Determinants of Cross-State Variation in Social Security Disability Rates

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1 Introduction

The last decades have witnessed a significant rise in the number of Social Security Disability Insurance's (SSDI) beneficiaries accompanied with an important decline in employment rates of non-disabled individuals.[1] These trends have generated an extensive amount of literature that seeks to explain both Disability Insurance's (DI) application and award process, and the relationship between DI generosity and labor force participation.

Benitez-Silva et al. (1999), Kreider (1999), Kreider and Riphahn (2000), and Mitchell and Phillips (2002) use individual data to identify the factors

[1]This fact was first noticed by Parsons (1980). Parsons noticed that, during the 60s and 70s, as the number of SSDI beneficiaries dramatically increased, the labor force participation of older men diminished. Furthermore, DeLeire (2000), Burkhauser and Daly (2002), and Bound and Waidmann (2002) among others, have noticed similar trends during the 90s. There is not a unique explanation for this empirical finding. DeLeire (2000) argues that there may be a causal connection between the Americans with Disabilities Act (ADA) and the downturn in employment among those with disabilities. That is, to the extent that the ADA increased the cost of hiring men and women with disabilities, we should expect to observe a reduction in their labor demand. Their explanation has been challenged by another equally plausible argument provided by Bound and Waidmann (2002). They suggest that, because the DI beneficiaries are precluded from working and are forced to leave the labor force, an increase in the number of recipients could lead to a decrease in their employment rates. On the contrary, Hotchkiss (2003) estimates the unconditional probability of employment among disabled people to control for selection into the labor market. She finds that the unconditional employment rate among disabled people, relative to among non-disabled people, did not change significantly after implementation of the ADA. She explains that the reduction in the labor force participation rate among those classified as disabled may not be the result of disabled people leaving the labor force but a reclassification of non-disabled labor force non-participants as disabled due to more stringent welfare reform requirements and more generous federal disability benefits.

that influence the individual's decision to apply for DI and the Social Security Administration award's decision.[2] These studies typically find that those who are initially in poor health and low economic status are more likely to apply for DI, and few factors distinguish those who are awarded from those who are not.

On the other hand, there has been little consensus about the magnitude of the effects of SSDI benefit levels on work behavior. While earlier studies such as Parsons (1980) attribute most of the decline in labor force participation to changes in DI, others find much smaller impacts (Bound 1989, Kreider 1999, Gruber 1999).[3]

The differences in their results could be attributed, to some extent, to certain statistical biases created by using self-recorded health data (and the different methods and assumptions used, if any, to correct them). As has been widely documented in most of this previous literature, self-reported health status may be subject to endogeneity problems and measurement error.[4] Endogenity problems arise due to various types of misreporting of the respondent's self-reported disability, and there has not been an agreement in the literature about the source of this problem. Self-reported disability measures may be endogenous because a) individuals may misreport their disability status to justify their labor force non-participation, creating a "rationalization bias," b) there may be financial incentives for individuals to identify themselves as disabled since only those are eligible to receive DI benefits, and c) responses may not be independent of unobserved factors that explain the dependent variable. In any event, the endogeneity bias overstates the effect of self-reported disability status.

Measurement error arises from many sources: a) surveying recording errors, b) sampling errors (when making inferences from the sample to the population), and c) differences between the respondent's true and self-reported disability status that are not endogenously determined. There are several studies that discuss the credibility of the self-reported disability status and the biases produced by measurement error. For example, Kreider and Pepper (2002) use non-parametric bounds methods to estimate correlations between employment and disability rates when the true disability status is unobserved and conclude that those who do not work tend to overreport their disability. Burkhauser,

[2]Benitez-Silva et al. (1999) estimate binary choice models to explore the Social Security Administration's application, appeal and award process. Kreider (1999) uses a dynamic structural model of applications, awards, and income flows, that takes into account long term opportunity costs associated with disincentives to applications resulting from the waiting period before any benefit may be received. Kreider and Riphan (2000) investigate the determinants of applying for SSDI accounting for many potential biases such as unobserved individual heterogeneity and selection biases. Mitchell and Phillips (2002) estimate a multivariate probit model to explore the determinants by which individuals apply and are granted SSDI.

