Disability Insurance Benefits and Labor Supply Decisions: Evidence from a Discontinuity in Benefit Awards

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Disability Insurance Benefits and Labor Supply Decisions:
Evidence from a Discontinuity in Benefit Awards[*]

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Abstract

This paper explores the effects of disability insurance (DI) benefits on the labor market decision of existing DI beneficiaries using data from the Swiss Household Panel. We use a fuzzy regression discontinuity (RD) design to identify the effect of DI benefits on the decision of working full-time, part-time or staying out of the labor force by exploiting a discontinuity in the DI benefit award rate. Overall, our results suggest that the Swiss DI system creates substantial lock-in effects which heavily influence the working decision of existing beneficiaries: the benefit receipt increases the probability of working part-time by about 41%-points, decreases the probability of working full-time by about 42%-points but has little or no effects on the probability of staying out of the labor force for the average beneficiary. Therefore, DI benefits induce a shift in the labor supply of existing beneficiaries in the sense that they reduce their work intensity from working full-time to part-time adding a possible explanation for the low DI outflow across the OECD.

JEL Classification: J2, C35

Keywords: Disability insurance benefits, Fuzzy regression discontinuity design, Labor market participation, Endogenous switching models, Maximum simulated likelihood

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1 Introduction

In most industrialized countries the costs of disability insurance (DI) programs are substantial in size and therefore place a serious fiscal burden on countries' finances. Many workers leave the labor market permanently due to health issues driving both the inflow and stock of DI beneficiaries. In fact, the number of DI benefit recipients as a share of the working age population (the disability recipiency rate) has risen rapidly over the past few decades across the OECD: from 1970 to 2013 the average annual growth rate in disability recipiency was at a level of 3.10% in the United States; 2.08% in Great Britain; 2.98% in Australia and 2.69% in Sweden (Burkhauser *et al.*, 2013). Growth can also be seen in Switzerland where the number of beneficiaries has risen from 199'000 in 2000 to 230'000 in 2013 (average annual growth rate of 1.1%). Of course, these growing trends in DI beneficiaries are also reflected in the national DI expenditure levels. For instance, the DI cash transfer payments totaled in the United States $25 billion in 1990, rising to a level of $140 billion in 2013 (Social Security Administration, 2015). Likewise, the expenditure figures in Switzerland show a similar but less dramatic pattern, jumping from 4.1 billion Swiss Francs in 1990 to 9.3 billion Swiss Francs in 2013 (Federal Social Insurance Office, 2015).

As a response to the unsustainable growth in program costs and the exploding number of beneficiaries, policy makers have introduced various reforms addressing the incentive structure of the DI programs. However, recent DI policy has mostly been focused on reducing the inflow of new DI beneficiaries by offering employment creating measures such as job placement and career advice for people applying for DI benefits. At the same time, most OECD countries have tightened the access to benefits and reduced compensation generosity over the past two decades. Despite these political efforts, very little has been done to address the stock of existing beneficiaries, which is surprising given the fact that the DI outflow for reasons other than death is as low as 1% across the OECD (OECD, 2010). What this low outflow suggests is that most DI programs create substantial lock-in effects given that beneficiaries rarely leave the DI system once they receive benefits, even though some of them might have a significant remaining work-capacity. Economic theory suggests here a classical moral hazard issue: individuals who receive high disutility from working remain out of the labor force permanently since the DI system redistributes resources to them so that there is no need to continue working (Bound & Burkhauser, 1999).

In light of the above, it is important to learn more about the mechanisms and determinants contributing to the low DI outflow. In this paper, we analyze how existing beneficiaries adapt their labor force participation (LFP) decision as a response to the financial incentives embodied in the Swiss DI system. Understanding the underlying incentive structure of the DI system is key in order to eliminate poor incentives, reduce DI spending and shape the system future reforms.

From an econometrician's point of view, an important issue when estimating working decisions is to address the endogeneity in the DI benefit status. Endogeneity is a problem in this context because participation in DI programs is the outcome of an individual decision to apply for the benefits. Furthermore, benefit applicants have to undergo an eligibility determination process that is based on a list of predefined medical and vocational criteria. As a consequence, comparing the working decision of beneficiaries and non-beneficiaries will be confounded by the differences in observable and unobservable characteristics which exist between the groups. In this paper, we address the endogeneity issue in the DI benefit status by using a fuzzy regression discontinuity (RD) design exploiting a discontinuity in the benefit award rate. The discontinuity in the benefit award rate arises due to the common practice of DI offices using the age of an applicant as a key factor when deciding the DI benefits (Chen & van der Klaauw, 2008). Individuals above the age of 55 are much more likely to receive DI benefits than people below. Given that applicants cannot manipulate their age, the discontinuity in the benefit award rate qualifies as a valid exogenous instrument for the DI benefits. Specifically, we use discrete endogenous switching (ES) models (Miranda & Rabe-Hesketh, 2006; Roodman, 2011) to estimate the benefit effects on the labor market decision regarding working part-time, full-time or staying out of the labor force for existing beneficiaries. A special feature of the discrete ES models is that, under the assumption of jointly normal errors, they allow one to estimate unconditional average treatment effects (ATE), as well as average treatment effects on the treated (ATT). In sharp contrast to that, 2SLS and therefore the classical fuzzy RD design only produce local average effects (Angrist & Pischke, 2009).

