Macroeconomic Influences on Social Security Disability Insurance Application Rates

Dana A. Kerr[1] and Bert J. Smoluk[2]

Abstract: It is generally accepted that Social Security Disability Insurance (DI) Program application rates are influenced by the macroeconomy. DI program data and previous research indicate that a disproportionate number of beneficiaries (past applicants) are less-educated, with low-skill employment histories. These applicants, while they worked, were likely to intertemporally shift their durables consumption expenditures in response to tight budget constraints over the business cycle. Many endured a decline in their wages relative to the average U.S. worker. A strategy for linking DI application rates to the economy, therefore, is one that focuses on durables consumption shifts and wage inequality. Consistent with our expectations, we find that aggregate DI application rates are inversely related to various durables consumption-to-wealth ratios and measures of wage inequality felt by less-educated/low-skilled workers. An interesting finding of this paper is that the national unemployment rate is not always a reliable predictor of DI application rates. [JEL code: H55, E21, E 24, J68; Social Security, disability insurance, macroeconomy.]

INTRODUCTION

The Social Security Disability Insurance (DI) program is enormous. In 2008 the DI Trust Fund paid approximately $106 billion in benefits, maintained a roll of 7.4 million disabled-worker beneficiaries, and received 2.3 million applications.[3] DI application rates over the last several decades

[1]Ph.D., CPCU, Assistant Professor of Risk Management and Insurance, University of Southern Maine, 96 Falmouth Street, Box 9300, Portland, ME 04103-9300, dkerr@usm.maine.edu, telephone: 207-780-4059.

[2]Ph.D., CFA, Associate Professor of Finance, University of Southern Maine, 96 Falmouth Street, Box 9300, Portland, ME 04103-9300, hsmoluk@usm.maine.edu, telephone: 207-780-4407.

[3]See the 2009 OASDI Trustee Report and application and awards data at www.ssa.gov.

Journal of Insurance Issues, 2011, **34** (2): 112–150.

indicate a counter-cyclical pattern relative to the U.S. business cycle, suggesting that macroeconomic conditions are influencing individuals' decisions to file disability claims. This paper examines the influence that the U.S. economy has on DI application rates over a period of 31 years. Since Social Security claimants often migrate from various private disability insurance rolls, an understanding of the macroeconomic influences on DI application rates is of interest not only to policy makers, but also to the private disability insurance industry and employers.

The application process and the decision by the Social Security Administration to award DI benefits primarily revolve around the extent to which an applicant is unable to work due to medical impairment. Eligible applicants must show that they have a medical condition that renders them unable to do the work they did before their condition and that the condition has lasted, or is expected to last, for at least one year, or will result in death. Over the past several decades DI application rates have been cyclical, and recent evidence shows they are on a strong upward trend. Because the DI application decision focuses on the applicant's ability to work despite being medically impaired, much of the literature attempting to explain the cyclical variability of DI application rates over the long run has been directed at analyzing labor market conditions. In this literature, the unemployment rate and proxies for the DI earnings replacement rate play prominent roles.[4]

The Social Security Administration's demographic data suggest that DI recipients (past applicants) are likely to be economically constrained, low-skilled, and less-educated individuals.[5] While DI applicants may be less educated and more economically constrained than the average American, we assume they are rational, forward-looking economic agents. They consider not only their current economic situations when deciding to file DI applications, but also their expected future economic situations. A strategy, therefore, for connecting DI application rates to the economy is to identify macroeconomic variables that possess a forward-looking component as well as reflect the hardships felt by economically constrained individuals over the business cycle.

[4] See for example, Rupp and Stapleton (1995), Autor and Duggan (2003, 2006, 2007), and Black, Daniel, and Sanders (2002).

[5] According to a Social Security Bulletin study that matched data from the U.S. Census Bureau to Social Security Administration records, the percentage of DI beneficiaries with at least a high school education increased from 43.7 percent to 66 .4 percent between 1984 and 1999. Comparative U.S. average data show an increase from 73.9 percent to 84.1 percent during the same period. While the positive trend in education attainment for DI beneficiaries and the U.S. overall are consistent, the education level of DI beneficiaries is still substantially below the national average (see Martin and Davies, 2003/2004).

It is widely known that consumer durables expenditures are strongly procyclical. Durables expenditures are often postponable, especially during economically difficult times, as consumers stretch the lives of their existing goods and attempt to meet tight budget constraints. Because the decision by Social Security Administration to award DI benefits is tied to the individual's health-related inability to earn income, DI ultimately is consumption and wealth insurance. DI insures an individual's consumption from significant drops and it also insures the wealth ultimately used for consumption. An interesting aspect of rational consumer behavior is that changes in spending are based on an individual's expectations. In the event of uncertainty about the future or an expected future economic downturn, for example, an individual will quickly reduce consumption beforehand. Using this idea as a basis for his paper, Smoluk (2009) finds a strong negative relation between total consumption-to-wealth, using various definitions of wealth, and private group long-term disability insurance claims rates.

In our paper we hypothesize that there is an inverse relationship between the durables consumption-to-wealth ratio and Social Security DI application rates. We employ durables consumption, rather than total consumption, since durables consumption is more sensitive to the economic conditions felt by applicants.[6] Therefore, one may conclude that individuals are using DI to insure their durables consumption risk, which ultimately insures their standard of living risk.

Over the last three decades low-skilled workers have experienced a decline in their real and relative wages. With the help of previous literature, we identify the sources of these declines and develop a measure of the wage inequality felt by low-skilled labor. We refer to this wage inequality measure as the "wage gap." Our wage gap measure is computed by dividing an index of national labor productivity by the average annual wages of individuals with only a high school degree. This variable, like the consumption-to-wealth variables, is interesting because it incorporates a forward-looking component. Increases in labor productivity, for example, signal higher future wages as employees share in the increases in future profitability of firms. We expect that Social Security DI application rates will be positively related to the wage gap measure.

The findings in this paper have important implications for public policy, private disability insurers, and employers providing group disability insurance to employees. If economic conditions in addition to the

[6]Durables expenditures are more likely to be intertemporally shifted by economic agents as they consider their near-term economic situations. Nondurables and services expenditures, on the other hand, are more likely to include spending on necessities (see Attanasio, 1999).

unemployment rate affect DI application rates, then it suggests that macroeconomic conditions are at least partly responsible for triggering an individual's decision to file for DI. Individuals are not simply becoming disabled and filing for DI solely based on their physical or mental condition, they are contemplating the severity of their disability relative to their expectation of future economic conditions. Halpern and Hausman (1986), Rupp and Stapleton (1995: 51), and Bound and Burkhauser (1999) recognize and discuss the economic trade-offs that individual DI applicants face when deciding to file a claim. A better understanding of these macroeconomic triggers can help improve DI application and awards forecasts, which in turn will improve upon the Social Security Administration's sizable long-run costs projections.

Private disability insurers are interested in these findings because many individuals migrate from private long-term disability (LTD) to DI provided they meet Social Security's stricter eligibility criteria. The migration pattern is discussed in Wagner et al. (2000). Typically, private group disability insurance payments are reduced dollar-for-dollar by DI benefits received, providing an incentive for private disability insurers and employers offering LTD as an employee benefit to encourage beneficiaries to apply for DI benefits. The group insurers' and employers' future costs and reserves drop when individuals are awarded Social Security benefits.

To the best of our knowledge, no one has shown a connection between durables consumption–to–wealth ratios, wage gaps that employ a forward-looking component such as labor productivity, and DI application rates. Our paper is outlined as follows. In section II we review the relevant literature and section III discusses the data and the motivation for our testing procedures. In section IV, under the assumption of data stationarity, we use ordinary least squares (OLS) and two-stage least squares (TSLS) regressions to show that DI application rates are negatively related to various durables consumption-to-wealth ratios and positively related to our wage gap measure over time. In section V, we employ cointegrating techniques to test whether DI application rates are in a long-run relationship with our macroeconomic variables under the assumption the data are nonstationary. Section VI concludes the paper.

LITERATURE REVIEW

The swings in DI application rates over the last several decades have led to a substantial volume of research attempting to explain the variation. The DI literature focuses on four main drivers: (i) changes in the administration and policies of the DI Program, (ii) changes in population factors,

(iii) changes in the relative value of earnings replacement rates for various workers, and (iv) the U.S. business cycle.[7]

Social Security Disability Policy Changes

Numerous policy changes have taken place in the Social Security Administration since 1978, the beginning of our sample period. For the study at hand, we will discuss the changes that the literature has identified as having a significant impact on DI application rates. For example, the early 1980s saw marked decline in disability applications as the DI program sped up the periodic review process for existing beneficiary cases. Beneficiaries whose disabilities were not permanent were subject to a continuing disability review at least every three years to confirm they still met the Social Security Administration's definition of disabled. Many individuals, especially those suffering from mental illness, had their benefits terminated. This review process not only affected disability rolls, but is suspected of indirectly reducing application rates as potential applicants received word of the outcome of many of these reviews. The stringency level of the DI program and its effect on application rates is studied in Parsons (1991), Gruber and Kubik (1997), Rupp and Stapleton (1995). Parsons (1991) estimates that a 10 percent increase in denial rates is followed by a decrease in applications of 4.5 percent. Gruber and Kubik (1997) reach similar conclusions, while Rupp and Stapleton (1995), conditioning on the unemployment rate and demographic data, find the impact is about half of that found by Parsons.

In reaction to the significant drop in applications and the increase in terminations from continuing disability review, Congress enacted the 1984 Disability Benefits Reform Act, effectively liberalizing the definition of disability. The Act relaxed the requirement that an individual must suffer from a single severe impairment to proceed through the evaluation process. Prior to this liberalization, a person could not continue through the determination process if she had multiple non-severe impairments that cumulatively resulted in disability. The change also made it easier for those unable to work due to mental illness and pain caused by ailments such as a back condition or arthritis to meet the disability requirements.

