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Characteristics and Employment of Applicants for Social Security Disability Insurance over the Business Cycle

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Abstract:

We investigate the relationship between the unemployment rate and characteristics of applicants for Social Security Disability Insurance using administrative records of the universe of applicants between 1991 and 2008. As the unemployment rate rises, applications shift to those with higher work capacity who are rejected early in the eligibility determination process and have higher pre-application earnings and employment. However, post-application earnings and employment of denied applicants are slightly negatively related to the unemployment rate, suggesting that both compositional changes toward applications with higher work capacity and adverse economic conditions affect their employment and earnings.

Keywords: Social Security Disability Insurance, business cycle, disincentive effect

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1 Introduction

It is well-documented that the number of applications and awards for Social Security Disability Insurance (DI) increases strongly with the unemployment rate (Rupp and Stapleton 1995). Figure 1 displays this relationship for applications for the years 1991–2008. Less known is how the composition of applications and awards changes over the business cycle. Changes to the composition of applicants can have important consequences for the performance of the program. For instance, if people with higher past earnings are more likely to apply and be awarded during recessions, then this changing composition by itself increases average expenditures of the program because DI benefits increase in past earnings.

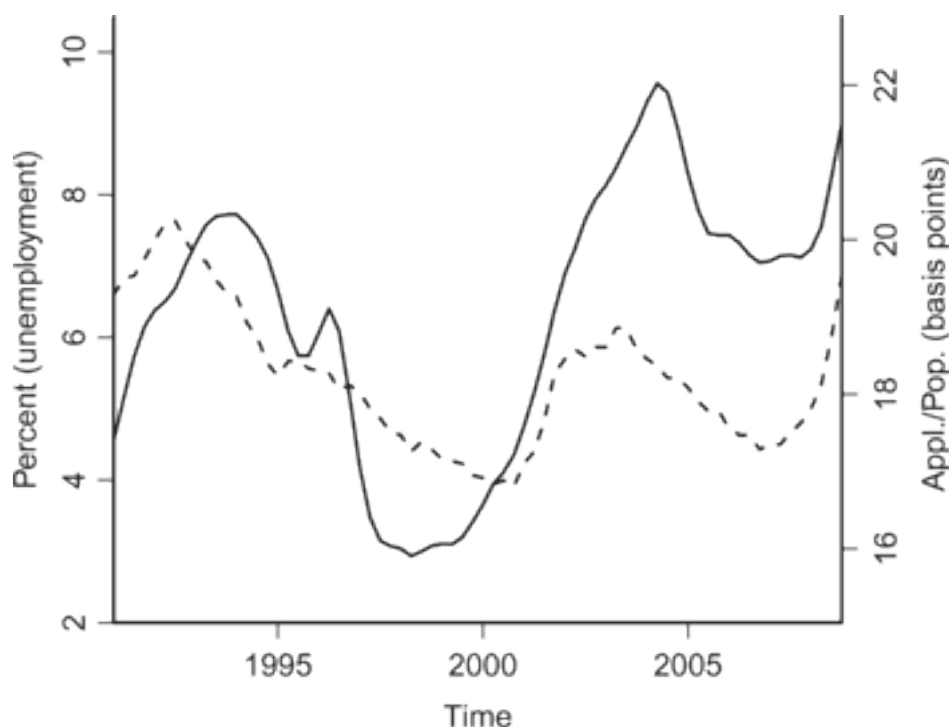


Figure 1: Number of applications for DI and the unemployment rate, 1991–2008.

In this paper, we use administrative records of all people applying for DI between 1991 and 2008 to examine compositional changes over the business cycle. Specifically, we investigate how the composition of applicants in terms of demographic factors and application outcomes changes with the unemployment rate and whether these compositional changes are similar for accepted versus denied applicants. We also analyze how such compositional changes translated into pre- and post-application earnings and employment.

We find that a higher unemployment rate is associated with a larger share of applicants with high work capacity whose applications are rejected earlier in the eligibility determination process. A substantial fraction of these initially rejected applicants are accepted into the program because of a successful appeal or re-application shortly after the initial application. Earnings and employment of denied applicants in the years before application also increase with the unemployment rate. However, their post-application earnings and employment are slightly negatively related to the unemployment rate. These results suggest that both compositional changes and economic conditions affect employment and earnings of denied applicants in opposing fashion. On the one hand, compositional shifts toward applicants with higher work capacity or during recessions would imply by itself that post-application earning and employment of denied applicants are positively related to the unemployment rate. On the other hand, applicants during recession periods face depressed demand for labor, which implies a negative association between the unemployment rate and post-application earning and employment of denied applicants.

In the final part of the paper, we develop a simple theoretical model to provide back-of-the-envelope calculations of how an increase in the unemployment rate affects earnings and employment of *accepted* applicants if they were not on the program. These hypothetical earnings or employment of accepted applicants are commonly known as the disincentive effect of the program because it measures how much participating in the program discourages work. It is a central measure of program performance: a high disincentive effect implies that the program is inefficient because it draws people out of the labor force who could otherwise work.¹ After calibrating the model using results from our empirical analysis, we find that the disincentive effect is also slightly negatively related to the unemployment rate.

Our paper contributes to the growing literature on compositional changes of DI applicants. Autor and Duggan (2003) first introduced the notion of “conditional applicants,” who have a health impairment that may qualify them for DI but prefer working as long as they are employed; only after having lost their jobs do they apply for DI. According to their theoretical and empirical analysis, the number of these conditional applicants has increased since the mid-1980s due to program liberalization, declining demand for low-skilled workers and higher DI benefits relative to wage earnings.²

Our paper applies their analysis to the business cycle. Consistent with their framework, we find evidence that the composition of applicants shifts toward conditional applicants with higher work capacity during recessions.³ However, our results also indicate that labor demand is depressed during recessions, as suggested by research on earnings losses of displaced workers over the business cycle (Davis and Wachter 2011). This

business cycle effect implies that the relationship between post-application employment or earnings and the unemployment rate of denied applicants may be either positive or negative.

Our findings therefore caution against equating increases in the share of conditional applicants and beneficiaries with an increase in the disincentive effect of the program. Rather, it is essential to identify the cause of these compositional changes. If policy changes contribute to program growth at a time of stable economic conditions, then a higher fraction of conditional applicants likely implies a higher disincentive effect of the program. If, however, dire economic conditions are the primary contributor of program growth, then compositional changes may not lead to a higher disincentive effect.

This study is most closely related to two recent articles on DI applications and the business cycle. Coe and Rutledge (2013) use the Health and Retirement Study (HRS) and the Survey of Income and Program Participation (SIPP) linked to Social Security benefits records to examine changes to the composition of DI applications between three business cycle periods: the 2001–2003 downturn, the 2004–2006 boom and the 2008–2010 great recession. They similarly find higher pre-application income during the recession period as compared to the boom periods for DI applicants. A second study, by Autor et al. (2015), uses similar administrative records to ours but also observes alleged disability onset dates of applicants. Focusing on the Great Recession, they report that applicants who applied during the recession had been struggling with their health impairment significantly longer than applicants who applied during non-recession periods.

Our paper is organized as follows. We first briefly describe the DI program and application process and our data (Section 2 and Section 3). We then present our methodology and main results (Section 4) and discuss these findings using a simple model (Section 5). Section 6 offers concluding remarks.

2 An Overview of the DI Program and Its Application Process

DI is the largest federal insurance program against loss of income due to a disability. It is administered by the Social Security Administration (SSA). Since its inception in 1956, the number of beneficiaries has steadily increased from 150,000 in 1957 to 8.6 million in 2011, interrupted only by a slight decrease during the mid-1980s when Congress passed laws tightening program eligibility rules (Bound & Waidmann, 2002; Social Security Administration, 2012). Beneficiaries receive monetary benefits that are tied to their past earnings. They also receive Medicare insurance starting two years after onset of their disability.

