Unemployment Insurance and Disability Insurance in the Great Recession

PRELIMINARY DRAFT – PLEASE DO NOT CITE OR CIRCULATE

Jesse Rothstein[1]
University of California, Berkeley and NBER

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Abstract:

Disability insurance applications and awards are countercyclical. One possible explanation is that unemployed individuals who exhaust their Unemployment Insurance benefits use DI as a form of extended benefits. I exploit the haphazard pattern of Unemployment Insurance (UI) extensions in the Great Recession to identify the effect of UI exhaustion on DI application, using both aggregate data at the state-month level and microdata on unemployed individuals in the Current Population Survey. I find no indication that expiration of UI benefits causes DI applications. Estimates are sufficiently precise to rule out effects of meaningful magnitude.

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I. Introduction

As of the end of 2011, 8.7 million adult Americans received Social Security Disability Insurance (SSDI) benefits. SSDI is a social insurance program that collects mandatory premiums from workers and uses them to pay benefits to former workers who have become disabled.[2] Figure 1 plots the share of the working-age population receiving SSDI over time. It shows that this share has more than doubled since 1990. The rapid growth has prompted concerns about SSDI's sustainability, and current projections indicate that the SSDI trust fund will be exhausted in 2016 (Social Security Administration Board of Trustees, 2012).

As Figure 1 indicates, the growth rate of SSDI rolls accelerated during the recessions of the early 1990s and early 2000s, and perhaps during the 2007-2009 recession as well. Figure 2 illustrates the number of applications for SSDI benefits and the number of new awards, both expressed as shares of the civilian non-institutional population aged 20-64, along with the unemployment rate. Since the 1980s, both SSDI applications and awards tend to rise in downturns, then fall beginning a year or two after the unemployment peak (Black, Daniel, and Sanders 2002; Autor and Duggan 2003; Duggan and Imberman 2009; Coe et al. 2012). SSDI applications per capita, for example, rose at a 6.7% annual rate between 1989 and 1994, fell at a 4.6% annual rate during the expansion years 1994 through 1999, then rose again at an 10.5% annual rate between 1999 and 2004. Duggan and Imberman

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[2] Another program, SSI, provides benefits to disabled adults and children based on financial need, regardless of work history. SSI caseloads have also grown rapidly in recent decades.

(2009) find that between 1984 and 2003 a one percentage point increase in the national unemployment rate was associated with an increase of roughly 8-9 percent in the number of applications filed for SSDI benefits. They conclude that the recessions of the early 1990s and early 2000s were responsible for nearly one quarter of the rise in male SSDI participation between 1984 and 2003.[3]

The cyclical pattern is notably weaker in the period since 2004: Applications declined only slightly (at a 0.3% annual rate) between 2004 and 2007, then grew at a 6.5% rate – far from proportional to the magnitude of the Great Recession – between 2007 and 2011.[4]

Neither the older strongly countercyclical pattern nor its dampening in the last decade are well understood. One explanation for countercyclical application rates that would be generally consistent with the purposes of the SSDI program is that employers' willingness to hire (and make accommodations for) individuals with moderately work-limiting disabilities may vary with the tightness of the labor market. A disabled worker can receive SSDI benefits only if he or she has a functional impairment that prevents him or her from performing a previous job or from adjusting to other types of work. The worker's age, education, and experience are considered in assessing his or her suitability for alternative employment; as the jobs available to a worker with a given profile likely depend on economic conditions,

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[3] Other contributing factors include aging of the population, increased female labor force participation (which increases women's eligibility for SSDI benefits), more generous benefits, rising income inequality, and changes in the disability determination process (Duggan and Imberman, 2009).

[4] The slow decline after the 2001 recession is consistent with other evidence that the subsequent expansion was relatively tepid.

there may well be workers who meet the medical eligibility criteria in bad economic times who would not be considered to be sufficiently disabled were the labor market tighter.[5]

Other potential explanations for the cyclical sensitivity of SSDI applications attribute it to moral hazard. Consider a worker who has a moderate health problem – e.g., serious back pain – that raises his disutility of work but does not actually prevent him from working. In principle, this worker should not be eligible for SSDI benefits. But he may be able to qualify for benefits if he encounters a generous medical examiner (Joffe-Walt 2013). His decision to apply for benefits will depend in part on the generosity of SSDI benefits relative to the market wage that he can command. If a recession reduces his market wage, he may be tipped over into SSDI application (Autor and Duggan 2003; Black, Daniel, and Sanders 2002).

A related hypothesis is that workers are using SSDI to insure employment losses rather than wage declines. Workers who lose their jobs can generally claim unemployment insurance (UI) benefits. But UI benefits are time-limited and recessions are associated with sharp increases in the duration of unemployment spells. Workers who exhaust their UI benefits but who are still unable to find work may turn to SSDI for ongoing income support.

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[5] In principle, the medical eligibility determination does not consider the availability of positions, but in practice it seems likely that workers' qualifications are judged relative to labor demand. See, e.g., Joffe-Walt's (2013) description of a doctor who "believes he needs [to know individuals' educational attainment] in disability cases because people who have only a high school education aren't going to be able to get a sit-down job."

SSDI recipients tend to remain on the program, and out of the labor market, until retirement (Autor and Duggan, 2006). As a result, any use of SSDI as a source of extended unemployment benefits is extremely expensive. Indeed, a back-of-the-envelope calculation, discussed below, suggests that savings from avoided SSDI cases could plausibly finance a large share of the costs of extensions of UI benefits. But little is known about the degree to which SSDI is in fact used in this way.

This paper uses data from the Great Recession and its aftermath to investigate the relationship between UI exhaustion and SSDI applications. My analysis takes advantage of a great deal of variability of UI benefit durations over time and across states during the downturn. Entering the recession, UI benefits lasted for no more than 26 weeks in any state. But after a series of extensions in 2008 and 2009, the potential duration of benefits reached an all-time high of 99 weeks in many states. These long durations were generally maintained through 2011, but then decline substantially in 2012.[6]

There was also substantial variation across states at any given time, due to vagaries of state law and to discontinuous triggers in the federal programs. This meant that workers laid off at roughly the same time were eligible for very different UI durations depending on their location and the exact timing of the layoff. This combined with sharp changes in layoff rates over time to produce a great deal of variation over time and across space in the number of UI exhaustees. I use this

[6] Many models show that UI should be more generous during recessions (e.g., Landais, Michaillat, and Saez 2010), as moral hazard costs are relatively low and consumption smoothing benefits relatively high when unemployment is elevated. A full discussion of optimal UI design is beyond the scope of this paper, however.

variation to identify the effect of UI exhaustion on SSDI usage, using time-series analyses, a state-by-month-level panel, and microdata on unemployed workers to isolate different components of the variation in exhaustion timing.

Several recent papers have explored UI-DI interactions. Lindner and Nichols (2012) use variation in both benefit amounts and eligibility criteria to identify the causal effect of UI participation on DI application decisions. The most relevant paper to the current project is Rutledge (2012). With both aggregate application data at the state-month level and microdata from the Survey of Income and Program Participation (SIPP), Rutledge examines the effect of UI benefit duration extensions on SSDI application decisions and allowance rates. He focuses on the effect of a UI extension on the behavior of those who were already claiming UI when the spell was announced.

I extend Rutledge's analysis in three important ways. First, my conceptual model views UI extensions as a source of variation in the time to UI exhaustion rather than as a direct determinant of SSDI applications, consistent with a behavioral model in which individuals make decisions based on the benefits available to them without regard to the legal labeling of those benefits. Second, my empirical specifications are closely tied to this conceptual model, and are thus easily interpretable in terms of the determinants of the underlying application decision. This contrasts with Rutledge's specifications, which are not closely aligned to a behavioral model and focus on legal labeling – is an extension in effect or not? – rather than on true incentives. Third, I introduce a new data source, based on matched Current Population Survey (CPS) samples, that has not previously been used to study UI-DI interactions. These data permit me to examine directly the enormous changes in UI durations over the 2008-2012 period.

II. A simple model of UI-DI interactions

Autor and Duggan (2003) model the choice between work and SSDI application for marginally disabled workers. They show that some partially disabled workers will stay in their existing jobs, but if displaced will prefer to exit the labor force in order to receive DI benefits rather than to search for a new job at a lower wage. Autor and Duggan interpret the cyclicality of SSDI applications as an indication that there are meaningful numbers of workers of this type.

Autor and Duggan's (2003) model does not incorporate unemployment insurance. To do so, I develop a simple model that merges insights from models presented by Autor and Duggan (2003) and Rothstein (2011). In my model, a displaced worker can choose in each period whether to search for a new job or to remain idle.[7] Only the first of these can lead to reemployment, while a DI application can be submitted only when in the second state.

Searchers must pay search costs c_U per period and have a probability f of finding employment during the period. They can draw on up to N periods of unemployment benefits, worth b_{UI} per period. By contrast, workers out of the labor force do not pay search costs but have probability 0 of finding employment and cannot draw UI benefits.

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[7] I focus on workers who prefer work to SSDI application, so will not voluntarily quit existing positions in order to apply for DI benefits.

In a period in which an individual is out of the labor force, he or she may decide to apply for DI benefits by paying an application cost c_A. The probability that an application is successful is p. I assume that DI eligibility decisions are perfectly correlated over time, so that a worker who is rejected once will not later reapply. A worker whose application is successful can draw a per-period benefit of b_{DI} in any future period in which he or she is out of the labor force, until such point as he or she is reemployed.