In 1983 the Social Security Administration began implementing a process of gradually increasing the full retirement age from 65 to 67 and increased the penalty for electing early retirement. While the implementation of this change did not directly affect the DI program, it nevertheless

[7] The size of the Social Security Disability Program has led some researchers to explore the impact that the program itself has had on labor force participation rates in the U.S., especially among low-skilled male workers. See Autor and Duggan (2003, 2006).

had an indirect impact on the DI application rate. Increasing the retirement age of Social Security caused many near-retirement working individuals with a disability to apply for disability benefits rather than waiting for Social Security retirement benefits. According to Duggan, Singleton, and Song (2007), these changes accounted for more than one-third of the increase in DI enrollment for men and more than one-fourth of the increase for women since 1983. These authors did not investigate the impact of the changes on DI application rates. However, given that increases in enrollment of this magnitude must come after an increase in applications, we can surmise that this policy change had a significant effect on application rates.

Changes in Labor Force Demographics

Older individuals, especially those in more physically demanding jobs, are more likely to find work difficult to perform, as they are prone to more physical ailments. Social Security Administration data show that the 55–64 age group accounts for the largest share of DI applications. Starting at the beginning of our sample period, 1978, the number of individuals in the 55–64 age group relative to the those in the 25–54 age group declined until the early 1990s and then increased through the end of the sample period.[8] This swing in labor force demographics, in conjunction with the findings of Duggan, Singleton, and Song (2007) claiming that increases in the retirement-age as defined by Social Security increased DI enrollment, indicates that accounting for the relative size of the near-retirement age labor force is sensible when accounting for changes in DI application rates over time.

Relative Earnings Shifts

Since 1978, monthly DI benefits have been computed in two steps. The first computation is a function of the worker's average actual past earnings adjusted for the overall U.S. wage growth (Average Wage Index) using a formula known as the Average Indexed Monthly Earnings (AIME). The AIME amount then is progressively adjusted so that lower-wage workers receive a higher earnings replacement rate. For an example of the degree of progressiveness, Bound and Burkhauser (1999) show that an individual (worker only) in 1996 whose average indexed yearly earnings were $11,256 had a replacement rate of 61 percent, while an individual with $51,276 average indexed yearly earnings received a replacement rate of only 32 percent. DI benefits therefore become more attractive to workers whose

[8] The relative size of the these two age groups is a function of the impact of the Great Depression, World War II, and the post–World War II era on population.

real wages relative to the U.S. average wage are falling over time. Wage inequality will ultimately help to explain the underlying trends in DI application rates.

Wage inequality and its sources are discussed at length in Acemoglu (2002). Acemoglu, assuming skilled workers to have college degrees and unskilled workers to have only high school degrees, identifies a wage inequality trend that continues to this day. Several sources for the inequality are identified. First, the technological revolution experienced in the U.S. allowed profit-maximizing firms to adopt skill-biased technology that increased the demand for skilled labor. Second, the adoption of skill-biased technology required additional education of skilled labor to maintain productivity and resulted in "skill-erosion" for unskilled workers who did not benefit from the augmented education. Third, increases in international trade with lesser-developed countries effectively increased the supply of unskilled workers in the U.S., resulting in lower wages for unskilled labor. The combined influence of these phenomena over the last several decades accounts for much of the decline in the relative wages of unskilled versus skilled labor, not to mention the decline in real wages for unskilled labor.

The decline in relative earnings of unskilled workers over the last several decades and its effects on DI rolls are studied in Autor and Duggan (2003). They argue that progressive DI earnings replacement combined with higher medical benefits through Medicare eligibility[9] increase the demand for DI benefits and reduce the labor force participation rate of less-skilled workers. They find that a male worker age 55–61 in 1979 at the low end of the earnings-age distribution would have received 67 percent earnings replacement in the form of DI cash transfers plus in-kind medical benefits, and 104 percent in these benefits in 1999.

Low-skilled workers, especially in the manufacturing and production sectors of the U.S. economy (see Rupp and Stapleton, 1995), have seen a significant decline in relative earnings, while the Social Security Administration has experienced a significant increase in DI applications coming from low-skilled workers. The hard physical nature of their jobs make enduring ailments and illnesses that much more difficult for less-skilled workers. These conditions, therefore, are more likely to interfere with their job performance, according to Loprest, Rupp, and Sandell (1995).

[9]DI beneficiaries are eligible for Medicare coverage 24 months after they begin receiving DI payments.

Business Cycle

The connection between the business cycle and *private* group long-term disability (LTD) insurance claims rates is examined in Smoluk (2009) and Smoluk and Andrews (2009). The data used in these two papers cover the period from 1988 to 2003, with the LTD incidence history from UNUM, a significant LTD insurer in the United States. In Smoluk (2009), the author shows that private group LTD submitted claim rates track (inversely) the consumption-to-wealth ratio. It is well known in the financial economic literature that individuals are risk averse and detest drops in their standard of living. LTD holders, whether they realize it or not, are much more (less) likely to exercise their LTD option when the consumption-to-wealth ratio is low (high). When the consumption-to-wealth ratio is low, individuals have lower expectations about their future economic situation, which makes it more likely they will exercise their option given a disabling medical condition exists. Wealth includes annual total income, which proxies the annuity value of human capital, and the market value of single-family housing. The author argues that LTD represents an option that is more likely to be exercised when an individual's economic situation is expected to deteriorate to the point that their total consumption, and their wealth used for total consumption, is at risk of falling. This option is extremely valuable, especially to work-impaired individuals who are capable, to some extent, of optimally timing the exercise.

In Smoluk and Andrews (2009) four different, but related, macroeconomic variables are examined. The first two variables are from the labor market: the unemployment rate and the social security disability income replacement rate. Social security disability income replacement rate measures the opportunity cost of not filing a claim for individuals who are work-impaired to some degree, but still employed. The second set of macroeconomic variables employed is based on measures of wealth. A durables consumption-to-housing wealth variable and also a stock market return variable are used. Their results indicate that the unemployment rate is not an important factor in explaining group LTD incidence rates, while social security disability income replacement rates are positively related and statistically significant. As in Smoluk (2009), the consumption-to-wealth variables are shown to be significant and negatively related to LTD incidence.

An increase in economic uncertainty is often linked with a drop in consumer demand for big-ticket items, such as durables goods. Over the early part of our sample period, unstable prices, associated with high inflation, were a source of economic uncertainty. Consumers sensed economic uncertainty because the relative price of goods and services were changing significantly. Real prices were difficult to determine and the ability of the consumer to meet their budget constraints became questionable. In the face of this uncertainty, households slowed their purchases of durable goods as energy expenditures became a larger portion of the household budget (see Friedman, 1975; Ball and Mankiw, 1995).

The sensitivity of consumer durables expenditures to the business cycle is examined in Browning and Crossley (1999), who develop and test the *internal* capital markets hypothesis. In contrast to the widely known external capital markets hypothesis, where the consumer uses the financial markets to intertemporally shift consumption, the internal capital markets hypothesis states that the economically-constrained consumer postpones expenditures on small durables such as clothing when facing the possibility of a temporary economic slow-down or unemployment. Consistent with the internal capital markets hypothesis, Attanasio (1999) finds empirical evidence that durables expenditures are substantially more volatile for households headed by less-educated individuals, such as high school dropouts (s = 22.85 percent) and high school graduates (s = 16.58 percent), compared to more-educated heads of household (s = 9.66 percent). While this finding may be anecdotal evidence as it applies to the study of disability insurance, it does suggest to us the strong possibility that individuals economically constrained by the effects of medical impairments on the ability to work may reduce their durables consumption around the time of filing DI applications.

For many households, the two most important sources of wealth are human capital (proxied by the annuity value of labor income) and housing wealth. Case, Quigley, and Shiller (2006) suggest that the wealth effects on consumption may vary by type of wealth. Consumers may compartmentalize their spending through "mental accounts" corresponding to different forms of wealth, especially if the gains from those forms of wealth are viewed differently—as either transitory or permanent. Recent stock market gains are often viewed as transitory wealth—and drive small changes in consumption, while housing gains are considered more permanent, leading to larger changes in consumption. Consistent with this hypothesis, Campbell and Cocco (2005) find that the elasticity of nondurables consumption of older homeowners from changing housing prices is statistically significant and positive. Predictable changes in house prices were found to influence consumption through a collateral channel, as owners extract the equity value of their homes via home-equity loans. Thus, it seems reasonable that the consumption of economically-constrained older households is significantly influenced by house prices.[10]

A successful outcome to filing a disability application—in other words, an award—is an uncertain event. Halpern and Hausman (1986) hypothesize that the level of uncertainty in the application process influences whether an individual suffering a disability, yet still working, files a claim. Using a Von Neuman-Morgenstern utility function, the authors consider this uncertainty and attempt to capture the costs and benefits of filing a disability application using data from a self-reporting survey conducted by the Social Security Administration on disabled and non-disabled adults. The cost of filing a claim is based on the possibility of rejection for benefits. Because there is a five-month waiting period plus processing time for the application, it is not unusual for an individual to be out of the labor force for one year before receiving a decision. In that time the individual experiences a decline in human capital, develops gaps in his/her employment record, signaling to future employers that the individual may have health problems, and creates a perception that the individual is marginally attached to the work force. The benefits of filing a claim are based on the higher future income from the Social Security Administration (DI benefits) relative to what could be earned by the applicant working with a disability. The earnings of a worker with a disability are typically lower than those of a non-disabled individual. Consistent with their hypothesis, the authors find evidence that an individual contemplates filing a DI application by comparing the utility obtained from not filing a claim to the expected utility from filing a claim with an uncertain application outcome.