One practical issue with discrete ES models is that they result in rather complicated likelihood functions which have to be maximized using maximum simulated likelihood[1] (MSL). The fact that these methods are not part of the toolkit of standard econometrics and the corresponding estimators are usually not implemented in statistical software packages might explain why this type of model is rarely used in applied econometrics. To the best of our knowledge, this paper is the first to look at the effects of DI benefits on labor supply through the lense of discrete ES models.

Another contribution of this paper is to analyze the discrete labor market participation decision of working part-time, full-time or staying out of the labor force instead of focusing on the binary decision of working versus not working. The existing literature entirely focuses on the latter (e.g. Parsons (1980), Bound (1989), Gruber (2000), Chen & van der Klaauw (2008)) neglecting the fact that many people are part-time employees, which is especially true in the population of people with a disability (OECD, 2010). Therefore, modeling the more complex discrete working decision has the potential to reveal interesting new facets of the incentive effects embodied in DI benefits.

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[1] The focus will be on the Geweke, Hajivassiliou and Keane (GHK) algorithm that allows estimating higher-order dimensional cumulative normal distributions (Roodman, 2011).

Overall, the results of this analysis show that the financial incentives in the Swiss DI system create substantial lock-in effects that heavily influence the working decision of existing beneficiaries. In fact, the discrete ES model shows an interesting new aspect which could not be captured when focusing on simple binary working decisions: the individual benefit receipt significantly increases the probability of working in a part-time job (ATT: 41%-points), reduces the probability of working full-time (ATT: –42%-points) but has little or no effect on the probability of staying out of the labor force (ATT: 3%-points). This allows for the interpretation that the incentives inherent in DI benefits do not force the beneficiaries out of the labor force but instead induces a shift in their LFP decision from working full-time to part-time.

The paper proceeds as follows. In the next section 2, we give an overview on the different identification strategies that have been used in the literature. Then, we discuss the structure of the Swiss DI system and give information on the eligibility determination process which is relevant for the identification strategy used in this paper. Section 4 describes the data set and variables that are used for the analysis and sheds light on the population of beneficiaries. The identification strategy, validity checks, the discrete ES model and estimation procedure is then outlined in Section 5. Section 6 provides an in-depth overview of the main results and robustness checks. Final conclusions are drawn in Section 7.

2 Literature Review

Different identification strategies have been used in the past to model the behavioral response to DI programs. Most of the earlier empirical studies ignored the endogeneity issue as outlined above and concentrated on estimating LFP equations using standard regression techniques.

Parsons (1980a, 1980b) uses cross-sectional data from the National Longitudinal Survey of Older Men to estimate the non-labor-force-participation as a function of the SSDI[2] replacement rate and demographic and health characteristics such as age, gender, education and health status. He obtains an elasticity of labor force non-participation with respect to benefit levels[3] for prime-aged men (age 45-59) of between 0.49 (1980a) and 0.93 (1980b) using a classical logit specification to estimate his LFP equations. One major drawback of the two studies is that the replacement rate, i.e., the Social Security benefits relative to the market wage is based on imputed wage histories which determine an individual's Social Security benefit level in the US.

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[2]The social security disability insurance (SSDI) program is one of the two main federal programs to provide cash assistance to the disabled in the US. The other program is the supplemental security income (SSI) program that was introduced in 1972 to provide a minimum level of income to impaired individuals (Social Security Administration, 2014).

[3]The elasticity of non-participation with respect to benefits is defined as the ratio of the change in the labor supply relative to the change in potential benefits (Gruber, 2000).

Slade (1984) reproduces Parsons' (1980a, 1980b) findings but uses instead data from the Retirement History Survey (RHS) in which individual responses were matched to actual Social Security earnings records. He estimates an elasticity of non-participation of 0.81, implying a drop in the labor market participation of 0.81% for every 1% increase in the SSDI replacement rate.