SSA case workers determine eligibility of applicants for DI using a five-step procedure. At the first two steps, applicants with earnings above a threshold called the substantial gainful activity (SGA) amount (step 1) and with a health impairment deemed not severe enough (step 2) are rejected.⁴ At step 3, applicants with a health impairment included in the Listing of Impairments are allowed into the program. This list includes severe medical conditions such as blindness, epilepsy, or inoperable tumors.⁵ All other applicants move to step 4, where case workers assess their residual functional capacity, i. e., capacity to perform work-related activities such as walking or lifting objects. Those deemed able to perform work done in the past are rejected, while the remaining applicants move to step 5. At this final determination step, case workers evaluate applicants' residual functional capacity together with vocational factors (i. e., age, education and work experience).⁶ Those deemed able to perform alternative work based on these factors are rejected, whereas those deemed unable to do such work are accepted.⁷

Applicants for DI can simultaneously apply for Supplemental Security Income for the blind and disabled (SSI). SSI is a means-tested program, i. e., only applicants with low resources qualify for the program. Joint DI/SSI applicants go through the same medical determination steps (steps 2–5). At the first step, they need to show that their earnings do not exceed SGA and that their income and assets are below thresholds specified by SSA.⁸ Joint DI/SSI beneficiaries are eligible for Medicaid while not receiving Medicare.

Denied applicants can ask Social Security to reconsider their cases, and a large fraction of them do so. For instance, in 2005, 45.8 percent of all initially denied applicants appealed at the reconsideration step (Autor and Duggan 2010). However, only a small minority of them (13 percent in 2005) are awarded benefits at this step. Those still not awarded benefits can further appeal the decision at the administrative law judge, appeal council, and federal court level. Administrative law judges reverse the majority of denials (69 percent in 2005), but the waiting time for decisions at this level often extends from several months to over a year. Only a small number of claimants rejected at this step further appeal the decision, and most of them are not successful. Overall, the average processing time of an application is around six months, but the lengthy appeals process implies that a substantial fraction of applications have an overall duration in excess of a year.

3 Data

Our primary data source is the Disability Research File (DRF) for the years 1991–2008. SSA creates the DRF file by combining several administrative records related to DI applications with the goal of providing researchers with accessible, consistent, and comprehensive information about DI applicants. The DRF contains the beginning date, duration, and outcome of applications. The DRF includes basic demographic information such as age and sex. It also has information about the step of initial determination.⁹ In creating the DRF, SSA matches application records to yearly summary earnings from the Internal Revenue Service (IRS) for the years 1980–2010. Unfortunately, the DRF only includes applicants who successfully pass the first step of initial application, where financial eligibility is determined.¹⁰

We primarily use data covering applications from 1991 to 2008. DRF files prior to 1991 do not exist, and DRF records after 2008 have a growing percentage of pending applications and right-censored earnings for some of the years following application. However, we extend our analysis to the years 2009 and 2010 as a robustness check (see Appendix for details). DRF records after 2010 were not available for our analysis. We include all adult applicants between the ages of 18–65, or a total of 22.7 million applications.

Based on individual-level filing dates, we create panels with quarterly and yearly frequencies by states.¹¹ We create a number of variables at this step. The ones presented in the subsequent results section include: percent joint DI/SSI applications; percent of applications determined at steps 2, 3, 4, and 5; average earnings (including zero earnings) and average employment rate (defined as any positive earnings during one year) ten years before to five years after application. Other information at the state level generated at this stage are the state unemployment rate and state population age 20–64.¹²

We use yearly frequencies for earnings and employment because they are observed only on an annual basis. For applicants' characteristics, we also experimented with month as unit of frequency, but found that higher frequencies do not add further benefit to our analysis. For each frequency, we calculate characteristics of applicants who apply during the respective quarter or year. For earnings, we include past earnings up to 10 years before and up to 5 years after the year of application. All earnings are expressed in 2010 values using the CPI-U. This panel is then matched to population numbers from the Census Bureau to express the number of applications relative to the number of people age 20–64.

About 30 percent of applications are re-applications. Such re-applications could influence our results if they vary systematically over the business cycle. For instance, if more initially denied applicants re-apply during recessions and if some of these re-applications are successful, then not accounting for re-applications would imply a more positive relationship between the unemployment rate and denial rates. Similarly, if applicants stay out of the labor force during such re-applications, then earnings and employment after the initial application would be lower during recessions simply because of more re-applications.

We follow other studies on DI and reclassify initially denied applications as successful applications if they are accepted at a later re-application (Von Wachter, Song & Manchester, 2011). For this purpose, we treat subsequent applications within five years of an initial application as re-applications. We use five post-application years instead of 10 years as done by Von Wachter, Song, and Manchester (2011) to avoid discarding applications with too few observed post-application years.¹³ Moreover, we calculate post-application earnings and employment without including earnings and employment of those in the process of a re-application.¹⁴ Based on the final determination outcome, we create two more panels, one for denied and one for accepted applicants as well as auxiliary panels for applicants whose applications are determined at step 2, 4 or 5, respectively.

4 Empirical Analysis

In this section, we first describe our empirical approach for analyzing application data and then discuss the results.

4.1 Empirical Methodology

To establish the relationship between the unemployment rate and characteristics of applicants such as the average age or the number of applicants who apply jointly for DI and SSI, we specify the following model:

$$y_{st} = \beta_0 + \beta_1 u_{st} + \eta_s + \eta_t + \eta_s \cdot t + \varepsilon_{st}, \quad (1)$$

where y_{st} denotes outcomes of interest per time period t and in state s , ue_{st} is the unemployment rate, η_s are state fixed-effects, η_t are year fixed effects, $\eta_s \cdot t$ are state-specific linear time trends and ε_t is the error term. Including both state fixed effects and state fixed effects interacted with a linear time trend controls for level and long-term trend differences across states.¹⁵ The coefficient β_1 measures the association between short-term fluctuations in the unemployment rate and applicants' characteristics. For each outcome that relates to a specific applicant group (e. g., joint DI/SSI applicants), we estimate eq. (1) twice, using first the number of applicants in the group expressed in basis points (i. e., number of applications per 10,000 people) and second the share of applicants in that group.¹⁶ We use weights equal to the number of applicants in a state and time period t relative to the number of all applications in that period because we want to estimate descriptive statistics for the application population (Solon, Haider & Wooldridge, 2013). Finally, we cluster standard errors at the state level to account for correlated error terms within states over time.¹⁷

We also estimate regressions of earnings and employment relative to the year of application. The main difference to the specification as shown by eq. (1) is that we use earnings and employment 10 years before to 5 years after the application year t . Denoting the year relative to the application year with τ and the difference to the application year with j , where $\tau = t + j$ and $j = -10, -9, \dots, 5$, we can rewrite eq. (1) as follows:

$$y_{s\tau} = \beta_0 + \beta_1 ue_{st} + \eta_s + \eta_t + \eta_s \cdot t + \varepsilon_{st}, \quad (2)$$

where the only difference to eq. (1) is the subscript τ for the outcome, i. e., $y_{s\tau}$ instead of y_{st} as in eq. (1).¹⁸

4.2 Results

In this section, we first present results for applicant characteristics, focusing on results for the number and share of applications determined at stage 2, 3, 4 and 5 as well as the number and share of joint DI/SSI applicants. We then discuss results for employment and earnings of denied applicants.

Table 1 displays results for characteristics of all applicants along with mean values.¹⁹ Mean values for number of applicants are expressed in basis points (i. e., number of applications per 10,000 people). The first row shows that a one percentage point increase in the unemployment rate increases applications by about 0.5 basis points, which is equivalent to a 3.1 percent increase. This result is in the ballpark of earlier studies, which report magnitudes ranging from 2 to 6 percent (Rupp and Stapleton 1995).