This basic setup gives rise to a dynamic decision problem with state variables $n \in \{0, 1, \ldots, N\}$, indexing the number of weeks of UI benefit entitlement remaining, and $A \in \{0; -1; 1\}$, describing the worker's DI entitlement. A=0 indicates a worker who has not applied for DI benefits; A=-1 a worker who has applied but been rejected; and A=1 a worker who has been awarded benefits. Letting δ indicate the discount rate, u(y) the flow utility associated with per-period cash income y,[8] and V_E the continuation value of a new job, the utility associated with job search is:

$V_U(n, A) = u(b_{UI}) - c_U + \delta[f\, V_E + (1\text{-}f)\, V_U(n\text{-}1, A)]$ for n>0 and

$V_U(0, A) = u(0) - c_U + \delta[f\, V_E + (1\text{-}f)\, V_U(0, A)]$.

Idle workers' utility depends on their DI application status. Those who have not yet applied for DI benefits or who have applied but been rejected receive:

$V_I(n, A) = u(0) + \delta \max\{V_U(n, A), V_I(n, A)\}$, for $A \in \{0; -1\}$ and any $n \geq 0$.

Those who have been approved for DI benefits receive:

$V_I(n, 1) = u(b_{DI}) + \delta \max\{V_U(n, 1), V_I(n, 1)\}$.

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[8] I do not model saving or borrowing.

Finally, the utility of a worker who applies for DI benefits is:

$$V_A(n, 0) = u(0) - c_A + \delta[\ p \max\{V_U(n, 1), V_I(n, 1)\} + (1\text{-}p) \max\{ V_U(n, \text{-}1), V_I(n, \text{-}1)\}].$$

Figure 3 shows how the worker's policy choice will vary with f and p, for a particular set of other parameters. First, workers with high job-finding probabilities search for work until they find jobs, even beyond the expiration of their UI benefits. This is the upper area in the figure. Second, the lower left portion of the figure represents workers with low job-finding probabilities but also low DI award probabilities, who search for work until their UI benefits are exhausted, then exit the labor force without applying for DI.[9] Third, workers in the lower right region, with very high DI award probabilities but very low job-finding chances, simply apply for DI immediately after displacement, without ever looking for work. Finally, workers with somewhat lower DI award chances and/or somewhat higher job-finding probabilities search for work until their UI benefits are exhausted, then apply for DI benefits.

It is this last type of worker that could produce a causal effect of UI benefit durations on DI applications – workers of this type can be deterred from applying for DI benefits by a UI extension. For some, this is temporary – they will still be jobless at the end of even the extended benefits, and will apply to DI then. But

[9] With the parameter values used, job search is worthwhile for the duration of UI benefits even if the job-finding probability is zero, as the UI benefit is larger than the search cost. If b_{UI} is low enough relative to c_U, however, a policy of exiting the labor force immediately after job loss becomes optimal for low-f, low-p workers.

others will find jobs during the extended search period, and thus may be permanently diverted from the DI program.

This diversion can be substantial. To see this, suppose that {f, p} have a uniform distribution on [0, 0.1] X [0, 1] among displaced workers and that other parameters are as in Figure 3. Then 17% of workers, and 35% of those who exhaust 26 periods of UI benefits, are of the UI-before-DI type. When UI benefits last for 26 weeks, UI-before-DI workers comprise 83% of DI applicants and 79% of DI awardees. The average UI-before-DI DI applicant has a per-period job-finding rate of 1.5%. Thus, some would find jobs if given longer UI benefit durations during which to search. With my parameters, a 26-period extension of UI benefits (to a total of 52 periods) would permit just under one-third of the UI-before-DI workers who would otherwise apply for DI to instead find new jobs before their benefits run out. This would reduce steady-state DI applications and awards by a bit over one-quarter, while increasing UI payments by about 40%.

An effect of this magnitude would be enormously important. Because individuals awarded DI benefits tend to draw them until retirement, the present value of a single DI award is around $300,000. By comparison, weekly UI payments average around $300. Thus, the parameters used in Figure 3 and a uniform distribution of {f, p} imply that DI savings from a 26-week UI extension would amount to over three times the on-budget cost of that extension. In other words, a UI extension would be self-financing even if the effect on steady-state DI awards were only one-third as large as in this simple simulation.

But the parameters used, while reasonable, are just approximations, and the assumption of a uniform {f, p} distribution is entirely unsupported. It seems more likely, for example, that f and p are negatively correlated. This would tend to increase the share of UI-before-DI workers, though perhaps also to reduce the average job-finding rates of such workers. In any event, non-uniformity of the two marginal distributions could offset any such effect. The effect of UI benefit duration on DI applications is thus an empirical question.

III. Data and DI trends

I rely on two data sources to measure trends in SSDI application and receipt. First, I use administrative data from the Social Security Administration that tabulates the number of SSDI, SSI, or SSDI/SSI applications and awards at the state-by-month level. Awards are tied to the month that they are made – usually several months after the initial application, and sometimes much longer if the initial application is denied but successfully appealed – rather than to the month of the initial application. I thus focus on the application data as a better indication of individual decisions.

Second, I use the Annual Social and Economic Supplement (ASEC) supplement to the Current Population Survey, administered in the spring of each year.[10] ASEC respondents are asked about their income from various sources in the previous calendar year. Since 2001, those who report having income from Social

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[10] The ASEC is often known as the "March CPS." The March sample from the regular monthly CPS survey is supplemented with additional individuals from the February, April, and November (of the previous year) monthly CPS samples.

Security are asked to name up to two reasons for this. The leading reason offered is of course retirement, but disability is the second most common reason named. I measure SSDI receipt as the presence of positive Social Security income for someone who names "disability" as one of the reasons.

Figure 4 shows trends in the number of disabled worker SSDI benefit recipients from the SSA administrative data, along with two series computed from the CPS ASEC data. One series counts all individuals aged 16 and over who report Social Security income for reason of disability. The second excludes those over age 66 (67 from 2010 forward, reflecting an increase in the Full Retirement Age), as individuals above this age receive retirement payments rather than SSDI benefits, even if they are disabled.. The former series matches the administrative records reasonably well, though shows a somewhat flatter trajectory. The latter is notably lower, suggesting both that many recipients continue believing they are receiving disability benefits even after they are formally converted to the retirement program and that the CPS survey misses some true SSDI recipients.

In the analysis below, I identify unemployed workers, aged 20-64, in the basic monthly CPS survey and ask whether the expiration of their UI benefits early in calendar year y is associated with a higher probability of receiving SSDI income in that year. This is made possible by the rotating panel design of the CPS, which means that just under half of the respondents in the y+1 ASEC file were interviewed for the basic CPS survey in February, March, or April of year y, or in November of year y-1. Identification codes make it possible to merge basic CPS observations from those months to the same individuals in the year-y+1 ASEC. The CPS is an address-based sample, so matches are only possible for individuals who do not move between surveys. I am able to match 100% of cases from the basic March CPS survey to the same year's ASEC (and around 95% of the ASEC respondents to one of the surrounding monthly surveys). Merges between year-y and year-y+1 ASECs are more difficult, with match rates around 75%.[11]

In the basic CPS survey, unemployed workers are asked the reason for their unemployment (e.g., layoff vs. voluntary quit) and the number of weeks that they have been unemployed. I use the former to proxy for UI eligibility and the latter to assign each unemployed individual to the date of displacement. I then use a database of state UI rules, discussed in Section IV, to assign the date that the worker would have exhausted his UI benefits if he was eligible for full benefits and if he drew benefits continuously from the date of displacement until exhaustion.

IV. UI during the Great Recession and its aftermath

A. Extended UI Programs

Workers displaced from covered employment with sufficient work histories are generally eligible for up to 26 weeks of regular unemployment insurance benefits. But at times during the last few years, workers who have exhausted their regular benefits might have drawn as many as 53 additional weeks of Emergency Unemployment Compensation (EUC) and as many as 20 more weeks of Extended

[11] This calculation excludes observations that should not match due to the structure of the survey (e.g., those in their second rotation in year y). In some cases, matched observations show implausible discrepancies in age, race, gender, or education between surveys. This occurs in about 1% of monthly-to-ASEC merges and about 6-8% of ASEC-to-ASEC merges. Discrepant observations are discarded.

Benefits (EB), bringing the total as high as 99 weeks. There has been substantial variation in this maximum over time and across states, resulting from differences in state policies, from changing Federal law, and from "triggers" that conditioned both EUC and EB benefits on state economic conditions.

The EUC program was first authorized in June 2008.[12] It initially provided 13 weeks of federally-financed benefits to supplement the regular 26 weeks. At the time, the recession was expected to be relatively brief, and EUC was set to expire in March 2009. As the downturn proved to be deeper and longer lasting than initially expected, EUC was gradually expanded. In November 2008, EUC benefits were extended to 33 weeks in states with unemployment rates above 6 percent and to 20 weeks elsewhere. They were extended again in November 2009, to 34 weeks in states with unemployment rates below 6.0%, 47 weeks in states with rates between 6.0 and 8.5%, and 53 weeks in states with rates above 8.5%.