These early studies encounter at least three econometric problems: (i) Endogeneity in the DI receipt is not addressed which leads to inconsistent and biased coefficient estimates on the replacement rate variable (Bound, 1989); (ii) By grouping the disability pension and wages into one single measure (the replacement rate), the separate impact of each is confounded by the other; (iii) In the US, the actual amount of disability benefits depends on a person's earnings history, thus generating a correlation between the level of benefits and past earnings, leading to additional omitted variable bias on the replacement rate (Chen and van der Klaauw, 2008).

One of the earliest attempts to deal with the endogeneity issue can be found in the study by Haveman and Wolfe (1984) who use a two stage least-squares approach. They calculate elasticities of participation with respect to expected invalidity benefits of between -0.0003 and -0.0005. In addition, they report predicted LFP rates at the mean of all explanatory variables, that suggest that a 20% increase in benefits decreases participation from 91.37% to 90.73%. While the studies by Parsons (1980a, 1980b) and Slade (1984) suggest a virtually one-for-one drop in participation rates, the IV estimates of Haveman and Wolfe (1984) suggest not much of an impact at all. The major problem with the latter study is that the authors fail to provide a convincing justification for their exclusion restrictions required in order to generate plausible instruments (Bound, 1989).

Other studies propose a fairly different and yet simpler approach to capture the effects of disability insurance benefits on LFP by comparing participation rates of disability payment recipients to appropriate comparison groups. Gastwirth (1972) uses the 1966 Survey of the Disabled to obtain an estimate of how many of those on SSDI might work if they were not receiving benefits. For that purpose, he compares the beneficiaries to the group of men with work impairments who received no income transfers. His empirical work suggests that about 87% of men in the latter group were in the labor force which he argues to be an upper bound for the proportion of recipients who would work in the absence of SSDI.

However, Swisher (1973) argues that the findings by Gastwirth (1972) clearly exaggerate the potential work disincentive effects of SSDI. She emphasizes the fact that in the 1966 Survey of the Disabled, only 27.3% of the men who reported to be disabled were severely disabled, 28.5% were occupationally disabled and the remaining 44.2% reported secondary work limitations. At the same time, the vast majority of men on SSDI claim to be severely disabled. From that she concludes that Gastwirth (1972) should have only included the severely disabled men who were not on the payroll as a credible control group for the SSDI recipients. Her findings show that only 44% of the control

group participated in the labor market and only a small fraction of them worked full-time the whole year (10.4%) (Bound and Burkhauser, 1999).

To summarize the magnitude of the potential work disincentives of the SSDI program crucially depends on the selected comparison group. If the comparison group contains all men who are to a certain extent impaired but do not receive any income transfer, then we would conclude that DI benefits heavily influence the individual labor force and work decision. On the other hand, if the relevant comparison group only includes the severely disabled who are not receiving benefits, the labor supply effects seem to be much less pronounced.

One of the most influential papers to this day is the study by Bound (1989) on "The Health and Earnings of Rejected Disability Insurance Applicants". Bound suggests that SSDI applicants who fail to pass the medical screening necessary to qualify for the program form a natural control group for the beneficiaries. As a rationale, he argues that the rejected SSDI applicants and beneficiaries should be quite similar with respect to observed and unobserved characteristics, thus making them comparable in their LFP decision. Using data from the 1972 Survey of Disabled and Non-Disabled Adults (SDNA) and the 1978 Survey of Disability and Work (SDW), his analysis shows that less than one-third of the rejected applicants were working at the time of the survey and less than 50% worked at some point the previous year. In addition, he finds that the earnings of those who do return to work are roughly 30% below pre-disability levels and more than 50% below their ablebodied counterparts. Bound argues that the rejected applicants are healthier and more capable of work than those who receive an income transfer. Therefore, their LFP rate forms an upper bound for the work participation behavior of the beneficiaries in the absence of the invalidity payments.

More recent studies use natural experiments to shed light on the labor force participation effects of DI benefits. For example, Gruber (2000) exploits a huge policy change in the Canadian DI system in the late 1980s. DI in Canada operates basically the same way as it does in the US but with the key difference that there are two distinct DI programs: the Quebec Pension Plan (QPP), which covers only the region of Quebec and the Canada Pension Plan (CPP), which covers the remaining regions of Canada. Until 1986, the QPP was substantially more generous in terms of benefits than the CPP. Then, in 1987, the CPP raised its benefits by 36% to the level of the QPP to equalize the generosity levels of the two systems. Gruber uses this exogenous policy change in disability benefits to estimate its labor supply effects using a difference-in-differences (DID) approach. The comparison in the change in the labor force participation of prime-aged men in Quebec to those in the rest of Canada over the period from 1985 to 1989 implies an elasticity of non-participation with respect to benefit levels of between 0.28 and 0.36. He concludes that the policy change and therefore the increase in benefit levels did not simply distort labor supply decisions but also induced positive welfare effects for those now qualified for the more generous disability transfers since replacement rates in Canada were historically much lower than in the US.

