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Articles

Using Survey of Income and Program Participation data linked to Social Security administrative files, the authors examine the preapplication employment patterns of Social Security Disability Insurance (DI) applicants for periods of varying lengths up to 24 months before application. The employment histories of about half of the applicants are characterized by stable employment in well-paying jobs; most policy proposals related to workforce retention or DI diversion target this type of worker. The other half of the applicants have either intermittent or no work experience in the preapplication period. Proposals that focus on DI applicants with recent or long-term attachments to the workforce are therefore likely to miss this other half of eventual DI applicants. Future policy proposals should consider outreach to people who lack a strong labor force attachment and who might need a broader array of supports to remain in or return to the workforce.

Perspectives

In this article, the authors examine the relationship between prevailing economic conditions and the likelihood of application for Supplemental Security Income (SSI) payments by jobless adults with disabilities. Using data for 1996–2010 from the Survey of Income and Program Participation linked to Social Security administrative records, the authors observe samples of jobless individuals and examine the state-level unemployment rates at both the time their unemployment spell began and at the time they applied for SSI.

Employment Patterns Before Applying for Disability Insurance

by Kara Contreary, Todd Honeycutt, Michelle Stegman Bailey, and Joseph Mastrianni*

Using Survey of Income and Program Participation data linked to Social Security administrative files, we examine the preapplication employment patterns of Social Security Disability Insurance (DI) applicants for periods of varying lengths up to 24 months before application. Based on their employment histories, we identify two types of applicants. Type 1 applicants are characterized by stable employment in well-paying jobs; most proposals related to workforce retention or DI diversion target this type of worker. Type 2 applicants have either intermittent or no work experience in the preapplication period. Proposals that focus on DI applicants who have recent or long-term attachments to the workforce are therefore likely to miss about half of those who eventually apply. Future proposals should consider outreach to people who lack a strong labor force attachment and who might need a broader array of supports to remain in or return to the workforce.

Introduction

Many Social Security Disability Insurance (DI) policy proposals feature early-intervention and worker-retention objectives. If workers with disabilities are provided with adequate supports, they may be diverted from applying for DI benefits. To be effective, these proposals should identify the types of people who could benefit most from such proposals, as DI applicants have varied backgrounds and characteristics (Thompkins and others 2014). Casting too broad a net might misplace resources on individuals who are not able to remain in or return to the labor force, or on those who already have adequate access to supports. Casting too narrow a net might miss people who could benefit from employment supports, which would limit the potential returns both for at-risk individuals and for the program.

This article examines the employment patterns and demographic characteristics of DI applicants in the period before application. Such information can help inform various policy proposals involving early intervention, worker retention, and program diversion by identifying how various groups of applicants could be better targeted and by assessing the potential reach of such proposals. We rely on Survey of Income and Program Participation (SIPP) data matched to Social Security Administration (SSA) records to answer questions about the employment, demographic, and other characteristics of DI beneficiaries before they apply for DI, with particular emphasis on their detailed employment patterns, their participation in non-DI public programs, and their coverage under selected types of insurance. For brevity, in this article, we use "program participation" to refer broadly to receipt of benefits provided by non-DI public programs or private insurance.

Selected Abbreviations

DI	Disability Insurance
SIPP	Survey of Income and Program Participation
SNAP	Supplemental Nutrition Assistance Program
SSA	Social Security Administration
TANF	Temporary Assistance for Needy Families
UI	unemployment insurance

** Kara Contreary is a researcher, Joseph Mastrianni is a systems analyst, and Todd Honeycutt is a senior researcher with Mathematica Policy Research. Michelle Stegman Bailey is with the Office of Retirement and Disability Policy, Social Security Administration.*

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Using four distinct preapplication observation periods ranging from 6 to 24 months, we find that about half of DI applicants were consistently employed until they applied or until they experienced a single definitive work cessation before application. The other half, all of whom met DI's overall work-history requirements, either did not work at all or had intermittent employment in the preapplication period. DI allowance rates, program-participation patterns, and demographic characteristics differed between those two halves of the observed applicant population.

Our findings contribute to the literature by identifying types of people, in terms of work histories and DI award probabilities, who might be likely candidates for early-intervention or worker-retention initiatives. DI proposals could target at-risk workers for supports either through their employers or through the public programs in which they participate. Evidence on the employment patterns of people who are likely to apply for DI can help policymakers identify potential target populations, tailor program changes to subgroups that may follow very different paths to DI, and more generally, ensure that program changes are successful and cost-effective.

Background

A substantial body of literature addresses policy proposals that aim to support employment retention before workers apply for DI, including several SSA studies (such as Kearney and others 2005/2006). Providing supports to workers while they still have jobs—at the time when they encounter a potentially disabling health condition or their existing health condition worsens—is widely seen as a better way to promote independence than waiting until they apply for DI to provide such supports (Autor and Duggan 2010; McCrery and Pomeroy 2016). Advocates of early-intervention initiatives cite the economic advantages to all parties involved—workers, employers, communities, and state and federal agencies—of keeping people with disabilities in the workforce when possible. These initiatives are informed by increasing evidence suggesting that some DI beneficiaries could work if given appropriate supports (Autor and Duggan 2003; Black, Daniel, and Sanders 2002; von Wachter, Song, and Manchester 2011). This evidence is not overwhelming, however, as other studies have found that the level of retained employment might be relatively low (for example, Maestas, Mullen, and Strand 2013). Evidence from SSA demonstrations (such as Frey and others 2011 and Gubits and others 2014) also shows that although some DI beneficiaries can work with targeted services and supports, few attain earnings levels sufficient to cease benefits.

What most proposals have in common is a need to identify workers who are likely to apply for and receive DI benefits before they actually do so—ideally, while they are still in the labor force. A related objective is to identify those potential applicants who would be most effectively served by a particular policy intervention, as well as the best time to intervene, especially given variations in the timing of earnings declines by age, sex, and disability type in the period before an individual applies for DI (Costa 2017). Successful targeting of potential applicants is crucial to the effectiveness of any proposed policy. Previous work has highlighted several characteristics that might provide a starting point for identifying such people.

Early-Intervention Approaches to Worker Retention

People rarely exit the DI rolls once they begin receiving benefits (Liebman and Smalligan 2013; Liu and Stapleton 2010), and many disability researchers and policymakers have concluded that the most effective intervention occurs before a person applies for benefits—preferably, while he or she is still working (Stapleton, Mann, and Song 2015). This conclusion adds an unanticipated dimension to policy considerations because the DI system was created to support people who can no longer work, rather than those who remain employed (Burkhauser and Daly 2011). Most early-intervention approaches, although designed to provide better supports to workers to divert them from needing benefits, target either employers or public programs.

Employer-focused proposals. These efforts would either mandate private (or hybrid) short-term disability insurance to cover employees who acquire a disabling condition or use an experience-rating approach in administering the disability portion of the Old-Age, Survivors, and Disability Insurance (OASDI) payroll tax. Mandatory short-term disability insurance would provide employers and employees with worker-retention supports (such as income replacement, vocational rehabilitation, and workplace accommodations) for up to 2 years. Eligibility for DI benefits would begin only at the end of the 2-year period. Depending on their size, employers would pay insurance premiums that vary based on the tendency of their employees to file claims, which would provide incentives for firms to retain their workers with disabilities (Autor and Duggan 2010). An alternative policy proposal would shift the disability portion of the OASDI payroll tax to an experience-rating system (Burkhauser and Daly 2011). Experience rating is already used in determining workers' compensation and unemployment insurance (UI) employer contribution amounts, for similar reasons. Employers with large numbers of employees claiming disability benefits would face higher tax rates, which would encourage them to lower disability claims by finding ways to keep workers with disabilities on the job.

Employer-focused approaches offer many advantages. For example, because employers are best positioned to observe their employees' work performances, policies can establish incentives or laws for small employers to provide accommodations (such as those mandated for employers of 15 or more workers by the Americans with Disabilities Act) that help workers stay in the labor force.[1] Employers and employees both might benefit from improved rehabilitation and vocational supports that encourage employees with work limitations to maintain employment. Taking a more longitudinal perspective, employers might also institute measures that can delay or prevent the onset of health conditions that could lead to work-limiting disabilities, such as promoting ergonomic work environments. An important downside, however, is that placing another burden on employers in the form of short-term disability insurance premiums or experience ratings might increase existing incentives to avoid hiring or retaining people who are at greater risk for disability.

Public program–focused proposals. These efforts could encourage program changes, either through SSA and the disability determination process or through the collaboration of state-level organizations, to provide more workplace supports to people with disabilities. Providing individualized supports and wage subsidies to potential DI applicants might encourage them to stay in the workforce, alleviating the need to apply (for example, Liebman and Smalligan 2013). More ambitious proposals would aim to identify individuals as they experience the onset or worsening of medical conditions that threaten their ability to remain employed and potentially qualify them for DI. Targeted individuals would receive appropriate supports that might enable them to remain in work (McCrery and Pomeroy 2016, Chapter 3). Expedited DI application and processing for individuals who are not capable of work could be included in either proposal.

Another public-program policy change would switch funding for state disability determination services from the discretionary to the mandatory side of the budget, making public disability programs more akin to Temporary Assistance for Needy Families (TANF), Medicaid, and the Supplemental Nutrition Assistance Program (SNAP) (Liebman and Smalligan 2013). This change would provide more resources for purposes such as reducing backlogs, performing continuing disability reviews, and collecting evidence that leads to better disability determinations early in the application process. If improved administration at the state level results in more appropriate benefit allowances or continuing disability decisions, marginal applicants might opt not to expend the effort to apply. On the other hand, faster decisions might reduce the opportunity cost of applying for DI. One important caveat of this approach is that if expenditures for administrative costs were mandatory rather than discretionary, there would be no effective limit on them.

Alternatively, government policymakers could offer or expand evidence-based early-intervention services to their own workforce or to the general population through incremental or targeted policies (Stapleton, Mann, and Song 2015). Those services could be delivered either as part of the package of benefits given to state and federal employees or, more broadly, as a coordinated part of the services already delivered by state-level labor and education agencies (such as American Job Centers and state vocational rehabilitation agencies) to a state's employers and employees. Such approaches would build on the experiences of states pursuing similar initiatives (Ben-Shalom and others 2017). The latter policy option might be bolstered by recent changes at the state and federal levels in the provision of such services resulting from the Workforce Innovation and Opportunity Act of 2014.

Research Questions

The proposals summarized above raise questions about who could be targeted for each type of initiative. DI applicants who meet the work-history requirements for DI eligibility provide a useful sample for considering these questions, as they have recent labor-force attachment and have health conditions that are serious enough to warrant an application for the economic supports that DI provides. DI applicants are not a homogeneous population (Honeycutt 2004; Lahiri, Song, and Wixon 2008; Lindner 2013; Livermore, Stapleton, and Claypool 2010). Some have strong work histories; others have sporadic or no labor-force attachment in the period before DI application. Applicants may also have widely varying levels of prior involvement with various types of public programs.

This analysis answers four research questions:

1. What are DI applicants' preapplication employment patterns?
2. How do employment patterns differ over varying preapplication time periods?
3. What demographic, job, and non-DI program participation characteristics are associated with each employment pattern?
4. How do these characteristics and patterns relate to the likelihood of DI allowance?

The temporal relation between DI application and prior labor-force and non-DI program participation can provide insights into how best to reach potential DI applicants and into identifying which applicants are more or less likely to be affected by various proposals.

Data

The analysis relies on a pooled sample from the 1996, 2001, and 2004 panels of the SIPP.[2] The SIPP is nationally representative of households in each panel's initial year, with its sample weighted to reflect the civilian noninstitutionalized population aged 15 or older.

We used Social Security administrative files linked to SIPP data to identify people who applied for DI, along with their application dates, their receipt of DI benefits and Supplemental Security Income (SSI), and the outcome of their application at the initial or reconsideration levels. We only considered applicants who met the earnings requirement for DI eligibility (meaning they had a qualifying work history and were fully insured for the program) and received a medical disability determination. Not all SIPP data could be matched to SSA records: Some SIPP respondents did not provide Social Security numbers, some respondents opted out of having their data matched to federal records (beginning in 2004), and some SIPP information (such as Social Security number, name, sex, and date of birth) that respondents provided did not match the administrative data (McNabb and others 2009). The match rates were 84 percent for the 1996 panel, 60 percent for the 2001 panel, and 79 percent for the 2004 panel. Using the Social Security administrative data, we excluded people who had already received DI benefits as of the first SIPP wave from our analysis sample. The statistics presented here could therefore be biased if nonmatched respondents differ systematically by DI receipt or application status from matched respondents; we did not calculate new weights based on the sample exclusions.

We restricted our sample to DI applicants aged 25–55 with matched data whose first survey response occurred in wave 1 of each SIPP panel (as opposed to including those who joined a panel after wave 1). We excluded applicants younger than 25 because they are less likely to qualify for DI and more likely to be enrolled in school.[3] We excluded applicants older than 55 to avoid tracking sample members who might qualify for early retirement benefits during our observation periods.

We tracked preapplication employment patterns to categorize and compare individuals according to various characteristics. We first established four observation periods, respectively consisting of the final 6, 12, 18, and 24 months before the month of DI application. The observation-period subsamples overlap in that each person included in the 24-month subsample is also included in the larger subsamples for each successively shorter observation period. That is, the subsample for the 6-month observation period is larger than the 24-month subsample because more applicants had 6 months of preapplication SIPP data than had 24 months of preapplication data. Second, for each observation period, we categorize applicants based on their employment data for all observed months before the month of DI application. The four mutually exclusive categories we consider are (1) *consistently employed:* employed in all months of the observation period; (2) *ceased employment:* consistent or intermittent employment that ended, without subsequent resumption, during the observation period; (3) *intermittent employment:* employed in some months but not others, with no single or definitive work cessation in the observation period; and (4) *not employed:* no employment in the entire observation period. A given individual's employment category might differ from a shorter observation period to a longer one. For example, an individual observed for 12 months who worked steadily until 8 months before DI application and then ceased employment would be classified as "ceased employment" in the 12-month period but as "not employed" in the 6-month period.

In addition to employment histories, we analyzed the following characteristics of the DI applicants in our sample:

- Demographic characteristics, including sex, age, race, marital status, presence of children in the household, poverty status of the household, and education. This information came from the earliest SIPP observation for each individual.