Hypothesis Summary

The onset of injury often does not immediately lead to the filing of a DI application. Individuals frequently work for years prior to filing claims. As their impairments slowly erode their capacity to work, absenteeism increases and they become the marginal employees most likely to be displaced during challenging economic periods, (see White, 2009). Given that the modal DI recipient is a near-elderly, high school–educated male with below median earnings potential, a DI applicant is likely to be financially strained at the time the application is filed.[11] Wage gaps and variation in consumer durables spending relative to wealth over the business cycle should reflect the economic pressures felt by these individuals and their

[10]While the average education level for DI beneficiaries is substantially below the national average, as discussed earlier, the percentage of DI beneficiaries owning a home (63.7) is much closer to the U.S. average (67) in 1999. Thus, housing values are a significant and important component of DI beneficiary wealth (see Martin and Davies, 2003/2004).

[11]In addition, an individual must wait at least five months before receiving cash DI benefits, while they are unable to perform "substantial gainful activity," and 24 months before becoming eligible for Medicare benefits. Also see Martin and Davies (2003/2004) for a review of the household financial situation of DI beneficiaries.

households, suggesting a link between these macroeconomic variables and DI applications rates.

To summarize, here are the six main variables of interest in this paper and the null hypotheses we testing:

(1) The estimated durables consumption–to–income ratio coefficient is expected to be negatively related to DI application rates and significantly different from zero. When the durables consumption–to–income ratio increases (decreases), individuals are assumed to have higher (lower) economic expectations about the future, and therefore consume more (less) relative to their income. Lower (higher) economic expectations implies a higher (lower) opportunity cost to filing a claim, hence a negative relation to DI application rates.

(2) The estimated durables consumption–to–wealth (income plus market value of housing) is expected to be negatively related to DI application rates and significantly different from zero. When the durables consumption–to–income ratio increases (decreases), individuals are assumed to have higher (lower) economic expectations about the future, and therefore consume more (less) relative to their wealth. Lower (higher) economic expectations implies a higher (lower) opportunity cost to filing a claim, hence a negative relation to DI application rates.

(3) The unemployment rate is expected to be positively related to DI application rates and significantly different from zero. When the unemployment rate increases (decreases), individuals with a disability are more (less) likely to file a DI claim as the opportunity cost of not filing a claim increases.

(4) The wage gap, proxied by national labor productivity over the wage income earned by individuals with a high school degree or less, is expected to be positively related to DI application rates and significantly different from zero. Intuitively, a higher (lower) wage gap for individuals with a high school degree or less suggests that these individuals are losing (gaining) their relative standard of living as they work. The less (more) attractive their job becomes, the higher (lower) the opportunity cost of not filing a DI claim.

(5) The age-distribution variable, which measures the proportion of the population age 55–64 to those age 25–54, is a demographic control variable. Since older individuals are more likely to file a DI claim, we expect this variable to be statistically significant different from zero and positively related to DI application rates.

(6) The productivity–to–hourly manufacturing wage variable is another measure of relative well-being derived from working. This ratio is expected to be statistically significant and positively related to DI application rates. Like the wage gap variable, an increase (decrease) in this variable

suggests that the opportunity cost of working relative to DI benefits for manufacturer workers has increased (decreased). This variable is used with quarterly data.

THE DATA

Primary Data Set

In 1977, amendments to the Social Security Act implemented the indexing of DI benefits to the average U.S. wage rate for applications received starting in 1978. Our sample period, therefore, begins in 1978 since the Social Security Administration has maintained the same earnings replacement formula for determining its benefits, as outlined in the previous section.[12] Earnings replacement, as mentioned above, is the most important motivation for filing an application with Social Security. DI application rates are computed by dividing the total number of annual applications received by the number of insured workers under the DI Program. Application rates averaged 1.1% during the sample period. Table 1 presents the mean, standard deviation, and unit root tests for the DI application rate as well as other variables used throughout this paper.

Two consumption ratios were estimated using different measures of wealth. The first, the consumption–to–housing value ratio, employs per capita durables consumption in the numerator and the market values of housing in the denominator. Total per capita durables consumption is from the Bureau of Economic Analysis (BEA) National Economic Accounts database. Per capita market value of housing is derived from the index of single-family detached-house prices published by the Office of Federal Housing Enterprise Oversight, now called the Federal Housing and Finance Agency. We transformed the index into a per capita series by first computing the ratio of per capita market value of housing to per capita total personal income as reported by the Consumer Expenditure Survey (CEX). We multiplied this ratio by per capita total personal income from the BEA to arrive at an estimate of the market value of housing on a per capita basis.[13] Per capita durables consumption spending-to-housing wealth averaged 4.6% over our 31-year sample period. The second consumption ratio employs durables consumption to wealth, where wealth is

[12]Also see Duggan and Imberman (2006).

[13]The CEX did not publish housing values prior to 1984. For 1978 to 1983, we estimated per capita market value of housing by multiplying BEA personal income by the CEX average of housing value to annual income ratio, 2.15.

Table 1. Summary Statistics

	Descriptive Statistics 1978 to 2008		Correlation Statistics 1978 to 2008								
Variable	Mean	Std dev	DI rates	cmh	cw	uemp	phs	ccf	per	pi	age
Regressand/regressors											
DI application rate	0.01	0	1								
Consumption-to-market value of housing ratio	0.05	0	–0.78	1							
Consumption-to-wealth ratio	0.03	0	–0.74	0.99	1						
National unemployment rate	0.07	0.01	–0.1	0	–0.1	1					
Wage gap: labor productivity–to–high school only earnings de-trended	0	0	0.83	–0.51	–0.46	–0.1	1				
Instruments											
Consumer confidence index	86.39	14.43	–0.48	0.65	0.68	–0.36	–0.36	1			
Production worker earnings replacement rate de-trended	0.388	0.01	0.29	–0.23	–0.25	0.34	0.18	–0.36	1		
Real personal income growth rate	0.01	0.02	–0.29	0.3	0.33	–0.21	–0.57	0.61	–0.11	1	
Age-distribution first-differenced	0.201	0.03	0.52	–0.38	–0.34	0.62	0.41	–0.15	0.26	–0.12	1

DI application rate is the number of Social Security disability applications received per quarter divided by the number of individuals insured; consumption ratios are based on durables consumption, with wealth defined as annual income plus the market value of housing; *unemployment rate* is the national unemployment rate from the Bureau of Labor Statistics; *wage gap: labor productivity–to–high school only earnings* is computed using a labor productivity index from the Bureau of Labor Statistics divided by average earnings of individuals with only a high school degree; *consumer confidence index* is produced by the Conference Board; *production worker earnings replacement rate* represents an instrument designed to proxy the Social Security earnings replacement rate for nonsupervisory production workers and is computed by dividing annual per capita DI benefits paid by annualized production worker hourly earnings; the *real personal income growth rate* represents the annual growth rate in per capita personal income; and *age-distribution* represents a demographic variable and is computed as the ratio of workers age 55–64 to workers of age 25–54.

DI rates denotes DI application rates; *cmh*, durable consumption–to–the market value of housing; *cw*, durable consumption-to-wealth; *uemp*, unemployment rate; *phs*, wage gap measure based on productivity and high school earnings; *ccf* consumer confidence index; *per*, production worker earnings replacement rate; *pi*, real personal income growth rate; *age*, the ratio of workers age 55–64 to workers age 25–54.

Annual data.

defined here as the annual per capita personal income (human capital) plus the per capita market value of housing. On average, the durables consumption spending to wealth averaged 3.1% over our sample period.

We employ two labor market independent variables. The first is the national unemployment rate from the Bureau of Labor Statistics. The unemployment rate averaged 6.8% over the sample period. The second labor market variable measures the degree of wage inequality experienced by low-skilled workers as discussed in Autor and Duggan (2006) and Acemoglu (2002). As it is a proxy for current and future wage inequality, we refer to this variable as the "wage gap." The wage gap is computed by dividing a national labor productivity index produced from data published by the Bureau of Labor Statistics by the annual earnings of individuals with only a high school degree.[14] The earnings of individuals with only a high school degree is from the Current Population Survey of the U.S. Census Bureau, Table A-3. The wage gap variable over time is a measure of the decline in wages of unskilled labor relative to national average wages. It is important to recognize that our wage gap variable, to some extent, is forward-looking. A change in labor productivity, according to Shimer (2005), signals a change in the present value of future wages. Furthermore, since the Average Wage Index (AWI) used by Social Security to compute DI payments is based on national average wages, and labor productivity is a long-run source of national wages, the numerator of our wage gap variable reflects earnings replacement trends.[15] We de-trended the wage gap variable as it exhibited a significant trend during the last three decades.

To provide a better context for the behavior of the wage gap variable, the average U.S. wage increased from $10,556 in 1978 to approximately $41,698 in 2008, while the average wages of individuals with only a high school degree increased from $9,834 in 1978 to $33,728 in 2008.[16] The

[14]We computed the lab or productivity index series simply by setting the 1977 data point to 100 and compounding one plus the growth rate in labor productivity published by the Bureau of Labor Statistics—In other words, the labor productivity index x (1+ lpg), where lpg is labor productivity growth. The trend in this series should track national wage trends over the long run.

[15]As an interesting side note, the Social Security Administration uses forecasts of national labor productivity in computing the AWI for its long-run projections. See the assumption section of "The 2009 Annual Report of the Board of Trustees of the Federal Old-Age and Survivors Insurance and Federal Disability Insurance Trust Funds."

[16]As this paper was being written, the 2008 AWI had not yet been published by the Social Security Administration. We estimated the 2008 figure by using the Administration's formula of multiplying the 2007 AWI by one plus the national average wage growth rate using wage growth of 3.2% from the Bureau of Labor Statistics.

relative decline in the earnings of low-skilled workers as discussed by Autor and Duggan (2006) is apparent.

The right-hand side of Table 1 provides estimates of the correlation coefficients for the variables employed in this paper. As expected, the DI application rates are strongly negatively correlated with the consumption ratios and highly positively correlated with the wage gap variable. Surprisingly, the unemployment rate is not very correlated with DI applications, and our estimate is negative. The instruments are correlated with the endogenous regressors (consumption–to–housing value, consumption-to-wealth, unemployment rate, and wage gap variable) consistent with the relevance requirement of TSLS. Another important, but expected, observation to note in Table 1 is that the proportion of near-retirement-age workers is highly positively correlated with the DI application rates.