[3]For example, using "difference-in-difference" methods, Gruber (1999) provides an estimate for the elasticity of labor force non-participation with respect to DI benefits of approximately 0.3. Kreider (1999) finds that the increase in real SSDI benefit levels between 1968 and 1978 was responsible for one-third of the decline in male labor force participation rates during that period.

[4]See for example, Parsons (1980), Bound (1989), Stern (1989), Bound (1991), Benitez-Silva et al. (1999), Kreider (1999), Bound and Waidmann (2002), Kreider and Pepper (2002), and Benitez-Silva et al. (2003).

Daly, Houtenville and Nargis (2002) evaluate the usefulness of self-reported work limitations as a measure of disability. They find that such questions are not ideal tools for identifying the size of the disabled population but can be used to monitor trends in employments of the disabled population. Benitez-Silva et al. (2003) estimate the size of the bias in self-reported disability. After performing a variety of tests, they are unable to reject the hypothesis that self-reported disability is an unbiased indicator of another objective measure of disability (the SSA's award decision). The "attenuation-bias" produced by the measurement error understates the effect of self-reported disability status on DI.

In our study, we employ county level aggregate data to analyze the determinants of variation in Social Security Disability rates and to control for any statistical biases (endogeneity or measurement error) that could affect our results. We use county SSDI rates, county characteristics, and Ordinary Least Squares (OLS) to explain how certain features of a locality affect the proportion of individuals who have been granted SSDI. In addition, we utilize a set of instruments and Two Stage Least Squares (TSLS) methods to correct the potential biases mentioned before and estimate the net magnitude of the biases. In both OLS and TSLS procedures, we also specify a flexible structure for the covariance matrix of the error term that is a function of the geographical distance between two counties. This structure identifies any correlation in unobserved factors that may exist between adjacent locations.

Previous studies that use individual data do not measure the effects of local characteristics on the likelihood of obtaining SSDI.[5] By using aggregate data, we are able to identify these effects which is particularly important for policy makers to evaluate and analyze the availability and accessibility of DI benefits to potential beneficiaries.[6] These effects can be identified only after controlling for the endogeneity and measurement error introduced by using self assessed disability variables and a sample (rather than the population) of people from each county. These two potential biases have opposite directions, and we are not aware of any other study that has evaluated their net magnitude. We find two surprising results. First, we provide evidence that, as the proportion of disabled people in a county increases, the proportion of SSDI beneficiaries rises more than proportionally. This finding suggests that there may be synergies for applying for SSDI when the disabled population is larger. Second, we show that measurement error is the dominating source of the bias and that the main source of measurement error is sampling error. Our results add to Benitez-Silva et al. (2003), providing additional evidence that the endogeneity problem associated with self assessed disability data may not be as important as previously thought in the literature.[7]

[5] Benitez-Silva et al. (1999), Kreider (1999), Kreider and Riphahn (2000), and Mitchell and Phillips (2002) use individual survey data that does not have detailed geographical information. Thus, they are unable to link the respondents to the locations where they reside.

[6] Other authors such as Rupp and Stapleton (1995) have used state aggregate data to analyze the growth of SSDI applications and awards. These studies, however, have not addressed the issues of endogeneity and measurement error.

[7] However, our results are not fully comparable with Benitez-Silva et al (2003) because of differences in the nature of the data in these studies. We use aggregate data, and our results

The rest of the paper is organized as follows. Section 2 provides a description of the data. Section 3 describes the statistical methods. In Section 4, we present and discuss our empirical findings. Finally, the last section concludes.

2 Data

To analyze geographical variation in Social Security disability rates, we use US county level data that was compiled from several sources. The Social Security Administration (SSA) provided us with the number of Disability Insurance (DI) beneficiaries during the year 1999. A beneficiary is defined as an individual who is between 18 and 65 years of age, has applied, and has been granted DI by the SSA (we do not differentiate beneficiaries by the source of their disabilities). From the US Census we have collected demographic and economic variables, such as population, age, gender, ethnicity, income, poverty, unemployment, the number of legal professionals that reside in a county, and disability status. The number of employees hired by the agriculture, mining, utilities, construction and manufacturing industries during the year 2000 was obtained from the US County Business Patterns. Finally, we have used the Area Resource File (ARF) to obtain the US number of active medical doctors in 1999 and an urbanicity index that captures differences between urban and rural areas. We have merged the datasets using FIPS county codes. To make meaningful comparisons across counties of different population size, we divide some of the variables by the total number of adults between 18 and 65 years of age.