EUC complemented an existing program, EB, that had existed since 1970 and that was designed to provide supplemental weeks of benefits in times of economic distress. States may choose whether to participate in EB and, if they participate, may select from a menu of possible triggers that will activate EB benefits. Activation provides 13 weeks of EB benefits (on top of the regular and EUC eligibility), or 20 weeks in states that have adopted a more generous trigger and that have unemployment rates above 8%. The first state to become eligible for EB benefits in

[12] It resembled other, similar temporary programs created in past recessions. The discussion here draws on Rothstein (2011) and Fujita (2010).

the Great Recession was Alaska, in June 2008; five additional participating states became eligible by January 2009.

The cost of EB benefits is ordinarily split between the state and the Federal government, but the American Recovery and Reinvestment Act of 2009 (ARRA; also known as the Obama Recovery Act) provided for full Federal funding. After this, a number of states passed legislation to adopt the program or to liberalize their triggers. By May 2009, recipients in 27 states could receive EB benefits, and 11 of these offered 20 weeks of benefits. Eligibility continued to expand, with between 36 and 39 states paying EB benefits through most of late 2009, 2010, and early 2011.

Both EUC and EB benefits were gradually rolled back starting in mid 2011, the two programs have gradually been rolled back. The EB rollback was largely automatic, due to a quirk in the EB rules. The program was designed for states facing temporary, sharp downturns, and the EB triggers are written to restrict eligibility to states with unemployment rates that exceed their values two years earlier. By late 2010, unemployment rates were slowly falling while two-year-lagged unemployment rates were rising quickly, bringing many states close to losing eligibility. The lookback period was extended to three years in December 2010, but this provided only a temporary reprieve. The number of states paying EB benefits fell gradually through the second half of 2011 and the first half of 2012. By July 2012, only Idaho was still paying benefits; it triggered off in early August.

The major rollback of EUC came in February 2012, when several changes were enacted. States with unemployment rates below 6% were eligible for only 20 weeks (down from 34) of EUC benefits; those with rates between 6 and 7% for 34 weeks (down from 47); and those with rates between 8.5 and 9% for 47 weeks (down from 53). States with rates between 7 and 8.5% or above 9% were unaffected, at 47 and 53 weeks, respectively. Second, effective September 2012 EUC durations were cut by an additional six weeks (ten weeks in states with unemployment rates above 7.0%). Third, additional weeks of EUC benefits were provided to high-unemployment states that did not qualify for (or did not participate in) the EB program. These additional weeks were provided in a highly variable way – ten extra weeks in March, April, and May of 2012; none in June, July, and August; and four extra weeks from September onward.

On top of the basic story of gradual expansion and rollback, additional variation in EUC durations arose from the temporary nature of the program. The program was initially set to expire in March 2009. In February 2009, the ARRA extended it through December of that year.[13] Congress then extended it several times for only a few months each: From December 2009 to February 2010, then to April, to June, and to November 2010. Several of these 2010 extensions were retroactive, authorized only after the program had already expired. The first expiration lasted only a few days, but two others lasted for about two weeks each and in June and July 2010 the program was allowed to expire for a full seven weeks. Finally, a longer-term extension in December 2010 authorized the program through January 2012; after another short-term extension in December 2011, another extension in February 2012 extended the program to January 2013.

[13] ARRA also made UI benefits more generous in a number of ways, including by providing a $25/week supplement to UI benefits and by exempting the first $2,400 of benefits from income taxes. Both provisions were temporary.

Figure 5 shows the average, minimum, and maximum number of weeks of benefits available over time through the recession, combining the regular, EUC, and EB programs. This figure is made from a database of UI availability at the state-by-week level, constructed by Rothstein (2011) but updated here to the end of 2012. Maximum benefit durations reached 99 weeks from late 2009 through mid 2012, and the average state was close to the maximum through much of this period. However, states began to fall away from the maximum during early 2012 as the EB lookback provision began to bind.

The three expirations of the EUC program in 2010 are quite prominent in the figure, as durations fall dramatically in each. However, the sharp declines indicated likely overstate the magnitude of the changes experienced by individual recipients. EUC benefits are divided into tiers – at its peak, the 53 weeks of maximum EUC benefits were divided into four tiers of 20, 14, 13, and 6 weeks, respectively. Under EUC program rules, when the program expired recipients were permitted to continue to draw benefits until they exhausted their current tier but could not begin a new tier, while people who exhausted their regular benefits were not permitted to enter the EUC program.[14] This tended to smooth over the expirations, limiting the disruption produced. But the degree of smoothing depended importantly on the

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[14] Many states that adopted the EB program subsequent to the ARRA included provisions to end the state's participation should the federal government ever stop financing 100% of the cost. The EB finance provision expired every time the EUC program did. Thus, recipients living in states that conditioned their EB participation on continued federal funding saw their benefits cut off within a week or two of the June 2 expiration. EB benefits lost during this period were in general not paid retroactively.

exact date of job loss, as this determined the worker's position in the tier structure at the time of EUC expiration.

Each eventual reauthorization provided for the retroactive payment of benefits to individuals who had exhausted their benefits in the meantime. So workers who anticipated this experienced the expirations as delays in their benefit payments rather than as complete exhaustion of their benefits. But the long-term unemployed are unlikely to have substantial liquid savings or easy access to credit (Gruber 1997), so many may have felt serious financial crunches during the these expirations, even if they were fully confident that Congress would come through.

B. Modeling UI Exhaustion

The complex history of EUC and EB created a great deal of variation in the duration of UI benefits and thus in the timing of UI exhaustion. Unfortunately, while the Employment and Training Administration (ETA) compiles weekly data on initial UI claims, no comparable data are collected on exhaustions. I take two approaches to approximating the number of exhaustions.

My first exhaustion series is constructed from state-by-month level ETA data on the numbers of first payments and final payments in the regular UI program, in each of the EUC tiers, and in the EB program. For each state in each month, I compute the number of final payments in any program or tier minus the number of first payments in the EUC tiers or EB. This closely approximates exhaustion, but there are three sources of slippage. First, this method incorrectly counts as exhaustions individuals who found new jobs or abandoned their job searches upon the expiration of a particular tier but who had more benefits available on another tier. Second, when individuals receive their final payments from one program or tier in the last week of a calendar month, the initial payment on the next program or tier appears in the next month's data. This creates excess volatility in measured exhaustions. Third, when EUC benefits were expanded – both when new tiers were introduced and when the program was retroactively reauthorized – many people received first payments who did not receive final payments in the previous week. Because my measure counts first payments negatively, I can estimate negative numbers of exhaustions at these times.

The solid line in Figure 6 shows the estimated number of UI exhaustions each month, using this method. Exhaustions were fairly stable, at around 210,000 per month, through early 2008. The measured number of exhaustions turned sharply negative in July and August of 2008, following the creation of EUC. It then became volatile, bouncing around a lower mean through the rest of 2008 and 2009 with two dips into negative terrain in February 2009 and December 2009-January 2010, each coinciding with an EUC expansion. Exhaustions spiked enormously during the temporary EUC expiration in June 2010, only to turn negative again in August 2010 after the program was reauthorized. Following this episode, the series has bounced around a mean that is similar to that seen before the recession but higher than that seen in 2008-9.

Although the spikes and negative values clearly represent measurement problems, the broad patterns – declines in exhaustion rates in 2009-10 followed by an increase in 2011-12 – correspond to real dynamics. In 2009-10, benefit durations were quite long, and many recipients found jobs or exited the labor force before they exhausted benefits, while the cohorts that were approaching exhaustion were primarily those that had lost their jobs before the recession so were not particularly large. In 2011-12, durations remained long, but the large cohorts from 2008-9 were beginning to exhaust their benefits, offsetting the effect of extended durations on the exhaustion rate.

As a check on the administrative data, I construct an alternative measure by simulating exhaustions using data on initial UI claims and on the availability of benefits over time. I begin with weekly data on initial claims for regular UI benefits by state. For each state and each initial claim week, I simulate the subsequent unemployment spell, using my state-by-week database of UI availability to identify the availability of each tier of benefits at each week of the spell. This simulation identifies the week that a member of the entering cohort would have exhausted his benefits, had he been eligible for full benefits and had he claimed benefits continuously in each week that they were available. Next, I estimate the probability that an individual entering unemployment in each week would have survived in that status (rather than becoming reemployed or exiting the labor force) until the expiration of benefits. The calculation of the survival probabilities is described in the appendix; they are based on estimated average UI exit hazards that are allowed to vary smoothly over time and discretely with unemployment duration (with multiplicative adjustments to the hazard at 3 and 6 months of unemployment). Finally, I multiply the size of the entering cohort by the survival probability to estimate the size of the remaining cohort at the time of exhaustion, then aggregate across all cohorts that exhausted their benefits in each month.[15]

Two series obtained via this method are plotted in Figure 6, corresponding to different definitions of "exhaustion." The first series, plotted as a dotted line, judges an individual to have exhausted her benefits in the first week that she did not receive an on-time benefit payment, even if she was later paid retroactively for that week. This series mirrors the general trends in the administrative measure, but shows zero exhaustions rather than negative numbers in months following EUC introduction and expansions. It also, however, shows an enormous spike in June 2010, when EUC was allowed to expire. (This data point is censored in the graph to control the overall scale; in fact, the series shows nearly 2.5 million exhaustions that month.) It is unclear whether this accurately reflects the expirations that are relevant to SSDI application decisions. If recipients were confident that Congress would eventually reauthorize the program retroactive to its expiration, and if they had access to sufficient credit to borrow against their eventual benefits, this spike dramatically overstates the number of true exhaustions.