Unit Root verses Trend Stationarity

We employed several different types of unit root tests on all the variables used in this paper and obtained mixed results. We were unable to draw firm conclusions as to which variables were nonstationary versus trend-stationary.[17] As a result, we employ the data in levels using ordinary least squares (OLS) and two-stage least squares (TSLS), which generally requires stationary data and cointegration analysis requiring nonstationary data. Using both least squares and cointegration analysis will allow us to better compare and contrast the results, to avoid model erroneous conclusions from model misspecification, and will strengthen our conclusions.

[17]This is not unusual. The unit root literature, for example, is unable to definitively conclude whether U.S. GDP since the first quarter of the 20th century is nonstationary or trend-stationary (see for example, Perron and Wada, 2009, for a recent discussion of this ongoing debate; also see Hamilton, 1994, pages 444–446). According to Cochrane (1991), “The problem with this procedure [unit root tests] is that, in finite samples, unit roots and stationary processes cannot be distinguished.” All the econometrically employed variables in our paper, except for consumer confidence, are in the form of ratios. Forming ratios from macroeconomic data may impose moving averages that are difficult to estimate over a finite sample of 31 observations. In his paper, Smoluk (2009) concludes that private-group LTD disability claims rates, the national unemployment rate, and several consumption-to-wealth ratios that are closely related to our consumption-to-wealth ratios are nonstationary. However, Smoluk’s sample period covers only 15¼ years of data. A single persistent trend can easily result in the failure to reject a unit root, especially given the small sample concerns of such tests.

Instrumental Variables, Omitted Variables, Simultaneity, and Control Variable

In the OLS and TSLS regression analysis performed in this paper, there are econometric issues due to the potential for omitted variable bias and simultaneity bias when performing a macroeconomic analysis of DI application rates. Given the size and reach of the Social Security Disability Program, a bewildering number of variables could have potentially influenced DI application rates over the last three decades. Excluding some of these variables in our analysis may lead to omitted variable bias. Furthermore, the size of the Social Security DI program is sufficient enough to generate feedback effects on the macroeconomy, resulting in simultaneous causality bias under OLS. For example, as mentioned above, Autor and Duggan (2003 and 2006) indicate that changes in the retirement age defined by the Social Security Administration can influence the DI application rates for near-retirement individuals, which in turn influences labor force participation rates. To control for omitted variable bias and simultaneity bias, we employ TSLS in addition to OLS for benchmarking purposes. Angrist and Krueger (2001) argue that with a careful selection of instruments, TSLS can often mitigate the biases caused by both omitted variables and simultaneity in empirical research attempting to establish causal relationships. TSLS regression is known to provide consistent, but not unbiased, parameter estimates.

We use several instruments in our TSLS estimation that are designed to be correlated with the endogenous variables (durables consumption–to–housing values, durables consumption–to–wealth, the unemployment rate, and the wage gap variable). The first instrument, the consumer confidence index, is employed as it measures consumers' attitudes towards current and near term future economic prospects. The index is estimated by the Michigan Index of Consumer Sentiment and published by the Survey Center of the University of Michigan. Our second instrument is a proxy for the increase in earnings replacement for production workers. It is computed by dividing annual per capita DI benefits by the annual wages of non-supervisory production workers. Production worker wages are from the Bureau of Labor Statistics. Over the sample period, this instrument has trended downward as DI benefits outpaced production worker wages for our sample period, leading us to de-trend this variable for modeling purposes. A third instrument used in TSLS estimation is national personal income growth, which reflects the well-being of labor and employment conditions in general. The growth rate of real personal income averaged 1.2 percent.

One of the most important variables influencing DI applications is the age distribution of the labor force. Older workers, rather than younger workers, are far more likely to file a claim. To control for demographic shifts in the age distribution in our estimate we compute the ratio of workers in the 55–64 age group to the number of workers in the 25–54 age group using data from the Bureau of Labor Statistics. We first-differenced the age-distribution variable. Given that this variable is in log form, as are all the variables used in this paper, the first-differencing actually transforms it into a compound growth rate of the 55–64 age group relative to the 25–54 age group. We expect a positive relationship between this variable and the DI application rate.

Cointegration Analysis

If the variables in our primary data set are nonstationary, cointegrating techniques can determine whether DI application rates are in a long-run equilibrium with our macroeconomic variables. With cointegrating relations, past equilibrium errors will predict short run changes in at least one of the cointegrating variables, measured in first-differences. We expect that DI applications rates will adjust to past equilibria (feedback), while the macroeconomic variables will not. In other words, we expect the macroeconomic variables to be weakly exogenous. We employ Johansen and Juselius (1990, 1992) cointegration methods.

OLS AND TSLS EMPIRICAL RESULTS

Annual Data

The relationship between DI application rates and labor market conditions is shown in Table 2. Results are shown for both OLS and TSLS regressions using the national unemployment rate, the wage gap variable for individuals with only a high school degree, and the lagged age-distribution variable as independent variables.[18] Since the variables are in natural logs, the coefficients in Table 2 (and in the other tables) are elasticity estimates. In the first two columns of estimates, we see that the OLS and TSLS parameter estimates for the unemployment rate are not statistically significant. The R^2 for the OLS estimate indicates that the unemployment rate explains none of the variation in DI application rates. For the TSLS estimates we used the lagged instruments of production worker earnings

[18]We assume that the age-distribution variable that controls for changes in age demographics in the labor force is exogenous, and therefore only provide OLS estimates.

Table 2. DI Application Rates, a Demographic Control Variable, and the Unemployment Rate, 1978 to 2008

Regressor	OLS	TSLS	OLS	TSLS	OLS	OLS	TSLS
Dependent variable: DI application rates							
Constant	–4.652 (0.000)	–5.384 (0.000)	14.968 (0.000)	17.535 (0.000)	–4.525 (0.000)	12.030 (0.000)	27.253 (0.000)
Unemployment rate	–0.048 (0.825)	–0.306 (0.307)				0.222 (0.001)	0.166 (0.422)
Wage gap: labor productivity–to–high school only earnings de-trended			5.330 (0.000)	6.030 (0.000)		4.355 (0.000)	8.560 (0.013)
Age-distribution {1} first-differenced					3.285 (0.004)	2.345 (0.001)	0.310 (0.897)
Instruments {lags} in addition to a constant		per{1} pi{1} age{1} trend		per{1} pi{1} uemp{1} age{1} trend			per{1} pi{1} age{1} trend
F-test on first-stage regression p-value		15.537 (0.000)		7.030 (0.009)			
Adjusted R^2 on first-stage regression		0.667		0.51			
Over-identifying restrictions J-test and p-value		4.525 (0.210)		4.625 (0.328)			0.457 (0.796)
Adjusted R^2	0		0.684		0.326	0.756	

OLS represents ordinary least squares and TSLS represents two-stage least squares. All variables are in natural logs so that the estimated coefficients may be interpreted as elasticities. p-values for the estimated coefficients, in parentheses, are based on Newey-West (1987) standard errors. The F-test statistic relates to instrument relevance and measures the joint significance of the instruments when regressed on the dependent variable in the first-stage regression where p-values less than 0.05 indicate a rejection of the null hypothesis of non-relevance. The J-test statistic indicates a failure to reject the null hypothesis that the instruments are exogenous at 5 percent significance with p-values greater than 0.05.

DI rates denotes DI application rates; *cmh* durable consumption–to–the market value of housing; *cw,* durable consumption–to–wealth; *uemp*, unemployment rate; *phs*, wage gap measure based on productivity and high school earnings; *ccf* , consumer confidence index; *per,* production worker earnings replacement rate; *pi*, real personal income growth rate; *age* the ratio of workers age 55–64 to workers age 25–54.

See Table 1 notes for a description of the data.

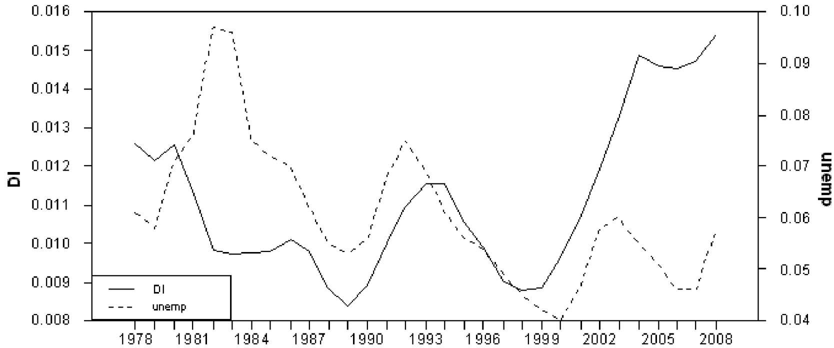

Fig. 1. DI application rate and national unemployment rate.

replacement rate, de-trended, real personal income growth, and age distribution as a demographic control variable plus a trend.[19] The F-test statistics with low p-values, and the reasonably high adjusted R^2's, indicate that we reject the null hypothesis of weak instruments (i.e., non-relevance) in the first-stage regression. Lagged instruments are used to support the assumption of exogeneity. The p-values on the J-test statistics are sufficiently large to provide evidence that the instruments are exogenous, as we fail to reject the null hypothesis that the instruments are uncorrelated with the residuals from the second-stage regression. Figure 1 shows the relation between the unemployment rate and DI application rates. The relationship is reasonably good in the middle of the sample period, but, it is poor during 1980–1983 and at the end of the sample. The 1980–1983 disconnect, according to Autor and Duggan (2003), is due to the Social Security DI Program's tightening of application requirements and conducting periodic case reviews to rein in program costs.[20]

The next two columns of data employ the wage gap variable, de-trended. Since this variable measures the decline in relative earning power of individuals with only a high school degree, the estimate signs should be positive. The p-values indicate that the variable is highly significant and

[19]The small-sample properties of TSLS are better than most other estimators, according to Kennedy (2003: 189). The asymptotic efficiency of the TSLS estimator increases with the number of instruments, though at the cost of worsening finite sample bias. According to Davidson and MacKinnon (1993: 222) the number of instruments should exceed the number of regressors by at least two, so the first two moments of the estimator is computable.

