ever prisoners of war.

4 Estimation

Using the data from the Union Army Dataset (UAD), the goal of this study is to estimate the effects of individual characteristics on the reporting and acceptance biases as represented by identities (**??**) and (**??**) and the underlying behavioral equations in (**??**), (**??**), and (**??**). The reduced for equations for the reporting and acceptance biases, respectively, are given by the following equations:

$$b_i^r = \boldsymbol{\beta}_r' \boldsymbol{X}_i + \omega_{r,i} \tag{6}$$

$$b_i^a = \boldsymbol{\beta}_a' \boldsymbol{X}_i + \omega_{a,i} \tag{7}$$

where $\boldsymbol{\beta}_r$ and $\boldsymbol{\beta}_a$ are vectors of coefficients, $\boldsymbol{X}_i$ is a matrix of individual characteristics made up of the variables listed in Table 1, and $\omega_{r,i}$ and $\omega_{a,i}$ are normally distributed

[5]The exact distributions of the reporting bias levels b_i^r and acceptance bias levels b_i^a are shown in Figure 1 of Appendix A-1.

mean-zero error terms. The estimated coefficients from equations (6) and (7) are presented in Table 2.

Table 2: Estimated coefficients of reporting bias and acceptance bias equation specifications

Independent variables	Reporting bias $\widetilde{b_i^r} = \boldsymbol{x}_i'\boldsymbol{\beta}_p$	Acceptance bias (1) $\widetilde{b_i^a} = \boldsymbol{x}_i'\boldsymbol{\beta}_a \mid \widetilde{b_i^r} \mid$	Acceptance bias (2) $\widetilde{b_i^a} = \boldsymbol{x}_i'\boldsymbol{\beta}_a \frac{(b_i^r)^2}{d_i^m}$	Acceptance bias (3) $\widetilde{b_i^a} = \boldsymbol{x}_i'\boldsymbol{\beta}_a$
	Estimating equation specification			
Age	0.012**	0.006**	0.0006**	0.002
	(0.002)	(0.0002)	(0.00004)	(0.001)
Number of children	0.013*	-0.001	0.0005	-0.003
	(0.006)	(0.002)	(0.0004)	(0.004)
Married	0.004	0.051**	0.011**	-0.011
	(0.043)	(0.012)	(0.003)	(0.027)
Number of battles	-0.029	0.022**	0.003**	-0.001
	(0.015)	(0.005)	(0.001)	(0.009)
Prisoner of war	-0.043	-0.019	-0.00003	-0.059
	(0.059)	(0.019)	(0.005)	(0.037)
Southern region resident	0.924**	-0.013	-0.007*	0.431**
	(0.079)	(0.015)	(0.003)	(0.049)
Midwestern region resident	-0.157**	0.076**	0.011**	-0.046*
	(0.037)	(0.010)	(0.002)	(0.023)
Western region resident	-0.120	0.017	0.010	-0.209**
	(0.111)	(0.032)	(0.007)	(0.069)
Number of observations (N)	7,228	7,228	7,228	7,228
$F\,(8, 7219)$	37.1	629.9	258.6	15.1

* Significant at the 5-percent level.
** Significant at the 1-percent level.

From the reporting bias estimation in column 1 of Table 2, disability applicants who are older, have more children, and live in the South are more likely to have high reporting. The results also suggest that the more an individual participated in the war, the smaller was his reporting bias. The coefficient on number of battles is almost significant at the 5-percent level (p-value 0.058), and it suggests having participated in one more battle reduces you reporting bias percentage $\widetilde{b_i^r}$ by nearly 3 percent.

It is understandable that the coefficient on the Western region in the reporting bias estimation is not significant, given its poor representation in the sample (see Table 3 in Appendix A-2). But the other regions are very significant. In particular, Southern residents had a 92 percent points higher reporting bias percentage than their Northeastern counterparts. The Midwesterners had the lowest estimated reporting bias, having 16 percentage points lower reporting bias percentage than the Northeasterners.

As was mentioned earlier, the first two acceptance bias specifications are structural equations corresponding to either the absolute value of the reporting bias in the administration's evaluation rule (**??**) or the squared reporting bias. In comparing the coefficients of the two, those in the second specification that uses the square of the reporting bias are all closer to zero. This is due to the squared coefficient being always greater than or equal to the absolute value coefficient. Keep in mind that a positive coefficient in columns 1 or 2 of Table 2 means that an increase in the variable results in a higher value of α_i. And because $\widehat{\alpha}_i$ is negative, a positive coefficient signifies that more of the independent variable results in a smaller penalty on reporting bias.