My second simulated exhaustion series, graphed as a dashed line, skips over temporary lapses caused by EUC expiration, counting individuals to exhaust their benefits only when they receive their final payments under any program as would be appropriate under the above conditions. This does not show a pronounced spike in June 2010 but does a better job of mirroring the patterns in the administrative

[15] There is an additional adjustment to account for the fact that not all claims for UI benefits lead to actual benefit payments.

data in 2011. I use this as my preferred exhaustion series in the analyses below, though I also present analyses with the first series.

My simulated final exhaustion series explains ##% of the time series variation in the administrative data measure (and ##% when June-August 2010 are excluded). There is substantial across-state variation concealed behind the aggregate time series shown in Figure 6. New York, for example, saw essentially zero exhaustions in 2008 and 2009, while Virginia saw as many or more exhaustions each month in 2008 as before the recession. I exploit this variation in many of the estimates below. A natural concern is that the state-by-month exhaustion measures may be particularly noisy at the state-by-month level. However, they do seem to have substantial signal: The elasticity of the administrative data exhaustion measure with respect to the simulated final exhaustion measure, controlling for a full set of state and month effects, is 0.24, with a standard error of 0.03.[16] When I exclude the June – August 2010 period, when the administrative data are particularly noisy, the elasticity rises to 0.28.

V. Analyses of UI-DI interactions using aggregate data

In this section, I present time-series and state-by-month panel data analyses of the relationship between UI exhaustions and DI applications. Recall that the model in section II suggested that some marginally disabled UI recipients might be

[16] It is not practical to analyze the logarithm of monthly exhaustions at the state level, as there are many zeros. As an alternative, I index exhaustions in each state relative to the average number of monthly exhaustions in that state in 2005-2007. The elasticity reported in the text is the coefficient from a regression of the normalized administrative data measure on the normalized simulated series. All further analyses rely on this index.

induced to apply for SSDI benefits by the impending or actual exhaustion of their UI benefits. This would imply a positive correlation between the two series.

I begin by overlaying my simulated final UI exhaustion series with the number of monthly SSDI applications, in Figure 7. The figure shows that UI exhaustions fell to well under half of their usual rate through most of 2009. DI applications, meanwhile, rose by about 20% in late 2008 and early 2009.[17] UI exhaustions returned to close to their pre-crisis level in late 2010; DI applications plateaued around that time and have remained roughly stable since. There is little sign in this graph of a positive relationship between UI exhaustions and DI applications.

Table 1 presents time-series analyses of the log of seasonally-adjusted aggregate DI applications, measured at the monthly level. The first column includes only the simulated number of final UI exhaustions in the month, measured as a share of their average level during calendar years 2005-2007. The coefficient is negative, the opposite of the expected sign if UI exhaustions lead to DI applications, but is insignificant and small. Column 2 adds a quadratic time trend, while column 3 adds a control for the unemployment rate. The unemployment rate coefficient is positive and quite precisely estimated, indicating that a one percentage point

[17] I focus here and in the regression analyses below on seasonally adjusted monthly DI application rates. Applications are originally measured at a weekly level, then aggregated to the month. I multiply reported claims by 80% in months containing 5 weeks. My seasonal adjustment is based on a regression of the log of adjusted monthly applications at the state level on calendar month dummies, controlling for a quadratic time trend, an indicator for observations since February 2009, and the number of weeks in the month; the seasonally adjusted state applications are then summed to form a national time series.

increase in unemployment is associated with a 3.9% increase in DI applications. The UI exhaustion coefficient becomes positive and marginally significant (t=2.01) when the unemployment rate is controlled, but is quite small: A doubling of UI exhaustions is associated with only a 1.5% increase in DI applications.

Column 4 adds several controls: the number of initial UI claims, seen as a proxy for economic conditions; an indicator for an observation from the June-August 2010 period when the expiration of EUC makes it difficult to measure perceived UI exhaustions; and an indicator for the period after February 2009. These have essentially no effect on the coefficient of interest.

Column 5 adds the average number of UI exhaustions in the three prior and in the three following months. Each of these might capture true effects of UI exhaustions on DI applications, which need not be exactly contemporaneous. But there is little indication that the contemporaneous specification misses an important part of the response – neither the lag nor the lead is significant, the contemporaneous effect is basically unchanged, and the point estimate of the cumulative effect is almost exactly zero.

Columns 6-8 explore alternative measures of UI exhaustions. In column 6 I use the simulated series for initial exhaustions (i.e., the dotted line in Figure 6), while in column 7 I use the exhaustion series computed from administrative records on EUC and EB initial and final payments (i.e., the solid line in Figure 6). Neither of these series indicates any relationship between exhaustions and DI applications. Finally, in column 8 I replace the counts of exhaustions with an indicator for the four months in which my simulations suggest that there were zero UI exhaustions, immediately following the introduction of the EUC program in mid 2008 and its expansion in late 2009. This specification indicates that DI applications fell about 1.9% in these months, implying a responsiveness of similar magnitude to that found in columns 3-5.

All told, the specifications in Table 1 indicate that any effect of UI exhaustions on DI applications, but that the magnitude is quite small and sensitive to the way that exhaustions are measured. By contrast, there is a robust and large relationship between the unemployment rate and DI applications that does not appear to reflect an association between overall unemployment and UI exhaustions.

Of course, time series analyses may be confounded by other determinants of applications over the business cycle. I next turn to panel data analyses of log monthly DI applications at the state level, in Table 2.[18] This allows me to control for other factors that influence the time pattern of DI applications, identifying the exhaustion effect from differences across states in exhaustion trends. There is substantial variation across states, driven in part by the timing of layoffs and in part by the differences in UI extension availability discussed in Section IV. This allows me to estimate the relationship between UI exhaustions and DI applications quite precisely.

Column 1 begins with a simple specification that includes state and month fixed effects, the unemployment rate, and the state-level index of final UI

[18] Each specification in this table includes full sets of state and month fixed effects, and standard errors are clustered at the state level. The DI applications data are adjusted for differences in month lengths and seasonality as described in the previous footnote.

exhaustions. The unemployment rate coefficient is positive and significant, though somewhat smaller than in Table 1. The UI exhaustion coefficient is almost exactly zero here. Moreover, it is extremely precisely estimated, with a standard error less than half the size of those in Table 1, and I can thus rule out elasticities of DI applications with respect to UI exhaustions larger than 0.005.

Columns 2 and 3 explore alternative controls for economic conditions, first including a cubic in the unemployment rate and then the log of the number of initial UI claims. Neither has much effect on the results. Column 4 includes lags and leads of the exhaustion index. These are both insignificant, and the point estimates indicate a cumulative elasticity of DI applications with respect to exhaustions of only 0.018. In column 5, I include each of the three leads and three lags of the exhaustion series separately. Point estimates (not shown) indicate a cumulative elasticity of 0.004, with negative coefficients for the contemporaneous and immediate leads and lags and positive coefficients on the longer leads and lags. This is the opposite of the pattern that one would expect from a causal effect of anticipated or recent past UI exhaustion.

Column 6 excludes the June-August 2010 observations, when UI exhaustions are difficult to define precisely. This has little effect.

Finally, columns 7-9 explore each of the alternative exhaustion measures used in columns 6-8 of Table 1. Here, the alternative exhaustion series indicate slightly more positive effects, though I can still rule out elasticities larger than 0.006. Moreover, column 9 indicates that DI applications are higher in months when new

UI extensions take effect, and the confidence interval rules out declines larger than 0.4%.

Taken together, the panel data analyses in Table 2 offer no sign that DI applications respond to UI exhaustions. I can always rule out elasticities larger than 0.02, and most specifications rule out elasticities one-quarter this size.

At this point, it is worth considering how large an effect would need to be to be quantitatively important. One way to approach this is to compare the empirical estimates to the elasticities implied by the toy model in Section II. In that model, a doubling of UI durations reduced steady-state UI exhaustions by about half and steady-state DI applications by a quarter. (The short-run effects would be much larger.) The estimates in Table 2, then – if they can be interpreted as causal – imply much, much smaller UI exhaustion effects.

Another approach is to compare the cost of UI extensions to the resulting DI savings. DI cases are extremely expensive, as people accepted into the SSDI program generally continue to receive benefits until age 65, and the present value of a single DI award is estimated at around $300,000. By contrast, the average UI recipient receives about $300 per week. Thus, if extending UI benefits by one week diverts even one in one thousand recipients from going on DI, the DI savings would pay the entire cost of the UI extension.

However, the first-order effect of a UI extension is likely to be to merely delay DI applications rather than to permanently displace them. Rothstein (2011) estimates that the long-term unemployed had monthly job-finding rates around 10 percent through 2009 and 2010. If we suppose that marginal DI applicants have similar job-finding rates to this – in fact, they are probably less employable than the average long-term UI recipient – and if we assume that one third of DI applications lead eventually to DI awards – this is roughly the recent average, but marginal applicants probably have lower award rates – then in order to finance a four-week UI extension through DI savings there would need to be 30 individuals per 1,000 potential UI exhaustees who would thereby be deferred from applying for DI benefits and thus given an extra opportunity to find a job first.