[20]Interestingly, the 1980–1983 anomaly with high unemployment and falling DI application rates coincides with a sharp drop in unemployment insurance recipient rates during the same time period, as noted by Wander and Stengle (1997).

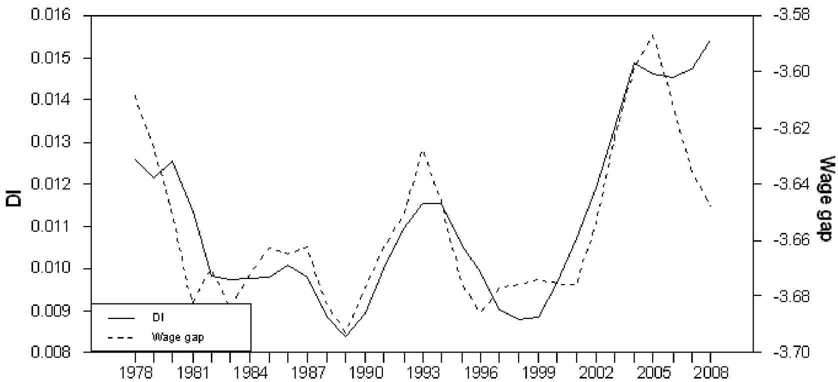

Fig. 2. DI application rate and wage gap for high school only, de-trended.

the adjusted R^2s on the OLS estimates indicate that 68.4 percent of the variation in DI application rates is accounted for by the wage gap. Figure 2 shows an extremely close relationship between the wage gap and DI application rates.

In the third column from the right in Table 2, we present the estimate of the relation between DI application rates and the age-distribution variable, using only OLS since we assume it to be exogenous as it is lagged. The parameter estimate is positive, as expected, and statistically significant, indicating that as the growth rate in the relative age of labor increases, DI application rates increase.

The last two columns are estimates for the combined labor market model. Interestingly, in the full labor market model, the unemployment rate is positively related to DI application rates, but is only statistically significant with the OLS estimate. The lagged age-distribution parameter estimates are also positive and inconsistently significant at the 5 percent level.

In Table 3 we estimate the relation between the per capita durables consumption–to–wealth ratios and DI application rates. The results across the table indicate that the consumption-to-wealth ratios are negative, as expected, and statistically significant. The adjusted R^2's for the OLS estimates show that the consumption–to–wealth variables (and a constant) explain over 50 percent of the variation in DI application rates for the 31-year sample period. The age-distribution estimates are positive and tend to be statistically significant at the 5 percent level.

How do the various durables consumption–to–wealth ratios perform when the wage gap variable is included in the regression? Table 4 shows

Table 3. DI Application Rates, Consumption–to–Housing Values, and Wealth Ratio, 1978 to 2008

Regressor	OLS	TSLS	OLS	TSLS	OLS	TSLS	OLS	T SLS
Dependent variable: DI application rates								
Constant	–6.978 (0.000)	–7.752 (0.000)	–7.902 (0.000)	–8.755 (0.000)	–6.570 (0.000)	–7.036 (0.000)	–7.337 (0.000)	–7.986 (0.000)
Durables consump-tion–to–housing ratio	–0.795 (0.000)	–0.970 (0.000)			–0.661 (0.000)	–0.811 (0.000)		
Durables consumption-to-income and housing ratio			–0.974 (0.000)	–1.218 (0.000)			–0.809 (0.000)	–0.996 (0.000)
Age–distribution {1} first-differenced					1.655 (0.028)	1.282 (0.136)	1.917 (0.013)	1.602 (0.055)
Instruments {lags} in addition to a constant		ccf{1} pi{1} age{1} trend		ccf{1} pi{1} age{1} trend		ccf{1} pi{1} age{1} trend		ccf{1} pi{1} age{1} trend
F-test on first-stage regression p-value		11.905 (0.000)		12.220 (0.000)				
Adjusted R^2 on first-stage regression		0.6		0.607				
Over-identifying restrictions J-test and p-value		1.515 (0.679)		1.454 (0.693)		0.456 (0.796)		0.219 (0.896)
Adjusted R^2	0.596		0.54		0.67		0.655	

OLS represents ordinary least squares and TSLS represents two-stage least squares. All variables are in natural logs so that the estimated coefficients may be interpreted as elasticities. p-values for the estimated coefficients, in parentheses, are based on Newey-West (1987) standard errors. The F-test statistic relates to instrument relevance and measures the joint significance of the instruments when regressed on the dependent variable in the first-stage regression, where p-values less than 0.05 indicate a rejection of the null hypothesis of non-relevance. The J-test statistic indicates a failure to reject the null hypothesis that the instruments are exogenous at 5 percent significance with p-values greater than 0.05.
See Table 1 notes for a description of the data and Table 2 notes for abbreviations.

the results. The consumption-to-wealth ratios and wage gap variables perform as expected. Their estimated coefficients are reasonably consistent in size, are statistically significant, and possess the correct sign. The age-distribution variable tends to be overwhelmed by the other variables; the

Table 4. DI Application Rates, Durable Consumption–to–Housing Ratio, Earnings Replacement Rate, and Age-Distribution
1978 to 2008

Regressor	OLS	TSLS	OLS	TSLS
Dependent variable: DI application rates				
Constant	7.221 (0.002)	9.266 (0.026)	7.045 (0.002)	9.168 (0.052)
Durables consumption–to–housing ratio	–0.452 (0.000)	–0.716 (0.004)	–0.560 (0.000)	–0.926 (0.004)
Wage gap: labor productivity–to–high school only earnings de-trended	3.593 (0.000)	4.376 (0.000)	3.695 (0.000)	4.623 (0.000)
Age-distribution {1} first-differenced	0.629 (0.078)	–0.360 (0.686)	0.754 (0.044)	–0.263 (0.764)
Instruments {lags} in addition to a constant		ccf{1} per{1} pi{1} uemp{1} age{1} trend		ccf{1} per{1} pi{1} umep{1} age{1} trend
Adjusted R^2	0.859		0.86	
Over-identifying restrictions *J*-test and *p*-value		1.166 (0.558)		0.356 (0.885)

OLS represents ordinary least squares and TSLS represents two-stage least squares. All variables are in natural logs so that the estimated coefficients may be interpreted as elasticities. *p*-values for the estimated coefficients, in parentheses, are based on Newey-West (1987) standard errors. The *J*-test statistic indicates a failure to reject the null hypothesis that the instruments are exogenous at 5 percent significance with *p*-values greater than 0.05.
See Table 1 notes for a description of the data and Table 2 notes for abbreviations.

statistical significance and sign estimates are inconsistent. The overall results indicate the models are reasonably well estimated; the adjusted R^2's are over 0.80, and we fail to reject the over-identifying restrictions, as the *p*-values on the *J*-statistics are greater than 0.05.

Figures 3 and 4 show the relationships between the various durables consumption–to–wealth ratios and DI application rates. They appear strong even at the end of sample period, when the labor market variables shown in Figures 1 and 2 tend to pull away from the DI application rates. However, the relationships shown in Figures 3 and 4 do break down during

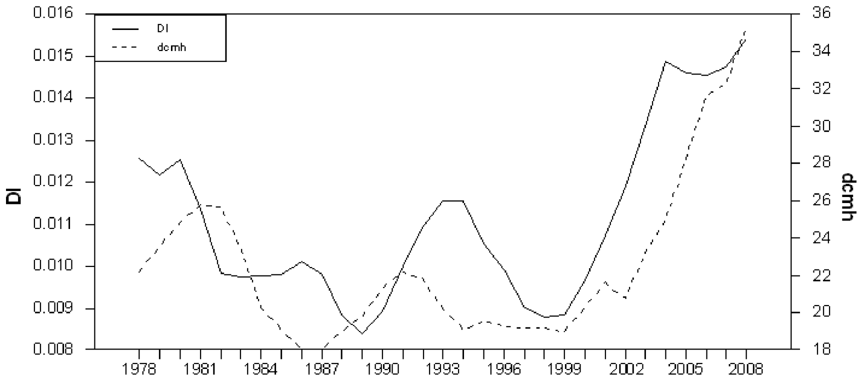

Fig. 3. DI application rate and durables consumption–to–market value of housing (inverted).

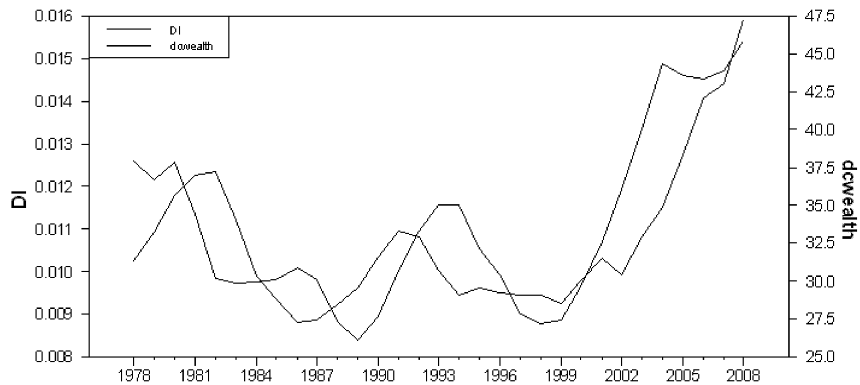

Fig. 4. DI application rate and durables consumtion–to–wealth (inverted).

the 1983–1986 period, around the time Congress enacted the 1984 Disability Benefits Reform Act, effectively liberalizing the definition of disability, resulting in a substantial increase in DI applications. The increase in DI applications actually started in 1983, according to Autor and Duggan (2003), as 17 states refused to comply with the continuing disability review procedure for beneficiaries with nonpermanent disabilities.