- Program participation, including receipt of Medicaid, SNAP, TANF, UI, and workers' compensation benefits. Under this category, we also analyzed private health insurance and employer- and self-provided disability insurance coverage. We used SIPP data to assess these measures across all months of an observation period; for some applicants, participation or coverage status varied from one time period to another.
- Job characteristics, including binary indicators for full-time status, ever being laid off, ever having two or more jobs (moonlighting), and union membership; industry division (services, goods-producing or other); and industry sector (private for-profit, public, nonprofit or self-employed). These data were based on the person's earliest employment experience in the SIPP observation period.[4]
- DI claim outcome. From the Social Security administrative data, we identified whether a DI claim was allowed at the initial or reconsideration levels of review. We did not consider the outcome of applications at the hearing or appeal levels, which account for about 1 in 3 ultimately successful applications.[5] We focus on the potential for early-intervention programs to offer an alternative to pursuing DI benefits.

Methodology

This analysis incorporated both descriptive statistics and regression models, with separate estimations for each observation period. We weighted the data using the wave-1 weights for each SIPP panel, and we applied the SIPP-recommended adjustment factors to our variance estimates to account for the survey's complex sampling design.

For the descriptive statistics, we started with the number of applicants in each employment category for each observation period, along with their DI allowance rates. Then, we stratified applicants in the 6-month period (the largest sample) by employment category to compare their demographic, program participation, and job characteristics (described above).

Next, we assessed the relationship between the preapplication employment category and each of the observable applicant characteristics, holding other characteristics constant. To do so, we used multinomial logistic regression models to estimate the sample members' preapplication employment categories; that is, the dependent variable for each of these regressions was the employment category. We ran two models four times each, once for each observation period. The first model included all DI applicants and only those characteristics that were observed for all of them. The second model used the subset of DI applicants who reported working at any point during the observation period and included job characteristics as predictors. In the results section, we report the average marginal effect of each predictor on the probability of belonging to a given employment category.[6]

Finally, we used logistic regression models to estimate DI allowance as a function of employment category and non-DI program participation during the preapplication period. We again ran two models four times each, with the first model including all applicants and the second including only those employed at some point during the relevant period. Both models also analyzed job characteristics. Again, we report the average marginal effects.

Results

In this section we present findings from our descriptive and regression analyses.

Descriptive Analyses

The sample distribution across the four employment categories varies based on the length of the observation period (Table 1 and Chart 1). In the 24-month period, only 13 percent of our sample was not employed, and only 22 percent was employed the whole time. This distribution shifts in shorter observation periods. In the 6-month preapplication period, one-third (33 percent) of the sample was not employed, and more than one-fourth (28 percent) was consistently employed.

To explore the changing distribution among employment categories over time, we further analyzed the subsample of applicants for whom we were able to observe the full 24-month preapplication employment history. We tracked that subgroup's employment-category patterns across each of the four observation periods. Additionally, for the consistently employed and not-employed categories, we distinguished the individuals who met the category definition in the 24-month period from those who met the definition only in one of the shorter periods (Table 2 and Chart 2). An individual who met the definition for ceased employment in the 24-month period could have been classified only as ceased employment or not employed in shorter periods. By contrast, an individual defined as intermittently employed in the 24-month period could have an employment history that meets the definition

Table 1.
DI applicants: Study sample size, distribution, and DI allowance rate, by preapplication employment category and observation period

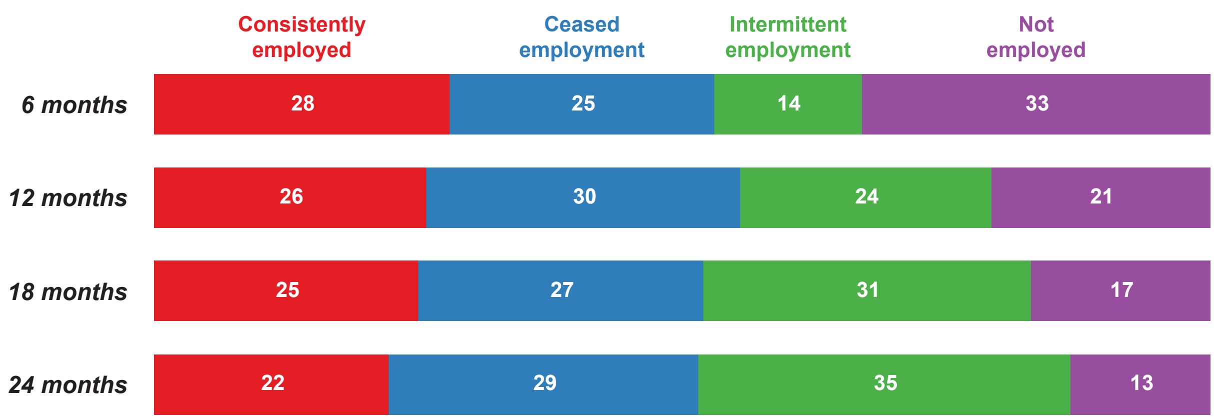
Observation period	Total	Type 1		Type 2	
		Consistently employed	Ceased employment	Intermittent employment	Not employed
		Number of applicants			
6 months	1,361	381	341	186	453
12 months	1,040	266	311	248	215
18 months	747	185	202	233	127
24 months	505	112	147	179	67
		Percentage of applicants			
6 months	100	28	25	14	33
12 months	100	26	30	24	21
18 months	100	25	27	31	17
24 months	100	22	29	35	13
		DI allowance rate (%)			
6 months	. . .	47	46	32	32
12 months	. . .	49	46	35	33
18 months	. . .	49	51	35	35
24 months	. . .	50	52	36	37

SOURCE: Authors' calculations using SIPP 1996, 2001, and 2004 panels and matched Social Security administrative records.

NOTES: Rounded components of percentage distributions do not necessarily sum to 100.

. . . = not applicable.

Chart 1.
Percentage distribution of DI applicants, by preapplication employment category and observation period



SOURCE: Authors' calculations using SIPP 1996, 2001, and 2004 panels and matched Social Security administrative records.

Table 2.
DI applicants in the 24-month preapplication period subgroup, by preapplication employment category and observation period

Observation period	Total	Type 1: Consistently employed—In all 24 months	Type 1: Consistently employed—For 6, 12, or 18 months [a]	Type 1: Ceased employment	Type 2: Intermittent employment	Type 2: Not employed—For 6, 12, or 18 months [b]	Type 2: Not employed—In all 24 months
				Number of applicants			
6 months	505	112	43	127	58	98	67
12 months	505	112	23	155	107	41	67
18 months	505	112	11	144	154	17	67
24 months	505	112	. . .	147	179	. . .	67
				Percentage of applicants			
6 months	100	22	9	25	11	19	13
12 months	100	22	5	31	21	8	13
18 months	100	22	2	29	30	3	13
24 months	100	22	. . .	29	35	. . .	13
DI allowance rate (%) [c]	. . .	50	42	52	36	37	37

SOURCE: Authors' calculations using SIPP 1996, 2001, and 2004 panels and matched Social Security administrative records.

NOTES: Sample size = 505 DI applicants.

Rounded components of percentage distributions do not necessarily sum to 100.

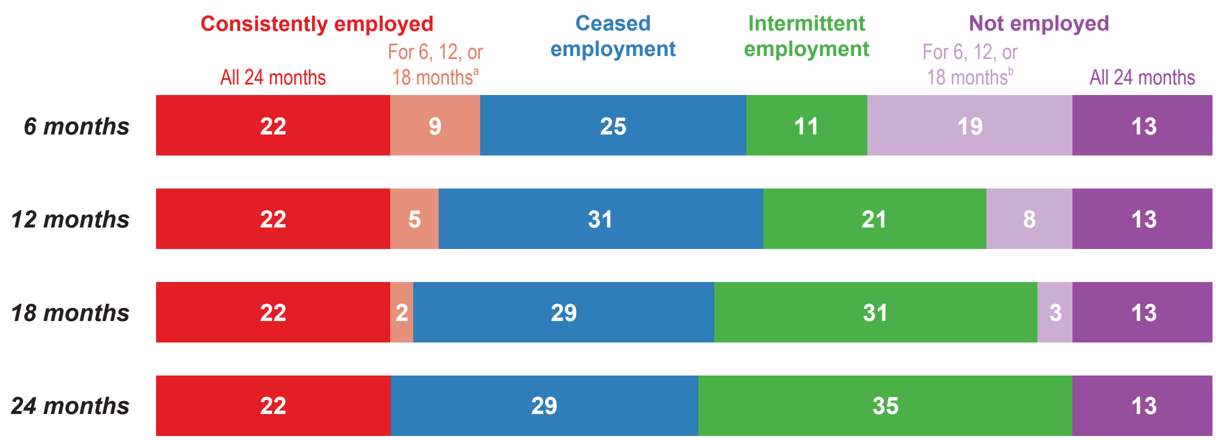
. . . = not applicable.

a. These individuals were in the intermittent employment category in the 24-month period.

b. These individuals were in either the intermittent employment or ceased employment categories in the 24-month period.

c. Allowance rates are shown by the employment categories that applied in the 6-month period.

Chart 2.
Percentage distribution of DI applicants in the 24-month preapplication period subgroup, by employment category and observation period



SOURCE: Authors' calculations using SIPP 1996, 2001, and 2004 panels and matched Social Security administrative records.

a. These individuals were in the intermittent employment category in the 24-month period.

b. These individuals were in either the intermittent employment or ceased employment categories in the 24-month period.

for any of the four employment categories in shorter periods. The majority of individuals classified as intermittently employed in the 24-month period were classified as either intermittently employed or consistently employed in the 6-month period, indicating that for some workers, intermittent work is the norm. In addition, a large proportion of those who worked consistently until a definitive cessation experienced that cessation within 6 months of applying for DI.

The patterns shown in Charts 1 and 2 suggest that we can consider DI applicants as being one of two types. The Type 1 applicant works consistently up to or shortly before the point of application. Such a person can be considered to have a strong attachment to the labor force. Policy proposals such as those described earlier are generally geared toward this type of worker in that they presume a substantial existing relationship with an employer that continues until or almost until the point of DI application. The Type 2 applicant has a weaker attachment to the labor force, working only intermittently or not at all for long periods (up to and possibly exceeding 24 months) before applying for DI. Early-intervention efforts that rely on identifying people with current or recent work attachments are likely to miss persons in this group. Because about half of the applicants in our sample were Type 2, policy proposals that tacitly focus on Type 1 applicants overlook a substantial target population.

Table 3 presents summary statistics for our 6-month subsample, the largest of the four, broken down by preapplication employment category.[7] Here again, we see differences between Type 1 and Type 2 applicants, with the former more likely to have higher educational attainment, more likely to have employer-provided health insurance, and less likely to have relied on public programs. Applicants who were consistently employed were more likely to be male, white, have a child in the household, have income above the poverty level, and have a college education than were applicants in other employment categories. In addition, compared with those in other employment categories, applicants who were intermittently employed were more likely to be black, to be never married, and to have a high school diploma or equivalent as their highest education level, while applicants who were not employed had a higher proportion with less than a high school education. Consistently employed applicants had the highest average annual household income; applicants who reported being not employed had the lowest annual household income.

Regarding program participation, applicants with intermittent or no employment were more likely to be receiving Medicaid, SNAP, or TANF benefits. Applicants who were consistently employed or had ceased employment were more likely to have had private health insurance. People with intermittent or

Table 3.
DI applicant demographic characteristics, non-DI program participation, and job characteristics, by employment category in the 6-month preapplication period

Characteristic	Type 1		Type 2	
	Consistently employed	Ceased employment	Intermittent employment	Not employed
Number of applicants	381	341	186	453
	Demographic characteristics (percentage distributions)			
Sex				
Men	49.9	42.6	46.3	44.9
Women	50.1	57.4	53.7	55.1
Age				
25–30	7.7	10.4	8.2	9.2
31–40	26.0	26.0	33.9	26.4
41–50	39.8	39.4	36.2	37.4
51–55	26.6	24.1	21.7	27.1
Race				
Black only	16.1	17.5	23.3	21.7
White only	81.4	78.7	72.3	73.6
Other	2.5	3.8	4.4	4.7

(Continued)

Table 3.
DI applicant demographic characteristics, non-DI program participation, and job characteristics, by employment category in the 6-month preapplication period—*Continued*

Characteristic	Type 1: Consistently employed	Type 1: Ceased employment	Type 2: Intermittent employment	Type 2: Not employed
	Demographic characteristics (percentage distributions) (cont.)			
Marital status				
Currently married	55.6	54.8	50.8	55.3
Never married	16.3	16.5	22.9	18.1
Other	28.1	28.7	26.3	26.6
Children in household				
Yes	61.2	57.7	59.9	57.8
No	38.8	42.3	40.1	42.2
Household in poverty				
Yes	38.6	46.1	44.8	45.4
No	61.4	53.9	55.2	54.6
Educational attainment				
Less than high school	17.2	17.2	17.8	26.5
High school graduate or equivalent	30.6	32.0	49.0	32.3
Some college	36.1	43.5	24.3	34.0
College graduate	16.1	7.4	8.9	7.2
Average household income ($)	62,986	56,897	51,126	46,178
	Program participation (%)			
Public programs				
Medicaid	11.7	14.0	26.9	30.7
SNAP	10.8	19.0	27.2	28.5
TANF	0.8	3.1	9.8	6.7
UI	1.9	8.9	11.1	10.1
Workers' compensation	4.4	7.6	12.3	12.9
Private insurance				
Disability insurance				
Employer-provided	6.8	6.1	7.4	6.3
Self-provided	0.8	4.1	0.0	2.7
Health insurance	76.6	78.4	63.4	51.3
	Job characteristics (%)			
Full-time status	61.1	63.1	56.5	. . .
Ever been laid off	1.7	4.4	4.8	. . .
Ever moonlighted	8.6	14.0	10.4	. . .
Union member	13.6	15.2	9.9	. . .
Industry division				
Services	69.3	65.6	73.1	. . .
Goods-producing or other	30.7	34.4	26.9	. . .
Industry sector				
Private for-profit	72.7	80.0	82.5	. . .
Public	17.7	11.4	9.9	. . .
Nonprofit or self-employed	9.7	8.6	7.6	. . .

SOURCE: Authors' calculations using SIPP 1996, 2001, and 2004 panels and matched Social Security administrative records.

NOTES: Rounded components of percentage distributions do not necessarily sum to 100.0.

. . . = not applicable.

no employment were more likely to report receiving UI or workers' compensation.