Table 1 presents descriptive statistics for the variables that we use to estimate our empirical model. The mean county employment disability rate is approximately 12%.[8] Furthermore, only one-third of this disabled population has applied and received SSDI assuming that all SSDI recipients have correctly reported their disability status to the Census (see Benitez-Silva et al. (1999) for a discussion of this point). The availability of legal and medical professionals is small. On average, 4 out of 1,000 individuals -in our age group- work as legal professionals, while only 2 out of 1,000 are active medical doctors.

As will be explained later, we use different sets of instruments to estimate our model. Our instruments consist of past county disability rates and industry labor participation. We have constructed past county disability rates using two different measures of employment disability available in the 1980 US Census. The first measure identifies disabled individuals who are not part of the labor force ("labor force" disability rate), while the second counts people who may or may not be part of the labor force but their disability status prevents them from

suggest that sampling error is the main source of the measurement error. On the other hand, their study uses individual data; thus, there is no sampling error per-se.

[8]To identify employment disability, we use the variable P41013 (employment disability) from the 2000 Census. The relevant question asked people aged 16 and older if a physical, mental, or emotional condition caused them difficulty working at a job or business. When computing the relevant shares, we divide this variable by the county population between 18 and 65 years of age. Thus, we have assumed that the number of disabled individuals of ages 16 and 17 is negligible.

working ("prevented from working" disability rate). The mean "labor force" disability rate in 1980 was approximately 4%. However, because the definitions of disability are different in the 1980 and 2000 Census, we cannot make any statements about the evolution of this variable in the last two decades.[9] Finally, we have estimated the share of the labor force working in physically demanding industries, such as mining or manufacturing.

Table 1
Sample Moments

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
log SSADI rate	-3.120	0.443	Urban	0.286	0.452
log employment disability rate	-2.109	0.272	Suburban	0.294	0.455
Share female	0.505	0.019	Instruments		
Share black	0.090	0.145	log "labor force" in 1980	-3.304	0.229
log share legal professionals	-5.628	0.662	log "prevented from working in 1980	-3.009	0.493
log share active medical doctors	-6.555	0.837	Fraction of labor force working in:		
log mean age	3.690	0.041	Agriculture	0.002	0.005
log median household income	10.454	0.233	Mining	0.004	0.015
log poverty rate	-2.380	0.518	Utilities	0.001	0.004
log unemployment rate	-2.870	0.463	Construction	0.028	0.021
			Manufacturing	0.099	0.090

3 Econometric Methodology

We use simple econometric methods to facilitate understanding of the results. In particular, we specify a linear model

$$y_i = X_i\beta + u_i \tag{1}$$

where the dependent variable is the log proportion of the population in county i recieving Social Security disability benefits and the explanatory variables are described above. We estimate the model using ordinary least squares (OLS)

[9] Using the Current Population Survey, Hotchkiss (2003) shows evidence that the overall employment disability rate (EDR) does not have any positive trend during the last two decades (except during the years 1991 to 1995). In addition, other studies have found that, during the last decade, there was a large growth of SSDI recipients and a systematic reduction in employment rates of non-disabled individuals.

but only to compare to two stage least squares (2SLS) estimates that control for the potential endogeneity of one of the explanatory variables.

Following Bolduc, Laferrière, and Santarossa (1992) and Conley (1999), we also consider the possibility that the covariance matrix of the errors exhibits correlation as a function of the geographical distance between counties. Let d_{ij} be the distance between two counties, and let $\phi(d)$ be a function with properties $\partial\phi/\partial d \leq 0$ and $\phi(d) = 0$ for all $d \geq D$ for some finite D. Then let

$$Cov(u_i, u_j) = \sigma_u^2 \phi(d_{ij}) + \sigma_\varepsilon^2 1(i = j),$$

and define $\sigma^2 = \left(\sigma_u^2, \sigma_\varepsilon^2\right)'$.