Results that stand out are that the pension boards seemed to reward older applicants more than younger ones and married applicants more than unmarried ones. An extra year of age translated into a reduction in the penalty (closer to zero) of 0.006, and being married translated into a smaller penalty of 0.51. The pension administrations also reduced the penalty for reporting bias on applicants who had been in more battles.

One might expect that a Southern bias might have existed in the period after the civil war. However, acceptance bias specifications 1 and 2 do not provide strong evidence for this. Specification 1 essentially says that the reporting bias penalty for Southerners was about the same as that of residents of the Northeast. However, a robust finding is that residents of the Midwest were penalized the least of all the regions.

The last specification discards the model and is the reduced form way of ascertaining how individual characteristics affect the acceptance bias percentage. It says that older applicants usually have lower discrepancies between pension awards and medical recommendations. It also says that the percentage deviation of the acceptance bias becomes more negative for midwesterners and westerners and less negative for southerners.

Taken together, the analyses in Table 2 show that older Southern residents with more children tend to over-report their disability levels more than others. However, for acceptance bias, older married Midwestern residents were rewarded more than others. The overarching result is that older applicants were simply awarded more disability benefits. One way of looking at the disability benefit system of the late 1800s is as a defacto social security.

5 Conclusion

Combining the three perspectives on disability—personal, medical, and administrative, from the Union Army Dataset (UAD) allows the reporting bias and acceptance bias to be derived from real data and studied together for the first time. Using the model of strategic interaction between the disability pension awarding administration and the individual disability applicant, a structural model of the number of disabilities reported and accepted, respectively, can be estimated.

The results of this paper suggest that older disability applicants both claimed more disabilities than they actually had (reporting bias) and received pensions closer to the amount recommended by the examining physician. Applicants with more children over-reported disabilities more, while married applicants and those who fought in more battles were treated more leniently by the pension boards. Region of residence was also found to be important with Southerners over-reporting disability nearly 100 percentage points more than their counterparts in the rest of the country, while they seemed to be penalized less on the administrative side of the process.

This study has some implications for disability policy in the United States. Given that the U.S. currently spends about 5 percent of its $2.8 trillion budget of disability program expenses, the results of this study might indicate which groups today have the most need of disability assistance given that they probably misperceive their disability level and which groups are most likely underserved by the administration in their area. Demographic and geographic characteristics affect how individuals report and receive disability benefits.

APPENDIX

A-1 Diagnosed Disabilities in the Surgeon's Certificates (SC)

Determining the number of disabilities diagnosed by a physician on a particular exam is difficult for a number of reasons. The Surgeon's Certificates (SC) dataset is replete with both text descriptions of the examining physician's findings as well as standardized variables that organize the diagnoses of the exam in discrete medical categories. The SC dataset presents multiple possible approaches, but one of the approaches is clearly optimal for the present study. For more detail on the SC dataset, see Fogel (2001).

1 The first potential method for determining the number of disabilities diagnosed by the examining physician is to add up the different items for which an applicant was rated on each of the disease screens. The SC dataset contains 18 disease screens that contain information on diagnoses of specific areas of health function—from cardiac conditions (the "*c_*" variables) to genito-urinary conditions (the "*u_*" variables). Each set of screen variables has at least one *_rat* variable in which the examining physician records a fraction that represents the portion of a full pension that the veteran's certain disease area merits. So, for example, the physician might have recorded the fractions 4/18 and 5/18 in the variables *c_rat1* and *u_rat1*, respectively. This would mean that the physician diagnosed the applicant with heart disabilities that merited 4/18 of a full pension amount and with genito-urinary disabilities that merited 5/18 of a full pension amount. The problem with using the *_rat* variables is that they cannot be compared to the count measures of self-reported disabilities and administratively accepted disabilities from the MV dataset.

2 Another possible way to determine the number of disabilities is to add up all the different items in each disease screen for which the examining physician rated the applicant. The problem with this method is that many of the items recorded in the disease screens are symptoms, and some of them are the doctor's acknowledgement that nothing is wrong. Also, these more detailed disease-screen variables have varying degrees of standardization. Trying to use the detail from the disease screens would result in a total number of diagnosed diseases that is almost always greater than both the self-reported number and the administratively accepted number.