Quarterly Results

Despite the robustness of our results for the consumption-to-wealth ratios and the wage gap variable in explaining the variation in DI

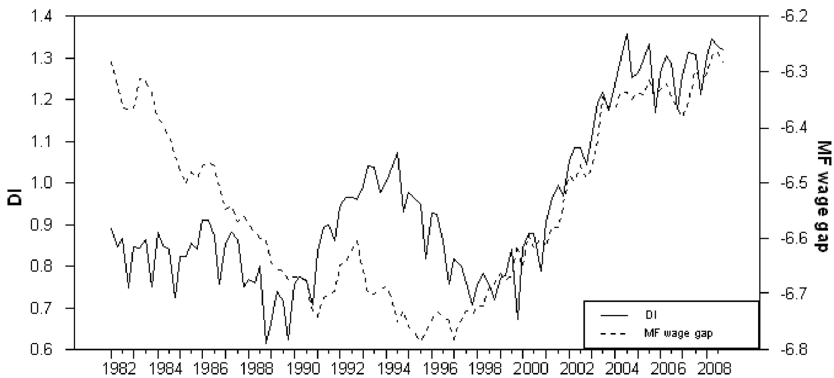

Fig. 5. DI application rate and manufacturing wage gap (de-trended).

applications over time, a sample of only 31 annual observations raises concerns about the reliability of our estimates. To address this concern we employ quarterly data to increase our sample size, but not without two important limitations. First, quarterly DI application data are available to the authors only as far back as 1982. Second, wage data for individuals with a "high school degree only" are not available quarterly from the U.S. Census Bureau. Despite the unavailability of quarterly data used in the tests above, we take advantage of this situation by employing a slightly different data set to examine the business cycle's influence on DI application rates, thereby testing the robustness of our hypotheses.

The most significant change in our model is that we employ a different wage gap variable to measure the decline in relative earnings of low-skilled workers. Our wage gap variable for quarterly analysis is the quarterly per capita DI benefits divided by the quarterly hourly wages, including overtime, of manufacturing workers. Following on the work of others, Rupp and Stapleton (1995: 51) speculate that the decline in the number of high-paying manufacturing jobs and corresponding increase in the number of low-paying service jobs in the U.S. over the last several decades has led to job losses that in the short run have led to an increase in DI application rates.[21] Therefore, we expect a positive statistical relationship between our manufacturing wage gap variable and DI application rates. Figure 5 shows a graph of DI application rates and the manufacturing wage gap variable that is consistent with our expectation.

[21]Rupp and Stapleton (1995) speculate further that in the long run, these transitions in the composition of the labor market may actually cause a decline in the number of DI applications, since workers in service industries are less prone to disabling injuries.

Table 5 presents our quarterly statistical results. Looking across the two rows for the consumption-to-wealth ratios we see that they are statistically significant at the 5 percent level, are negative as expected, and have approximately the same magnitude as other estimates shown in previous tables. The manufacturing wage gap estimated coefficients are positive, as expected, and statistically significant. The age-distribution variable is not statistically significant, while the quarterly dummy variables and trend estimates are all significant.

COINTEGRATION RESULTS

Annual and Quarterly Data

The results of our bivariate cointegration analysis are in the columns of Table 6 for annual data and Table 7 for quarterly data.[22] The results in the two tables are similar enough that we can discuss both the annual and quarterly results together. The small *p*-values on the first row of trace statistics indicate that we can reject the null hypothesis of no cointegration for DI application rates and each variable. In other words, we reject the hypothesis that there are zero common stochastic trends in the system. The second row shows that the tests fail to reject the null of no cointegration and indicates that one common stochastic trend, denoted r, is shared among the two variables shown in each column. We used Perron (1997), Zivot and Andrews (1992), and graphs of the cointegrating relations to aid in the estimation of break dates in the cointegrating space. The second panels in Tables 6 and 7 provide estimates of the cointegrating vectors. The estimated coefficients have the correct sign and are statistically significant as the *p*-values are smaller than the 5 percent significance level. The estimated coefficients in Table 6 should approximate the estimates from OLS and TSLS in Table 2.[23] There are, however, interesting differences to note. The unemployment rate coefficient 1.068 for annual data in Table 6 is positive, as we hypothesized, but differs from the negative estimates in

[22]The cointegration analysis was performed in CATS in RATS, version 2, by J. G. Dennis, H. Hansen, S. Johansen, and K. Juselius, Estima 2005.

[23]We employed only bivariate cointegrating analysis and did not extend the models to three variables as based on the irreducible relation concept introduced in Davidson (1998). An irreducible cointegrating relation is a set of cointegrating variables that becomes nonstationary when just one variable is removed from the relationship. From another perspective, since we isolated a set of cointegrating variables that form a stationary relationship, adding one more nonstationary variable would create a nonstationary (non-cointegrating) relationship among the three variables.

Table 5. DI Application Rates, Various Forms of Consumption–to–Wealth Ratio, and Productivity–to–Manufacturing Wages, De-trended (Quarterly Data: 1982:1 to 2008:4)

Regressor	OLS	TSLS	OLS	TSLS
Dependent variable: DI application rates				
Constant	1.174	0.011	1.290	–0.205
	(0.358)	(0.994)	(0.313)	(0.897)
Durables consumption–to–housing ratio	–0.565	–0.746		
	(0.000)	(0.000)		
Durables consumption–to–income and housing ratio			–0.592	–0.847
			(0.001)	(0.000)
Productivity–to–manufacturing hourly wages, de-trended	0.454	0.348	0.525	0.417
	(0.002)	(0.036)	(0.000)	(0.006)
Age-distribution	–0.028	0.464	–0.130	0.469
	(0.976)	(0.645)	(0.890)	(0.650)
Q 1	0.077	0.072	0.079	0.073
	(0.000)	(0.000)	(0.000)	(0.000)
Q 2	0.092	0.100	0.092	0.100
	(0.000)	(0.000)	(0.000)	(0.000)
Q 3	0.093	0.089	0.094	0.090
	(0.000)	(0.000)	(0.000)	(0.000)
Trend	0.243	0.228	0.247	0.229
	(0.000)	(0.000)	(0.000)	(0.000)
Instruments {lags} in addition to a constant		ccf{1} uemp{1} ot{1} pi{1} age{1} Q1, Q2, Q3 trend		ccf{1} uemp{1} ot{1} pi{1} age{1} Q1, Q2, Q3 trend
Adjusted R^2	0.824		0.819	
Over-identifying restrictions J-test and p-value		9.876		10.202
		(0.190)		(0.177)

OLS represents ordinary least squares and TSLS represents two-stage least squares. All variables are in natural logs so that the estimated coefficients may be interpreted as elasticities. p-values for the estimated coefficients, in parentheses, are based on Newey-West (1987) standard errors. The J-test statistic indicates a failure to reject the null hypothesis that the instruments are exogenous at 5 percent significance, with p-values greater than 0.05. Instruments: *ccf* denotes consumer confidence, *uemp* denotes the national unemployment rate, *ot* denotes average weekly manufacturing overtime hours worked, *pi* denotes real personal income growth, *age* denotes the proportion of workers age 55–64 to workers age 25–54, *Q1*, *Q2*, *Q3* represent quarterly seasonal dummy variables, and *trend* denotes a deterministic time trend. Lags are in brackets.

Table 6. Cointegration Analysis of DI Application Rates, 1978 to 2008

Cointegration rank trace test					
	$k-r=2, r=0$	$k-r=2, r=0$	$k-r=2, r=0$	$k-r=2, r=0$	$k-r=2, r=0$
Trace statistic	35.191	34.411	34.416	33.831	34.508
p-value	(0.001)	(0.002)	(0.002)	(0.030)	(0.029)
	$k-r=1, r=1$	$k-r=1, r=1$	$k-r=1, r=1$	$k-r=1, r=1$	$k-r=1, r=1$
Trace statistic	7.631	8.091	8.487	12.094	9.037
p-value	(0.319)	(0.285)	(0.249)	(0.103)	(0.202)
Cointegrating space					
Break type	level	level	level	level	trend
Break date	1998	1998	1998	1995	1996
Unemployment rate	1.068				
p-value	(0.000)				
Durables consumption–to–housing ratio		–0.882			
p-value		(0.000)			
Durables consumption–to–income and housing ratio			–1.129		
p-value			(0.000)		
Wage gap: labor productivity–to–high school only earnings				3.405	
p-value				(0.000)	

Table continues

Table 6. *continued*

Age-distribution					15.907
p-value					(0.000)
Trend	0.029	0.008	0.007	–0.258	0.064
p-value	(0.000)	(0.004)	(0.012)	(0.000)	(0.000)
Lags	3	3	3	3	2
Residual-based tests					
Autocorrelation					
LB, lags = 7, test statistic	24.081	23.865	21.822	22.415	25.335
p-value	(0.152)	(0.160)	(0.240)	(0.214)	(0.280)
Normality test statistic	2.709	2.766	1.514	0.699	4.280
p-value	(0.608)	(0.598)	(0.824)	(0.951)	(0.369)
Diagnostic tests					
Test for stationarity DI application rates					
test statistic	16.587	19.506	17.923	5.684	17.190
p-value	(0.000)	(0.000)	(0.000)	(0.017)	(0.000)
Other variable					
test statistic	23.559	24.278	23.539	11.242	24.099
p-value	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)

Test for weak exogeneity					
DI application rates					
test statistics	26.720	22.979	20.918	4.564	15.961
p-value	(0.000)	(0.000)	(0.000)	(0.033)	(0.000)
Other variable					
test statistic	3.556	1.396	1.568	3.741	7.354
p -value	(0.059)	(0.237)	(0.210)	(0.053)	(0.007)

The cointegrating rank trace test is read sequentially starting from the top at $k - r = 2$ and $r = 0$ where k denotes the number of variables in the system and r is the number of common stochastic trends among the variables. Applied to the data above, a small p-value in the top row indicates rejection of two unit roots in the system, or in other words, no common stochastic trends among the nonstationary variables. Drop down to the second row, $k - r = 1$ and $r = 1$. A small p-value (less than 0.05) indicates a rejection of one unit root in the system, indicating no common stochastic trends as the system is stationary. On the other hand, a large p-value (greater than 0.05) in the second row indicates that we fail to reject the null hypothesis that the system includes one unit root, a root that represents a common stochastic trend. The critical values for the trace rank test statistics were simulated based on 2,500 repetitions, 31 observations, and the deterministic variables in the cointegrating space, and reflect a small-sample Bartlett adjustment. Cointegrating space parameter estimates with p-values in parentheses. Small p-values indicate that we fail to reject the null hypothesis that the variable is not significant in the cointegrating vector. For the Ljung and Box (1978) autocorrelation test statistics, small p-values (less than 0.05) indicate a rejection of the null hypothesis of no autocorrelation with a 7-year lag window. Small p-values (less than 0.05) for the normality test statistics indicate a rejection of the null hypothesis that the residuals are multivariate normal using Doornik and Hansen (2008) tests. The stationarity tests reject the null hypothesis of stationarity for each variable conditional on the rank of the system with p-values smaller than 0.05. The tests for weak exogeneity reject the null hypothesis of weak exogeneity for p-values smaller than 0.05.