Table 1: Regression results for applicant characteristics and the unemployment rate.

Variable	Mean	Estimate /SE
Applications (b.p.)	19.8	0.53*** (0.09)
Appl. for DI/SSI (%)	51.3	0.81*** (0.13)
Appl. for DI/SSI (b.p.)	10.3	0.40*** (0.06)
Step 2 applicants (%)	14.9	0.59** (0.19)
Step 2 applicants (b.p.)	3.0	0.15*** (0.05)
Step 3 applicants (%)	21.9	-0.47** (0.15)
Step 3 applicants (b.p.)	4.2	0.05 (0.03)
Step 4 applicants (%)	17.5	0.35 (0.20)
Step 4 applicants (b.p.)	3.5	0.14** (0.04)
Step 5 applicants (%)	37.1	-0.35 (0.26)
Step 5 applicants (b.p.)	7.4	0.18** (0.07)

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Notes: Each cell of the third column represents a separate regression and displays the coefficient for the unemployment rate in a regression with the dependent variable as given by the first column. All regressions use the number of applications of a state per period as weights and include state fixed effects, year fixed effects, and state fixed effects interacted with linear time trends. All variables are either expressed as percentage of all applicants or as basis points (number of applicants with that characteristic per 10,000 adults for a time period and state). Standard errors are clustered at the state level and displayed in parentheses below corresponding coefficients. Mean values refer to weighted averages over all states and the time period 1991–2008. The sample size for all regressions is 3,744.

The number of applications determined at steps 2, 4, and 5 is positively related to the unemployment rate. By contrast, the number of step 3 applications, which are all accepted based on the Listing of Impairments, does not change with the unemployment rate. The share of steps 2 and 4 applicants increases with the unemployment rate, whereas the share of step 5 applicants decreases slightly with the unemployment rate because the increase in the number of step 5 applications is not quite as strong as overall increase in applications. Overall, these results indicate a shift toward conditional applicants with high work capacity.

The increase in the number of steps 2 and 4 applicants may only affect the composition of denied applicants because all applications determined at these steps are initially rejected. However, rejected applicants can re-apply or file an appeal and thereby get into the program. Table 2 presents regression results of applicants' characteristics separately for accepted and denied applicants, using the broadest definition of determination that includes future re-applications within 5 years.²⁰ The number of steps 2 and 4 applications that are ultimately allowed also increases with the unemployment rate. Even more, the *share* of steps 2 and 4 accepted applicants increases with the unemployment rate as well because the increase in the number of these applicants outweighs the increase in the overall number of accepted applicants.²¹

Table 2: egression results for characteristics of accepted and denied applicants and the unemployment rate.

Variable	Accepted	Denied
Applications (b.p.)	0.23 *** (0.06)	0.31 *** (0.05)
Appl. for DI/SSI (%)	0.59 *** (0.12)	0.78 *** (0.17)
Appl. for DI/SSI (b.p.)	0.17 *** (0.03)	0.23 *** (0.04)
Step 2 applicants (%)	0.36 ** (0.13)	0.58 * (0.28)
Step 2 applicants (b.p.)	0.05 ** (0.02)	0.11 *** (0.03)
Step 4 applicants (%)	0.39 * (0.19)	−0.11 (0.28)
Step 4 applicants (b.p.)	0.06 * (0.03)	0.08 *** (0.02)
Step 5 applicants (%)	−0.38 (0.28)	0.00 (0.24)
Step 5 applicants (b.p.)	0.08 (0.05)	0.11 *** (0.02)

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Notes: Each cell of the second and third column represents a separate regression and displays the coefficient for a regression with the dependent variable as given by the first column. All regressions use the number of applications in a state per period as weights and include state fixed effects, year fixed effects, and state fixed effects interacted with linear time trends. All variables are either expressed as percentage of all applicants or as basis points (number of applicants with that characteristic per 10,000 adults for a time period and state). Standard errors are clustered at the state level and displayed in parentheses below corresponding coefficients. The sample size for all regressions is 3,744.

Table 1 and Table 2 also show that the share of joint DI/SSI total, accepted and denied applicants increases during times of high unemployment. This result is surprising because applicants with higher work capacity should have higher income, thus be less likely to qualify for SSI.²² We next turn to earnings and employment to further investigate how compositional changes to applicants affect their labor market outcomes.

Figure 2 (for earnings) and 3 (for employment) display coefficients and confidence intervals for regressions of denied applicants as shown in eq. (2). Each coefficient corresponds to a regression of earnings or employment in the year relative to the application year shown by the x-axis on the unemployment rate *of the year of*

application.²³ Therefore, these coefficients measure how earnings and employment before and after application change with the unemployment rate.

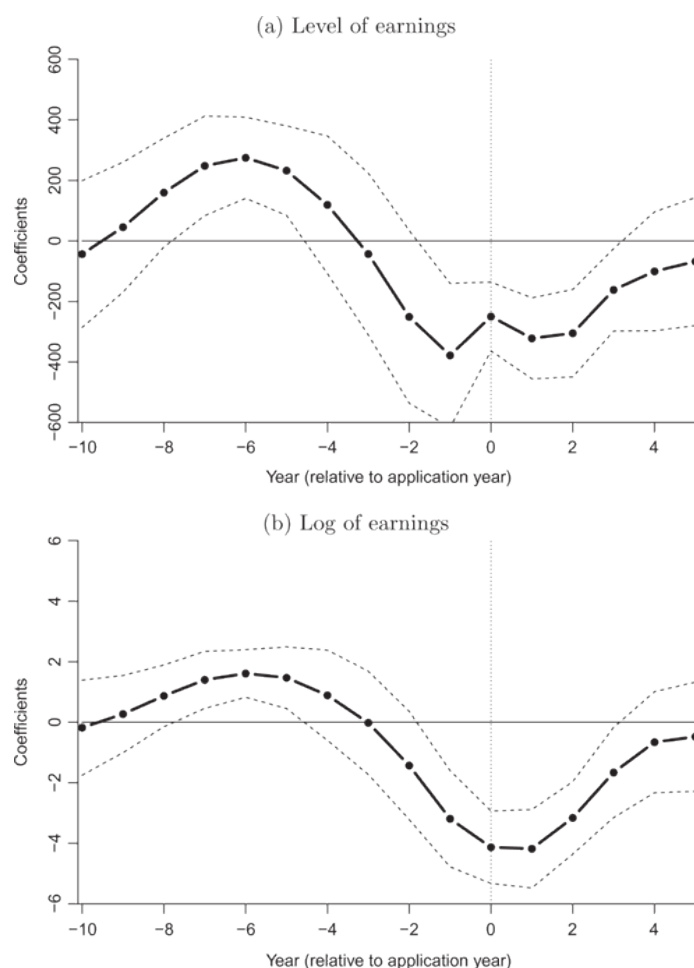


Figure 2: Earnings of denied applicants and the unemployment rate: regression results: (a) level of earnings; (b) Log of earnings.

Coefficients on unemployment for the level of earnings regressions (Figure 2(a)) are about zero 10 years before application; they then increase and attain their highest magnitude seven to five years before application. Coefficients during these years before the application year are slightly above \$200, meaning that a one percent higher unemployment rate at the time of application is associated with roughly \$200 higher earnings of denied applicants seven to five years before applications. Coefficient values then decrease and are negative three years before application to five years after application. In other words, applicants who apply during times of high unemployment rates have lower earnings shortly before and during the years after application. Figure 2(b) shows results for log of earnings as dependent variables. For most years except for the immediate years after application, coefficient values are modest, ranging between -2 and 2 percent of earnings. Coefficients for the years after application decrease in magnitude, suggesting that the negative relationship between the unemployment rate and post-application earnings fades out over time.