Building on work by Ichimura (1993), we can get a semiparametric estimate of σ^2 by solving

$$\min_{\widehat{\sigma}^2} \sum_i \sum_j \left[\widehat{u}_i \widehat{u}_j - \widehat{\sigma}_\varepsilon^2 1(d_{ij} = 0) - \widehat{\sigma}_u^2 \widehat{\phi}(d_{ij})\right]^2 \tag{2}$$

where $\widehat{u}_i$ is the OLS (or 2SLS) residual for county i and

$$\widehat{\sigma}_u^2 \widehat{\phi}(d) = \frac{\sum_i \sum_j \left[\widehat{u}_i \widehat{u}_j - \widehat{\sigma}_\varepsilon^2 1(d_{ij} = 0)\right] K\left(\frac{d_{ij} - d}{b}\right)}{\sum_i \sum_j K\left(\frac{d_{ij} - d}{b}\right)}. \tag{3}$$

where $K(\cdot)$ is a kernel function[10] and b is a bandwidth.[11] We normalize $\widehat{\phi}(\cdot)$ by setting

$$\widehat{\phi}(0) = 1. \tag{4}$$

Equations (3) and (4) imply that

$$\widehat{\sigma}_e^2 = \frac{\sum_i \sum_j \left[\widehat{u}_i \widehat{u}_j - \widehat{\sigma}_\varepsilon^2 1(d_{ij} = 0)\right] K\left(\frac{d_{ij}}{b}\right)}{\sum_i \sum_j K\left(\frac{d_{ij}}{b}\right)}.$$

[10] We use a standard normal density function truncated at ± 4.

[11] Bertrand, Duflo, and Mullainathan (2004) focus on time series correlation in panel data. If our data was a panel, we could generalize equations (2) and (3) to

$$\min_{\widehat{\sigma}^2} \sum_{it} \sum_{js} \left[\widehat{u}_{it} \widehat{u}_{js} - \widehat{\sigma}_\lambda^2 \psi(|t-s|) - \widehat{\sigma}_\varepsilon^2 1(d_{ij} = 0) - \widehat{\sigma}_u^2 \widehat{\phi}(d_{ij})\right]^2$$

and

$$\widehat{\sigma}_u^2 \widehat{\phi}(d) = \frac{\sum_i \sum_j \left[\widehat{u}_i \widehat{u}_j - \widehat{\sigma}_\lambda^2 \psi(|t-s|) - \widehat{\sigma}_\varepsilon^2 1(d_{ij} = 0)\right] K\left(\frac{d_{ij} - d}{b}\right)}{\sum_i \sum_j K\left(\frac{d_{ij} - d}{b}\right)}$$

where $\psi(\cdot)$ is a specified function of $|t-s|$.

4 Results

Estimation results are presented in Table 2. OLS results are reported in the first column. The OLS estimate of the effect of the log employment disability rate (LEDR) is 0.675. However, we are concerned that a) the LEDR may be endogenous and b) it may be measured with error. The first problem is the issue discussed in papers such as Parsons (1980), Bound (1989), Stern (1989), Benitez-Silva et al. (1999), Bound and Waidman (2002), and Kreider and Pepper (2002). The second issue is that the LEDR variable is based on a survey which, in some counties, relies on a small number of observations. Note that the two issues would cause bias in different directions. The endogeneity problem causes an upward bias, and the measurement error problem causes a bias towards zero. A similar point is made in Bound (1991).

In either case, the use of appropriate instrumental variables corrects for the bias caused by inclusion of the LEDR. We consider three separate 2SLS procedures varying by what instrument is used for LEDR. The three instruments are listed in Table 1. While there is significant variation in the estimates of the effect of LEDR across the different 2SLS equations, all are significantly larger than the OLS estimate, and all are significantly larger than one.[12] The effect on standard error estimates of accounting for correlation depending on geographic distance turns out to be minimal. In all specifications of the equation of interest, the point estimate of $\widehat{\sigma}_u^2$ is essentially zero. This is quite surprising especially in light of results in Jordan, Merwin, and Stern (2004) that show important cross county effects in the provision of medical care.