Recall that the estimates in Table 2 always ruled out elasticities of DI applications with respect to UI exhaustions larger than 0.02. For a state with average UI exhaustion and DI application rates, this means that a UI extension that reduced exhaustions to zero would see only a 2% decline in DI applications. DI applications are of the same rough order of magnitude as UI exhaustions, so this implies a reduction of 20 DI applications per 1000 UI exhaustees whose benefits are extended. This is well below the break-even point. Of course, a calculation based on point estimates rather than confidence intervals would imply an even smaller effect.

VI. Analysis of UI-DI interactions using Current Population Survey microdata

Table 3 presents summary statistics for the merged CPS monthly – ASEC sample, pooling data for calendar years 2005 – 2011 (with ASEC observations from the 2006-2012 surveys). I restrict the sample throughout to individuals aged 20-64 (in the base month survey), and I exclude individuals whose unemployment spells started in 2003 or earlier.

The first column presents statistics for the full sample of 240,163 observations. Of these, 75% are employed at the initial monthly survey (generally in March of year y, though some are from February or April, or from November of year y-1), 5% are unemployed, and 21% are out of the labor force. Summary statistics for unemployed workers are reported in column 2, while column 3 presents statistics for unemployed workers who appear to be eligible for UI by virtue of having lost their previous jobs involuntarily. Unfortunately, I cannot measure UI receipt directly. However, the reason for unemployment appears to be an adequate proxy: Of those who were unemployed at the initial monthly survey and said that they had been involuntarily displaced, 40% report on the following March's ASEC survey having positive UI income for the year. This compares to only 9% of those who say that they had voluntarily left their previous job or were a new entrant or reentrant to the labor force.

Finally, column 4 presents statistics for UI-eligible workers who would have exhausted their benefits before the end of the year in which they were initially observed, had they remained unemployed for that long. (Of course, not all workers reached that point – some presumably were reemployed before exhausting their benefits. But I cannot measure these transitions.) All UI recipients in 2005-2007 are in this category, as the base surveys were completed by April and UI benefits lasted only 26 weeks in those years. In later years, only workers who had already been unemployed for some time by the initial survey were at risk of exhausting their UI benefits within the calendar year.

Unemployed workers are more male and younger than the population as a whole, with notably lower education levels. UI eligible workers are quite similar to the overall pool of the unemployed, but are somewhat older and more male on average. Of the UI eligible workers in the base month survey, 57% would have exhausted their benefits by the end of the calendar year, and 37% would have exhausted them by the midpoint of the year. The potential exhaustees closely resemble the overall pool of UI eligible workers in their demographic characteristics. The average time of expiration is in early March of year y.

The final rows of the table show the share of individuals who report in the year-y+1 ASEC survey having received SSDI income during year y. This is 3.2% for the full sample, but over half of these also reported having SSDI income in year y-1. Such individuals – the vast majority of whom were out of the labor force at the base monthly survey – are excluded from my analysis of the effect of UI expiration. Only 1.4% of individuals who did not have SSDI income in year y-1 had it in year y. Workers who were unemployed at the base month survey have notably lower SSDI receipt rates, and UI eligible workers are somewhat less likely to receive SSDI income than are the ineligible unemployed. Finally, UI recipients who would have exhausted their benefits before the end of year y have somewhat higher SSDI recipiency rates than do those whose benefits would have continued beyond the end of the year.

Table 4 presents my analysis of UI expiration and DI receipt in the matched CPS-ASEC sample. I estimate specifications of the form:

$$DI_{isy} = \text{logit}(UR_{sy}\,\beta + LF_{isy}\,\gamma + X_{isy}\,\delta + D_{isy}\,\theta + \kappa_s + \pi_y),$$

where DI_{isy} is an indicator for receipt of SSDI income by individual i in state s in year y (as reported on the y+1 ASEC survey); UR_{sy} is the unemployment rate in state s in year y; LF_{isy} is a vector of measures of the individual's labor force status, including dummies for unemployment and NILF (employment is the excluded category) and measures of unemployment duration; and X_{isy} is a measure of UI exhaustion before the end of year t. D_{isy} is a vector of demographic controls – dummies for ages 40-49, 50-54, 55-59, and 60-64, with 20-39 the excluded category; a linear age control; and a gender indicator. κ_s and π_y are fixed effects for states and years, respectively. The sample in all columns excludes individuals who had SSDI income in year y-1, so the outcome variable equals one only for individuals who began new SSDI spells in year y. Its average value is 1.44% in the full sample and 0.97% in the subsample of individuals who were unemployed at the base month survey.

Table 4 reports logit coefficients and standard errors. Logit coefficients can be difficult to interpret, particularly when positive outcomes are rare. To indicate the magnitude of the effects that I estimate, I carry out two counterfactual exercises. First, I ask how much lower the SSDI receipt rate among the initially unemployed would be if their UI benefits were extended through the end of calendar year y, holding constant state conditions and the timing of their initial job loss. Second, to provide a point of comparison, I also ask how much lower the SSDI receipt rate would be if the individuals observed in unemployment at the baseline survey had instead been employed. This latter counterfactual is not meant to reflect the causal effect of unemployment, but is useful for gauging the magnitude of the former estimates. Estimates are reported in the bottom rows of Table 4.

Column 1 presents a specification that includes only the demographic controls, state and year FEs, and the state unemployment rate. The latter enters with a negative coefficient, though it is insignificant and the implied effect is very small. Column 2 adds indicators for four labor force statuses at the base survey: Unemployed due to job loss, unemployed due to voluntary quit or to labor market entry or reentry, non-participation in the labor force due to disability, and non-participation for other reasons. (The excluded category is employment at the base survey.) Those who are not employed at the base survey have substantially higher probabilities of receiving SSDI than are the base-survey employed. Those out of the labor force have higher probabilities than the unemployed, particularly so for those who attribute their non-participation to disability.

At the bottom of the table, I show that the model indicates that the subsample of individuals who were initially unemployed would have been 0.68 percentage points less likely to have had DI income had they been employed, on a base of 0.97 percentage points.

Column 4 adds the unemployment duration (measured as of the end of the calendar year, assuming that the initial unemployment spell lasts until then) as a covariate, interacting it with UI eligibility. Those who are employed or out of the labor force at the base survey are assigned durations of 0. The longer-term unemployed are more likely to receive SSDI income than are those unemployed for shorter periods, particularly among job-losers. But accounting for this does not change the implied total effect of unemployment on DI receipt.

Column 5 adds the UI expiration variables. I include two measures. The first is a continuous measure of the date of UI expiration, measured in years relative to the end of the focal year. Earlier expirations are coded as larger numbers – an individual whose UI benefits were set to expire on September 30 would be coded as a 0.25, while one whose benefits expired on June 30 would be coded as a 0.5. Those whose benefits continued beyond the end of the focal year are coded as zeros. The second variable is an indicator for an expiration before June 30. Because DI applications take several months to process, an individual whose UI benefits expired late in the year and who applied for SSDI immediately thereafter would be unlikely to receive DI income in that calendar year. Those whose applications were filed early in the year, however, should have reasonable probabilities of receiving DI income by the end of the year. Thus, if UI expirations lead in relatively short order to DI applications and if some of those applications are successful, both variables should be positively associated with DI receipt.[19]

The results in column 5 do not indicate this. Expiration before June 30 has a positive coefficient while the continuous time since UI expiration is negative, but they are not individually or jointly (p=0.84) significant, and both are quite small. In the bottom of the table, I report the implied effect of UI expiration on the average DI receipt rate among the initially unemployed: 0.01 percentage points.

Because I control for the timing of job loss, variation in the date of UI exhaustion comes from variation in the duration of UI benefits, with later

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[19] Implicit in this parameterization is an assumption that the probability of DI receipt rises with the time elapsed since the DI application, perhaps particularly quickly around 6 months after the initial application.

exhaustions in periods when UI benefit durations were longer. To ensure that the results are not confounded by the economic conditions that give rise to longer UI durations, in column 6 I add quadratic and cubic terms in the state unemployment rate. This has no effect on the results.

Columns 7 and 8 restrict the sample, first to the unemployed and then further to just those who are unemployed due to job loss. These dramatically reduce the sample size, reducing precision. Point estimates indicate somewhat larger effects – in the final column, they suggest that expiration of UI benefits raises the probability of DI receipt among the UI-eligible unemployed by 0.32 percentage points.

Recall that Figure 6 indicated that approximately 250,000 individuals exhaust their UI benefits each month. The estimate in column 8 of Table 4 indicates that this induces about 800 DI awards over the next 6-12 months. This should be inflated by about 50% to account for awards made on appeal, for a total of 1,200 eventual induced awards.[20] This is about 1.4% of the average number of awards per month in recent years. This figure is strikingly consistent with the application elasticity obtained from the aggregate analysis in Table 3, and again indicates that any effects of UI exhaustion on DI uptake are quite small relative to the overall flow.

[20] Benítez-Silva et al. (1999) estimate that 46% of applicants are awarded benefits in the first stage of review and that this rises to 73% after appeals. First-stage awards are made in 5 months, on average, but awards made on appeal take an average of 15 months.

VII. Conclusion

As SSDI applications, awards, and caseloads have risen in the last several decades, analysts have speculated about the causes. One often-cited potential explanation is the inadequacy of the safety net for non-disabled workers in the United States – perhaps people are using SSDI as a substitute for other, missing safety net programs. A particularly plausible candidate is unemployment benefits: Individuals who have exhausted their regular unemployment benefits may use SSDI as a form of continued support, particularly when the economy is weak and new jobs are hard to find.