Figure 3 shows corresponding results for employment. Coefficients exhibit a similar pattern as earnings regressions. The unemployment rate is slightly positively associated with employment several years before application but negatively associated with employment starting 4 to 2 years before application and during the years after application. The negative relationship between the unemployment rate and post-application employment is small, about -1 two years after application (-2 in log terms) and less than -0.5 five years after application (less than -1 in log terms).²⁴

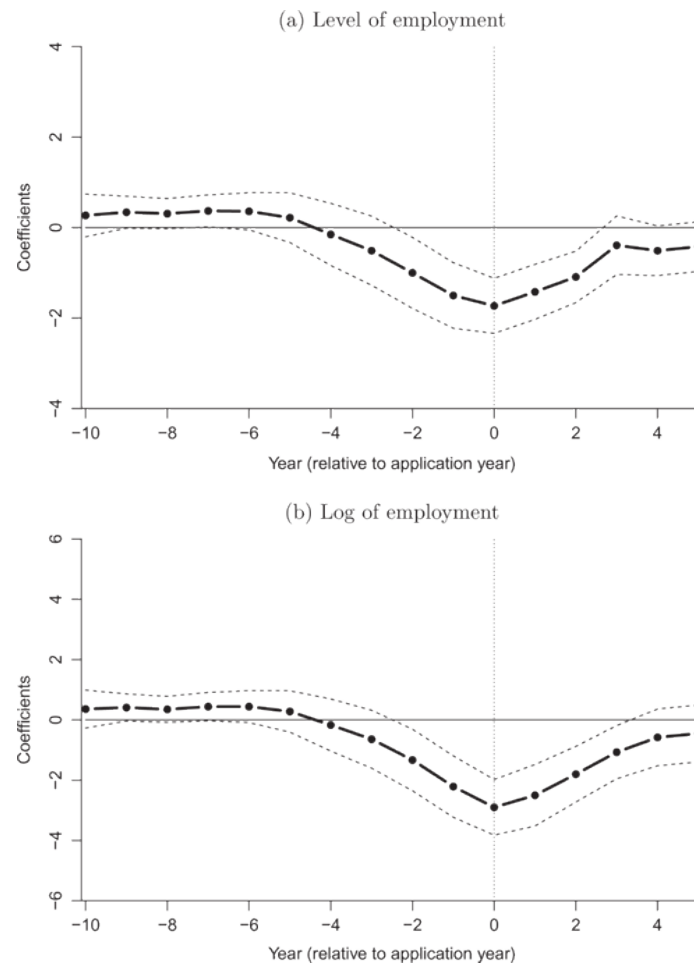


Figure 3: Employment of denied applicants and the unemployment rate: regression results: (a) level of employment; (b) log of employment.

5 Discussion

Our results provide clear support for the idea that conditional applicants are more likely to apply when the unemployment rate is high. Specifically, the share of applicants denied at steps 2 and 4 of the determination process increases with the unemployment rate. Consistent with a shift toward conditional applicants, we furthermore find that earnings and employment of denied applicants several years before application are slightly higher when the unemployment rate is high. However, post-application earnings and employment are negatively associated with the unemployment rate. Together with the positive relationship between the unemployment rate and the share of joint DI/SSI applications, these results suggest that applicants who apply during recessions suffer from income losses around the time of application because of adverse economic conditions.

In the remainder of this section, we develop a simple model that builds on Autor and Duggan (2003) to demonstrate how our findings relate to their analysis and to provide back of the envelope calculations of changes to the disincentive effect of the program. As in **Autor and Duggan (2003)**, we assume that there are two types of applicants: n_i inframarginal applicants and n_c conditional applicants. Inframarginal applicants have sudden, severe disabilities and apply for DI following the onset of their disability irrespectively of the unemployment rate. By contrast, conditional applicants apply for DI only after having lost their jobs because they otherwise prefer working. For this discussion, we assume that $n_c(u)$, with $n_c'(u) < 0$, and note that Autor and Duggan (2003) show how an increase in the probability of a job loss and a decrease in the probability of re-employment after job loss decrease the value of job search relative to applying for DI, and thus increases the number of conditional applicants applying for benefits.

A fraction α_i of inframarginal applicants and a fraction $\alpha_c(u)$ of conditional applicants are accepted into the program. We assume that the acceptance rate for inframarginal applicants does not depend on the unemployment rate, which implies that the number of accepted and denied inframarginal applicants ($\alpha_i n_i$ and $(1 - \alpha_i) n_i$, respectively) is also independent of the unemployment rate.²⁵ Finally, we denote post-application earnings or

employment of conditional and inframarginal applicants if they were not in the program with $e_c(u)$ and $e_i(u)$, respectively. Note that we only observe such post-application earnings or employment absent of program participation for denied applicants.

Average earnings or employment of denied applicants $\bar{e}_d$ is then:

$$\bar{e}_d(u) = \frac{(1 - \alpha_c(u))n_c(u)}{n_d(u)} \cdot e_c(u) = \sigma_{c,d}e_c, \quad (3)$$

where $n_d(u) = (1 - \alpha_c(u))n_c(u) + (1 - \alpha_i) n_i$ denotes the number of denied applicants and $\sigma_{c,d}$ is the fraction of conditional applicants among all denied applicants. The change in average employment of denied applicants as a result of a marginal change in the unemployment rate is then:

$$\frac{d\bar{e}_d}{du} = \left(\frac{d\sigma_{c,d}}{du}\right)e_c + e_c'(u)\sigma_{c,d}. \quad (4)$$

The first term of eq. (4) is the compositional effect toward conditional applicants and positive, whereas the second term is the negative business cycle effect due to adverse labor market conditions. By contrast, Autor and Duggan (2003) focus on explaining how the number of conditional applicants has increased as a response to policy and economic changes but do not also consider whether such factors affect average earnings of denied applicants. Put differently, they examine factors influencing $\sigma_{c,d}$ but do not investigate whether such factors also affect e_c .

We can further use this result to assess how earnings and employment of accepted applicants, were they not on the program, would change with the unemployment rate. Ignoring for now a possible effect of application waiting time on post-application earnings and employment, we can write earnings of employment of accepted applicants were they not on the program as follows:

$$\bar{e}_a^*(u) = \frac{\alpha_c(u)n_c(u)}{n_a(u)} \cdot e_c^*(u) = \sigma_{c,a}e_c^*, \quad (5)$$

where the asterisk in $\bar{e}_a^*(u)$ and $e_c^*(u)$ is used to mark these earnings or employment as counterfactual earnings (i. e., earnings or employment of applicants if they were not on the program), $n_a(u) = \alpha_c(u)n_c(u) + \alpha_i n_i$ denotes the number of accepted applicants and $\sigma_{c,a}$ is the fraction of conditional applicants among all accepted applicants. If the application process does not affect post-application outcomes, then it follows that $e_c^* = \bar{e}_d/\sigma_{c,d}$ because in this case, $e_c^* = e_c$ and $\bar{e}_d/\sigma_{c,d}$ from eq. (3). Therefore,

$$\bar{e}_a^*(u) = \frac{\sigma_{c,a}}{\sigma_{c,d}} \bar{e}_d. \quad (6)$$

Expressing eq. (6) in logs and taking the derivative with respect to the unemployment rate implies:

$$\frac{d \log(\bar{e}_a^*)}{du} = \frac{d \log(\sigma_{c,a})}{du} - \frac{d \log(\sigma_{c,d})}{du} + \frac{d \log(\bar{e}_d)}{du}. \quad (7)$$

We can use results from our empirical analysis to obtain approximations of all three right-hand side expressions of eq. (7). Specifically, average log employment and earnings changes for years two to five after application are about -0.98 and -1.49 , respectively (see Table 5). We estimate log specifications of eq. (1) for the other two right-hand side expressions. Treating all applicants whose applications are determined at step 2, 4, or 5 and calculating weighted marginal changes yields $\frac{d \log(\sigma_{c,a})}{du} \approx 0.81$ and $\frac{d \log(\sigma_{c,d})}{du} \approx 0.50$ for denied applicants.²⁶ Putting these numbers together implies that $\frac{d \log(\bar{e}_a^*)}{du}$ is -0.7 and -1.2 for earnings and employment, respectively. These negative changes are smaller than those of denied applicants because the compositional effect toward conditional applicants appears to be stronger for accepted than for denied applicants.²⁷

Table 3: Diagnosis code groups.