The fact that the 2SLS estimates are larger than the OLS estimate suggests that measurement error is the dominating cause of bias in the OLS results. Figure 1 shows the estimated density of the ratio of the minimum standard deviation of measurement error of $\widehat{p}$ to its point estimate across US counties.[13] The minimum is the standard deviation that would occur solely from the sampling procedure of Census even if all respondents answered the relevant question without error. In fact, response error may occur because people interpret the question differently, they choose not to answer it honestly, or the question itself is flawed. The last possibility would occur if the correct measure of disability

[12] There is significant variation between the OLS and 2SLS estimates for the other coefficients as well. We choose not to focus on these given the evidence in favor of endogeneity.

[13] To estimate the measurement error in each county disability rate, we use the recommendations of the Technical Documentation of the US Census. For every county, we first use a sample proportion standard deviation formula that computes an unadjusted measure of the sampling error,

$$SE(\hat{p}) = \sqrt{\frac{\hat{p}(1-\hat{p})}{N/5}}$$

where N is the county's population of interest (adults between 18 and 64 years of age), $\hat{p}$ is the county's disability rate, and the 5 is based on a 1-in-6 sample and is derived from the inverse of the sampling rate minus one. We then multiply these unadjusted measures by weights provided by Census to give a point estimate of the measurement error.

was not a binary variable. The mean minimum standard deviation is 0.078, and its standard deviation is 0.068. Table 1 reports that the standard deviation of the log employment disability rate is 0.272; thus measurement error represents 8.2% of the total variation in the variable.[14]

Table 2
Regression Results

Variable	OLS	2SLS^a	2SLS^b	2SLS^c
Constant	-0.661 (0.896)	15.679*** (4.012)	19.425*** (2.104)	13.471*** (2.362)
log Employment Disability Rate	0.675*** (0.034)	1.996*** (0.317)	2.298*** (0.132)	1.836*** (0.174)
Share Female	1.715*** (0.330)	-1.323 (0.825)	-2.003*** (0.551)	-0.955* (0.571)
Share Black	0.144*** (0.044)	-0.165* (0.086)	-0.234*** (0.065)	-0.126* (0.066)
log Share Legal Professionals	-0.050*** (0.010)	0.001 (0.019)	0.013 (0.016)	-0.005 (0.015)
log share active medical doctors	-0.007 (0.007)	0.026** (0.012)	0.033*** (0.011)	0.022** (0.010)
log Mean Age	2.259*** (0.167)	-0.894 (0.764)	-1.620*** (0.390)	-0.498 (0.448)
log Median Household Income	-1.017*** (0.055)	-1.098*** (0.083)	-1.117*** (0.090)	-1.069*** (0.076)
log Poverty Rate	-0.143*** (0.028)	-0.547*** (0.106)	-0.639*** (0.060)	-0.491*** (0.063)
log Unemploy-ment Rate	0.117 (0.015)	0.082*** (0.022)	0.074*** (0.023)	0.087*** (0.019)
Urban	0.109*** (0.017)	-0.030 (0.041)	-0.062** (0.028)	-0.017 (0.029)
Suburban	0.065*** (0.012)	-0.022 (0.027)	-0.042** (0.020)	-0.011 (0.019)
R^2 or pseudo R^2	0.685	0.366	0.209	0.443
# Observations	2913	2897	2901	2909

Notes:

1. Standard errors are in parentheses. Single starred items are significant at the 10% level, double starred items are significant at the 5% level, and triple starred items are significant at the 1% level.

2. Instruments for the 2SLS regressions are (a) log county "labor force disability rate" in 1980; (b) log county "prevented from working" disability

[14] $(0.078/0.272)^2 = 0.082$.