Campolieti (2004) follows the path by Gruber to examine a $50 increase in monthly disability benefits on labor supply for the QPP program in 1973, which did not occur in the CPP program. She uses the same empirical strategy as Gruber, but unlike Gruber her estimates mostly suggest that disability benefits are not associated with higher non-participation rates of older men. Campolieti argues that the differences in estimates to Gruber (2000) can be mostly explained by the changes in the screening stringency regimes between the 1970s and 1980s.

Chen and van der Klaauw (2008) use a fuzzy regression discontinuity (RD) approach to exploit a special feature of the eligibility determination process in the US DI program: both the SSDI and SSI program base their disability determination decision for some individuals not solely on medical grounds but also on vocational factors (age, education and work experience) as well. They use the fact that the award rate (the probability of receiving benefits) is a function of the age of an applicant which is discontinuous at known age levels. The rationale is that individuals just below the cutoff age can be expected to be fairly similar to individuals just above the cutoff age in terms of observed and unobserved characteristics. Therefore, comparing the two groups around the cutoff age with respect to their LFP reveals the causal effect of the DI benefit receipt. Overall, they find relatively small distorting effects: the LFP rate of beneficiaries would have been at most 20%-points higher had they not received benefits.

Another strand of the literature examines the effects of stricter screening of applicants and tighter eligibility rules on LFP. The idea here is that policy changes affecting either screening stringency or eligibility rules that apply only for a subset of the population can be used to quantify potential participation effects of DI benefits for that group. The study by Staubli (2011) analyzes the impact of a tightening in disability eligibility rules on the labor supply of older workers in Austria. He uses the policy change introduced by the Structural Adjustment Act in 1996 which most importantly lead to stricter disability eligibility criteria for men at the age of 55 to 57 to examine (i) how tighter criteria for benefits affect enrollment and employment and (ii) whether a tightening in eligibility rules leads to spillover effects into other programs. Relying on a DID approach, he finds that the share of beneficiaries in the affected age group significantly decreased by 6 to 7.2%-points after the reform was implemented. In addition, his estimates indicate an increase in employment by 1.7 to 3.4%-points after the policy change. At the same time, his results suggest a raise in the share of individuals receiving unemployment or sickness insurance benefits indicating substantial spillover effects.

Similarly, Karlström et al. (2008) exploit a policy change that tightened eligibility rules for older workers in Sweden. Unlike Staubli (2011), they find only small declines in the DI enrollment and no effects on employment. The main reason for such differences can be found in the difference of the marginal applicant in Sweden versus Austria. Studies concerning the effects of screening stringency on LFP have been done for the case of the US by Gruber and Kubik (1997) and Autor and Duggan

(2003). The US studies are conclusive since they both find that stricter screening leads to significant increases in labor supply among older males.

Finally, the study by De Jong *et al.* (2010) is a rare and therefore special example of an empirical study in the field of economics where they use a field-experiment to investigate the effects of intensified screening of DI benefit applications on the working decision in the Netherlands. The experiment was designed such that in two of the 26 Dutch regions, case workers of the National Social Insurance Institute (NSII) were instructed to screen DI benefit applications more intensely. They find that intensified screening leads to a significant decrease in both 13 weeks sickness absence reports and DI applications. Moreover, their experiment does not show any spillover effects to the inflow into unemployment insurance. Using a crude cost-benefit analysis, they conclude that the benefits of the intensified screening clearly exceed its costs.

3   Institutional Background

The Swiss DI is a nationwide, compulsory social insurance that provides rehabilitation measures and cash benefits for Swiss citizens who are disabled. As the social security disability insurance (SSDI) program in the United States, it is mainly financed by social insurance contributions of the working population and public funding. In 2012, the Swiss DI accounts for about 6.5% of the total social security expenditures in Switzerland and is therefore the fourth biggest branch in the Swiss social security system, after sickness insurance (16.5%), old-age insurance (27.2%) and occupational pension plans (33.3%) (FSIO, 2014). Swiss citizens are eligible for benefits if there is a causal connection between the impairment to health[4] and the corresponding earnings loss. Furthermore, residence of Switzerland are only entitled to DI payments if the working incapacity has lasted for at least a year and is likely to persist and the rehabilitation option has been entirely exhausted.