Diagnosis code group	Primary diagnosis code	Percentage
Infection	0110–1380	2.1
Neoplasms	1410–2390	7.0

Endocrine	2460–2790	5.1
Blood	2810–2890	0.3
Mental disorders	2940–3195	20.9
Nervous/Senses	3300–3890	7.5
Circulatory	3910–4590	10.4
Respiratory	4910–5190	3.8
Digestive	5300–5780	2.3
Genito-Urinary	5810–6290	1.4
Skin	6940–7090	0.3
Musculoskeletal	7100–7370	27.8
Congenital	7400–7590	0.1
Unknown/Accident	7600–9999	11.1

Notes: The table shows diagnosis code groups, corresponding primary diagnosis codes in the DRF and percentages of applicants for each group for the years 1991–2008. The classification of primary diagnosis codes into diagnosis code groups is based on Appendix C of Panis et al. (2000). Unknown diagnosis codes also include all codes in between the primary diagnosis code blocks that correspond to RAND's diagnosis groups (e. g., code 1400).

Table 4: Comparison of earnings and employment of denied applicants to Von Wachter, Song, and Manchester (2011).

Von Wachter, Song, and Manchester (2011)		Our sample
<i>Rejected male 1997 applicants age 45–64, 2 years after application</i>		
Percent positive earnings	52.6	45.9
Average annual earnings	7,639	7,031
Median positive annual earnings	10,000	11,144
<i>Rejected male 1997 applicants age 30–44, 2 years after application</i>		
Percent positive earnings	69.6	67.1
Average annual earnings	8,440	9,676
Median positive annual earnings	8,000	11,325

Notes: All monetary values are expressed in 1997 dollars. Results from Von Wachter, Song, and Manchester (2011) are from Table 1, year 1997, rejected applicants.

Table 5: Regression results for earnings and employment.

Year relative to appl. year	Earnings			Employment		
	Mean	Level	Log	Mean	Level	Log
–10	14,921	–43.52 (123.66)	–0.18 (0.80)	75.9	0.27 (0.24)	0.36 (0.32)
–9	15,284	45.39 (109.48)	0.27 (0.65)	77.9	0.34 (0.18)	0.41 (0.23)
–8	15,623	159.56 (91.65)	0.87 (0.52)	79.7	0.31 (0.17)	0.35 (0.22)
–7	15,834	248.11** (83.84)	1.40** (0.48)	81.1	0.37* (0.18)	0.44 (0.24)
–6	15,833	274.66*** (68.33)	1.61*** (0.40)	81.7	0.36 (0.21)	0.44 (0.27)
–5	15,648	232.20** (75.33)	1.47** (0.52)	81.5	0.22 (0.28)	0.28 (0.35)
–4	15,280	119.19 (115.96)	0.89 (0.76)	80.5	–0.15 (0.35)	–0.17 (0.44)
–3	14,632	–43.23 (136.29)	–0.02 (0.87)	78.6	–0.51 (0.39)	–0.64 (0.49)
–2	13,363	–250.92 (145.45)	–1.43 (0.91)	75.1	–1.00* (0.40)	–1.33* (0.52)
–1	10,453	–378.11** (121.23)	–3.19*** (0.81)	68.8	–1.50*** (0.37)	–2.21*** (0.52)
0	5,317	–249.86*** (57.89)	–4.13*** (0.61)	58.3	–1.73*** (0.31)	–2.90*** (0.47)
1	6,440	–321.80*** (68.18)	–4.18*** (0.66)	53.6	–1.42*** (0.31)	–2.50*** (0.52)

2	8,137	−305.05*** (73.67)	−3.16*** (0.61)	55.3	−1.09*** (0.29)	−1.80*** (0.47)
3	8,614	−161.83* (69.47)	−1.66* (0.76)	53.3	−0.39 (0.33)	−1.07* (0.45)
4	9,783	−100.54 (100.07)	−0.66 (0.85)	56.7	−0.51 (0.28)	−0.58 (0.48)
5	10,222	−68.13 (107.81)	−0.48 (0.92)	56.5	−0.42 (0.28)	−0.45 (0.48)

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Notes: Each cell of the third, fourth, sixth and seventh column represents a separate regression and displays the coefficient for the unemployment rate with the dependent variable being earnings or employment during a year X relative to the application year as dependent variable, where X is the number shown by the first column. Earnings are expressed in 2010 dollars. All regressions use the number of applications of a state per period as weights and include state fixed effects, year fixed effects, and state fixed effects interacted with linear time trends. Standard errors are clustered at the state level and displayed in parentheses below corresponding coefficients. Mean values refer to weighted averages over all states and the time period 1991–2008. The sample size for all regressions is 936.

Thus far, we have ignored the effect of waiting time on earnings and employment. However, Autor et al. (2015) estimate that employment and earnings of DI applicants decreases as a result of a longer waiting time; they call this the “decay effect.” The decay effect implies that earnings and employment of denied and accepted applicants is higher before they apply for the program and therefore is part of the program effect, i. e., the negative effect of applying for DI on subsequent labor market outcomes. The decay effect is important in this context because the waiting time *decreases* with the unemployment rate (see Table 6), implying that the decay effect decreases with the unemployment rate as well.

Table 6: Regression results for application outcomes and the unemployment rate.

Variable	Mean	State-specific FE Level	Applicants' characteristics
Application duration (days)	162.3	−2.24 (1.61)	−3.49** (1.33)
Accepted at initial determination (%)	40.6	−1.40*** (0.36)	−0.52* (0.23)
Accepted at final determination (%)	57.5	−0.84*** (0.22)	−0.37** (0.14)
Accepted including future determinations (%)	65.5	−0.77*** (0.18)	−0.38** (0.12)
Application duration (days)	162.3	Log −1.08 (0.87)	−1.95* (0.77)

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Notes: Each cell of the third and fourth column represents a separate regression and displays the coefficient for the unemployment rate in a regression with the dependent variable as given by the first column. All regressions use the number of applications of a state per period as weights. Regressions with state-specific fixed effects (third column) include state fixed effects, year fixed effects, and state fixed effects interacted with linear time trends. Regressions with applicants' characteristics (fourth column) include these fixed effects and also the following covariates: number of applicants in basis points; average age of applicants, fraction of male applicants, fraction of applicants classified as white, fraction of applicants with a high-school degree and with some college experience (base category: fraction of applicants with no high-school degree), fraction of applicants who apply for DI only, fraction of applicants whose initial application is determined at steps 3, 4, and 5 (base category: step 2), and the fraction of applicants in one of the diagnosis code groups (base category: infection). Mean values refer to weighted averages for the time period 1991–2008. Standard errors are clustered at the state level and displayed in parentheses below corresponding coefficients. The sample size for all regressions is 3,744.

How big is the change of the decay effect for accepted applicants? The decrease in the waiting time due to a one-unit change in the unemployment rate for accepted applicants is similar to that for all applicants, namely about two to three days. Autor et al. (2015) estimate that a one-month increase in application processing time

reduces employment by 0.47 points and earnings by \$133 three years after the initial decision. Therefore, a one-tenth of a month decrease in processing time would increase earnings by about \$15 and employment by about 0.05 points, which is between 5 and 10 percent of the marginal effects found for earnings and employment regressions (see Table 5). Therefore, including the decay effect in the above calculation would change the average log employment and earnings changes from -0.98 and -1.49 to about -0.88 and -1.00 , respectively, but $d \log(\bar{e}_a^*)/du$ would still remain negative.