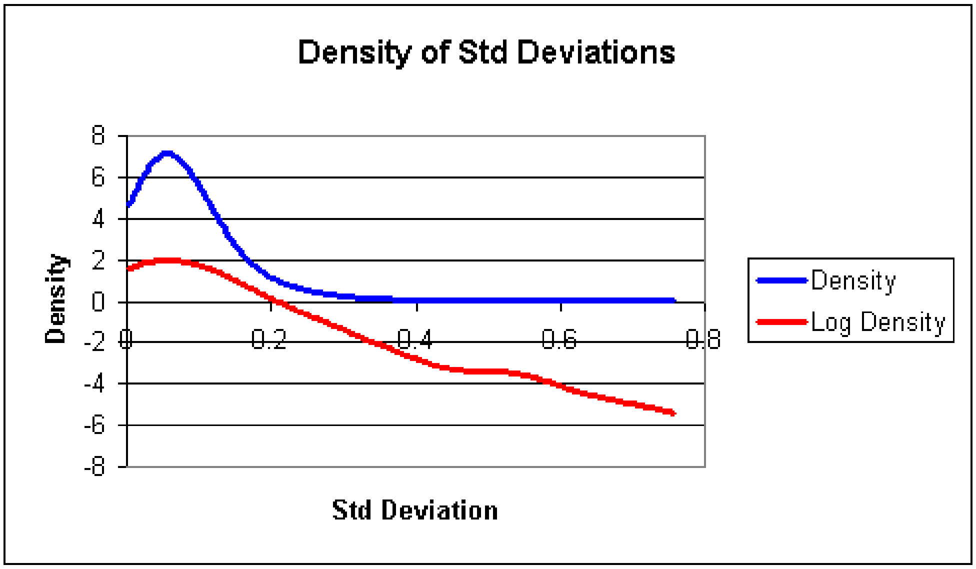

Figure 1:

rate in 1980; and (c) fraction of the labor force working in each industry (agriculture, mining, utilities, construction, and manufacturing).

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Let X be the set of true explanatory variables, W be the set of explanatory variables measured with error,[15] Z be the set of instruments, $X^* = (X \mid Z)$, and $W^* = (W \mid Z)$. The maximum standard deviation is bounded by the condition that

$$X^{*\prime}X^* = W^{*\prime}W^* - Ee'e$$

is positive definite. Given $W^{*\prime}W^*$, the upper bound on σ_e is 0.1684.[16] If the equation of interest is in equation (1), then

$$plim\widehat{\beta}_{OLS} = \left(plim\frac{X'X}{n} + plim\frac{e'e}{n}\right)^{-1}\left(plim\frac{X'X}{n}\right)\beta$$

Given the sample we have and treating the 2SLS estimates in column 2 of Table 2 as "the true values of β", the value of σ_e necessary to bring the ratio of the employment disability coefficient from $plim\widehat{\beta}_{OLS}$ to the corresponding element

[15]We assume that only the employment disability rate is measured with error. Thus $W = X + e$ where all of the elements of e not corresponding to employment disability are zero.

[16]At $\sigma_e = 0.1684$, the smallest eigenvalue of $W^{*\prime}W^* - Ee'e$ is 0.0.

of β_{2SLS} closest to unity is $\sigma_e = 0.079$, almost exactly the minimum standard deviation of measurement error. The value of $0.078 \leq \sigma_e \leq 0.1684$ necessary to minimize

$$\left\| plim\widehat{\beta}_{OLS} - \widehat{\beta}_{OLS} \right\|$$

using a $L-1$ norm is at $\sigma_e = 0.078$, the minimum standard deviation of measurement error. At this value, the coefficients with large absolute deviations are "Share Female" and "log Mean Age," both with an absolute deviation of about 3.0. The next two largest absolute deviations are 0.4 for "Poverty" and 0.3 for "Black." Thus, with the exception of two coefficients, the minimum standard deviation of measurement error performs well in explaining the deviations between the OLS and 2SLS estimates, implying that the main source of measurement error is sampling error.

The fact that the 2SLS estimates are larger than one requires some discussion. If a fixed proportion of employment disabled people recieved social security disability insurance (SSDI), then the true value of the coefficient would be one. The interpretation of an estimate more than one is that there are synergies for applying for SSDI when the disabled population is larger. This may take the form that the Social Security office is more organized with respect to processing SSDI applications or more sensitive to the preferences of disabled people. Or it may be that other sympathetic forces in the community become more powerful or outspoken when the disabled population is larger. Bearse et al. (2004) find similar results with respect to the use of specialized transportation by disabled people.