To this day, the DI remains a prominent topic in the political discourse which can be seen by the periodical reforms to the system: the 4th revision of the Swiss DI Act (2004) most importantly introduced regional medical screening institutions, abolished additional pensions for spouses and introduced the three-quarter pension. The more recent reforms are mostly focused on employment and reintegration measures: starting with the 5th revision in 2008, the leading principle of the Swiss DI was changed to *"rehabilitation before a pension"*, which broadly extended the range of possibilities to offer disabled individuals the proper incentives and support to stay in the labor market instead of depending entirely on DI benefits. Rehabilitation measures include medical measures to treat congenital disabilities, supply of appliances (wheel chairs, hearing aid devices, implants, etc.), occupational measures (career advice, re-training, vocational training, job placement, capital grants,

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[4]Any physical or psychological health impairment, irrespective whether it is congenital, illness-related or accident-related entitles claimants to DI benefits (FSIO, 2014).

etc.) and daily cash benefits as ancillary benefits (FSIO, 2013). However, the 5th revision was primarily focused on measures to reduce the inflow of DI beneficiaries. Measures to reduce the stock of existing beneficiaries were only introduced with the most recent DI revision in 2012 (revision 6a). The DI outflow is aimed to be increased by reassessing and possibly terminating existing cases with pathogenesis-etiologically unclear syndromes such as somatoform pain disorders, whiplash and hypersomnia among others (FSIO, 2015).

Even though the Swiss DI emphasizes the importance of reintegration measures, examining the DI statistics presents a slightly different picture: the 2013 statistics show that of the total expenditures of approximately 9.3 billion CHF, only 23% were spent on rehabilitation measures. The lion's share or 60.1% were used on DI pensions or helplessness allowances. A significant difference between the Swiss system and the SSDI program lies in the method to calculate the amount of the DI benefits: in Switzerland, the degree of disability determines the type of pension a claimant receives. The degree of disability is defined as the percentage of the loss of earnings due to disability ("Erwerbseinbusse") to the potential earnings of a claimant in the absence of the impairment ("Valideneinkommen"). Table (1) gives an overview of the types of pensions and minimum and maximum amounts that are associated with different degrees of disability. For example, claimants with a degree of disability less than 40% are not entitled to any pension at all, whereas claimants with a degree of disability higher than 70% are entitled to a full pension. Overall, the Swiss DI system is very generous in terms of benefits, ranking on a top spot alongside the Scandinavian countries. In comparison to that, many Anglo-Saxon countries are found on the other end of the compensation rank (OECD, 2009).

In 2013, a total of 402'000 Swiss residence received DI services including rehabilitation measures, benefits or helplessness allowances. Out of the 402'000 individuals, 230'000 received cash benefits and another 192'000 participated in reintegration measures. It is Important to know that about 75% of the pensions were full pensions. In our data, the share of beneficiaries receiving a full pension is at 72%. Furthermore, as in most Western societies, the probability of receiving disability pensions drastically increases for the group of prime-aged men and women in Switzerland. In numbers, about 60% of all recipients are aged between 40-64 and overall, about 16% (13%) of men (women) aged 60-65 are recipients of DI benefits. From an economic point of view, these numbers raise the question whether DI is used as means of early retirement or if it simply reflects the fact that the occurrence of illnesses increases as a part of the process of aging. At the same time, only 15% of recipients can be found among individuals aged 20-39. This age category primarily uses of job re-integration measures offered by local DI offices. Finally, the insured in the age group below 20 years account for about 25% of all recipients. In this age segment, congenital disorders are the main cause for the benefit receipt (FSIO, 2014).

3.1 Eligibility Determination Process

A person seeking benefits applies at the cantonal DI office. In a first step, the applicant submits the medical documentation of his condition, as well as his previous earnings records. Caseworkers at the local DI office in collaboration with an interdisciplinary team of medical doctors, specialists and vocational consultants then decide whether a person qualifies for benefits. Whether or not an applicant is eligible for benefits is based on a predefined set of medical and vocational factors such as education and age to assess a persons' capability to work. Before the 4th revision of the Swiss DI in 2004, the health assessment of the applicant was entirely based on the medical certificates issued by the applicant's chosen doctor. To standardize and improve the quality of screening, the reform in 2004 introduced several supra-regional medical audit institutions that are authorized to conduct appraisals of benefit claims and to carry out medical examinations. In addition to the medical assessment, a team of vocational consultants evaluates the personal and vocational situation of the applicant. The team has to check for possible reintegration and rehabilitation measures reflecting the guiding principle *"rehabilitation before a pension"*. After all the relevant information is gathered, the caseworkers have to decide on each case within 12 months. If the decision is not accepted by the applicant, appeals can be submitted to the cantonal insurance court within 30 days. Further levels of appeal are conducted in Federal Supreme Courts (FSIO, 2013).