Table 2. The unemployment rates for both annual and quarterly data appear cointegrated.[24]

The residuals in each system appear reasonably well-behaved.[25] We fail to reject the null hypothesis of no autocorrelation and fail to reject the null hypothesis of normality, as the p-values in each case are larger than 0.05. Under the diagnostic section of Tables 6 and 7 we reject the null hypothesis of stationarity tests for each variable in the cointegrating space. The stationarity tests are dependent on the cointegrating rank of the system and the deterministic variables, including break variables. The weak exogeneity tests provide information about the dynamics of each system. In all systems shown in Tables 6 and 7 we reject the null hypothesis of weak exogeneity for DI application rates, as the p-values are smaller than 0.05. In many cases the weak exogeneity tests on the other stochastic variable in the system show that we fail to reject weak exogeneity at the five percent significance level.[26] These findings indicate that the other stochastic variable is the source of the common driving trend among the two variables in the system. In other words, DI application rates are adjusting to stochastic shocks coming from the other variable in the system.

Comparison to Other Research

It is important to differentiate our paper, which focuses on the relation between claims rates for Social Security–administered long-term disability insurance, from Smoluk (2009) and Smoluk and Andrews (2009). These later two papers examine the relationship between application rates for privately administered group long-term disability and the economy. While it is generally known that both private and public disability insurance application rates are related to the economy, a priori, one would not necessarily expect to see a strong relationship between our paper's results and the findings of Smoluk (2009) and Smoluk and Andrews (2009) for several reasons. First, DI is administered by a not-for-profit agency of the U.S. government under the direct control of Congress. Over the last 31

[24]In Table 6 the estimated coefficient on the age-distribution variable is large compared to the estimates found in Tables 2 through 5, but can be explained. In Tables 2 through 5 we used the age-distribution variables in first-differenced form and in the cointegration analysis we used it in levels.

[25]We employed an occasional dummy variable in some models to eliminate outliers.

[26]The two most notable exceptions to this statement are the age-distribution control variable in Table 6 and the unemployment rate in Table 7, as both variables reject the null hypothesis of weak exogeneity. We can understand some small feedback effects from DI application rates to the unemployment rate, but not to the proportion of age 55 and older individuals in the general population.

Table 7. Cointegration Analysis of DI Application Rates (Quarterly Data, 1982:1 to 2008:4)

Cointegration rank trace test					
	$k - r = 2, r = 0$	$k - r = 2, r = 0$	$k - r = 2, r = 0$	$k - r = 2, r = 0$	$k - r = 2, r = 0$
Trace statistic	33.925	28.649	28.835	31.526	48.449
p-value	(0.008)	(0.037)	(0.032)	(0.013)	(0.000)
	$k - r = 1, r = 1$	$k - r = 1, r = 1$	$k - r = 1, r = 1$	$k - r = 1, r = 1$	$k - r = 1, r = 1$
Trace statistic	9.874	10.754	10.209	8.005	4.933
p-value	(0.201)	(0.144)	(0.185)	(0.348)	(0.556)
Cointegrating space					
Break type	level	level	level	level	levels
Break date	1997:3	1998:1	1998:1	1996:1	1995:1
Unemployment rate	0.284				
p-value	(0.000)				
Durables consumption–to–housing ratio		–1.321			
p-value		(0.000)			
Durables consumption–to–income and housing ratio			–1.756		
p-value			(0.000)		
Productivity–to–manufacturing hourly wages				0.906	
p-value				(0.000)	

Table continues

Table 7. *continued*

Age-distribution					3.367
p-value					(0.012)
Trend	0.007	0.001	0.001	0.003	
p-value	(0.002)	(0.352)	(0.424)	(0.060)	
Lags	6	5	5	5	9
Residual-based tests					
Autocorrelation					
LB, lags = 25, test statistic	93.322	89.965	95.518	76.738	72.412
p-value	(0.114)	(0.256)	(0.146)	(0.643)	(0.172)
Normality test statistic	3.861	4.727	6.260	2.953	3.344
p-value	(0.425)	(0.389)	(0.181)	(0.566)	(0.502)
Diagnostic tests					
Test for stationarity DI application rates					
test statistic	13.674	7.002	8.027	13.205	4.366
p-value	(0.000)	(0.008)	(0.005)	(0.000)	(0.037)
Other variable					
test statistic	4.392	5.301	5.614	15.497	12.993
p-value	(0.036)	(0.021)	(0.018)	(0.000)	(0.000)

Test for weak exogeneity					
DI application rates					
test statistics	3.676	4.834	5.582	10.767	38.094
p-value	(0.055)	(0.028)	(0.018)	(0.001)	(0.000)
Other variable					
test statistic	8.265	1.470	1.719	2.813	2.677
p -value	(0.004)	(0.225)	(0.194)	(0.093)	(0.102)

The cointegrating rank trace test is read sequentially starting from the top at $k - r = 2$ and $r = 0$ where k denotes the number of variables in the system and r is the number of common stochastic trends among the variables. Applied to the data above, a small p-value in the top row indicates rejection of two unit roots in the system, or in other words, no common stochastic trends among the nonstationary variables. Drop down to the second row, $k - r = 1$ and $r = 1$. A small p-value (less than 0.05) indicates a rejection of one unit root in the system, indicating no common stochastic trends as the system is stationary. On the other hand, a large p-value (greater than 0.05) in the second row indicates that we fail to reject the null hypothesis that the system includes one unit root, a root that represents a common stochastic trend. The critical values for the trace rank test statistics were simulated based on 2,500 repetitions, 31 observations, and the deterministic variables in the cointegrating space, and reflect a small-sample Bartlett adjustment. Cointegrating space parameter estimates with p-values in parentheses. Small p-values indicate that we fail to reject the null hypothesis that the variable is not significant in the cointegrating vector. For the Ljung and Box (1978) autocorrelation test statistics, small p-values (less than 0.05) indicate a rejection of the null hypothesis of no autocorrelation with a 7-year lag window. Small p-values (less than 0.05) for the normality test statistics indicate a rejection of the null hypothesis that the residuals are multivariate normal using Doornik and Hansen (2008) tests. The stationarity tests reject the null hypothesis of stationarity for each variable conditional on the rank of the system with p-values smaller than 0.05. The tests for weak exogeneity reject the null hypothesis of weak exogeneity for p-values smaller than 0.05.

years, Congress has modified, sometimes substantially, the eligibility requirements and screening process for DI applicants, as noted above. Private group LTD insurance is not directly subject to these changes. Coverage under group policies is often negotiated, to some extent, between an employer or group and the insurance company. Premiums are charged according to the coverage provided. Second, Social Security Disability eligibility criteria, in general, are stricter than private LTD. For example, an important criterion for public DI is that the individual must be unable to perform "substantial gainful activity." This essentially means that the individual is unable to hold any reasonably paying job regardless of whether he or she was trained for it. With private LTD, the criteria are narrower. Typically, with private LTD, the individual is disabled if he or she unable to perform the duties of any gainful activity for which the individual was trained, was educated, or has experience. Last, after receiving 24 months of benefits, Social Security DI recipients under the age of 65 are eligible for health insurance through Medicare, while individuals collecting private LTD payments do not have these benefits. These benefits can be significant, especially for an individual with a disability.

A comparison of our findings to those of Smoluk (2009) will highlight the interesting and important differences between the two papers. Smoluk (2009) finds that various consumption-to-wealth ratios composed of *total* consumption, personal income, and the market value of housing are cointegrated with private group LTD claims rates. That is, private group claims rates and the consumption-to-wealth ratios are in a long-run equilibrium with the claims rates series adjusting to past equilibrium. The private group LTD insurance was underwritten by UNUM Group, a large long-term disability insurer. The claims rates used in Smoluk (2009) were from employers in the manufacturing and wholesale-retail sector only and covered only the period 1988 to 2003 using quarterly data. The consumption-to-wealth ratios in Smoluk (2009) were found to be inversely related to incidence, as in our paper, and covered individuals across five income quintiles. He also finds that the unemployment rate is inconsistently related to claims rates. Our results find no clear relationship between application rates and the unemployment rate.