Job characteristics did not vary widely across the three applicable employment categories. Applicants who were consistently employed were slightly less likely to work in the private sector or to have moonlighted in a given month and more likely to work in the public sector.

Another way Type 1 and Type 2 applicants differed is in the likelihood of DI allowance. Tables 1 and 2 show the allowance rates for the full sample and the 24-month subsample, respectively, across employment categories.[8] In all time periods, applications of persons who were employed or who ceased employment after working consistently were much more likely to be allowed than were those filed by persons who worked only intermittently or not at all (a difference of more than 10 percentage points in any time period).

Regression Analyses

In the previous section, we identified two types of DI applicants, characterized primarily by their labor force attachment in the preapplication period. In this section, we summarize the findings from logistic regression models that predict preapplication employment category. We first consider the association of demographic, program participation, and job characteristics with the likelihood of an individual's falling into a given employment category for a given observation period. We then use employment categories (along with program participation and job characteristics) as predictors of DI allowance.

Predicting employment category. Many of the age, marital-status, and educational-attainment categories were consistently significant predictors of employment category (Table 4). For instance, being older than 40 reduced the chances of being intermittently employed. Unmarried applicants were more likely than married ones to be consistently employed and less likely to be not employed. Relative to college graduates, applicants with lower educational attainment were less likely to be consistently employed.

Within the Type 1 employment categories, receipt of self-funded private disability insurance, UI, or workers' compensation benefits was associated with lower probability of consistent employment and higher probability of employment cessation. This pattern generally held across the four observation periods. The explanation seems clear: These programs are designed to help established workers who lose their jobs because of a newly disabling condition or, in the case of UI, an involuntary layoff for any reason.

Among Type 2 applicants, program participation is weakly associated with whether a person was employed intermittently or not at all. There is some evidence that receipt of UI benefits correlates positively with intermittent employment and negatively with not being employed, but only in the longer observation periods. In the 6-month period, receipt of UI benefits is actually associated with increased odds of being not employed, likely because most job losses that precipitated UI benefits occurred more than 6 months before DI application. UI may be associated with not being employed in part because of a pattern wherein people lose their jobs, collect UI benefits for the typical duration of 6 months, then apply for DI either while still receiving UI benefits or directly after they are exhausted (Lindner 2016). Another factor might be that DI requires a 5-month waiting period between the established onset date and initial benefit eligibility.

We also observed significant associations between employment category and use of programs such as private health insurance, SNAP, and TANF. We do not believe the model identifies a causal relationship, but we think this association likely reflects the effect of employment status on program participation rather than the other way around. For example, we observed that having private health insurance was positively associated with consistent employment and ceased employment, and was negatively associated with not being employed; we observed the opposite for SNAP and TANF. People who are consistently employed often have health insurance through their employer and earn too much to qualify for means-tested programs such as SNAP and TANF.

Our analysis of the relationship between job characteristics and preapplication employment category necessarily excluded applicants in the not-employed category, as they had no job characteristics to observe. Controlling for demographic characteristics, we found that job characteristics were generally weakly and inconsistently related to preapplication employment categories (Table 5). Union membership was associated with a higher probability of employment cessation and a lower probability of intermittent employment. However, this result emerged only in the two longest observation periods. Not surprisingly, having ever been laid off is positively correlated with intermittent employment and negatively correlated with consistent employment. (Being laid off and subsequently

Table 4.
Multinomial logistic regression estimates: Preapplication employment category related to demographic characteristics and non-DI program participation

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Sex								
Men (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Women								
6 months	-0.064**	0.025	0.035	0.029	0.001	0.021	0.028	0.030
12 months	-0.036	0.026	0.002	0.027	0.025	0.033	0.009	0.033
18 months	-0.051	0.031	-0.022	0.034	0.061	0.033	0.013	0.033
24 months	-0.019	0.032	-0.023	0.047	0.027	0.045	0.015	0.039
Age								
25–30 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
31–40								
6 months	0.051	0.066	-0.056	0.073	0.042	0.042	-0.037	0.050
12 months	0.059	0.079	0.011	0.068	-0.104	0.058	0.034	0.055
18 months	-0.050	0.061	0.058	0.091	-0.061	0.062	0.054	0.069
24 months	-0.108*	0.055	0.094	0.104	-0.054	0.078	0.068	0.099
41–50								
6 months	0.033	0.063	-0.047	0.077	0.010	0.040	0.004	0.053
12 months	0.059	0.073	0.114	0.062	-0.171**	0.062	-0.002	0.052
18 months	-0.014	0.064	0.139	0.081	-0.150**	0.059	0.024	0.063
24 months	-0.035	0.065	0.121	0.095	-0.159*	0.076	0.073	0.096
51–55								
6 months	0.005	0.066	-0.066	0.076	-0.002	0.040	0.063	0.056
12 months	0.016	0.075	0.102	0.064	-0.197**	0.055	0.079	0.058
18 months	-0.056	0.062	0.125	0.080	-0.175**	0.056	0.106	0.069
24 months	-0.048	0.063	0.114	0.093	-0.239**	0.067	0.173	0.114

(Continued)

Table 4.
Multinomial logistic regression estimates: Preapplication employment category related to demographic characteristics and non-DI program participation—*Continued*

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Race								
Black only								
6 months	-0.039	0.032	-0.024	0.034	0.024	0.026	0.040	0.035
12 months	-0.015	0.033	-0.018	0.039	0.002	0.037	0.031	0.030
18 months	0.011	0.038	0.013	0.044	-0.028	0.045	0.004	0.031
24 months	-0.015	0.046	-0.006	0.050	0.002	0.050	0.018	0.038
White only (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Other								
6 months	-0.110*	0.055	0.007	0.062	0.039	0.063	0.064	0.067
12 months	-0.087	0.061	0.031	0.068	0.026	0.071	0.030	0.052
18 months	-0.047	0.069	0.046	0.082	-0.025	0.073	0.026	0.056
24 months	-0.143**	0.050	0.113	0.105	0.037	0.115	-0.007	0.055
Marital status								
Currently married (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Never married								
6 months	0.051	0.043	0.015	0.046	0.016	0.028	-0.083*	0.036
12 months	0.079	0.051	-0.018	0.043	0.000	0.049	-0.062*	0.030
18 months	0.116*	0.049	-0.081*	0.040	0.011	0.055	-0.045	0.035
24 months	0.140*	0.060	-0.130**	0.047	0.011	0.069	-0.021	0.036
Other								
6 months	0.068*	0.032	0.038	0.031	-0.011	0.025	-0.095**	0.030
12 months	0.082*	0.032	0.020	0.037	-0.011	0.031	-0.091**	0.029
18 months	0.076	0.039	0.050	0.039	-0.012	0.037	-0.114**	0.031
24 months	0.029	0.042	0.055	0.049	0.012	0.048	-0.096**	0.034

(Continued)

Table 4.
Multinomial logistic regression estimates: Preapplication employment category related to demographic characteristics and non-DI program participation—*Continued*

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Children in household								
Yes								
6 months	0.016	0.026	0.033	0.030	-0.031	0.022	-0.018	0.030
12 months	0.007	0.029	0.053	0.035	-0.025	0.034	-0.036	0.031
18 months	0.047	0.032	-0.008	0.039	0.048	0.042	-0.087**	0.031
24 months	0.049	0.034	-0.023	0.041	0.040	0.047	-0.066	0.034
No (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Household poverty								
Yes								
6 months	-0.035	0.026	0.044	0.027	0.003	0.021	-0.012	0.029
12 months	-0.041	0.028	0.026	0.032	-0.032	0.028	0.048	0.029
18 months	-0.080**	0.030	0.004	0.033	0.049	0.039	0.027	0.031
24 months	-0.074*	0.029	0.025	0.037	0.009	0.045	0.040	0.032
No (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Educational attainment								
Less than high school								
6 months	-0.130**	0.037	0.054	0.057	-0.021	0.036	0.096	0.055
12 months	-0.112**	0.041	0.053	0.065	0.033	0.062	0.025	0.053
18 months	-0.094	0.048	-0.001	0.071	0.052	0.079	0.043	0.059
24 months	-0.078	0.053	-0.005	0.085	0.051	0.102	0.032	0.072
High school graduate or equivalent								
6 months	-0.134**	0.033	0.069	0.047	0.045	0.037	0.020	0.047
12 months	-0.106**	0.039	0.071	0.055	0.071	0.056	-0.036	0.049
18 months	-0.112*	0.047	0.038	0.067	0.091	0.071	-0.017	0.056
24 months	-0.066	0.052	-0.025	0.081	0.130	0.087	-0.040	0.064
Some college								
6 months	-0.117**	0.035	0.118*	0.050	-0.044	0.036	0.042	0.047
12 months	-0.073	0.039	0.032	0.054	0.041	0.058	0.000	0.050
18 months	-0.072	0.047	0.010	0.058	0.030	0.064	0.032	0.058
24 months	-0.060	0.051	-0.049	0.070	0.059	0.081	0.051	0.076
College graduate (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .

(Continued)

Table 4.
Multinomial logistic regression estimates: Preapplication employment category related to demographic characteristics and non-DI program participation—*Continued*

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Program participation								
Public programs								
Medicaid								
6 months	-0.032	0.039	-0.071*	0.036	0.012	0.031	0.091*	0.044
12 months	-0.063	0.038	-0.027	0.043	0.038	0.047	0.052	0.041
18 months	-0.096**	0.034	0.076	0.048	0.024	0.047	-0.004	0.037
24 months	-0.054	0.043	0.078	0.049	0.037	0.057	-0.061	0.032
SNAP								
6 months	-0.095**	0.034	0.039	0.038	0.010	0.028	0.045	0.043
12 months	-0.127**	0.035	0.092*	0.042	0.028	0.041	0.007	0.042
18 months	-0.107**	0.035	0.031	0.047	0.035	0.050	0.041	0.046
24 months	-0.112**	0.040	-0.012	0.056	0.076	0.063	0.048	0.058
TANF								
6 months	-0.183**	0.045	-0.017	0.071	0.156*	0.075	0.043	0.072
12 months	-0.148**	0.054	0.048	0.070	0.008	0.064	0.092	0.071
18 months	-0.077	0.071	-0.012	0.086	-0.108	0.058	0.198*	0.093
24 months	-0.158*	0.065	0.036	0.101	-0.173**	0.067	0.294**	0.107
UI								
6 months	-0.227**	0.027	0.058	0.049	0.055	0.037	0.114*	0.047
12 months	-0.182**	0.031	0.212**	0.054	0.080	0.050	-0.111**	0.034
18 months	-0.183**	0.032	0.101*	0.049	0.183**	0.056	-0.101**	0.030
24 months	-0.169**	0.033	0.061	0.055	0.166**	0.058	-0.058	0.031
Workers' compensation								
6 months	-0.173**	0.034	-0.066	0.037	0.054	0.043	0.185**	0.048
12 months	-0.156**	0.037	0.113*	0.053	-0.040	0.043	0.083	0.048
18 months	-0.122**	0.042	0.139*	0.063	-0.037	0.052	0.019	0.046
24 months	-0.152**	0.036	0.214**	0.080	0.000	0.065	-0.062	0.038

(Continued)

Table 4.
Multinomial logistic regression estimates: Preapplication employment category related to demographic characteristics and non-DI program participation—*Continued*

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Program participation (cont.)								
Private insurance								
Disability insurance								
Employer-provided								
6 months	-0.036	0.045	-0.050	0.044	0.035	0.040	0.051	0.048
12 months	-0.027	0.048	0.132*	0.053	-0.039	0.047	-0.066	0.051
18 months	0.006	0.057	0.111	0.072	-0.065	0.066	-0.052	0.063
24 months	-0.051	0.062	0.155	0.093	-0.117	0.068	0.013	0.057
Self-provided								
6 months	-0.192**	0.048	0.182	0.096	-0.138**	0.011	0.149	0.095
12 months	-0.135*	0.059	0.213*	0.098	0.062	0.091	-0.141**	0.050
18 months	-0.222**	0.031	0.318**	0.113	0.014	0.115	-0.110	0.075
24 months	-0.183**	0.043	0.481**	0.123	-0.149	0.122	-0.149**	0.019
Health insurance								
6 months	0.083*	0.033	0.135**	0.032	0.008	0.024	-0.225**	0.035
12 months	0.110**	0.032	0.126**	0.037	-0.039	0.042	-0.196**	0.038
18 months	0.111**	0.034	0.117**	0.035	-0.004	0.039	-0.225**	0.044
24 months	0.088**	0.032	0.049	0.054	0.040	0.053	-0.178**	0.055

SOURCE: Authors' calculations using a multinomial logistic regression model, SIPP (1996, 2001, and 2004 panels), and matched Social Security administrative records.

NOTES: Observation-period sample sizes are 1,361 (6 months), 1,040 (12 months), 747 (18 months), and 505 (24 months).

. . . = not applicable.

* = statistically significant at the *p* = 0.05 level.

** = statistically significant at the *p* = 0.01 level.

Table 5.
Multinomial logistic regression estimates: Preapplication employment category related to demographic and job characteristics

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed [a]	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Sex								
Men (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Women								
6 months	-0.066	0.036	0.078*	0.035	-0.013	0.031	. . .	. . .
12 months	-0.042	0.034	0.022	0.031	0.020	0.037	. . .	. . .
18 months	-0.088*	0.040	0.002	0.041	0.087*	0.042	. . .	. . .
24 months	-0.030	0.041	-0.013	0.055	0.043	0.054	. . .	. . .
Age								
25–30 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
31–40								
6 months	0.040	0.084	-0.092	0.086	0.052	0.062	. . .	. . .
12 months	0.020	0.082	0.066	0.078	-0.086	0.057	. . .	. . .
18 months	-0.084	0.074	0.121	0.099	-0.037	0.075	. . .	. . .
24 months	-0.112	0.069	0.189	0.101	-0.076	0.084	. . .	. . .
41–50								
6 months	0.056	0.084	-0.055	0.085	-0.001	0.062	. . .	. . .
12 months	0.049	0.078	0.139*	0.071	-0.187**	0.058	. . .	. . .
18 months	-0.009	0.084	0.161	0.091	-0.152*	0.068	. . .	. . .
24 months	0.005	0.077	0.183	0.095	-0.188**	0.073	. . .	. . .
51–55								
6 months	0.049	0.089	-0.052	0.095	0.003	0.061	. . .	. . .
12 months	0.032	0.088	0.157*	0.080	-0.189**	0.054	. . .	. . .
18 months	-0.036	0.086	0.182	0.095	-0.147*	0.071	. . .	. . .
24 months	0.015	0.079	0.221*	0.094	-0.236**	0.066	. . .	. . .