4 Data

We use data from the Swiss Household Panel (SHP) for the year 2012. The SHP is especially suitable to analyze the financial incentives inherent in DI benefits on the working decision of existing beneficiaries because it offers two desirable features: *first*, it provides data on a stock of actual DI beneficiaries. Figure (1) gives an overview of the dynamics of the shares of DI beneficiaries in the whole sample as well as in different age groups since the year 2002. Overall, the share of beneficiaries is fairly stable at around 3.5% on average. However, figure (1) shows that there exist remarkable differences in the pool of recipients between age groups. The data set resembles what we observe in most OECD countries: prime-aged men and women are clearly over-represented amongst the beneficiaries. On average about 7.1% of individuals between the age of 55 and 65 collect DI pensions. In the subpopulation of individuals aged 20-54 on the other hand, only about 2.5% are entitled to benefits.

Second, the SHP contains rich information on numerous background characteristics which allow to isolate the effect of DI benefits on the labor supply decision of beneficiaries. The data set includes information on demographic, socio-economic and various health related indicators. The demographic and socio-economic status variables include the age of the respondent at the time of the interview, an

indicator for gender, dummies for region of residence[5], indicators for type of community[6], the weight of a person in kilograms, the height of a person in centimeters, the number of kids living in the household between the age of 0 and 17, an indicator for Non-Swiss citizens, marital status, logarithmized gross household income in Swiss Francs, years of schooling and an indicator for life satisfaction. The health indicators that we focus on in our analysis are: the number of doctor consultations and the number of ill-days in the past 12 months, a physical activity indicator, an indicator for health impediments in everyday activities, an indicator for medication needed in everyday functioning, a dummy for self-assessed well-being and indicator variables for depression, anxiety and blues, back problems, weakness and weariness, sleeping problems and headaches[7].

Throughout the entire analysis the sample is restricted to individuals between the age of 18 and 65, since there are no DI benefit recipients below and above these cutoff values. Moreover, the data cleaning procedure excludes all observations without accurate information such as filter errors, inapplicability, no answer or does not know. The final estimation sample contains 3'531 observations.

4.1 DI Beneficiaries vs. Non-Beneficiaries

Before turning to the identification strategy, it makes sense at this point to shed some light on the endogeneity issue concerning the benefit status by characterizing the subpopulation of DI beneficiaries. Table (2) reports the mean values and differences in means for a selection of variables for the DI beneficiaries and non-beneficiaries. The comparison of demographic characteristics reveals that the beneficiaries are on average significantly older, heavier in body weight, smaller in body size and live in households with less children than the non-beneficiaries. The difference in demographic characteristics brings home an important point: when comparing the working decision of recipients and non-recipients, one has to keep in mind that these groups differ along many dimensions besides their benefit status. In this context for example, we see that non-beneficiaries are much younger on average. At the same time, we know that younger individuals are more likely to be employed since they are usually more productive and typically earn less than their older counterparts. As a result, the difference in working behavior not only reflects the benefit effects but also the age differences[8]. Furthermore, the comparison of socio-economic characteristics suggests that the non-recipients are more educated than the recipients, as they attend school for about one and a half additional years on average. In addition to that, non-beneficiary households earn about 44'500 Swiss Francs more a year and the proportion of individuals who report to be satisfied with their life exceeds that of

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[5]Central Switzerland (Lucerne, Uri, Schwyz, Obwalden, Nidwalden and Zug) is used as the base category.

[6]Rural communes are chosen to be the base category.

[7]See Appendix A for a detailed description of the variable construction.

[8]Controlling for such age effects bears no econometric problem since the age of a respondent can be simply included in the analysis as a confounder. The more serious issue arises since there are many unobservable factors that differ between the two groups.

the beneficiaries by about 26%-points. Next, the comparison of the health indicators shows substantial differences between the groups: the beneficiaries visit the doctor about 3 times as often as the non-beneficiaries and the amount of ill-days is more than seven times as large as in the group of the non-beneficiaries. Moreover, the DI benefit recipients are significantly less involved in sports activities and the share of individuals reporting a "very well" or "well" health status is about 38%-points lower for the beneficiaries. In addition to that, more than 70% of beneficiaries claim to have health impediments that severely affect their everyday life and about 66% of them depend on medication to complete everyday tasks. As for the medical conditions, depression, anxiety and blues, back problems, weakness and weariness, sleeping problems and headaches, we find a significantly higher prevalence of such diseases in the group of beneficiaries. Overall, the data on the health indicators draws a consistent picture that suggests that the majority of those on DI benefits suffer from substantial health limitations.