6 Conclusions

In this paper, we examine how the composition of applicants for DI changes over the business cycle. Using panel data derived from the universe of all applications between 1991 and 2008, we find that a higher unemployment rate is associated with a higher number of applicants whose applications are determined at step 2, 4 or 5 of the initial determination process. The overall share of these applicants also increases with the unemployment rate, but the increase is concentrated among steps 2 and 4 applicants. These findings are consistent with the idea that the share of conditional applicants increases during economic downturns. However, the share of joint DI/SSI applications increases with the unemployment rate, and average post-application employment and earnings of denied are negatively related to the unemployment rate. Together, these findings suggest that adverse economic conditions both increase the share of conditional applicants and decrease their employment and earnings prospects. We propose a simple model that includes these two effects and use it to calculate how the disincentive effect changes with the unemployment rate. Our calculations suggest that the disincentive effect also declines with the unemployment rate.

Regarding the design of the DI program, our study suggests that a large number of the additional people who apply during recessions are quickly rejected at steps 2 and 4 of the initial application determination, only to be admitted to the program later. Instead of going through the lengthy appeals process that might further diminish their chances of finding new employment, it might be better to provide short-term financial support together with re-employment services to them. However, people who apply during recessions also appear to face severe barriers to employment even if they are on average less disabled than people who apply during non-recession periods. Therefore, providing adequate training and other services to reintegrate these people into the labor market instead of simply letting them slip into the DI program could be challenging.

This figure shows trends in the unemployment rate and applications per population for DI. The unemployment rate (dashed line) is expressed in percentage points as shown on the left y-axis. Applications per population for DI (solid line) are expressed as one hundredth of a percentage point, or one part per 10,000 (basis points) as shown on the right y-axis. Population is the number of people age 20 to 64. Both trends are by calendar quarters and seasonally adjusted.

These figures display the relationship between the unemployment rate and past and future earnings of denied applicants. Each point represents results from a separate regression with earnings during year X relative to the application year as dependent variable, where X is the number on the x-axis, ranging from 10 years before to 5 years after the year of application. Regressions include the unemployment rate as well as state fixed-effects, year fixed effects, and state fixed effects interacted with linear time trends. Points show estimates for the unemployment rate. Figure 2(a) shows results for level or earnings and Figure 2(b) shows results for log of earnings. Dashed lines indicate 95 percent confidence intervals. All standard errors are clustered at the state level.

These figures display the relationship between the unemployment rate and past and future employment of denied applicants. Each point represents results from a separate regression with employment during year X relative to the application year as dependent variable, where X is the number on the x-axis, ranging from 10 years before to 5 years after the year of application. Regressions include the unemployment rate as well as state fixed-effects, year fixed effects, and state fixed effects interacted with linear time trends. Points show estimates for the unemployment rate. Figure 3(a) shows results for level or employment and Figure 3(b) shows results for log of employment. Dashed lines indicate 95 percent confidence intervals. All standard errors are clustered at the state level.

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Notes

¹For relevant literature on DI's disincentive effect, see for instance Bound (1989), Bound and Burkhauser (1999), Chen and Klaauw (2008), French and Song (2014), and Maestas, Mullen, and Strand (2013).

²In a related article, Von Wachter, Song, and Manchester (2011) investigate changes to the composition of denied applicants between 1981 and 1999 and find that the fraction of younger applicants and beneficiaries increased between the early 1980s and early 1990s. These compositional changes have increased post-application earnings and employment of denied applicants because younger applicants have higher post-application earnings and employment than older applicants.

³Ben-Shalom and Mamun (2015), using a sample of DI beneficiaries, report that these beneficiaries are less likely to meet return-to-work milestones during times of economic expansion. This result is consistent with our observed shift toward applicants with higher work capacity.

⁴The substantial gainful activity (SGA) amount is \$1,130 per month for the non-blind and \$1,820 for the blind in 2016 (see <http://www.ssa.gov/OACT/COLA/sga.html>, last accessed: 7/20/2016).

⁵See <http://www.ssa.gov/disability/professionals/bluebook/AdultListings.htm> (last accessed 7/20/2016).

⁶Specifically, a case worker uses an applicant's previously assessed residual work capacity along with vocational factors to determine whether the applicant can or cannot perform alternative work. For instance, a case worker might reject an applicant with high school degree who is less than 55 years old but might accept an applicant with the same health impairment who does not have a high school degree and is older than 55 years (Chen and Klaauw 2008).

⁷Case workers use a grid for this determination step that combines the residual functional capacity with vocational factors. Chen and Klaauw (2008) for details.

⁸The current asset limit is \$2,000 for individuals and \$3,000 for couples. Assets include accessible resources such as defined-contribution retirement accounts but exclude a claimant's house or car. The income limit depends on a claimant's sources of income.

⁹See Wixon and Strand (2013) for details.

¹⁰This data limitation exists because the first step is determined by SSA field workers and their records are not included in the DRF files. All other steps are determined by states' Disability Determination Services and their records are included in the DRF (Wixon and Strand 2013).

¹¹We aggregate individual application data for three reasons: first, the unemployment rate is measured at the state level and therefore, linear individual-level or state-level regressions produce the same estimates for the unemployment rate as explanatory variable as long as state-level regressions are weighted by the number of applicants per state and time (Solon, Haider & Wooldridge, 2013); second, we can calculate aggregate-level outcomes (such as the number of applications for various types of applicants) to examine both the share of applicants and the number of applicants from such groups in one, coherent framework; and third, estimating models with state-level panel data is much faster than estimating regression models with all 22.7 million individual records.

¹²We also create a number of other variables pertaining to characteristics of applicants and application outcomes. These include: Average age; percent male; percent white; percent high-school drop-outs / high-school graduates / applicants with college experience (we define educational groups as follows: high-school drop-outs: less than 12th grade completed; high-school graduates: 12th grade completed; some college: All others); percent of applicants with health limitation included in each of the diagnosis groups as defined by RAND's manual (see Panis et al. (2000) for more information about the RAND manual and Table 3 for a list of these diagnosis groups and prevalence in our data); percent accepted and denied at initial determination; percent accepted and denied at final determination after a possible appeal and after future re-applications; and average application duration.

¹³In Table 4, we compare employment and earnings estimates of rejected male applicants in 1997 as found in our study to results presented by Von Wachter, Song, and Manchester (2011). Employment rates (i. e., percent positive earnings) are lower in our study as compared to employment rates in their study, especially for younger applicants. Average earnings and median positive annual earnings are somewhat higher in our study as compared to such estimates in their study. This discrepancy likely occurs because von Wachter, Song, and Manchester use 10 years for re-applications and we only five.

¹⁴We also examined whether including earnings and employment of re-applicants changes our results and found no substantial differences.

¹⁵See for instance Hellerstein and Morrill (2011) for a similar approach in the context of divorce risk over the business cycle.

¹⁶We also estimate these regression equations using the log of the outcome variable to obtain semi-elasticities, i. e., percent changes in the outcome as it relates to a marginal change in the unemployment rate.