(Continued)

Table 5.
Multinomial logistic regression estimates: Preapplication employment category related to demographic and job characteristics—*Continued*

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed [a]	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Race								
Black only								
6 months	-0.049	0.046	-0.014	0.043	0.063	0.039	. . .	. . .
12 months	-0.016	0.044	-0.033	0.046	0.049	0.045	. . .	. . .
18 months	0.008	0.043	-0.009	0.051	0.001	0.051	. . .	. . .
24 months	-0.017	0.052	-0.023	0.054	0.041	0.055	. . .	. . .
White only (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Other								
6 months	-0.139	0.091	0.009	0.091	0.130	0.097	. . .	. . .
12 months	-0.117	0.077	0.053	0.083	0.064	0.081	. . .	. . .
18 months	-0.056	0.080	0.040	0.092	0.016	0.080	. . .	. . .
24 months	-0.148*	0.066	0.166	0.125	-0.018	0.118	. . .	. . .
Marital status								
Currently married (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Never married								
6 months	0.017	0.050	-0.059	0.053	0.042	0.041	. . .	. . .
12 months	0.023	0.057	-0.037	0.051	0.014	0.053	. . .	. . .
18 months	0.064	0.060	-0.116*	0.046	0.052	0.063	. . .	. . .
24 months	0.124	0.075	-0.163**	0.049	0.039	0.076	. . .	. . .
Other								
6 months	0.023	0.040	-0.011	0.035	-0.012	0.035	. . .	. . .
12 months	0.013	0.039	-0.001	0.038	-0.012	0.039	. . .	. . .
18 months	0.014	0.042	0.028	0.041	-0.042	0.042	. . .	. . .
24 months	-0.025	0.042	0.051	0.045	-0.025	0.049	. . .	. . .

(Continued)

Table 5.
Multinomial logistic regression estimates: Preapplication employment category related to demographic and job characteristics—*Continued*

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed [a]	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Children in household								
Yes								
6 months	-0.007	0.034	0.030	0.041	-0.023	0.030	. . .	. . .
12 months	-0.033	0.036	0.045	0.041	-0.013	0.038	. . .	. . .
18 months	0.000	0.038	-0.028	0.046	0.028	0.043	. . .	. . .
24 months	0.009	0.037	-0.033	0.047	0.024	0.046	. . .	. . .
No (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Household in poverty								
Yes								
6 months	-0.076*	0.036	0.062	0.039	0.015	0.026	. . .	. . .
12 months	-0.066*	0.033	0.062	0.037	0.004	0.032	. . .	. . .
18 months	-0.117**	0.035	0.031	0.038	0.086*	0.043	. . .	. . .
24 months	-0.096**	0.034	0.063	0.042	0.033	0.045	. . .	. . .
No (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Educational attainment								
Less than high school								
6 months	-0.144*	0.061	0.121	0.075	0.023	0.057	. . .	. . .
12 months	-0.151**	0.050	0.061	0.076	0.090	0.076	. . .	. . .
18 months	-0.121*	0.060	0.019	0.084	0.102	0.090	. . .	. . .
24 months	-0.090	0.070	0.038	0.095	0.051	0.102	. . .	. . .
High school graduate or equivalent								
6 months	-0.189**	0.052	0.100	0.058	0.089	0.052	. . .	. . .
12 months	-0.154**	0.054	0.075	0.062	0.079	0.064	. . .	. . .
18 months	-0.141*	0.062	0.044	0.075	0.097	0.077	. . .	. . .
24 months	-0.112	0.074	-0.010	0.087	0.123	0.088	. . .	. . .
Some college								
6 months	-0.138*	0.055	0.199**	0.064	-0.061	0.050	. . .	. . .
12 months	-0.084	0.053	0.049	0.064	0.036	0.064	. . .	. . .
18 months	-0.076	0.065	0.046	0.069	0.030	0.071	. . .	. . .
24 months	-0.066	0.075	0.010	0.085	0.056	0.083	. . .	. . .
College graduate (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .

(Continued)

Table 5.
Multinomial logistic regression estimates: Preapplication employment category related to demographic and job characteristics—*Continued*

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed [a]	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Job characteristics								
Full-time status								
6 months	-0.011	0.036	0.054	0.038	-0.043	0.033	. . .	. . .
12 months	-0.016	0.037	0.075	0.039	-0.059	0.040	. . .	. . .
18 months	-0.043	0.037	0.088*	0.040	-0.045	0.039	. . .	. . .
24 months	0.020	0.040	0.073	0.047	-0.093*	0.047	. . .	. . .
Ever been laid off								
6 months	-0.164	0.085	0.075	0.092	0.088	0.070	. . .	. . .
12 months	-0.165*	0.065	-0.071	0.080	0.235**	0.082	. . .	. . .
18 months	-0.258**	0.035	-0.055	0.070	0.313**	0.078	. . .	. . .
24 months	-0.123	0.070	-0.125	0.081	0.248*	0.109	. . .	. . .
Ever moonlighted								
6 months	-0.096	0.071	0.117	0.079	-0.021	0.044		. . .
12 months	-0.065	0.058	-0.098	0.051	0.164**	0.062	. . .	. . .
18 months	0.033	0.058	-0.067	0.047	0.034	0.059	. . .	. . .
24 months	-0.040	0.049	-0.024	0.063	0.064	0.067	. . .	. . .
Union member							. . .	
6 months	-0.039	0.052	0.078	0.055	-0.039	0.044		. . .
12 months	-0.026	0.052	0.103	0.056	-0.076	0.050	. . .	. . .
18 months	0.016	0.053	0.161**	0.059	-0.178**	0.053	. . .	. . .
24 months	-0.026	0.052	0.194**	0.065	-0.168**	0.057	. . .	. . .

(Continued)

Table 5.
Multinomial logistic regression estimates: Preapplication employment category related to demographic and job characteristics—*Continued*

Variable and observation period	Type 1				Type 2			
	Consistently employed		Ceased employment		Intermittent employment		Not employed [a]	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Job characteristics (cont.)								
Industry division								
Services								
6 months	-0.036	0.034	-0.037	0.036	0.073*	0.030	. . .	. . .
12 months	-0.038	0.037	0.032	0.034	0.006	0.037	. . .	. . .
18 months	-0.025	0.035	0.047	0.035	-0.022	0.036	. . .	. . .
24 months	-0.039	0.042	0.029	0.043	0.010	0.044	. . .	. . .
Goods-producing or other (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Industry sector								
Private for-profit (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Public								
6 months	0.098	0.052	-0.061	0.051	-0.037	0.041	. . .	. . .
12 months	0.102	0.060	-0.070	0.050	-0.032	0.054	. . .	. . .
18 months	0.104	0.063	-0.111*	0.053	0.006	0.062	. . .	. . .
24 months	0.091	0.076	-0.113	0.065	0.022	0.068	. . .	. . .
Nonprofit or self-employed								
6 months	0.032	0.064	0.004	0.062	-0.036	0.050	. . .	. . .
12 months	0.096	0.073	-0.010	0.072	-0.086	0.062	. . .	. . .
18 months	0.047	0.080	0.015	0.088	-0.063	0.079	. . .	. . .
24 months	0.159	0.115	-0.019	0.114	-0.140	0.102	. . .	. . .

SOURCE: Authors' calculations using a multinomial logistic regression model, SIPP (1996, 2001, and 2004 panels), and matched Social Security administrative records.

NOTES: Observation-period sample sizes are 908 (6 months), 825 (12 months), 620 (18 months), and 438 (24 months).

. . . = not applicable.

* = statistically significant at the p = 0.05 level.

** = statistically significant at the p = 0.01 level.

a. The "not employed" category is not applicable because the regression model considers preapplication job characteristics. The observation-period samples omit individuals in this category.

finding another job meets our definition of intermittent employment.)

Predicting DI allowance. With our second set of regressions, we found that the preapplication employment categories serve as useful predictors of DI allowance at the initial or reconsideration levels after controlling for individual characteristics (Table 6). The difference between the probability of allowance for applicants who were consistently employed and the probability for applicants who ceased employment was not statistically significant. By contrast, applicants who were intermittently or not employed were less likely to be allowed, with the effect most significant in shorter observation periods.

Age was the only demographic characteristic for which we found statistically significant results. Relative to applicants in their 20s, older applicants were more likely to be allowed. This finding is not surprising, as most disabled-worker beneficiaries are aged 50 or older and DI eligibility rules consider age in the last step of the determination process. With few exceptions, we found that participation in a specific non-DI program was not significantly associated with DI allowance. The most noteworthy finding is that receipt of workers' compensation was negatively associated with DI allowance, with statistically significant estimates in the 6- and 12-month preapplication periods.

We found similar results when we limited the sample to applicants who reported some employment during the observation period (Table 7). Again, intermittent employment was associated with a significantly reduced likelihood of DI allowance, and employment cessation was not associated with a probability of allowance that differed from that for people who were consistently employed. We again found that older applicants were more likely to be allowed. We did not find any evidence that the job characteristics we analyzed were associated with the probability of DI allowance.

Conclusion

This study uses Social Security administrative data to examine patterns of employment and non-DI program participation in the months leading up to DI application. People follow different preapplication paths, and a given individual's path may indicate the likelihood of his or her application being allowed at the initial or reconsideration level. About half of DI applicants worked consistently either to the point of application or shortly before application, with a cessation and no subsequent resumption. We call these individuals Type 1 applicants. They are characterized by stable employment in well-paying jobs, often with benefits such as private health insurance. Applicants from this group had a higher likelihood of DI allowance.

The other half—the Type 2 applicants—either had been out of the workforce for a long time (many for at least 24 months) or had intermittent work histories. Members of this group were less likely to receive DI benefits than were the Type 1 applicants, and they tended to rely more on means-tested and social insurance programs (such as UI and workers' compensation) for support.

Based on our results, early-intervention or return-to-work programs that focus on DI applicants with more recent attachments to the workforce (Type 1) are likely to fail to target about half of the individuals who eventually apply. The question, therefore, is whether policy proposals can capture Type 2 applicants while those applicants, even without a long-term attachment to an employer, still consider themselves to be in the labor force. Type 1 applicants likely have better human capital and skills to build upon as they attempt to return to—or maintain—their employment, so early interventions that provide high-quality and timely medical and rehabilitative services, accommodations, and assistive technologies may help them to use those skills, potentially with the same employer. However, their higher rate of DI allowance may indicate that Type 1 applicants have impairments that clearly inhibit their ability to work at substantial levels, in which case interventions may be less likely to succeed.

Type 2 applicants typically have comparatively limited human capital and skills, as well as lower income and fewer resources—characteristics which, when combined with medical problems, make it difficult for them to find and maintain good jobs. Given their economic situations, their opportunity costs of applying for DI might be lower than those of Type 1 applicants, and their lower DI allowance rates might indicate less severely disabling conditions on average. To succeed, efforts to help these applicants should identify them either when they are still working (with early-intervention services that address the full array of issues that prevent them from holding better jobs) or after they have left the labor market (with services that help them to reconnect with employers). Identifying such people before they apply may require outreach via health care providers, administrators of other programs in which they may participate, and the media.

Table 6.
Multinomial logistic regression estimates: DI allowance related to age, preapplication employment category, and non-DI program participation, by observation period

Variable	6 months		12 months		18 months		24 months	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Age								
25–30 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
31–40	0.141*	0.063	0.144*	0.068	0.060	0.075	0.091	0.088
41–50	0.127*	0.060	0.148*	0.063	0.096	0.073	0.137	0.093
51–55	0.302**	0.069	0.309**	0.073	0.246**	0.084	0.263**	0.099
Employment category								
Consistently employed (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Ceased employment	-0.012	0.039	-0.001	0.043	0.030	0.058	0.050	0.065
Intermittent employment	-0.098*	0.039	-0.120**	0.046	-0.103*	0.050	-0.073	0.059
Not employed	-0.095*	0.039	-0.079	0.049	-0.059	0.064	-0.046	0.085
Program participation								
Public programs								
Medicaid	0.026	0.045	0.018	0.047	-0.021	0.051	-0.104	0.067
SNAP	-0.031	0.039	-0.072	0.048	-0.013	0.054	-0.109	0.071
TANF	-0.051	0.065	-0.073	0.072	-0.250**	0.074	-0.150	0.110
UI	0.084	0.054	0.043	0.056	0.061	0.060	0.050	0.063
Workers' compensation	-0.130**	0.047	-0.106*	0.053	-0.053	0.064	-0.034	0.078
Private insurance								
Disability insurance								
Employer-provided	-0.039	0.049	-0.031	0.056	-0.006	0.065	-0.054	0.085
Self-provided	0.003	0.090	-0.054	0.094	-0.026	0.109	-0.026	0.141
Health insurance	0.077*	0.038	0.043	0.042	0.033	0.053	0.023	0.065

SOURCE: Authors' calculations using a multinomial logistic regression model, SIPP (1996, 2001, and 2004 panels), and matched Social Security administrative records.

NOTES: Observation-period sample sizes are 1,361 (6 months), 1,040 (12 months), 747 (18 months), and 505 (24 months).

Estimates are for allowances at the initial and reconsideration levels only.

Control variables are age, sex, race, marital status, educational attainment, household poverty status, and presence of children in household.

. . . = not applicable.

* = statistically significant at the *p* = 0.05 level.

** = statistically significant at the *p* = 0.01 level.

Table 7.
Multinomial logistic regression estimates: DI allowance related to age, preapplication employment category, and job characteristics, by observation period

Variable	6 months		12 months		18 months		24 months	
	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error	Marginal effect	Standard error
Age								
25–30 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
31–40	0.101	0.082	0.153*	0.072	0.060	0.087	0.078	0.099
41–50	0.126	0.076	0.189**	0.065	0.134*	0.085	0.176	0.100
51–55	0.295**	0.081	0.365**	0.071	0.301**	0.087	0.318**	0.097
Employment category								
Consistently employed (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Ceased employment	-0.014	0.039	-0.030	0.041	0.012	0.057	0.018	0.067
Intermittent employment	-0.120**	0.040	-0.150**	0.046	-0.128*	0.051	-0.099	0.063
Not employed [a]	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Job characteristics								
Full-time status	0.028	0.033	-0.021	0.035	-0.014	0.039	-0.002	0.042
Ever been laid off	0.010	0.092	0.171*	0.075	0.111	0.083	0.048	0.100
Ever moonlighted	-0.097	0.060	-0.080	0.049	-0.063	0.052	0.041	0.055
Union member	0.001	0.056	-0.011	0.060	-0.080	0.058	-0.021	0.063
Industry division								
Services	0.033	0.035	0.032	0.035	0.005	0.046	-0.027	0.049
Goods-producing or other (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Industry sector								
Private for-profit (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Public	-0.054	0.044	-0.060	0.049	-0.025	0.063	0.039	0.074
Nonprofit or self-employed	0.005	0.070	-0.078	0.068	0.058	0.091	0.076	0.100

SOURCE: Authors' calculations using a multinomial logistic regression model, SIPP (1996, 2001, and 2004 panels), and matched Social Security administrative records.