The bottom line from this mean-comparison is that the population of beneficiaries differs substantially from the population of non-beneficiaries in many observable and unobservable[9] factors. Any attempt to compare the groups with respect to their working decision is therefore doomed to fail, since we are not comparing apples and apples but rather apples and oranges. Revealing the isolated effect of DI benefits therefore at least involves controlling for these observable characteristics.

5 Identification Strategy

The main purpose of this paper is to identify the effect of DI benefits on the labor market decision of existing DI beneficiaries. We apply a fuzzy regression discontinuity (RD) design exploiting a discontinuous jump in the benefit award rate at the age of 56 as an instrument for the individual benefit status. Specifically, we estimate the benefit effects on the individual decision to work part-time, full-time or stay out of the labor force using discrete endogenous switching (ES) models (Miranda & Rabe-Hesketh, 2006; Roodman, 2011).

5.1 Discontinuity in the Benefit Award Rate

The benefit award rate is the probability of receiving DI benefits in relation to a person's age and is depicted in figure (2). The dots represent the mean share of beneficiaries over bins of half-years of age. The scatter plot is overlaid with a linear fit and a corresponding 95%-confidence interval. The dashed red vertical line indicates the age of 56. The graph shows that for the individuals below the age of 56, the benefit award rate is roughly stable at a level of about 4-5%. Above the age of 55, the probability of receiving DI benefits is well above the 5%-mark indicating a discontinuous jump in the

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[9]Plausible candidates that are likely to differ between groups are factors such as risk preferences, genetic endowments, innate abilities, etc.

benefit award rate at the age of 56. This means that individuals just below that age cutoff have a significantly lower probability of receiving DI benefits than people just above the discontinuity. The discontinuity is also confirmed when running classical first stage regressions using the benefit status as the dependent variable. Table (3) shows the first stage effects for two different model specifications. In both cases, the discontinuity is estimated to be approximately 4%-points which coincides with the graphical evidence in figure (2). The Cragg-Donald Wald F-statistics are above the usual critical values rejecting the null of a weak instrument and therefore indicating instrument relevance (Stock & Yogo, 2005).

Why do we observe a discontinuity in benefit awards? As in most OECD countries[10], the eligibility determination process in Switzerland is explicitly based on both medical and vocational factors including the social situation and the age of an applicant (FSIO, 2013). The fact that local DI offices take into account such background characteristics when deciding the DI benefits leads to differences in the likelihood of receiving DI benefits for different subgroups of applicants. For example, individuals losing their job around the age of 55 have much bigger problems re-entering the job market than younger individuals. This is particularly true for unskilled workers where job reintegration measures are usually no valid option. In such cases, DI is often used as a substitute for early retirement which in turn explains the sharp increase in the share of beneficiaries above the age of 55[11].

5.2 RD Validity Checks

The key identifying assumption in any RD framework is based on the inability of individuals to precisely control the assignment variable near the threshold. Since applicants cannot manipulate their age, they have no control on whether they are to the left or the right of the cutoff at the age of 56 and thus those below form a natural control group for those above ("local randomization"). As a consequence, observable as well as unobservable characteristics are balanced around the cutoff and treatment is "as good as randomized" (Lee & Lemieux, 2009).

To assess the validity of the RD design we check for discontinuities in the forcing variable and baseline covariates. Both a discontinuity in the assignment variable and predetermined variables would cast doubt on the validity of the RD design and thus our identification strategy. A common check for local random assignment is given by investigating the density of the forcing variable around the threshold. To this end, we conduct the two-step procedure proposed by McCrary (2008) and the resulting density graph can be found in figure (3). The graph does not provide evidence for a

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[10]For example, Chen & van der Klaauw (2008) clearly show that the age of an applicant is a key factor in the benefit determination screening process in the United States.

[11]We talked to several heads of DI departments and they confirmed this common practice of DI being used as a substitute for early retirement.

discontinuity at the age of 56 as the confidence intervals clearly overlap reinforcing local random assignment.