This sort of dynamic could help to explain the apparent countercyclicality of SSDI applications over the last several business cycles. However, it has not been easy to test, as other explanations could also account for the cyclical pattern.

This paper has used variation in UI durations created by the uneven extension of UI benefits during and after the Great Recession to isolate variation in UI exhaustion that is not confounded by variation in economic conditions more broadly. Using a variety of analytical strategies, I have examined the relationship between UI exhaustion and uptake of DI benefits. None of the analyses presented here indicate quantitatively meaningful effects.

There are a number of caveats to the analysis. Most importantly, I must make assumptions about the timing of DI applications and awards induced by UI exhaustion. For the aggregate analyses, I must assume that any induced applications occur within three months (before or after) the date of UI exhaustion, while for my analysis of microdata I must assume that any induced SSDI awards lead to receipt of payments within the same calendar year as an earlier UI exhaustion. Either or both of these assumptions could be incorrect – UI exhaustees may wait six months or more before applying for SSDI, or awards made to exhaustees might be disproportionately likely to require an appeal of an initial rejection. These possibilities mean that a causal link between UI exhaustion and DI cannot be conclusively ruled out.

Nevertheless, the analysis here counsels against the likelihood of such a link. It rather tends to support alternative explanations for the countercyclicality of DI applications. For example, the cyclical pattern may simply reflect variation in the employment opportunities of the marginally disabled that influences SSA's evaluation of the applicant's employability. These alternative explanations may have quite different policy implications than would a link to UI. It is not clear, for example, that more stringent functional capacity reviews would reduce recession-induced DI claims if these claims reflect examiners' judgments that the applicants are truly not employable in the extant labor market.

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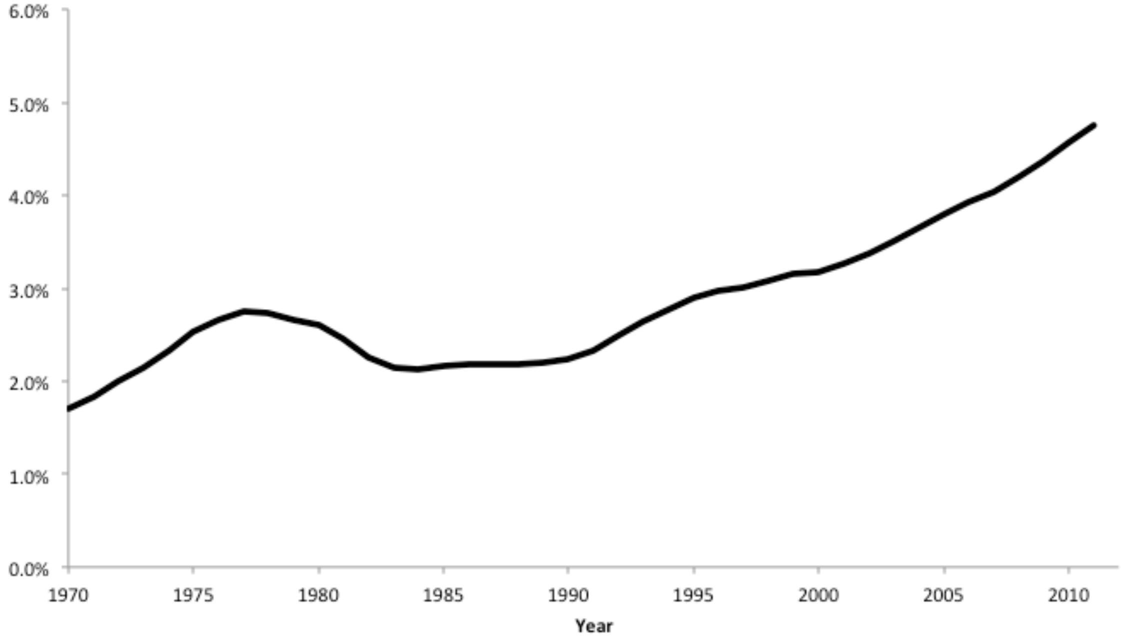
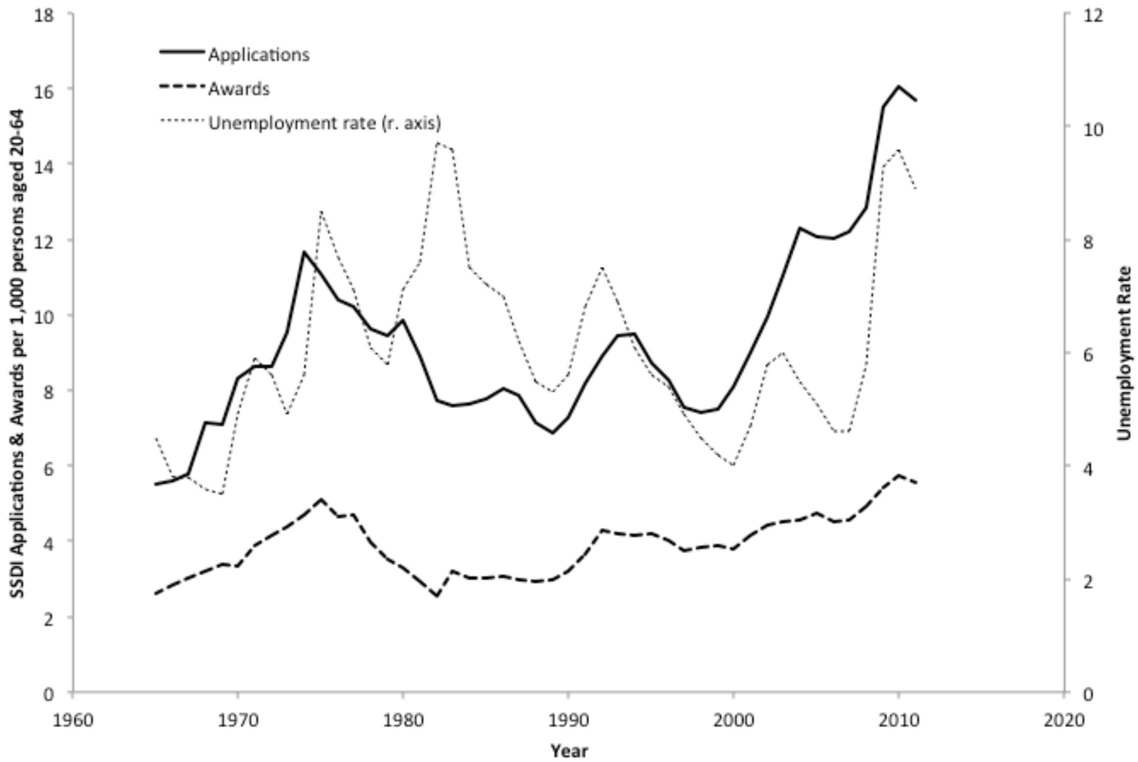
Figure 1. DI recipients as share of civilian noninstitutional population aged 20-64, 1970-2011



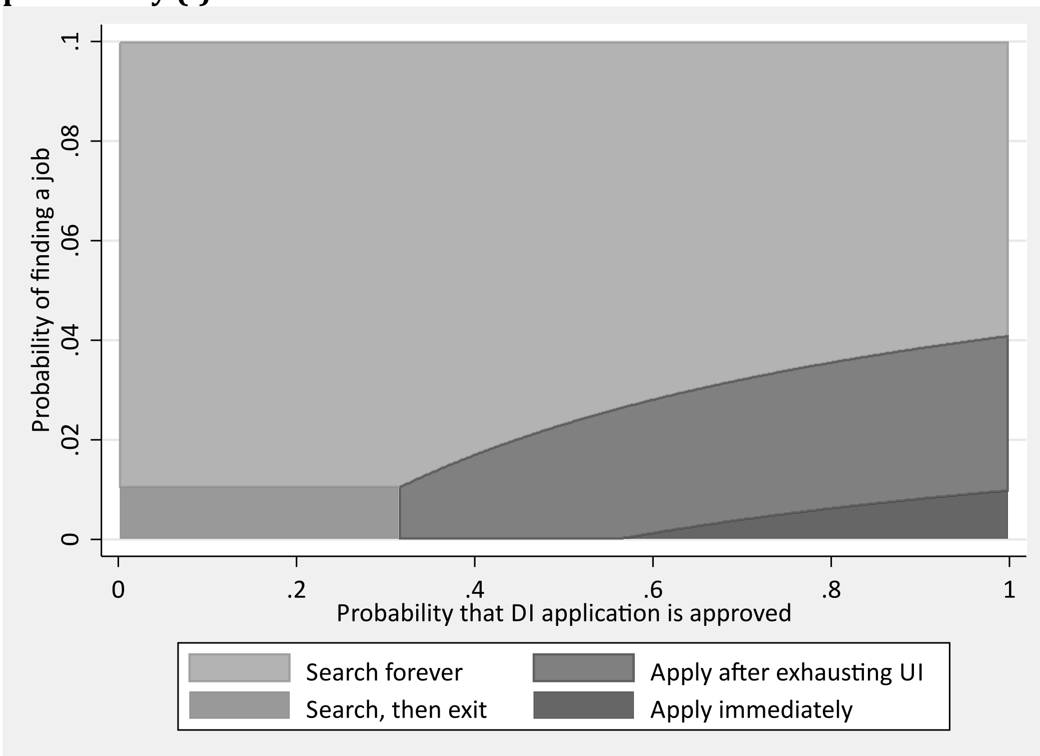
Notes: DI recipients include disabled workers and spousal beneficiaries, and are measured as of December 31 of each year.
Sources: Social Security Administration, Office of the Actuary, and Bureau of Labor Statistics