Our findings extend Smoluk's work in two important ways. First, we show that the application rates of public LTD administered by the Social Security Administration across all industries over the period 1978 to 2008 are linked to other areas of the macroeconomy. Specifically, we show that public DI application rates are related to the macroeconomy through the wage gap between national productivity (earnings) and the wages of individuals with a high school degree or less. These findings are important because they show linkages to a specific demographic group even in the presence of an age-related control variable (the proportion of individuals ages 55–64 versus ages 25–54 in the population). Second, our results indicate that private group long-term disability rates and public DI application rates are related despite the structural shifts in Social Security's eligibility requirements, changing screening processes, and the vast differences in the organizations that administer them. Our main point here is that public and private LTD are administered very differently and by very different organizations, yet despite these differences the application rates of the two forms of insurance appear connected through a common driver—the macroeconomic environment.

CONCLUSION

For many individuals contemplating filing a DI application, the decision is influenced, in part, by economic considerations. Social Security disability payments replace, to a varying degree, lost wages due to a disabling injury or illness. These payments allow individuals to maintain their standard of living and reduce draw-downs on their accumulated wealth such as housing. Assuming that DI applicants are rational forward-looking economic agents, the decision to file a claim is based not just on current economic conditions, but also on the individual's expected future financial situation. A working individual with a nagging medical impairment affecting his or her productivity, but who has been reluctant to apply for DI benefits, is more likely to do so if future economic conditions are considered bleak. Because a significant proportion of DI applicants are low-skill/low-wage workers facing tight economic circumstances, a strategy for relating DI application rates to macroeconomic factors should focus on variables that are forward-looking and measure tight economic conditions over the business cycle.

We identify several such forward-looking macroeconomic variables that strongly predict Social Security DI application rates over the last three decades. For example, we find that durables consumption–to–wealth ratios are inversely linked to DI application rates. Consumer durables spending is often postponable by individuals facing economic hardships and is procyclical over the business cycle. Wealth is ultimately used to fund consumption. The ratio of durables consumption to various forms of wealth provides a measure of consumer hardship and consumer expectations. When these durables consumption–to–wealth ratios decline, such as during an economic slowdown, DI benefits become more attractive and application rates are expected to increase. OLS regressions that include the durables consumption–to–housing values or the durables consumption–to–income and housing values (total wealth) result in adjusted R^2's of 0.596 to 0.540. The strength of the durables consumption–to–wealth ratios in relation to DI application rates remains fairly strong throughout the sample period, except during the DI program liberalization period of 1983–1986.

Wage inequality has increased significantly over the last three decades, eroding the economic situation of low-skilled labor relative to the average worker. Since DI payments are a function of the growth in average U.S. wages, the earnings replacement capacity of disability payments has trended upward over the last three decades for low-skilled/low-wage labor. A current and forward-looking measure of this trend is computed by dividing national labor productivity by the wages of individuals with only a high school degree. We find a significant positive relationship between this ratio and DI application rates that is robust even in the presence of the consumption-to-wealth ratios and a demographic age-distribution variable.

An interesting finding of this paper is that despite all of the policy changes implemented by the Social Security Administration and the changes in epidemiological factors facing the program over the last 31 years, none of which we explicitly modeled, we find that DI application rates are directly related to the macroeconomy. More specifically, our tests did not condition on the recipient crackdown in the early 1980s and the subsequent 1983 liberalization of DI eligibility or the 1996 law tightening the eligibility standards for individuals suffering mainly from alcohol and drug addiction, although our cointegration analysis did employ structural breaks. Changes in the gender composition of the labor force, changing attitudes towards mental illness over the last 31 years, and the impact of HIV/AIDS were not modeled. We conclude that a substantial portion of the long-run volatility in DI application rates is driven by economic factors.

REFERENCES

Acemoglu, D (2002) Technical Change, Inequality, and the Labor Market, *Journal of Economic Literature* XL: 7–72.

Angrist, JD and AB Krueger (2001) Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments, *Journal of Economic Perspectives* 15(4): 69–85.

Attanasio, O (1999) Consumption, in John B. Taylor and Michael Woodford, eds., *Handbook of Macroeconomics*, Vol. IB, chapter 11.

Autor, D and M Duggan (2003) The Rise in the Disability Rolls and the Decline in Unemployment, *Quarterly Journal of Economics* 118(1): 157–205.

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

Autor, D and M Duggan (2007) Distinguishing Between the Income and Substitution Effects in Disability Insurance, *American Economic Review* 97(2): 119–124.

Ball, L and NG Mankiw (1995) Relative Price Changes as Aggregate Supply Shocks, *Quarterly Journal of Economics* 110(1): 161–193.

Black, D, Daniel, K, and SG Sanders (2002) The Impact of Economic Conditions on Participation in Disability Program: Evidence from the Coal Boom and Bust, *American Economic Review* 92(1): 27–50.

Bound, J and RV Burkhauser (1999) Economic Analysis of Transfer Programs Targeted on People with Disabilities, in O Ashenfelter and D Card, eds., *Handbook of Labor Economics*, New York, Amsterdam: Elsevier, Vol. 3: 3,417–3,528.

Browning, M and T Crossley (1999) Shocks, Stocks and Socks: Consumption Smoothing and the Replacement of Durables During an Unemployment Spell, *Australian National University, Working Paper in Economics and Econometrics*, No. 376.

Campbell, JY and J Cocco (2005) *How Do House Prices Affect Consumption*?, NBER Working Paper No. 11,534.

Case, KE, JM Quigley, and R Shiller (2006) Comparing Wealth Effects: The Stock Market vs. The Housing Market, *Cowles Foundation Paper No. 1181*, Cowles Foundation for Research in Economic,s Yale University.

Cochrane, J (1991) Comment on "Pitfalls and Opportunities: What Macroeconomists Should Know about Unit Roots," *NBER Macroeconomics Annual* 6: 201–210.

Davidson, J (1998) Structural Relations, Cointegration and identification: Some Simple Results and their Application, *Journal of Econometrics* 87(1): 87–113.

Davidson, R and JG MacKinnon (1993) *Estimation and inference in Econometrics*, New York: Oxford University Press.

Doornik, JA and H Hansen (2008) "An Omnibus Test for Univariate and Multivariate Normality, *Oxford Bulletin of Economics and Statistics* 70(Supplement): 927–939.

Duggan, M and S Imberman (2006) Why Are the Disability Rolls Skyrocketing? in D Cutler and D Wise, edds., *Health in Older Ages: The Causes and Consequences of Declining Disability among the Elderly*, Chicago: University of Chicago Press.

Duggan, M, Singleton, P, and J Song (2007) Aching to Retire? The Rise in the Full Retirement Age and its Impact on the Disability Rolls" *Journal of Public Economics* 91(7): 1327–1350.

Friedman, M (1975) Perspectives on Inflation, *Newsweek* (June 24), 73.

Gruber, J and JD Kubik (1997) Disability Insurance Rejection Rates and the Labor Supply of Older Workers, *Journal of Public Economics* 64(1): 1–23.

Halpern, J and JA Hausman (1986) Choice Under Uncertainty: A Model of Applications for the Social Security Disability Insurance Program, *Journal of Public Economics* 31: 131–161.

Hunt, SR and J Baumohl (2003) Drink, Drugs, and Disability: An Introduction to the Controversy, *Contemporary Drug Problems* 30: 9–76.

Johansen, S and K Juselius (1990) Maximum Likelihood Estimation and inference on Cointegration with Application to the Demand for Money, *Oxford Bulletin of Economics and Statistics* 52: 169–209.

Johansen, S and K Juselius (1992) Testing Structural Hypotheses in a Multivariate Cointegration Analysis of PPP and the UIP for UK, *Journal of Econometrics* 53: 211–244.

Kennedy, P (2003) *A Guide to Econometrics*, Cambridge, Massachusetts: The MIT Press.

Loprest, P, K Rupp, and SH Sandell (1995) Gender, Disabilities, and Employment in the Health and Retirement Study, *The Journal of Human Resources* XXX (Supplement).

Ljung, GM and GEP Box (1978) On a Measure of Lack of Fit in Time Series Model, *Biometrika* 67: 297–303.

Martin, T and PS Davies (2003/2004) Changes in the Demographic and Economic Characteristics of SSI and DI Beneficiaries Between 1984 and 1999, *Social Security Bulletin* 65(2).

Newey, W and K West (1987) A Simple Positive-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55: 703–708.

Parsons, DO (1991) Measuring and Deciding Disability, in Carolyn Weaver, ed., *Disability and Work*, Washington, DC: AEI Press.

Perron, P (1997) Further Evidence on Breaking Trend Functions in Macroeconomic Variables, *Journal of Econometrics* 80(2): 355–385.

Perron, P and T Wada (2009) Let's Take a Break: Trends and Cycles in US Real GDP, *Journal of Monetary Economics* 56(6): 749–765.

Rupp, K and D Stapleton (1995) Determinants of the Growth in the Social Security Administration's Disability Programs—An Overview, *Social Security Bulletin* 58(4).

Shimer, R (2005) The Cyclical Behavior of Equilibrium Unemployment and Vacancies, *American Economic Review* 95(1): 25–49.

Smoluk, HJ (2009) Long-Term Disability and the Consumption-to-Wealth Ratio, *The Journal of Risk and Insurance* 76(1): 109–131.

Smoluk, HJ and BH Andrews (2009) Group Long-Term Disability Insurance Claims and the Business Cycle, *Journal of Insurance Issues* 32(2): 154–172.

Wagner, CC, CE Danczyk-Hawley, K Mulholland, and BG Flynn (2000) Older Workers' Progression from Private Disability Benefits to Social Security Disability Benefits, *Social Security Bulletin* 63(4): 27–37.

Wander, SA and T Stengle (1997) Unemployment Insurance: Measuring Who Receives It, U.S. *Department of Labor, Monthly Labor Review*: 15–24.

White, J (2009) Job Losses Send Disability Claims Soaring, MSNBC.com, 17 December 2009 <www.msnbc.msn.com/id/34381782/ns/us_news-the_elkhart_project/> .

Zivot, E and K Andrews (1992) Further Evidence on the Great Crash, the Oil Price Shock, and the Unit Root Hypothesis, *Journal of Business and Economic Statistics* 10: 251–270.