NOTES: Observation-period sample sizes are 908 (6 months), 825 (12 months), 620 (18 months), and 438 (24 months).

Estimates are for allowances at the initial and reconsideration levels only.

Control variables are age, sex, race, marital status, educational attainment, household poverty status, and presence of children in household.

. . . = not applicable.

* = statistically significant at the p = 0.05 level.

** = statistically significant at the p = 0.01 level.

a. The "not employed" category is not applicable because the regression model considers preapplication job characteristics. The observation-period samples omit individuals in this category.

Because Type 2 applicants do not have secure labor force attachment in the preapplication period, employer-focused proposals might have less reach than do broader systemic approaches that improve supports for those seeking DI benefits or that focus on work capacity. If an intermittent work history is symptomatic of a disability that could be managed with appropriate supports, then providing ongoing and condition-specific supports might be logical policy objectives.

It is hard to know whether the return on investment for early-intervention services that target Type 2 applicants is higher or lower than that for services that target Type 1 applicants. On one hand, Type 1 workers' longstanding attachment to the workforce—and potentially to a particular employer—might make it easier to retain them in the workplace, as they may need only timely access to rehabilitation services, workplace accommodations, or supportive technology to remain productive. On the other hand, Type 1 applicants may already have access to such services through their employers, and to the extent that their higher allowance rate reflects impairments that more clearly meet SSA's disability definition, focusing efforts on these people may not offer the greatest return on investment for early-intervention programs. Type 2 applicants likely have lower human capital, are harder to target, and may require a broader array of services (including ongoing support) to stay employed, but they may be less likely than Type 1 applicants to already have access to services that would keep them in the workforce. Furthermore, the benefits of enhancing the capacity for independence among Type 2 applicants would include not just diversion from DI, but a potential decrease in reliance on the other public programs that these individuals turn to for support. Even if investments in Type 2 applicants ultimately provide a lower return, efforts to target them could likely be justified on equity grounds because of their low income, frequency of experiencing poverty, and other potential barriers to employment.

Although this information adds to our understanding of DI applicants, important unknown factors remain. SIPP information on health and disability characteristics is incomplete, and this analysis would have benefited from having additional information to allow the consideration of health status over time, condition type, and the timing of the health-condition onset that precipitated the DI application. Future research could explore these relationships, as well as the reasons for possible denial and whether they differ between Type 1 and Type 2 applicants.

We imposed further data limitations as well. Specifically, we did not include more recent SIPP waves, and we assessed application outcomes only at the initial and reconsideration levels. In addition, even after we pooled the three SIPP panels, the number of people whom we observed applying for DI benefits was small, particularly for some of the characteristics in which we were most interested. The sample was further restricted in that not all SIPP respondents could be matched to SSA records. The small sample sizes, particularly for the 18- and 24-month subgroups, provided less precision for our results than we would like, and may explain why we found that job characteristics are, for the most part, not predictive of preapplication employment categories or DI awards.

Notes

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[1] Although the Americans with Disabilities Act requires most employers to make reasonable accommodations for persons with disabilities, the employment-to-population ratio for persons with disabilities is less than one-third that of the general population (Bureau of Labor Statistics 2010). The cost of providing reasonable accommodations is among the most common reasons cited by small employers for not hiring or retaining workers with disabilities (Kaye, Jans, and Jones 2011).

[2] Although data for the 2008 SIPP panel were also available, we availed ourselves of an existing analytic file that was used in an earlier analysis (Thompkins and others 2014).

[3] Less than 1 percent of DI beneficiaries are younger than 25 (SSA 2015).

[4] Our findings were similar whether we used the SIPP data for the person's earliest or latest employment experience.

[5] Of more than 2.2 million applications filed in 2007 (our last SIPP observation year), 29 percent were allowed at the initial or reconsideration levels and 12 percent were allowed after appeal (SSA 2015).

[6] The use of the term *effect* is standard in the literature, but is not meant to imply causality.

[7] The results for longer preapplication periods were qualitatively similar.

[8] Recall that although Table 2 covers the 24-month subsample, its allowance rates are broken out by the employment categories observed in the 6-month preapplication period.

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Economic Conditions and Supplemental Security Income Application

by Austin Nichols, Lucie Schmidt, and Purvi Sevak*

Supplemental Security Income (SSI) is one of the most important means-tested transfer programs in the United States. This article examines whether economic conditions affect the likelihood that jobless adults with disabilities apply for SSI payments. Using data for 1996–2010 from the Survey of Income and Program Participation linked to Social Security administrative records, we examine jobless individuals and observe state unemployment rates at both the time their unemployment spell began and the time they applied for SSI. Hazard model estimates suggest that SSI application is positively associated with an increase in the unemployment rate during an individual's jobless spell but is less likely for an individual whose jobless spell begins when the unemployment rate is comparatively high. Omitting the baseline unemployment rate from the analysis distorts the estimate of the relationship between SSI application and the contemporaneous economic conditions. Our findings suggest long-term fiscal implications for SSI of sustained high unemployment.

Introduction

Over the last 30 years, the Supplemental Security Income (SSI) program, which provides federally funded income support for individuals with disabilities, has become one of the most important means-tested cash aid programs in the United States. In 2015, SSI provided payments to 4.9 million low-income adults aged 18–64 who met its disability criteria (Social Security Administration [SSA] 2017a, Table 7.A1). That figure represents a doubling in the adult SSI caseload since 1990 (Chart 1). The federal government spent $46.9 billion on payments to SSI recipients with disabilities in 2015 (SSA 2017a, Table 7.A4), representing a 155 percent increase in real dollars since 1990.[1]

Because SSI is a means-tested program, one might expect application trends to be countercyclical—decreasing when the economy is expanding and increasing during recessions. However, the cyclicality of application has varied over time. Chart 2 graphs SSI applications for adults aged 18–64 (left axis) against the unemployment rate (right axis) for 1990–2015. For most of the period—from 1990 through about 2002 and from 2008 to 2015—the trend in SSI application followed the trend in the national unemployment rate fairly closely. For example, the steady decline in SSI application in the 1990s began about 1 year after the unemployment rate began to decline; SSI application increased as unemployment rates rose during the Great Recession of 2008–2010 and application declined during the subsequent recovery. However, the 2003–2007 period presents an anomaly: Although the unemployment rate fell, SSI application continued to rise. Rutledge and Wu (2014) offer a number of explanations

Selected Abbreviations

DI	Disability Insurance
SIPP	Survey of Income and Program Participation
SSI	Supplemental Security Income
TANF	Temporary Assistance for Needy Families
UI	unemployment insurance

* *Austin Nichols is a researcher with Abt Associates. Lucie Schmidt is associate professor of economics at Williams College. Purvi Sevak is a researcher at Mathematica Policy Research and a professor of economics at Hunter College.*

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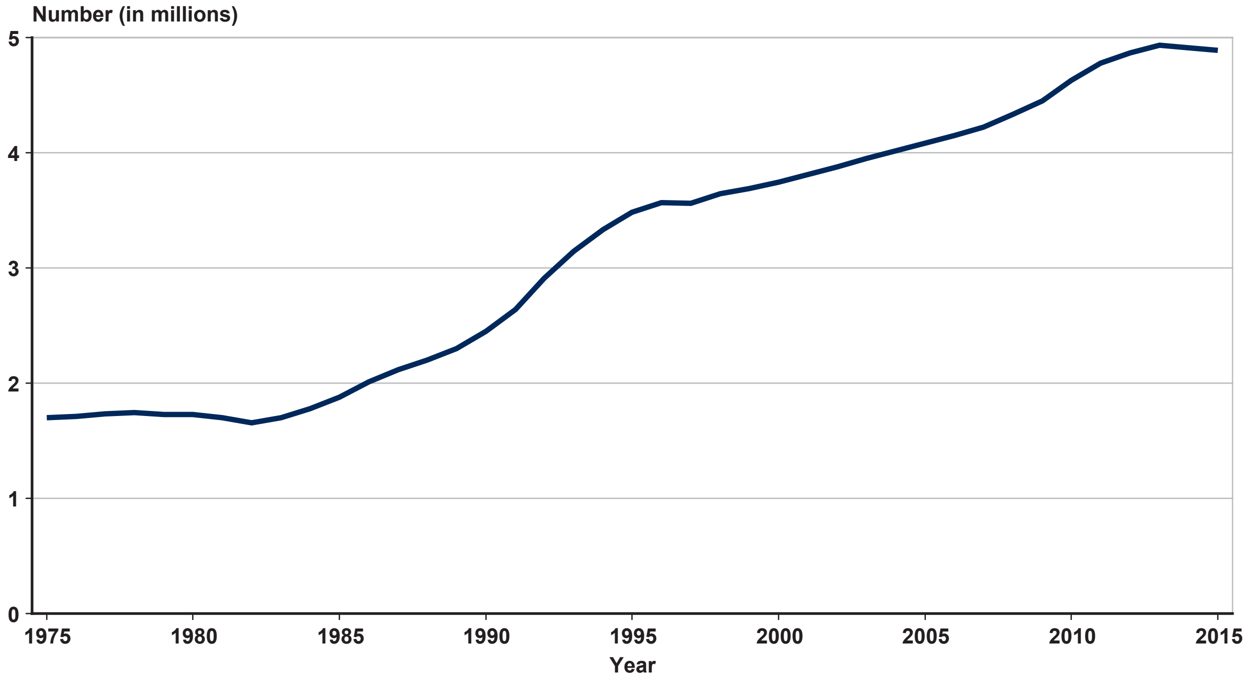
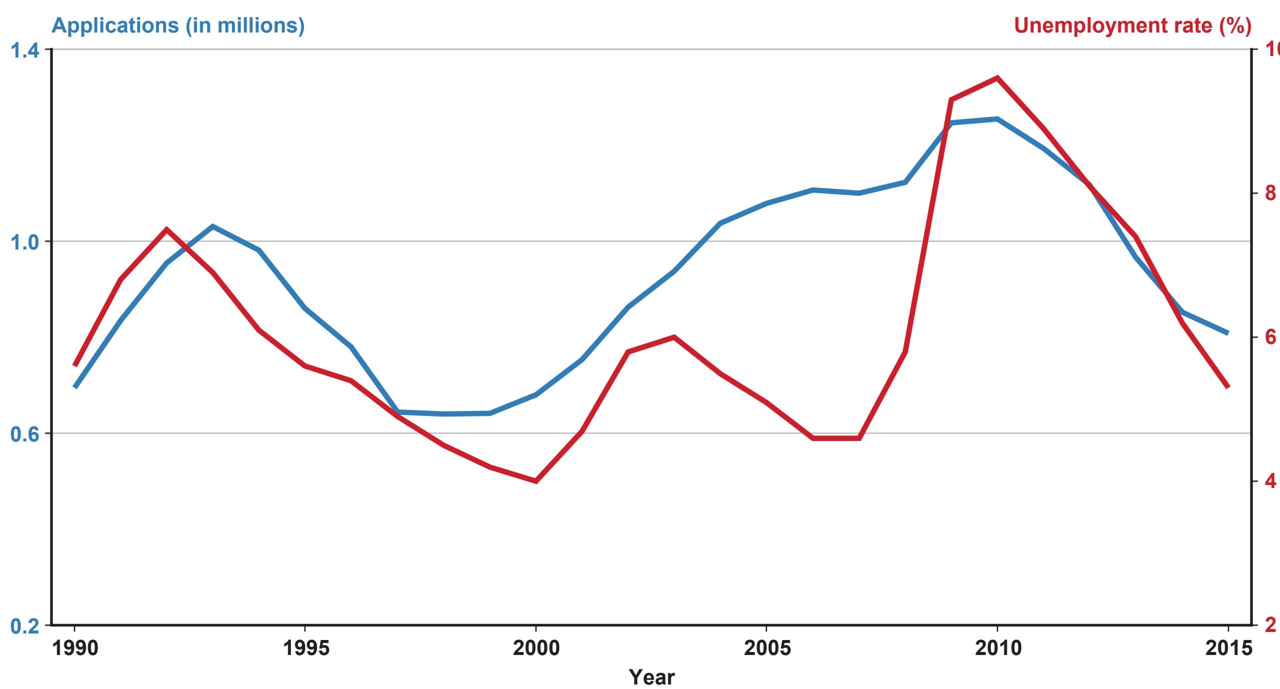
Chart 1.
Number of SSI recipients aged 18–64, 1975–2015



SOURCE: SSA (2017a and prior editions).

Chart 2.
Number of SSI applications filed by adults aged 18–64, and U.S. unemployment rates, 1990–2015



SOURCES: SSA (2017b, Table 62); Bureau of Labor Statistics (2017, Table 1).

for the continuing rise in applications during that period, including the lagged effects of prior welfare reforms that induced Temporary Assistance for Needy Families (TANF) program participants to switch to SSI, persistently high poverty rates, and increases in the share of the population in fair or poor health.

A number of previous studies looked at the effects of economic conditions on growth in disability program caseloads. However, much of that work focused on Social Security Disability Insurance (DI), which is limited to individuals who meet that program's earnings-history thresholds and who therefore may be more responsive to economic conditions. Most research focusing specifically on SSI dates from the 1990s. Those studies found that higher unemployment was associated with increases in SSI application and caseloads (Rupp and Stapleton 1995; Stapleton and others 1998; Stapleton and others 1999). The relationship between economic conditions and SSI application may have evolved significantly since then. Given rapid growth in the SSI rolls and the slow pace of recovery from the Great Recession, understanding the role that business cycles play in determining SSI participation has become increasingly important.