Figure 2. SSDI applications and awards as share of population aged 20-64, 1965-2011



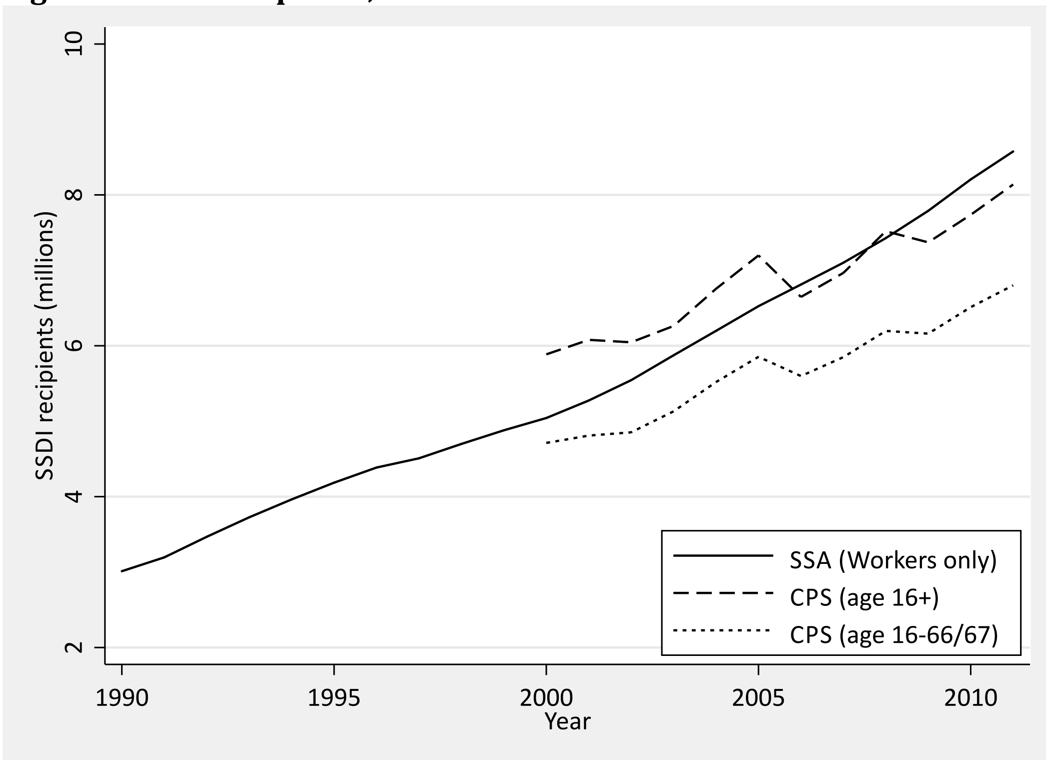
Notes: Applications and awards data apply to new disabled worker cases.
Sources: Social Security Administration, Office of the Actuary, and Bureau of Labor Statistics

Figure 3. Worker policies by degree of disability (p) and job-finding probability (f)



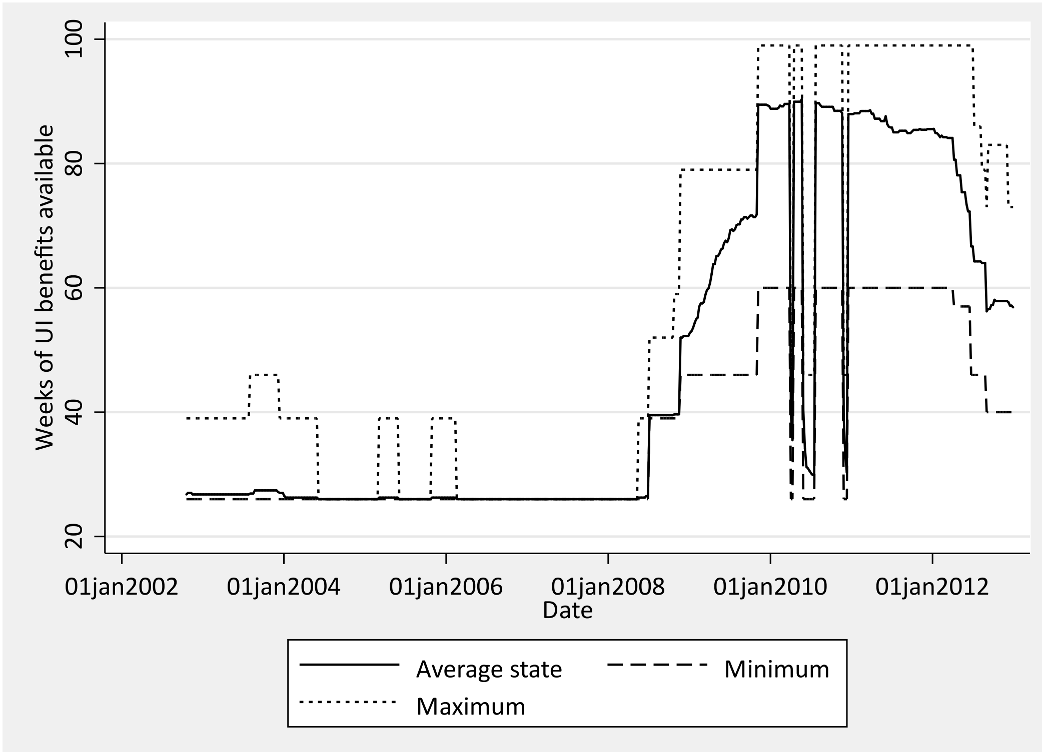
Notes: See text for description of model. Other model parameters are $V_E = 1/(1\text{-}\delta)$ (corresponding to a per-period wage normalized to 1 and a job that lasts forever); $b_{UI} = 0.4$; $b_{DI} = 0.5$; $c_U = 0.2$; $c_A = 3$; $\delta = 0.95$; and $u(y)=y$.

Figure 4. SSDI recipients, SSA data vs. CPS ASEC



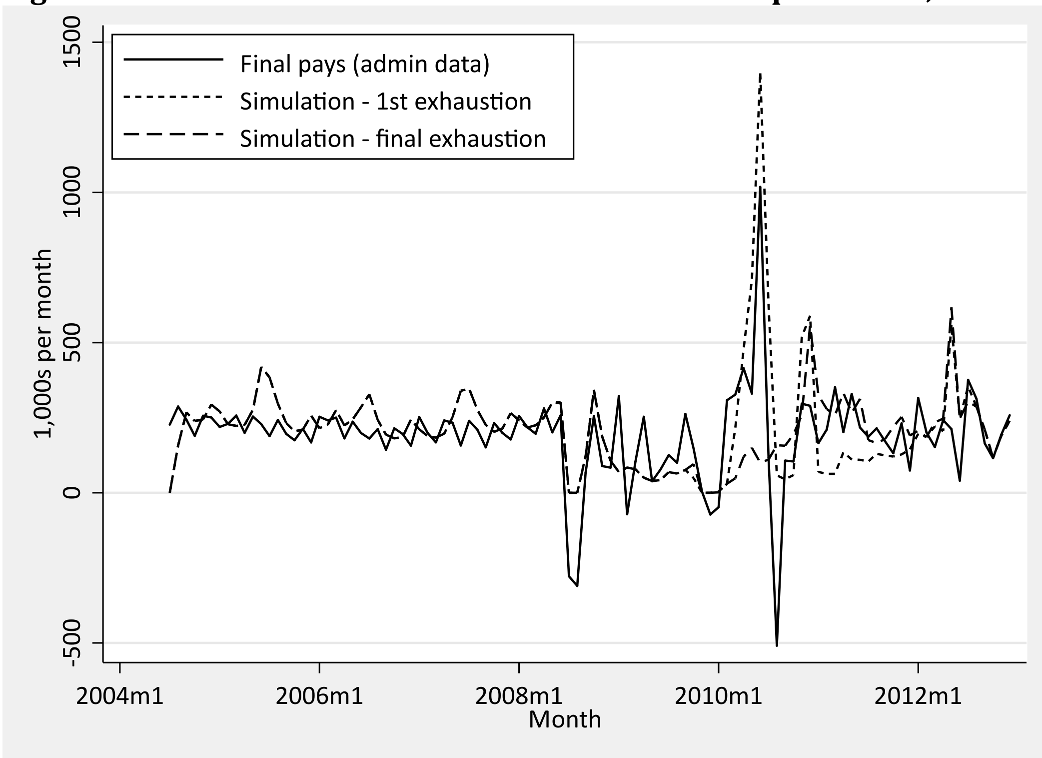
Notes: SSA series includes only disabled worker cases.

Figure 5. Unemployment insurance benefit availability over the Great Recession



Notes: "Average state" series represents a simple, unweighted average across 50 states plus the District and Columbia.

Figure 6. Estimates of the number of UI exhaustions per month, 2004-2012.



Notes: "Simulation – 1st exhaustion" series is censored at 1.4 million in June 2010; true value is 2.46 million.