¹⁷Aside from applicants' characteristics, we also examine the relationship between the unemployment rate and application outcomes (i. e., application duration, acceptance at initial and final determination). For these outcomes we present results for regressions with and without applicants' characteristics as additional covariates because such characteristics might change with the unemployment rate and also affect application outcomes. We control for such confounding factors by including applicants' characteristics as additional controls as follows:

$$y_{st} = \mu + \beta_1 u_{st} + \gamma x_{st} + \eta_s + \eta_t + \eta_s \cdot t + \varepsilon_t, \quad (8)$$

where x_{st} are characteristics of applicants who apply in state s at time t . Characteristics included in the regression are: number of applicants, average age, average age squared, percent male, percent white, percent with a high-school degree, percent with some college, percent with joint DI/SSI applications and percent of applications within each of the diagnosis groups as shown in Table 3. Results are included in the appendix because they are only auxiliary to our main analysis.

¹⁸Parallel to eq. (8), we also estimate the relationship between earnings and employment and the unemployment rate with applicants' characteristics as additional covariates. For this specification, we also control for the fraction of applicants determined at each of the initial determination steps.

¹⁹Mean values are weighted averages over all time periods and states for the years 1991–2008 and therefore represent average values of the applicant population.

²⁰Step 3 is not shown as a separate group in this table because all of these applicants are accepted.

²¹Other results not shown in these tables are as follows. The number of applicants with musculoskeletal impairments or mental disorder, two diagnosis groups with low mortality rates, increases with the unemployment rate but their share does not. We also find that the number of applicants with circulatory impairments and neoplasms is positively related to the unemployment rate, two diagnosis groups that should show little change over the business cycle. Apparently, these broad diagnosis groups are too heterogeneous to identify well conditional applicants. Average age of applicants remains almost unchanged over the business cycle. This seems surprising because average age of applicants has declined over time as the program has grown (Von Wachter, Song & Manchester, 2011). One explanation for this discrepancy is that we focus on long-term, structural changes to the applicant population whereas we examine short-term changes due to economic conditions. Specifically, while younger workers see higher increases in unemployment during recessions (Brault 2012), the increase in unemployed workers who struggle to find new employment and consider applying for DI is plausibly relative balanced across age because unemployment duration and health limitations both increase in age (Abraham & Shimer, 2001; Brault, 2012).

²²Recall from Section 1 and Section 3 that financial eligibility is determined at step 1 and only applicants who pass this first step are included in the DRF. Therefore, all of the joint DI/SSI applicants in our data are financially eligible for SSI because of low income and assets.

²³Table 5 presents regression coefficients and mean values.

²⁴We also estimate earnings and employment regressions with applicants' characteristics (i. e., number of applicants, age, age squared, male, white, high-school degree, some college, joint DI/SSI application, diagnosis groups and initial determination steps). Results are fairly similar to those presented here and can be obtained from the authors upon request.

²⁵Alternatively, it would be consistent with our empirical results to assume that $\alpha_c(u) < 0$. Table 6 shows that the fraction of accepted applicants (including future determinations) decreases with the unemployment rate, and similar regressions for step 2, step 4 and step 5 applicants reveal that the relationship between the acceptance rate and unemployment rate is either negative (step 4 and step 5) or zero (step 2). Introducing a negative effect of the unemployment rate on the acceptance probability in the model would increase the compositional shift toward conditional applicants for denied applicants but decrease the compositional shift for accepted applicants.

²⁶The log change of the share of accepted applicants for a one-unit change in the unemployment rate is 5.96, 4.32 and -1.11 for steps 2, 4 and 5 applicants, respectively, whereas the log change of the share of denied applicants is 1.66, -0.02 and -0.21, respectively. We use shares of accepted and denied steps 2, 4 and 5 applicants to obtain weighted averages. For accepted applicants, these shares are (relative to the total number of accepted applicants) 6.9, 12.5 and 41.4 percent, respectively. For denied applicants, these shares are 29.9, 26.8 and 28.9 percent, respectively. Full table of these log specifications can be obtained from the authors upon request.

²⁷If only step 2 and step 4 applicants were to be considered conditional applicants, then the calculations would suggest a positive relationship between the unemployment rate and changes to the employment and earnings of accepted applicants were they not on the program. However, applications at step 5 are determined by vocational factors, which suggests that these applicants should be considered conditional applicants as well.

References

- Abraham, Katharine G., and Robert Shimer. (2001). National Bureau of Economic Research. DOI:October. "Changes in Unemployment Duration and Labor Force Attachment." Working Paper 8513.
- Autor, David, and Mark Duggan. 2010. *Supporting Work: A Proposal for Modernizing the U.S. Disability Insurance System*. Washington, DC: Center for American Progress and the Hamilton Project.
- Autor, David, Nicole Maestas, Kathleen Mullen, and Alexander Strand. (2015). "Does Delay Cause Decay? The Effect of Administrative Decision Time on the Labor Force Participation and Earnings of Disability Applicants." NBER Working Paper No 20840.
- Autor, David H., and Mark G. Duggan. 2003. "The Rise in the Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics* 118(1): 157–205.
- Ben-Shalom, Yonatan, and Arif A. Mamun. 2015. "Return-To-Work Outcomes Among Social Security Disability Insurance Program Beneficiaries." *Journal of Disability Policy Studies* 26(2): 100–110.
- Bound, John 1989. "The Health and Earnings of Rejected Disability Insurance Applicants." *American Economic Review* 79(3): 482–503.
- Bound, John, and Richard V. Burkhauser. 1999. "Economic Analysis of Transfer Programs Targeted on People with Disabilities." In *Handbook of Labor Economics*, edited by O. Ashenfelter, and D. Card, Vol. 3, 3418–3528. Elsevier Chapter 51.
- Bound, John, and Timothy Waidmann. 2002. "Accounting for Recent Declines in Employment Rates among Working-Aged Men and Women with Disabilities." *Journal of Human Resources* 37(2): 231–250.
- Brault, Matthew 2012. *Americans with Disabilities: 2010*. Washington, DC: U.S. Census Bureau.
- Chen, Susan, and Wilbert Van Der Klaauw. 2008. "The Work Disincentive Effects of the Disability Insurance Program in the 1990s." *Journal of Econometrics* 142: 757–784.
- Coe, Norma B., and Matthew S. Rutledge. (2013). "How Does the Composition of Disability Insurance Applicants Change across Business Cycles?" Center for Retirement Research at Boston College Working Paper No. 2013-5.
- Davis, Steven J., and Till Von Wachter. 2011. "Recessions and the Costs of Job Loss." *Brookings Papers on Economic Activity* 1–72.
- French, Eric, and Jae Song. 2014. "The Effect of Disability Insurance Receipt on Labor Supply." *American Economic Journal: Economic Policy* 6(2): 291–337.
- Hellerstein, Judith K, and Melinda Sandler Morrill. 2011. "Booms, Busts, and Divorce." *The B.E. Journal of Economic Analysis & Policy* 11(1).
- Hoynes, Hilary, Douglas L. Miller, and Jessamyn Schaller. 2012. "Who Suffers During Recessions?." *The Journal of Economic Perspectives* 26(3): 27–47.
- Lindner, Stephan 2013. "From Working to Applying: Employment Transitions of Applicants for Disability Insurance in the United States." *Journal of Social Policy* 42(2): 329–348.
- Maestas, Nicole, Kathleen Mullen, and Alexander Strand. 2013. "Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt." *The American Economic Review* 103(5): 1797–1829.
- Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand. 2015. "Disability Insurance and the Great Recession." *American Economic Review* 105(5): 177–182.