In this article, we examine the relationship between economic conditions and working-age adult SSI application from 1996 through 2010 using data from the Survey of Income and Program Participation (SIPP) linked to SSA's 831 data file. These restricted-access data allow us to link detailed SIPP information on demographic conditions and unemployment spells with precise SSA records on the month of first application for SSI and DI benefits. Using hazard models, we estimate SSI and DI application risk among individuals who were working when first observed in the SIPP but were unemployed during follow-up surveys in their respective SIPP panels, and examine the effect of the unemployment rate both at the time of job loss (the *baseline* rate) and at the time of—that is, *contemporaneous* with—SSI application. Whereas the contemporaneous measure reflects local labor market conditions at the time of application, the baseline rate may reflect differential characteristics of the pool of unemployed workers related to the business cycle. Our results suggest that application risk increases significantly with higher contemporaneous state unemployment rates. The magnitude of this effect is large—suggesting that a 1 percentage point increase in the state unemployment rate would lead to a 20 percent increase in the risk of applying for SSI or DI, raising the probability from 0.30 percent to 0.36 percent. Conversely, workers who began their unemployment spell in a time of high unemployment were less likely to apply for SSI, consistent with the hypothesis that the characteristics of the pool of newly jobless workers varies systematically with the business cycle, generally displaying a lower intrinsic propensity to apply for disability benefits in a period when more workers are being laid off. We also find that omitting the baseline unemployment rate from the analysis would lead to a substantial underestimation of the relationship between SSI application and contemporaneous economic conditions.

Once enrolled in SSI, very few recipients leave the program. Our findings suggest that short-term fluctuations in economic conditions may have substantial long-term effects on program participation and expenditures, and that countercyclical stimulus spending could have greater impacts over time by deterring disability-program application.

Background

SSI provides means-tested cash assistance to the elderly, to children, and to adults who are blind or have disabilities. Enacted in 1972, SSI replaced an uneven range of state programs and thereby standardized income support for those groups (Berkowitz and DeWitt 2013). The SSI disability determination process is complicated; most claims must pass through five stages before the applicant receives payments.[2] At the first stage, individuals must meet the income and asset eligibility requirements and show that they are not involved in "substantial, gainful" economic activity. The second and third stages involve medical evaluations. Applicants with impairments that are deemed "nonsevere" or that are not expected to end in death or to last at least 12 months are denied in stage 2; those with impairments deemed "extremely severe" are allowed in stage 3. Stages 4 and 5 assess capacity to work. Applicants who are able to work in jobs that they held in the past are denied in stage 4, and applicants who, given their age, education, and work experience, are judged able to work in any type of employment in the economy are denied in stage 5. As noted by Chen and van der Klaauw (2008), the vocational grid used in stage 5 creates age discontinuities in eligibility determinations beginning with age 45. Less than half of SSI applicants are ultimately approved (Duggan, Kearney, and Rennane 2016). Although the majority of SSI payments are federally funded, many states supplement payments with state funds.[3] The maximum monthly individual federal benefit was $733 in 2015. Benefit levels are adjusted annually for increases in the cost of living.

SSI is one of two major U.S. programs targeted to individuals with disabilities. The other, DI, provides benefits to individuals with disabilities who are insured by the contributions they made to the Social Security system while they were working. The disability determination process for DI is the same as that for SSI. However, DI benefits are not means-tested; instead, they depend on an individual's having a sufficient earnings history. DI enrollment is greater than that of SSI and is growing more rapidly. In 2015, 8.9 million workers with disabilities received DI benefits, an increase of 196 percent since 1990 (SSA 2017a, Table 5.D3). Primarily because of the work-history requirements, DI applicants and beneficiaries are less economically disadvantaged than are those who apply for and receive SSI payments. DI applicants are typically older, more highly educated, and wealthier than SSI applicants are. They are also more likely to be male, white, non-Hispanic, and married (Bailey and Hemmeter 2015).

However, many individuals are concurrently eligible for benefits from both SSI and DI. These beneficiaries have work histories sufficient to qualify for DI but their asset, income, and benefit levels are low enough that they still meet the means test to qualify for SSI. Of the 12.9 million working-age (18–64) adults receiving benefits administered by SSA on the basis of a disability in 2015, 8.0 million (62 percent) received DI benefits only, 3.5 million (27 percent) received SSI payments only, and 1.3 million (10 percent) received SSI and DI benefits concurrently (SSA 2017a, Table 3.C6.1).[4] Many applicants may not know how the eligibility rules for the two programs differ, and SSA staff may need to direct them toward one program or the other. In fact, the online application (https://www.socialsecurity.gov/applyfordisability) does not mention either program; it only describes how to apply for "disability benefits."

Macroeconomic Conditions and SSI Participation

For several reasons, changes in macroeconomic conditions may reduce the extent to which the stringency of the disability determination process discourages SSI participation. First, the SSI means test examines family (not individual) income, so if other family members experience income declines related to the business cycle, the lower family-level means may establish SSI eligibility. In addition, as a local labor market declines, an individual's physical or mental impairment may represent a relatively greater impediment to employment, making SSI participation more viable. Finally, an economic downturn that leads to an exogenous job separation may lower the opportunity cost of remaining out of work for an individual with disabilities who applies for SSI. These effects are all consistent with evidence suggesting that the rates at which individuals self-report disabilities respond to the relative costs and benefits of disability program participation (Waidmann, Bound, and Schoenbaum 1995).

A number of studies have looked at the effects of economic conditions on disability program caseloads. Autor and Duggan (2003) found that shifts in state-level labor demand predict changes in DI participation. Black, Daniel, and Sanders (2002) used changes in coal prices as a shock to local earnings growth to examine the effects of earnings on disability program participation. They found that both DI and SSI participation respond to earnings shocks, but that SSI participation is less responsive than that of DI.

A series of related studies found that increased unemployment rates associated with the recession of the early 1990s played an important role in the growth of SSI application and awards, with the effect on application being the stronger of the two (Rupp and Stapleton 1995; Stapleton and others 1998; Stapleton and others 1999). More recent studies found positive relationships between unemployment rates and DI application (Soss and Keiser 2006; Guo and Burton 2012; Coe and others 2011). Recent evidence that focuses primarily on SSI is less plentiful. Soss and Keiser (2006) found a positive and significant relationship between the unemployment rate and SSI application when estimated jointly with DI application. Rutledge and Wu (2014) found that SSI enrollment is negatively and significantly correlated with unemployment rates, but that the relationship has grown less negative over time and even turned positive during the Great Recession. They also found a relationship between SSI application flows and local unemployment rates that has weakened in recent years.

In this article, we extend the existing literature in three important ways. First, we examine the relationship between state-level economic conditions and SSI application in the late 1990s and 2000s, focusing on policy-relevant changes in the application flows rather than in the program rolls.[5] Second, we demonstrate the importance of examining the unemployment rates at both the time of job loss and the time of application. The first measure provides a baseline that captures differential selection into unemployment. The second measure reflects the labor market conditions contemporaneous with the application decision. Omitting the baseline rate—which can be correlated with the contemporaneous rate—could lead to biased estimates of the relationship between SSI application and contemporaneous economic conditions. Third, we provide evidence suggesting that higher *current* unemployment rates alone do not predict higher application rates, but that *persistently* higher unemployment rates do, with important consequences for policies aiming to limit the long-term consequences of a recession, both for program budgets and for individuals with extended periods of unemployment.

Data

We use SIPP data matched to Social Security administrative records. The SIPP is a nationally representative longitudinal survey which collects data on a number of topics including employment, demographics, income, and program participation. Because it focuses on program participation, the SIPP oversamples low-income households. Monthly data are available for sample members for as long as about 3 years. We use data from the four most recent SIPP panels, which began in 1996, 2001, 2004, and 2008, respectively. Each panel lasted 3 to 5 years, and taken together, they covered calendar years 1996–2010. The initial sample size for individuals of all ages in each panel ranges from 95,315 in the first wave of the 1996 panel to 105,663 in the first wave of the 2008 panel. We link the SIPP data to SSA's 831 file, which provides data on the timing of the first application for SSI and DI.

There are several advantages to using the matched SIPP/SSA data. First, SIPP's monthly data allow us to examine dynamics related to employment, unemployment, and benefit receipt. Second, because the 831 file contains records on applications for DI or SSI that cleared the financial screen (stage 1) of the disability determination process—including the decisions on those applications—we are able to avoid standard concerns about survey respondents underreporting program participation (Meyer, Mok, and Sullivan 2009). In addition, the SSA data allow us to observe the exact date of application, whereas data from the SIPP alone would provide only the month of first benefit receipt (subject to error, as respondents do not always report the correct source of income). This is potentially important because applicants must remain out of the labor force until their application is resolved. Applicants may wait months or years before receiving benefits. As a result, the date of allowance or first receipt of benefits is much less likely to be tied to economic conditions than is the date of first application.[6] A third benefit of using the matched SIPP/SSA data is that they include information on nonapplicants (and on demographic characteristics of applicants) that are unavailable from administrative-only data. Research has shown that using matched administrative records in this fashion provides more accurate estimates of SSI participation and payment amounts than using SIPP self-reported information does (Huynh, Rupp, and Sears 2002).

The matched SIPP/SSA data have several limitations. First, SSA cannot match records for all SIPP respondents. Survey respondents are matched to the Protected Identification Key (PIK) using a Social Security number, where available; or name, date of birth, and location, where other identifiers are unavailable. Behind a firewall, the survey data are matched to administrative earnings and disability-determination records using the PIK. SIPP panels vary in the proportion of cases that are matched to administrative records: The 2008 panel exceeded a 90 percent match rate, and the 1996 and 2004 SIPP panels achieved close to 90 percent match rates. However, the 2001 SIPP match rate was less than 70 percent. One possible way to deal with the imperfect matching would be to reweight the sample. However, that would require untenable assumptions about the selection process for those cases not matched to administrative data, namely that selection is on the observable characteristics in the survey only. For this reason, we do not reweight; however, we do include dummies for individual characteristics such as education, age, race, time period, and state in our regressions. This means that reweighting on those factors would have little impact on our regression estimates. That is, the factors used to adjust the baseline hazard also effectively adjust for differences in sample characteristics. Second, because an 831 record is not created for applicants whose claims are rejected because of financial ineligibility at stage 1 of the determination process, those applicants are miscoded as nonapplicants in our data. Our estimates should be biased toward zero if those applicants are particularly sensitive to the unemployment rate.[7,8]

We limit our sample to individuals who were newly unemployed during the SIPP panel so that we observe periods out of work for which the onsets are not censored. This restriction also helps select a sample whose members are subject to the strict income limits for SSI eligibility. SSI application is a relatively low-probability event, and those who are either continuously working or already in a long unemployment spell in our sample are much less likely to apply. Consistent with Mueller, Rothstein, and von Wachter (2016), who examine the risk of disability application at the time of unemployment insurance (UI) benefit exhaustion, our sample restriction allows us to focus on the population and the time period in which individuals are most at risk of applying for SSI.

To implement this restriction, we select all SIPP respondents aged 20–59 who were employed at the time of the first wave of their SIPP panel and were newly out of work for at least 1 month during the remainder of the period in which they were observed. Hereafter, we use "unemployed" to describe individuals with this specific experience (including those who separate from a job and do not report looking for another). We limit our analysis sample to those with an unemployment spell that began during the survey observation period for several reasons. First, we rely on SIPP data to identify state of residence so we can accurately measure local labor market conditions. If a respondent's unemployment spell begins before the initial SIPP interview, we cannot be confident that we are matching the correct unemployment rate for their location. Second, we would not be able to identify when an unemployment spell began for individuals who were unemployed at the start of their SIPP spell. To include such individuals in our sample would left-censor our data, meaning that we would not know the duration of their unemployment spell nor the labor market conditions when the spell began. Restricting the sample to individuals whose unemployment spell began during the SIPP panel may exclude a disproportionate share of long unemployment spells. Therefore, our results should be interpreted as identifying the relationship between unemployment rates and SSI application over the first few years of an unemployment spell. Individuals who have long unemployment spells are less likely to apply for SSI; again, we are interested in examining the population most at risk for application.

We identify spells of nonwork, which we define as months during which individuals are out of work after an observed job separation, whether or not they are actively looking for work. We observe a job separation for about one-quarter of the sample in each SIPP panel. Respondents enter our analysis sample in the month of job separation, and we follow them until they apply for disability benefits, become reemployed, or leave the SIPP sample. Our sets of matched survey and administrative data thus represent the U.S. non-institutionalized population who had earnings during the time covered by the first wave's survey (that is, the year for which the panel is named) but stopped working in a subsequent month. We measure the duration of the unemployment spell in months.

As discussed earlier, we are primarily interested in SSI. However, many potential beneficiaries may not fully understand eligibility rules and may not be sure which programs they should apply for. Staff at Social Security field offices may steer individuals toward one program versus the other. People may apply for both, and then find out which program they are eligible for (or whether they are eligible for both). As noted earlier, 10 percent of working-age beneficiaries with disabilities receive concurrent benefits from both programs. Therefore, in addition to examining SSI applications (which comprise SSI-only and concurrent SSI/DI applications), we examine applications to *any* federal disability program (that is, the sum of applications for DI only, for SSI only, and for DI and SSI concurrently).

We merge state-level measures (including unemployment rate and a number of policy variables) to the matched SIPP/SSA data by state and month. Although SSI payments are determined at the federal level, a number of states supplement payments, so we include the dollar amount of state-level SSI supplements. Because research has documented a link between welfare reform and SSI participation (for example, Schmidt and Sevak 2004), we also control for a number of TANF-related variables, including the maximum TANF benefit for a family of three[9] and indicators of whether state TANF programs have strict sanctions, strict time limits, and few exemptions from work requirements. Finally, we include a state fiscal distress measure. Kubik (2003) shows that states undergoing unexpected fiscal distress in the 1990s were likely to have SSI caseloads increase more sharply than did participation in Aid to Families with Dependent Children, the program that TANF replaced. Further information on the policy variables is provided in Appendix A.