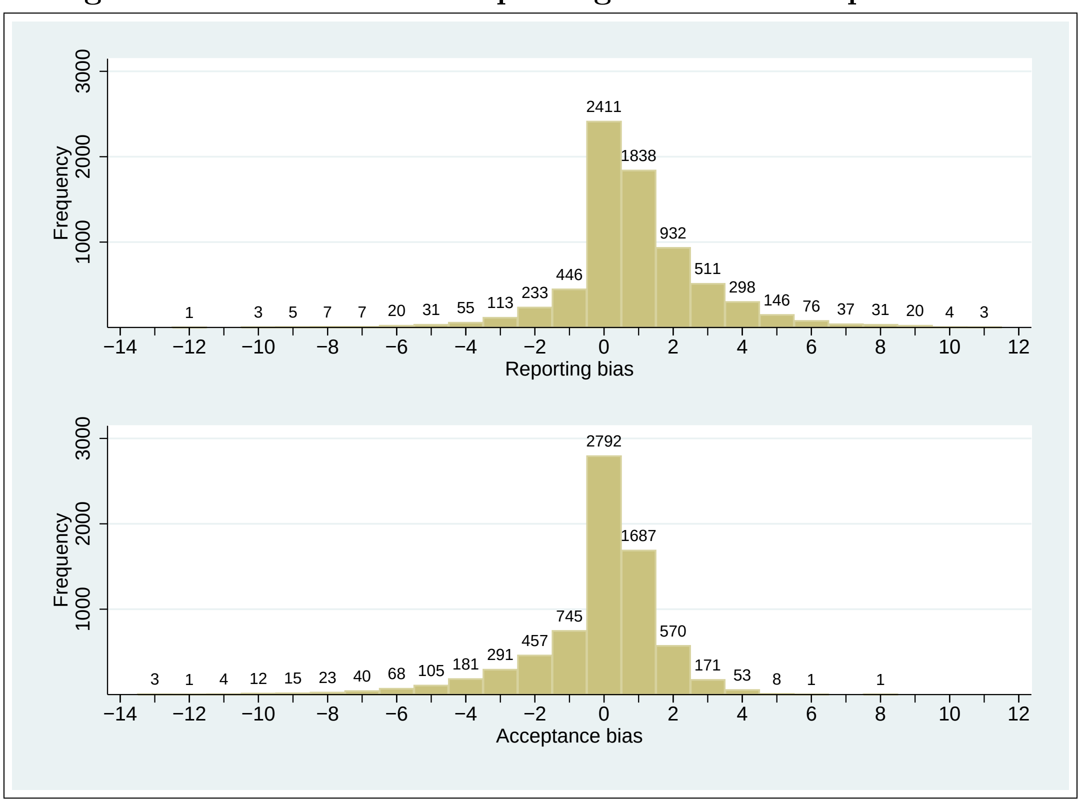
3 A third possibility stems from an index and dollar amount calculations produced by Linares (2003). Her indices range from 0 to 1 for a particular disease screen and give the total fraction of full pension that the examining physician deemed the given disability category merited. Linares also used the full pension amounts of the time to generate the dollar amount to which the physicians judgment equated. The problem with both the index variables and dollar-amount

variables from Linares (2003) is that they can only be related to the administration decision variables in the MV dataset (e.g., the final pension award amount, *rulamt*). There is no analogous variable among the self-reported disabilities.

4 Lastly, the general information in the SC dataset contains a variable, *a_ratfor*, that is described as listing "the diseases for which the previous rating was given and/or additional diseases claimed by the claimant." As is clear from the variable definition, this variable is not clearly defined. It contains the list of disabilities on which the previous pension amount was based, the list of disabilities for which the current examination is based, and the continuum in between. Although the variable is problematic in this sense, it is the only source of number of disabilities diagnosed by the examining physician that can be related to the self-reported and administratively accepted disabilities from the MV dataset. To reduce the problem with the broad variable definition, I use only first applications in the analyses in this study. Thus, the panel dimension of the data is sacrificed for reduced error in the data.

Of the four methods, only the last one allows the comparison and analyses of reporting bias and acceptance bias in the manner proposed in this study. The number of disabilities diagnosed by an examining physician in a given examination that belongs to a first disability application is, therefore, taken to be the number of disabilities listed in the *a_ratfor* variable.