Figure 7. UI exhaustions and SSDI applications by month, 2004-2012

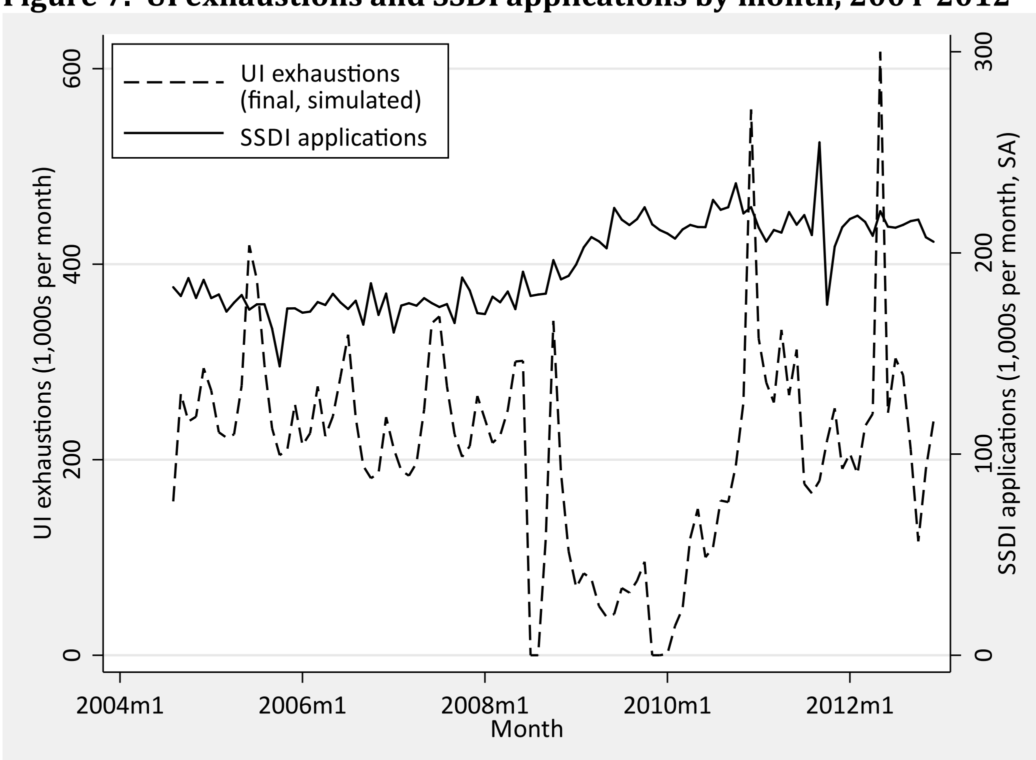


Table 1. Time series analysis of national DI applications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Final UI exhaustions (index:	-0.053	-0.038	0.015	0.014	0.018			
multiple of 2005-7 avg.)	(0.042)	(0.024)	(0.008)	(0.008)	(0.009)			
Exhaustions index (avg.,					-0.022			
prev. 3 months)					(0.020)			
Exhaustions index (avg.,					0.015			
next 3 months)					(0.014)			
Initial UI exhaustions (index)						-0.001		
						(0.004)		
UI final pays (index)							0.001	
							(0.005)	
1(No exhaustions this month)								-0.019
								(0.007)
Unemployment rate (SA)			0.039	0.037	0.031	0.036	0.036	0.037
			(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
ln(initial UI claims)				-0.021		-0.025	-0.025	-0.025
				(0.019)		(0.018)	(0.019)	(0.018)
1(June, July, August 2010)				0.023		0.025	0.022	0.020
				(0.008)		(0.015)	(0.008)	(0.008)
Post-ARRA				0.018	0.031	0.018	0.018	0.013
				(0.017)	(0.015)	(0.017)	(0.017)	(0.017)
Quadratic time trend	n	y	y	y	y	y	y	y
N	101	101	101	101	95	101	101	101

Notes: Sample in all columns is a national time series spanning August 2004 (November 2004 in column 5) to December 2012. Dependent variable is ln(receipts for SSI, SSDI, or SSI/SSDI claims), measured at the monthly level and seasonally adjusted. Newey-West standard errors, allowing for autocorrelations at up to four lags, in parentheses.

Table 2. Panel data regressions for SSDI applications at the state-month level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment rate (SA)	0.017		0.016	0.016	0.016	0.017	0.017	0.018	0.017
	(0.006)		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Final UI exhaustions (index:	-0.002	-0.003	-0.003	-0.004	-0.003	0.000			
multiple of 2005-7 avg.)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.004)			
Exhaustions index (avg.,				0.003					
prev. 3 months)				(0.005)					
Exhaustions index (avg.,				0.005					
next 3 months)				(0.007)					
ln(initial UI claims)			0.038						
			(0.032)						
Initial UI exhaustions (index)							0.002		
							(0.002)		
UI final pays (index)								0.001	
								(0.002)	
1(No exhaustions this month)									0.010
									(0.007)
State FE	y	y	y	y	y	y	y	y	y
Month FE	y	y	y	y	y	y	y	y	y
Cubic UE rate control		y							
3 leads and lags of exhaustion index					y				
Exclude June-Aug 2010						y			
N	5,151	5,151	5,151	4,845	4,845	4,998	5,151	5,151	5,151
R2	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991	0.991

Notes: Dependent variable is ln(receipts for SSI, SSDI, or SSI/SSDI claims), measured at the state-by-month level and seasonally adjusted. Panel ranges from August 2004 - December 2012. Samples in Columns 5 and 6 range from November 2004-September 2012. Standard errors, clustered on the state, in parentheses.

Table 3. Summary statistics for matched CPS-ASEC sample, 2005-2011

	All (1)	Unemployed at base survey (2)	Unemployed & UI eligible (3)	Exhaust UI before end of calendar year (4)
N	240,163	10,195	6,865	3,976
Female	51%	43%	36%	37%
Age	42.5	39.3	41.1	41.6
	[12.0]	[12.2]	[11.7]	[11.7]
Age 50+	32%	24%	28%	29%
Education				
LTHS	10%	16%	16%	17%
HS	31%	39%	41%	40%
Some college	28%	27%	26%	27%
BA+	31%	18%	17%	16%
Labor force status				
Employed	75%	0%	0%	0%
Unemployed	5%	100%	100%	100%
Not in labor force (NILF)	21%	0%	0%	0%
UI eligible	3%	67%	100%	100%
Unemployment duration, years		1.32	1.31	1.46
(as of 12/31)		[0.56]	[0.54]	[0.63]
UI expired before 12/31			57.3%	100.0%
UI expired before 6/30			36.7%	64.1%
Time since UI expiration, years				0.72
(as of 12/31)				[0.51]
SSDI income in year y	3.2%	1.4%	1.2%	1.4%
SSDI income in year y if none in y-1	1.4%	1.0%	0.9%	1.1%

Notes: Standard deviations in square brackets. All statistics use sampling weights from the initial monthly CPS sample.

Table 4. Analyses of SSDI receipt in matched CPS data

	All						Unemp.	UI elig.
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Economic conditions								
Unemployment rate	-0.003	-0.014	-0.018	-0.019	-0.019	0.400	-0.339	-0.345
	(0.008)	(0.028)	(0.030)	(0.030)	(0.030)	(0.246)	(0.139)	(0.184)
UR squared						-0.062		
						(0.033)		
UR cubed						0.003		
						(0.001)		
Individual labor force status (measured in spring)								
Unemployed*UI elig			1.09	0.05	-0.02	-0.02		
			(0.14)	(0.32)	(0.40)	(0.40)		
Unemployed*UI inelig			1.49	1.19	1.19	1.19	1.00	
			(0.19)	(0.45)	(0.45)	(0.45)	(0.59)	
NILF - disabled			4.56	4.56	4.56	4.56		
			(0.06)	(0.06)	(0.06)	(0.06)		
NILF - non-disabled			2.09	2.09	2.09	2.09		
			(0.07)	(0.07)	(0.07)	(0.07)		
Unemp. duration (years)*UI elig				0.72	0.75	0.75	0.54	0.16
				(0.18)	(0.32)	(0.32)	(0.40)	(0.45)
Unemp. duration (years)*UI inelig.				0.21	0.21	0.21	0.16	
				(0.27)	(0.27)	(0.27)	(0.30)	
UI expiration								
Time since UI expiration, years					-0.17	-0.17	0.07	0.32
(as of 12/31)					(0.43)	(0.43)	(0.53)	(0.55)
UI expired before 6/30					0.25	0.25	0.14	0.26
					(0.43)	(0.43)	(0.46)	(0.49)
N	232,998	232,998	232,998	232,998	232,998	232,998	9,217	4,832
Average probability of DI receipt among (initially) unemployed, in p.p.								
	0.97	0.97	0.97	0.97	0.97	0.97	1.06	1.27
Effect of (in p.p.):								
UI expiration					0.01	0.01	0.07	0.32
Own unemployment			0.68	0.68	0.67	0.67	0.59	0.19

Notes: Table reports coefficients (and standard errors) from logit models. Dependent variable is an indicator for receipt of SSDI income during the calendar year, as reported on the ASEC. All specifications include state & month FEs and demographic controls (age, 4 age group dummies, & gender). Sample spans calendar years 2005-2011. Individual labor force status is drawn from the baseline monthly CPS sample. Unemployment duration and expiration are measured as of December 31 of the year. Counterfactual effects in bottom rows set UI expiration date to after the end of the year or own labor force status to employed (with unemployment duration of zero)