- Panis, Constantijn, Roald Euler, Cynthia Grant, Melissa Bradley, Christine E. Peterson, Randall Hirscher, and Paul Steinberg. 2000. *SSA Program Data User's Manual*. Baltimore, MD: Social Security Administration.
- Rupp, Kalman. 2012. "Factors Affecting Initial Disability Allowance Rates for the DI and SSI Programs: the Role of the Demographic and Diagnostic Composition of Applicants and Local Labor Market Conditions." *Social Security Bulletin* 72(4): 11–35.
- Rupp, Kalman, and David Stapleton. 1995. "Determinants of the Growth in the Social Security Administration's Disability Programs – An Overview." *Social Security Bulletin* 58(4): 43–70.
- (Social Security Administration) (2012). Annual Statistical Supplement to the Social Security Bulletin, 2012SSA Publication No. 13-11700.
- Solon, Gary, Steven J. Haider, and Jeffrey Wooldridge. (2013).. DOI:February. What Are We Weighting For? NBER Working Paper No 18859.
- Von Wachter, Till, Jae Song, and Joyce Manchester. 2011. "Trends in Employment and Earnings of Allowed and Rejected Applicants to the Social Security Disability Insurance Program." *American Economic Review* 101(7): 3308–3329.
- Wixon, Bernard, and Alexander Strand. 2013. "Identifying SSA's Sequential Disability Determination Steps Using Administrative Data." In *Research and Statistics Note*. Office of Retirement and Disability Policy /Office of Research, Evaluation, and Statistics (2013-01).

Appendix: Robustness Checks and Auxiliary Results

Application duration and outcome: Concerning application outcome, we present results for three measures: initial determination, determination including appeals, and determination including appeals and re-applications within 5 years. Table 6 first shows mean values, then results for regressions with state-specific fixed effects, and results for regressions that also include applicants' characteristics.²⁸ Both the application duration and the application success rate are negatively related to the unemployment rate. The coefficient for application duration becomes more negative when other covariates are included, whereas the coefficient for application success becomes less negative with such covariates included in the regression. Apparently, applicants who apply more frequently during economic downturns have a longer application processing time and lower application success chance. Still, coefficients for application duration and determination remain negative even after controlling for such compositional changes, suggesting that case workers process claims more quickly and tend to be slightly more strict during economic downturns.²⁹

Unweighted regressions: We estimate our regressions using no weights and find very similar results, as shown in Table 7 for applicant characteristics. A few coefficients are somewhat different as compared to Table 1. For instance, coefficients of the log of the share of high-school drop-outs and joint DI/SSI applications are more positive when no weights are used. However, we find no substantial differences for applications determined at step 5 and applicants with a musculoskeletal impairments or mental disorder. Overall, these results suggest that the relationship between short-term fluctuations of the unemployment rate and characteristics of applicants are similar across states.

Table 7: Regression results for applicant characteristics and the unemployment rate, unweighted regressions.

Variable	Estimate /SE
Applications (b.p.)	0.57*** (0.10)
Appl. for DI/SSI (%)	0.99*** (0.14)
Appl. for DI/SSI (b.p.)	0.45*** (0.07)
Step 2 applicants (%)	0.50* (0.21)
Step 2 applicants (b.p.)	0.15*** (0.04)
Step 3 applicants (%)	−0.56*** (0.15)
Step 3 applicants (b.p.)	0.05 (0.03)
Step 4 applicants (%)	0.51** (0.19)
Step 4 applicants (b.p.)	0.17*** (0.04)
Step 5 applicants (%)	−0.22 (0.20)
Step 5 applicants (b.p.)	0.20*** (0.06)

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Notes: Each cell of the second column represents a separate regression and displays the coefficient for the unemployment rate in a regression with the dependent variable as given by the first column. All regressions are unweighted and include state fixed effects, year fixed effects, and state fixed effects interacted with linear time trends. All variables are either expressed as percentage of all applicants or as basis points (number of applicants with that characteristic per ten thousand adults for a time period and state). Standard errors are clustered at the state level and displayed in parentheses below corresponding coefficients. The sample size for all regressions is 3,744.

Distributed lag models: Because many applicants for DI do not immediately file an application after losing their job (Lindner 2013), it is plausible that lagged values of the unemployment rate are also associated with applicants' characteristics and outcomes. We estimate models with two, four and six quarters of lags of the unemployment rate (for regressions with years as frequency we estimate one regression with one year as lag). Results for these distributed lag models are very similar to results from our main specification without lags. Table 8 presents regression results for applicant characteristics with six lags of the unemployment rate (we show summed lagged coefficients in the table). As expected, the correlation between the number of applications and the sum of the lagged unemployment coefficients is larger as compared to Table 1. In terms of coefficients, a few appear to be slightly larger with lags included (e. g., the log of the share of step 2 applications) but our main conclusions are robust to including such lags.

Table 8: Regression results for applicant characteristics and the unemployment rate: distributed lag model.

Variable	Estimate /SE
Applications (b.p.)	0.74*** (0.11)
Appl. for DI/SSI (%)	0.91*** (0.26)
Appl. for DI/SSI (b.p.)	0.53*** (0.09)
Step 2 applicants (%)	1.1*** (0.26)
Step 2 applicants (b.p.)	0.26*** (0.05)
Step 3 applicants (%)	−0.81*** (0.19)
Step 3 applicants (b.p.)	0.03 (0.04)
Step 4 applicants (%)	0.48 (0.30)
Step 4 applicants (b.p.)	0.18** (0.07)
Step 5 applicants (%)	−0.53 (0.37)
Step 5 applicants (b.p.)	0.26* (0.11)

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Notes: Each cell of the second column represents a separate regression and displays the coefficient for the summed unemployment rate coefficients in a distributed lag regression with the dependent variable as given by the first column and six quarters of lags for the unemployment rate. All regressions use the number of applications of a state per period as weights and include state fixed effects, year fixed effects, and state fixed effects interacted with linear time trends. All variables are either expressed as percentage of all applicants or as basis points (number of applicants with that characteristic per 10,000 adults for a time period and state). Standard errors are clustered at the state level and displayed in parentheses below corresponding coefficients. Mean values refer to weighted averages over all states and the time period 1991–2008. The sample size for all regressions is 3,744.

Including years of the Great Recession: We have excluded years of the Great Recession available to us (2009 and 2010) for our main analysis because an increasing fraction of applications filed during these years are still pending. Still, we can estimate regressions for characteristics of applicants with these years included to see whether our main results are robust to including years with much higher unemployment rates and application numbers. Table 9 displays these results. The correlation between the unemployment rate and applications for DI is somewhat smaller as compared to Table 1 and so are most coefficients. Step 2 and 4 applications still rise with the unemployment rate but the coefficient for the relative change in the share of step 4 applicants is now not statistically significant (albeit still substantial). The negative relationship between step 5 applications and

the unemployment rate is smaller, however, the coefficient for the change in the relative share of applicants with musculoskeletal impairments is more negative. These differences suggest that changes to applicants' characteristics during the Great Recession might be different compared to earlier period of economic downturn. Future research could look more carefully at the Great Recession when sufficient post-recession data is available.

Table 9: Regression results for applicant characteristics and the unemployment rate, 1991–2010.

Variable	Level
Applications (b.p.)	0.50*** (0.10)
Appl. for DI/SSI (%)	0.67*** (0.12)
Appl. for DI/SSI (b.p.)	0.35*** (0.07)
Step 2 applicants (%)	0.53*** (0.16)
Step 2 applicants (b.p.)	0.14*** (0.04)
Step 3 applicants (%)	−0.40** (0.14)
Step 3 applicants (b.p.)	0.05 (0.03)
Step 4 applicants (%)	0.18 (0.20)
Step 4 applicants (b.p.)	0.11* (0.04)
Step 5 applicants (%)	−0.28 (0.23)
Step 5 applicants (b.p.)	0.17* (0.07)

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$.

Notes: Each cell of the second column represents a separate regression and displays the coefficient for the unemployment rate in a regression with the dependent variable as given by the first column. All regressions are weighted and include state fixed effects, year fixed effects, and state fixed effects interacted with linear time trends. All variables are either expressed as percentage of all applicants or as basis points (number of applicants with that characteristic per ten thousand adults for a time period and state). Standard errors are clustered at the state level and displayed in parentheses below corresponding coefficients. The sample size for all regressions is 4,160.