Table 1 provides summary statistics for the individual variables included in the SIPP for our analysis sample. Each of the four SIPP panels contributes 20 to 30 percent of the full sample.[10] Most individual variables are measured in the month that the individual enters the sample (is first jobless); we report the means of those values. As described earlier,

Table 1.
Selected characteristics of sample members in the first month of their unemployment spell

Variable	Mean	Standard deviation
	Demographic characteristics (%)	
SIPP panel		
1996	27.4	0.450
2001	20.9	0.406
2004	30.4	0.460
2008	21.3	0.410
Foreign-born	13.1	0.337
Married	50.5	0.500
Female	56.4	0.496
Age		
20–24	20.5	0.404
25–29	14.8	0.355
30–34	13.8	0.345
35–39	12.6	0.331
40–44	12.1	0.327
45–49	10.9	0.312
50–54	9.4	0.292
55–59	5.9	0.236
Race		
White non-Hispanic	76.3	0.426
Black non-Hispanic	12.4	0.330
Educational attainment		
High school graduate	91.4	0.281
Attended college	62.5	0.484
Family income < twice the federal poverty level	35.1	0.477
	Monthly application rates (per 1,000)	
DI only, SSI only, or both	3	0.053
SSI only or both	1	0.039
	Monthly state-level economic indicators	
Unemployment rate (%)	5.267	1.893
Maximum TANF benefit, family of three ($)	385.60	149.50
State SSI supplement ($)	28.49	61.48
Per capita unexpected deficit shock	0.0	0.3
Percentage of states with strict TANF—		
Time limits	32.0	0.467
Sanctions	32.3	0.468
Work exemptions	86.0	0.347

SOURCE: Authors' calculations using SIPP 1996, 2001, 2004, and 2008 panels matched to Social Security administrative records.

NOTES: Sample size = 26,077; application person-months = 199,870; indicator state-months = 9,180.

individuals who enter the sample are considered to be at risk for SSI application beginning with the month in which they are newly reported in the SIPP as not employed. Fifty-six percent of sample members are female. Half of the sample members were married when they entered. Thirteen percent of the sample is foreign-born. Respondents range in age from 20 to 59, but are disproportionately found at the younger end of that range. Roughly three-quarters are non-Hispanic whites and 12 percent are non-Hispanic blacks. Ninety-one percent have graduated from high school and 62 percent have attended college. On entry, approximately one-third of the sample had family income of less than twice the federal poverty level. The sample statistics differ from those for a nationally representative sample because our sample is restricted to individuals who are first observed as employed and then lose employment during the SIPP panel.

We report summary statistics for selected time-varying variables across person-month records. In a given month out of work after a job separation, about 3 out of 1,000 sample members apply for either SSI or DI (or both) and about 1 in 1,000 apply for SSI (alone or concurrently with DI). This means that more than twice as many individuals apply for DI as apply for SSI, a finding that is consistent with the relative caseloads of the two programs. The mean value of our key variable of interest, the monthly state unemployment rate, is 5.3 percent. We also report summary statistics for state policy variables at the state-month level.

Model Specification

We examine the relationship between application for federal disability benefits and prevailing economic conditions by estimating with a series of discrete-time hazard models the risk of application for (1) any such benefits (DI alone, SSI alone, or both concurrently) and (2) SSI (alone or concurrently with DI). In other words, the "SSI application" category differs from the "any-program application" category in that it excludes DI-only applications. To address the fact that both current and lagged labor-market conditions should be related to one's current employment status and risk of program application, we use two unemployment rate measures: The baseline rate, which is current in the month when the individual's unemployment spell begins; and the contemporaneous rate, which is current in the month of application.

The contemporaneous measure captures an individual's perception of his or her chance of gaining employment. The baseline measure provides an indicator of two factors. For the first, a persistent economic downturn might be indicated if the baseline rate is higher than the level of the unemployment rate in a subsequent observation month. For the second, differential characteristics of the jobless population during periods of high versus low unemployment might be captured. For example, in recessions, the pool of unemployed individuals shifts toward those with higher skill or employability (Mueller 2012). Those individuals should be less likely to apply for SSI. The baseline and contemporaneous unemployment rates are highly correlated; it is therefore important to include both, even if the research objective focuses on the relationship between SSI application and the contemporaneous rate.

Because the duration of an unemployment spell may be related to SSI application in ways that could also be related to the unemployment rate, it is important to control for it. First, the likelihood of financial eligibility for SSI may increase with spell duration, as individuals deplete their assets; this circumstance can also lead individuals who applied for DI at the outset of the spell to subsequently apply for SSI as well, placing their applications in the "concurrent" category. For this reason alone, we would want to compare application for SSI to application for either DI or SSI; but it is also of substantive interest to compare SSI application *rates* to the any-program application rates.

Second, many unemployed workers will receive UI benefits during the early months of their spell, and some of them will apply for disability benefits when the UI benefits expire (Lindner 2016). On the other hand, a long unemployment spell may indicate ineligibility for SSI because disability has not been determined; or, it may reflect increasing selection into the pool of applicants who have not applied. In this circumstance, duration could negatively affect application. In our preferred model specification, we control for the duration of unemployment with a measure of the natural log of months of unemployment. We also present results from an alternative specification that controls for duration nonparametrically with a series of variables indicating unemployment spells ranging from 3–5 months to 36–38 months (with 0–2 months being the reference category). Duration variables measure the baseline hazard (that is, the chance of application in each month, conditional on not yet having applied) for a case with all covariates set to zero. The covariates are then used to adjust hazards proportionally at all points in time.

All models control for age (in 5-year bands), sex, race, and educational attainment, as well as for indicators of marital status and immigrant status. We also control for whether an individual had low income at the start of the unemployment spell (indicator is equal to one if the respondent's family income was less than twice the federal poverty level) and for the state TANF policy parameters discussed earlier.

All specifications include state fixed effects and controls for secular shifts over time. In our preferred specification, we control for secular shifts with an indicator for the SIPP panel (1996, 2001, 2004, or 2008). The inclusion of dummy variables for each panel adjusts not only for different initial labor market conditions in the panel, but also for differential inclusion probabilities by panel because of SIPP/SSA data matches. We also test the robustness of our results by flexibly controlling for secular trends with year-fixed effects.

Although DI and SSI application trends are likely to be strongly influenced by additional factors such as disability status, spousal and other income, and asset levels over the duration of the panel, we do not control for them because they are likely to be endogenous. Waidmann, Bound, and Schoenbaum (1995), Benítez-Silva and others (2004), and Benítez-Silva, Disney, and Jiménez-Martín (2010) found that survey measures of work-related disability are sensitive to labor market conditions and the availability of disability benefits. There is substantial disagreement about the quality of survey measures of disability or of related health conditions or limitations. Self-reported disability is both a subjective judgment of inability to work and a perception about one's ability to find work given both health and labor market conditions. Including self-reported measures of disability in regression analysis could be problematic, given that changes in labor market conditions after job separation could affect both a decision to apply for benefits and a self-report of disability. That is, the variable of self-reported disability is an outcome as well as a potential control. Assets and individual and spousal income are also outcomes of processes that may evolve in response to both time out of work and choices about spending and work in response to health and labor market conditions. Because these factors may therefore reflect an individual's plan to apply for benefits, we do not adjust for them in the regressions.

As a result, we omit health and asset variables as controls because of potential endogeneity. Although the SIPP data sets include information on health and assets that would support formal endogeneity tests, we do not have reliable instruments. We have therefore traded a potential endogeneity problem for a potential omitted-variable bias problem because people with longer unemployment spells and greater exposure to weaker labor markets may also be in marginally better health or have greater financial assets than do those who have already applied for disability benefits or returned to work. The omission has no consequence for the empirical work if the correlation between the omitted variables and the regressors of interest is small or zero, but it could bias our findings on current unemployment rates downward if individuals who remain exposed to higher unemployment rates without applying are those who are better able to weather the downturn. That is, we expect that a positive measured effect of contemporaneous unemployment rates on application could represent a lower-bound estimate if those in the risk pool for longer periods have better health and asset levels because those characteristics are negatively correlated with application but are positively correlated with ongoing high unemployment rates in that situation.

We examine the heterogeneity of our results by estimating the hazard of SSI application by age group (44 or younger, 45 or older) for a number of reasons. First, the vocational grid used in stage 5 of the disability determination process introduces discontinuities by age beginning at age 45. Second, the hazard could also differ because of variations in human capital and health that are correlated with age.

We also estimate the hazard of application by sex. Evidence suggests that SSI has become a more important part of the safety net since welfare reforms were enacted in the 1990s, and this development is likely to affect women disproportionately (Wittenburg and others 2015).

Results

Table 2 presents coefficient estimates and *z*-statistics from four hazard models of application for disability benefits, estimated on the full sample at risk. The table presents results under a specification that controls only for the contemporaneous unemployment rate and under a specification that also controls for the baseline unemployment rate (respectively labeled "without" and "with" the baseline unemployment rate). Results are given for any federal disability benefit application (DI only, SSI only, or both) and for SSI application (alone or concurrent with DI). The coefficient on the contemporaneous state unemployment rate is positive in all four specifications, suggesting that as the unemployment rate increases, the hazard of application increases. In addition, using the model that includes the baseline unemployment rate roughly doubles the magnitude of the coefficient on the contemporaneous unemployment rate and increases its statistical significance. This result is consistent with a conclusion that the baseline unemployment rate reflects unobserved variation in the composition of newly unemployed individuals. When the baseline rate is excluded, the estimated coefficient on the contemporaneous unemployment rate is biased downward. This finding has important implications for other research examining the effects of contemporaneous unemployment rates on disability program participation. As a result, in the rest of the article, we focus on results from specifications that control for the baseline unemployment rate.

The coefficient on the contemporaneous state unemployment rate on the hazard for any-program application (0.186) implies that, after controlling for the baseline unemployment rate, a 1 percentage point increase in the unemployment rate would lead to an increase of 0.186 in the natural log of the odds of DI or SSI application. Given the mean monthly application rate of 3 in 1,000, this translates to a 20 percent increase in the probability of application among those with recent job separations from 3.0 to 3.6 per thousand.[11]

The coefficient on the baseline state unemployment rate at the beginning of the unemployment spell for the hazard of any-program application (−0.117) is negative, supporting the theory that the pool of individuals who are jobless in periods of higher unemployment may be more employable and thus at lower risk of SSI application. This finding is consistent with previous research on application trends (Bound, Burkhauser, and Nichols 2003).

The coefficient on the indicator for duration of unemployment spell (−0.312 for any-program application, −0.348 for SSI application) is negative, suggesting that the risk of application declines with each additional month elapsed. As described above, there are a number of reasons why the hazard could increase with duration, such as depletion of assets and exhaustion of UI benefits. However, our empirical estimates of negative duration dependence likely reflect medical ineligibility for SSI and DI; that is, those who can apply will tend to do so, leaving the pool of remaining potential applicants less likely to apply over time.

Table 2.
Logistic regression results: Hazards of filing an application for any disability program and for SSI

Variable	Without baseline unemployment rate				With baseline unemployment rate			
	Any application [a]		SSI application [b]		Any application [a]		SSI application [b]	
	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic
State unemployment rate at the time of—								
Unemployment onset (baseline)	. . .	. . .	. . .	. . .	-0.117**	-2.49	-0.127	-1.58
Application (contemporaneous)	0.100*	1.65	0.108	1.14	0.186**	2.73	0.202*	1.81
Log duration of unemployment	-0.309**	-5.99	-0.343**	-4.98	-0.312**	-5.92	-0.348**	-4.80
SIPP panel								
1996 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
2001	-0.064	-0.32	-0.091	-0.35	-0.085	-0.42	-0.112	-0.44
2004	0.033	0.18	-0.183	-0.68	0.035	0.19	-0.183	-0.69
2008	-0.830*	-1.93	-1.112	-1.57	-0.783*	-1.85	-1.064	-1.53
Foreign-born	-1.012**	-3.06	-1.053**	-3.94	-1.010**	-3.07	-1.054**	-3.96
Married	-0.285*	-1.88	-0.769**	-3.84	-0.291*	-1.90	-0.773**	-3.83
Female	-0.193*	-1.87	0.148	0.90	-0.189*	-1.83	0.151	0.92
Age								
20–24	-2.516**	-11.26	-1.419**	-5.59	-2.529**	-11.23	-1.433**	-5.56
25–29	-1.299**	-3.19	-0.352	-0.75	-1.310**	-3.23	-0.363	-0.78
30–34	-1.308**	-6.54	-0.508*	-1.66	-1.319**	-6.59	-0.517*	-1.68
35–39	-0.827**	-4.96	-0.162	-0.45	-0.835**	-5.01	-0.171	-0.47
40–44	-0.451**	-2.59	0.264	0.84	-0.458**	-2.62	0.260	0.83
45–49	-0.088	-0.54	0.542*	1.72	-0.098	-0.60	0.533*	1.69
50–54	0.191	1.47	0.797**	3.89	0.186	1.42	0.794**	3.88
55–59 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
Race								
White non-Hispanic	-0.194	-0.99	0.176	0.54	-0.193	-1.00	0.177	0.55
Black non-Hispanic	-0.076	-0.31	0.195	0.50	-0.077	-0.32	0.194	0.50
Educational attainment								
High school graduate	-0.247*	-1.71	-0.244*	-1.75	-0.243*	-1.66	-0.239*	-1.71
Attended college	-0.220*	-1.90	-0.477**	-2.39	-0.220*	-1.89	-0.476**	-2.37
Family income < twice the federal poverty level	0.483**	4.02	1.056**	6.27	0.480**	4.04	1.057**	6.32

SOURCE: Authors' calculations using SIPP 1996, 2001, 2004, and 2008 panels matched to Social Security administrative records.

NOTES: Regressions include state TANF policy parameters, state fixed effects, and a constant term.

Sample sizes are 193,450 person-months for SSI applications and 199,870 person-months for all applications.

. . . = not applicable; * = statistically significant at the 10 percent level; ** = statistically significant at the 5 percent level.

a. Includes DI only, SSI only, and concurrent DI and SSI applications.

b. Includes SSI only and concurrent DI and SSI applications.