Figure 1: Distribution of Reporting Bias and Acceptance Bias



As a technical note, the convention is followed in the *a_ratfor* variable of separating each distinct disability by a comma. So the programming method of determining the number of disabilities for a given examination is the number of commas plus one.

Because the number of medically diagnosed disabilities is assumed to be the true level of disability in this study, it forms the foundation of all the analyses herein. Figure 1 shows the histograms of the reporting bias b_i^r and the acceptance bias b_i^a, respectively, as defined in equations (**??**) and (**??**). As was described in Table 1, the mean value of the reporting bias is positive (0.89), and the mean value of the acceptance bias is only slightly negative (-0.19). The distribution of the reporting bias is skewed to the right while the distribution of the acceptance bias is skewed to the left. These values and the distributions in Figure 1 fit well with the theory described in Section 2.

A-2 Regional Categorizations

Because pension applicants came from numerous states, I chose to use the standard U.S. regional classifications to aggregate region of residence at the time of the pension application. The classification into the four regions, Northeast, South, Midwest, and West are given in Table 3.

Table 3: Regional classification and frequencies of states represented in sample

Northeast	freq.	South	freq.	Midwest	freq.	West	freq.
Connecticut	98	Alabama	1	Illinois	704	Alaska	1
Delaware	83	Arkansas	25	Indiana	568	Arizona	1
District of Columbia	17	Florida	4	Iowa	464	California	71
Maine	128	Georgia	4	Kansas	220	Colorado	29
Maryland	69	Kentucky	170	Michigan	495	Hawaii	1
Massachusetts	152	Louisiana	2	Minnesota	127	Idaho	8
New Hampshire	133	Mississippi	4	Missouri	337	Montana	9
New Jersey	136	North Carolina	3	Nebraska	96	Nevada	1
New York	842	South Carolina	1	North Dakota	7	New Mexico	8
Pennsylvania	561	Tennessee	18	Ohio	940	Oregon	18
Rhode Island	4	Texas	22	Oklahoma	23	Utah	2
Vermont	87	Virginia	34	South Dakota	27	Washington	23
		West Virginia	96	Wisconsin	350	Wyoming	4
Total	2,310		384		4,358		176

References

Bound, J., and T. Waidmann (1992): "Disability Transfers, Self-Reported Health, and the Labor Force Attachment of Older Men: Evidence from the Historical Record," *The Quarterly Journal of Economics*, 107(4), 1393–419.

Durbin, D. L., and J. Kish (1998): "Factors Affecting Permanent Partial Disability Ratings in Workers' Compensation," *The Journal of Risk and Insurance*, 65(1), 81–99.

Evans, R. W. (2003): "Integration of the Surgeon's Certificates with the Pension Application Groupings in the Union Army Dataset," CPE Working Paper Series, Center for Population Economics, University of Chicago Graduate School of Business.

Fogel, R. W. (2000): *Public Use Tape on the Aging of Veterans of the Union Army: Military, Pension, and Medical Records, 1860-1940, Version M-5*. Center for Population Economics, University of Chicago Graduate School of Business, and Department of Economics, Brigham Young University.

——— (2001): *Public Use Tape on the Aging of Veterans of the Union Army: Surgeon's Certificates, 1862-1940, Version S-1 Standardized*. Center for Population Economics, University of Chicago Graduate School of Business, and Department of Economics, Brigham Young University.

Kreider, B. (1998): "Workers' Applications to Social Insurance Programs when Earnings and Eligibility are Uncertain," *Journal of Labor Economics*, 16(4), 848–77.

——— (1999): "Latent Work Disability and Reporting Bias," *The Journal of Human Resources*, 34(4), 734–69.

Linares, C. (2003): "Coding of Union Army Disability Rating," CPE Working Paper Series #2003-1, Center for Population Economics, University of Chicago Graduate School of Business.

Office of Management and Budget (2006a): *Budget of the United States Government, Fiscal Year 2007*. U.S. Government Printing Office.

——— (2006b): *Budget of the United States Government, Fiscal Year 2007—Appendix*. U.S. Government Printing Office.

Parsons, D. O. (1991): "Self-Screening in Targeted Public Transfer Programs," *The Journal of Political Economy*, 99(4), 859–76.