The results suggest that women and blacks are less likely to apply for SSDI even after controlling for other characteristics. Our findings for women are consistent with previous results in the literature such as Benitez-Silva et al. (1999) and Bound and Waidmann (2002). Bound and Waidmann (2002) show that during 1990 (for example), 31% of disabled women between 55 and 59 years old were on DI while 70% of disabled men in the same age group were on DI. This implies that women are less likely to receive DI than men, and they suggest this is due to women being less attached to the labor market. On the other hand, previous studies such as Kreider and Riphan (2000), Kreider (1999) and Mitchell and Phillips (2002) find evidence that blacks are more likely to apply for DI after controling for their disability status.[17] The difference between their results and ours may be due to the type of data used in each study. While other studies use individual records, we use aggregate county level data instead. The uniqueness of our results can be explained if there are any unobserved characteristics of the county that affect both the proportion of blacks in the county and the number of SSDI beneficiaries living in it.

There are three included economic variables: log median household income, log poverty rate, and log unemployment rate. All three are consistent with other results in the literature suggesting that Social Security disability claims are

[17]Kreider and Riphan (2000) results are statistically significant, while the results in Kreider (1999) and Mitchell and Phillips (2002) are not.

countercyclical.[18] Our estimate provides no information on whether potential claimants, the local Social Security office, or both are changing behavior with the robustness of the economy.[19]

Estimates of coefficients associated with dummies for Urban and Suburban show that, the more urban a community, the less likely disabled people in the community are to receive SSDI. This may be because there are more work opportunities and, maybe more importantly, more diverse opportunities in urban areas. For example, while a physical disability in a rural mining town would prevent one from working, the same disability in a city would not preclude someone from working in an available job requiring less physical exertion.

Finally, we include measures of the availability of legal and medical professionals who might be of assistance in applying to and navigating the SSDI system. While we find that the prevalence of lawyers has no effect on SSDI rates, the prevalence of physicians has a positive effect on SSDI rates.

5 Conclusions

By using cross-section data across counties of the United States, we are able to measure the effect of various local population characteristics on Social Security Disability Insurance participation rates. We find that inclusion of the local disability rate results in biased estimates mainly because the local disability rate is measured with significant error. However, all of the error can be attributed to sampling error rather than the types of reporting biases discussed in much of the literature. Once we control for the measurement error by using instrumental variables, we find that the results suggest that variation in local disability rate, the local economic conditions, and the availability of medical professionals all help to explain variation in SSDI participation rates.

In theory, the inclusion of local conditions could be incorporated in other work relying on a cross-section of individuals. However, in almost all cases in the literature, it has not been done, frequently because the data sets used do not provide information on the county of residence of each individual or enough information on the relevant local conditions. Of course, we lose something of

[18] Several studies have found that the number of disability applications rises during economic downturns. For example, Benitez-Silva et al. (1999) find that an individual's net worth and earnings have a negative effect in the probability of applying for DI. In addition, Kreider (1999) also finds evidence that increases in labor income and the local employment rate diminish the likelihood of applying for DI. Finally, a considerable amount of government-sponsored work has found that the unemployment rate has a positive effect in DI's growth (see Rupp and Stapleton 1995 for a survey of this literature).

[19] On the other hand, other papers such as Kreider (1999) and Benitez-Silva et al (1999) have modeled both the individual choice of applying for DI and the SSA award decision. Hence, they have been able to assess how changes in the economic environment affect both of these variables separately. Kreider's (1999) results suggest that a higher unemployment rate increases the likelihood of a potential claimant to apply for DI but has no (statistically significant) effect in the SSA's award decision. Benitez-Silva et al (1999) finds that households with lower income have a higher probability of applying for DI and that there is no (statistically significant) evidence that it affects the SSA's grant decision.

importance by not having individual data (e.g., our discussion of the effects of race and gender). Thus, each type of data analysis provides useful information.

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