Individual characteristics are associated with application risk in expected directions, both for any application for disability benefits (including DI-only applications) and for SSI applications specifically. The risk of any application for benefits is lower for married individuals and for women, but there is no statistical difference in rates between men and women in SSI application rates (implying that differential eligibility for DI plays a large role in gender differences). There are no significant differences in application risk by race. Those living in households with foreign-born individuals are significantly less likely to apply for benefits, which is consistent with post-1996 restrictions on immigrant receipt of SSI (Bitler and Hoynes 2013). Relative to those who did not graduate from high school, the risk of application is lower for those who did. Having baseline family income that is less than twice the federal poverty level significantly increases the risk of application. The SIPP panel fixed effects (with 1996 as the excluded category) show a large and significant decrease in any-program application risk in the 2008 panel (−0.783), which coincides with the Great Recession, suggesting that individuals who were unemployed during this recent, deep recession were less likely to apply for SSI or DI than were those unemployed in earlier years. This finding is consistent with a large shift observed in the characteristics of the population newly out of work during 2008 and subsequent years.[12]

The pattern of results for SSI application is similar to that for any-program application. In the model that controls for the baseline rate, the coefficient on the baseline unemployment rate for SSI application (−0.127) is negative and of similar magnitude as the coefficient for any-program application (−0.117), but is less precisely estimated. The coefficient on the contemporaneous unemployment rate (0.202) is positively and significantly associated with the risk of SSI application, and the coefficient on duration of unemployment (−0.348) is negative and statistically significant. The effects of demographic variables for SSI application are qualitatively the same as those for any-program application, with the exception of sex. Women have significantly lower risk for any-program application but show no significant difference from men for SSI application. This difference would be consistent with women having lower labor-force attachment than men and therefore being less likely to have amassed sufficient work history to qualify for DI, implying that sex differences are driven by DI application. The estimated relationship between low family income and application is much larger for SSI than for federal disability programs overall, which reflects the fact that SSI, unlike DI, is a means-tested program.

In Table 3, we present results from a number of alternative specifications to check the robustness of our findings to controls for unemployment duration and year of observation. All results in Table 3 are for the dependent variable of any-program application. The first column repeats, as applicable, the results from Table 2 of our preferred specification (controlling for both baseline and contemporaneous unemployment rates). The alternative specifications include replacing the log duration of unemployment variable with nonlinear controls for duration and controlling for time with calendar-year effects. The results for our main explanatory variables of interest—the unemployment rate variables (both baseline and contemporaneous)—are consistent with the results for the preferred specification. The nonlinear duration indicators are relatively consistent with the log specification, in that they show application probabilities that tend to decline as unemployment spells grow longer. Although there are reasons (discussed earlier) why application hazards might increase with spell duration, it is likely that selection plays a large role, such that the pool of individuals who have been unemployed longer and have not yet applied includes more people who will never apply. The pattern of year effects shows large decreases in the hazard of applying during the recession of the early 2000s, as well as during the Great Recession in 2008–2010.

Table 4 shows the estimated hazard of any-program application on subpopulations stratified by sex and age.[13] Although the unemployment-rate coefficients are greater for women than for men, the differences are not statistically significant. The relationship between economic conditions and application risk is not significant for the younger workers in our sample; but for those aged 45 or older, we observe a negative and significant effect of the baseline unemployment rate (−0.183) and a positive significant effect of the contemporaneous unemployment rate (0.251). The relationship may differ by age for several reasons. First, the long-term costs of leaving the labor force may be lower for older workers. Second, the composition of older and younger applicants may vary by type of disability and age of onset, with a smaller share of older applicants having childhood onset. Third, as noted earlier, the disability determination process introduces age-related discontinuities beginning at age 45, which Chen and van der Klaauw (2008) have shown to be associated with reduced labor supply.

Table 3.
Robustness checks of logistic regressions on hazard of filing any disability-program application, controlling for baseline and contemporaneous unemployment rates

Variable	Log duration of unemployment spell and—				Months of unemployment spell and—			
	Panel		Year		Panel		Year	
	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic
State unemployment rate at the time of—								
Unemployment onset (baseline)	-0.117**	-2.49	-0.127**	-2.59	-0.096**	-2.05	-0.108**	-2.25
Application (contemporaneous)	0.186**	2.73	0.164**	2.41	0.162**	2.36	0.149**	2.20
Log duration of unemployment spell	-0.312**	-5.92	-0.302**	-4.73	. . .	. . .	. . .	. . .
Unemployment spell (months)								
0–2 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
3–5	. . .	. . .	. . .	. . .	-0.151	-1.17	-0.158	-1.16
6–8	. . .	. . .	. . .	. . .	-0.408**	-2.36	-0.430**	-2.33
9–11	. . .	. . .	. . .	. . .	-0.380*	-1.79	-0.415*	-1.79
12–14	. . .	. . .	. . .	. . .	-0.444*	-1.87	-0.467*	-1.87
15–17	. . .	. . .	. . .	. . .	-0.763**	-2.52	-0.763**	-2.35
18–20	. . .	. . .	. . .	. . .	-0.866**	-2.18	-0.834**	-2.05
21–23	. . .	. . .	. . .	. . .	-1.475**	-2.86	-1.410**	-2.60
24–26	. . .	. . .	. . .	. . .	-1.341**	-2.46	-1.260**	-2.14
27–29	. . .	. . .	. . .	. . .	-1.552**	-2.97	-1.459**	-2.74
30–32	. . .	. . .	. . .	. . .	-0.426	-0.86	-0.322	-0.63
33–35	. . .	. . .	. . .	. . .	-1.558**	-2.18	-1.455**	-1.96
36–38	. . .	. . .	. . .	. . .	-2.816**	-2.78	-2.678**	-2.61
SIPP panel								
1996 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
2001	-0.085	-0.42	. . .	. . .	-0.097	-0.48	. . .	. . .
2004	0.035	0.19	. . .	. . .	0.022	0.13	. . .	. . .
2008	-0.783*	-1.85	. . .	. . .	-0.811*	-1.92	. . .	. . .

(Continued)

Table 3.
Robustness checks of logistic regressions on hazard of filing any disability-program application, controlling for baseline and contemporaneous unemployment rates—*Continued*

Variable	Log duration of unemployment spell and—				Months of unemployment spell and—			
	Panel		Year		Panel		Year	
	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic
Year								
1996	. . .	. . .	-0.180	-0.58	. . .	. . .	-0.147	-0.45
1997 (reference category)	. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
1998	. . .	. . .	-0.495**	-2.44	. . .	. . .	-0.459**	-2.23
1999	. . .	. . .	-0.365**	-2.00	. . .	. . .	-0.290	-1.52
2000	. . .	. . .	-1.445	-1.43	. . .	. . .	-1.367	-1.33
2001	. . .	. . .	-0.677**	-1.99	. . .	. . .	-0.644**	-1.97
2002	. . .	. . .	-0.099	-0.33	. . .	. . .	-0.096	-0.32
2003	. . .	. . .	-0.609**	-2.62	. . .	. . .	-0.545**	-2.26
2004	. . .	. . .	-0.454	-1.64	. . .	. . .	-0.424	-1.50
2005	. . .	. . .	-0.215	-1.12	. . .	. . .	-0.214	-1.11
2006	. . .	. . .	-0.198	-0.91	. . .	. . .	-0.152	-0.68
2007	. . .	. . .	-0.504	-1.31	. . .	. . .	-0.424	-1.07
2008	. . .	. . .	-1.271*	-1.72	. . .	. . .	-1.184	-1.57
2009	. . .	. . .	-0.950**	-2.25	. . .	. . .	-0.949**	-2.25
2010	. . .	. . .	-1.023*	-1.90	. . .	. . .	-1.033*	-1.90

SOURCE: Authors' calculations using SIPP 1996, 2001, 2004, and 2008 panels matched to Social Security administrative records.

NOTES: Regressions include state TANF policy parameters, state fixed effects, and a constant term.

Sample size is 199,870 application person-months.

. . . = not applicable; * = statistically significant at the 10 percent level; ** = statistically significant at the 5 percent level.

Table 4.
Logistic regression results: Hazard of filing any disability-program application, by selected population subgroup

Variable	Overall		Sex: Women		Sex: Men		Age: 20–44		Age: 45–59	
	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic	Coefficient	*z*-statistic
State unemployment rate at the time of—										
Unemployment onset (baseline)	-0.117**	-2.49	-0.131*	-1.85	-0.070	-0.76	-0.027	-0.34	-0.183**	-2.64
Application (contemporaneous)	0.186**	2.73	0.209**	2.38	0.143*	1.70	0.109	0.95	0.251**	3.04

SOURCE: Authors' calculations using SIPP 1996, 2001, 2004, and 2008 panels matched to Social Security administrative records.

NOTES: Regressions include state TANF policy parameters, state fixed effects, and a constant term.

Sample sizes (in person-months) are 199,870 for applications overall, 126,462 for women, 70,468 for men, 135,660 for applicants aged 20–44, and 61,366 for applicants aged 45–59.

* = statistically significant at the 10 percent level; ** = statistically significant at the 5 percent level.

Conclusion

Using SIPP data linked to SSA's 831 data file, we find that individuals who begin their unemployment spell in a time of high unemployment are less likely than those with job loss during a low-unemployment period to apply for SSI or DI, consistent with the idea that the characteristics of the newly unemployed vary with the business cycle. However, application risk among individuals with a recent job separation increases significantly when the state unemployment rate rises as their jobless period continues. In addition, omitting the baseline unemployment rate from the analysis leads us to substantially underestimate the relationship between SSI application and contemporaneous economic conditions.

Our findings suggest that recessions can have long-term fiscal implications for SSI. If the flow of allowances tracks that of applications, and if exits from SSI are rare, then extended periods of high unemployment may permanently expand SSI caseloads.[14] Policymakers should account for that cost when considering programs to help at-risk or unemployed workers. The Congressional Budget Office (2014) estimates that the 2009 American Recovery and Reinvestment Act (ARRA) reduced the unemployment rate by between 0.4 and 2.0 percentage points during the third quarter of 2010. Our results suggest that a reduction in the current unemployment rate of 1 percentage point reduces SSI application among the recently unemployed by approximately 20 percent. However, stimulus spending such as that authorized by ARRA would also tend to restrict the pool of individuals at risk of applying for SSI by reducing the number of unemployed persons, so this estimate should be viewed as an upper bound on reductions in SSI application among the entire pool of the unemployed. The net effect on application would depend on reductions in separations and in the duration of unemployment. These results suggest on net that the ARRA dampened potential recession-induced increases in SSI (and DI) application. If so, the net benefits of federal aid during economic downturns may be underestimated, because even small changes in SSI application rates can have large budgetary consequences. Lindner and Nichols (2014) suggest that aid tied to labor-market attachment may reduce application rates, while increases in unconditional aid may increase application rates. Further research is needed to pinpoint the cyclical determinants of SSI application and the nature of the impacts of cyclical federal aid.

Appendix A

Listed below are the sources of the input data used in this analysis.

SSI application. This variable is coded using data from SSA's 831 data file, which are merged to the SIPP and are available for analysis at SSA through restricted access. The 831 file contains a record for all individuals who have ever applied for SSI or DI. We use variables noting date of application and type of application to identify whether an individual applied for SSI or DI in a given month.

Unemployment rates. Bureau of Labor Statistics.

Maximum TANF (or Aid to Families with Dependent Children) benefit for a family of three. Data for 1997–2010 are from Urban Institute's Welfare Rules Database (Table IIA4). Multiple values were given for California, Massachusetts, and Wisconsin; for those states, we used the highest value.

Maximum SSI state supplement. Data for 2002–2010 are from the SSA publication *State Assistance Programs for SSI Recipients* and indicate the maximum state supplement available to an individual with a disability who lives alone. Data for 1999–2001 are from the 2004 edition of the SSA publication *Consultative Examinations: A Guide for Health Professionals* (known as the Green Book). Data for 1996–1998 come from various earlier editions of the Green Book, as collected by the University of Kentucky's Center for Poverty Research, with values converted to 2000 dollars.

Welfare reform variables. Inputs for earlier years were provided by Rebecca Blank and Jordan Matsudaira; those for later years were updated using the Urban Institute's Welfare Rules Database.

Unexpected deficit shock. Calculated as in Kubik (2003). Data on actual state expenditures and revenues (per capita) in year t are obtained from the National Association of State Budget Officers' State Fiscal Survey in year $t + 1$. Forecasted state expenditures and revenues in year t are obtained from State Fiscal Survey in year $t - 1$. Fiscal shock = (actual state expenditure − forecasted state expenditure) − (actual state revenue − forecasted state revenue).

Notes

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[1] Payment data are for all SSI recipients with a disability, including those aged younger than 18 and older than 64, and therefore do not exactly correspond with the caseload data, which include only recipients aged 18–64 with a disability (or blindness).

[2] The description of the determination process that follows draws heavily from Wixon and Strand (2013).

[3] Duggan, Kearney, and Rennane (2016) note that 45 states currently supplement benefits for some or all of their recipients.

[4] The sums of these beneficiary counts and percentages do not equal the totals because of rounding.

[5] Trends in allowances affect the flow onto the SSI rolls more directly than trends in applications do, and may therefore be more important from a budgetary perspective for SSA. However, we focus on application for several reasons. First, application provides a direct measure of the decision an individual makes in response to personal and economic factors, while allowance measures administrative judgments. Second, given the long application and appeal process, the low (31.4 percent) allowance rate (Rupp 2012), and the harm that time out of the labor force does to an individual's employment opportunities (Kroft, Lange, and Notowidigdo 2013), fluctuation in the application volume is of independent research interest.

[6] Similarly, labor market conditions that affect aggregate application rates also affect the timeliness with which state Disability Determination Services process claims, and therefore could affect the average lag from first application to eventual receipt of benefits.

[7] For a detailed discussion of measurement issues in matched data, see Davies and Fisher (2009).

[8] Applications denied at stage 1 are not especially policy-relevant because in such cases the total social cost of application is minimal (in sharp contrast with applicants who remain out of work for months as they await a determination).

[9] Using TANF benefit levels for a fixed family size is standard in the welfare literature, in part because actual family size could be endogenous to benefit levels.

[10] The sample is not distributed evenly across the years because the SIPP panel sizes and employment outflows vary.

[11] A logit coefficient of 0.186 translates to an increase in odds of 20.0 percent; the increase in probability is very close for low baseline probabilities but declines to zero as the baseline probability increases. For a baseline probability of 3 in 1,000, we can convert the coefficient to a marginal effect of a 1.0 percentage point increase in the unemployment rate on the probability of application by adding the coefficient estimate (0.186) to the natural log of the baseline odds (−5.806). We then exponentiate the sum to get the revised odds and back out the revised probability (0.0036), which is 22 percent higher than the baseline probability of 0.003.

[12] The TANF policy variables described earlier are in most cases not statistically significant and are omitted from Table 2. Their inclusion does not significantly affect the unemployment rate results. Full results are available from the authors on request (lschmidt@williams.edu).

[13] Because sex- and age-stratified results for SSI application resemble those in Table 3, they are omitted from Table 4.

[14] However, initial allowance rates are negatively related to high unemployment (Rupp 2012), which would tend to diminish the fiscal implications.

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