As an additional validity check, we compare observable characteristics to see whether they are locally balanced around the cutoff. In fact, local random assignment implies that both observable and unobservable factors should not systematically differ between people below and above the cutoff. In table (4), we report differences in means for a selection of baseline covariates for individuals below and above the age threshold. If the full sample is considered, we see that those below the cutoff differ substantially from those above regarding their health, demographic and socio-economic background. This should not be a surprise since those below the cutoff are much younger and thus healthier than those above. However, as we compare people within a small range around the cutoff ($\pm$ 1 year), these differences in observables tend to vanish. Of course, the difference in the benefit award rate remains significant which is key for our identification of the benefit effects. Other than that, individuals below and above the cutoff are on average very similar to each other with respect to their health status, demographic and socio-economic characteristics. It is also interesting to see that the difference in annual benefit levels disappears which indicates that the beneficiaries below the cutoff are in fact comparable to those above.

Overall, the inspection of the density of the forcing variable and the baseline covariates supports the validity of the RD design and therefore reinforces our identification strategy.

5.3   The Discrete ES Model

Before going into detail about the structure of the discrete ES model, it is worth while mentioning some estimation issues at this stage since estimation of the model parameters is not trivial. The estimation of discrete ES models involves some complications since the likelihood function of the model cannot be expressed in closed-form. As a consequence, the model parameters have to estimated by maximum simulated likelihood (MSL). To simulate the labor market choice probabilities, we use the famous Geweke, Hajivassiliou and Keane (GHK) algorithm (Geweke, 1991; Hajivassiliou and McFadden, 1998; Keane, 1990 & 1994a) which has been proven to be the most accurate method to simulate normal probabilities in many studies (Hajivassiliou, McFadden & Ruud, 1994). As for the statistical properties of the MSL estimator, Gouriéroux & Monfort (1991) show that the MSL estimator is asymptotically equivalent to the maximum likelihood (ML) estimator and thus consistent under the condition that both the number of draws and the sample size approach infinity.

The discrete ES model is used to quantify the incentive effects of DI benefits on the discrete working decision of existing beneficiaries. The theoretical model is derived using the framework of additive random utility models (ARUM) providing a natural connection to economic choice theory (Marschak, 1960). It is assumed that each decision maker i faces three working choices: y_i

ϵ {working part-time ($j = 1$), full-time ($j = 2$) or staying out of the labor force ($j = 3$)}. Furthermore, agents are assumed to be rationale in the sense that they choose the alternative that is associated with the highest utility for them. Utility is known by the decision maker but not by the researcher. The researcher only observes some attributes of the agent and the final working decision the individual makes (Train, 2009). In this model, utility for individual i from working option j is specified as:

$$U_{ij} = x_i'\beta_j + D_i\gamma_j + \varepsilon_{ij} \qquad \forall \qquad j = 1, 2, 3; \ n = 1, ..., N \tag{1}$$

where x_i is a vector of observable characteristics including the health indicators, demographic and socio-economic factors described in section 4; $D_i \ \epsilon \ \{0, 1\}$ is the binary treatment indicator for the DI benefits; $\theta_j \equiv \{\beta_j, \gamma_j\}$ is the vector of model parameters and ε_{ij} includes all unobserved factors that have an effect on utility but are not included in x_i. A binary threshold crossing model is introduced to address the endogeneity in the benefit status:

$$D_i^* = w_i'\delta + v_i \qquad\qquad (i = 1, ..., N) \tag{2}$$

$$D_i = \begin{cases} 1 & \text{if } D_i^* > 0 \\ 0 & \text{if } D_i^* \leq 0 \end{cases}$$

where D_i^* is a continuous, latent random variable reflecting the net utility from the DI benefit receipt; w_i is the vector of exogenous variables which are the same as in x_i but in addition to that, w_i includes the age cutoff as instrumental variable for the benefit status; δ is the vector of parameters and v_i a classical error term.

The vector ψ_i is composed of all error terms from equation (1) and (2) and is assumed to be multivariate normal distributed with a mean vector of zero and covariance matrix Ω:

$$\psi_i = \begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \varepsilon_{i3} \\ v_i \end{pmatrix} \sim \mathcal{MVN}(\mathbf{0}, \mathbf{\Omega}) \qquad\qquad \Omega = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \sigma_{1v} \\ \cdot & \sigma_2^2 & \sigma_{23} & \sigma_{2v} \\ \cdot & \cdot & \sigma_3^2 & \sigma_{3v} \\ \cdot & \cdot & \cdot & \sigma_v^2 \end{pmatrix} \tag{3}$$

where e.g. σ_{12} is the covariance between ε_{i1} and ε_{i2}. To ensure parameter identification of the model, one needs to account for the fact that the level and scale of utility are irrelevant. The absolute level of utility is irrelevant because adding any constant k to the utility of each working option does not change the ordering of utilities and therefore has no effect on the final labor supply choice of a beneficiary. The level of utility is normalized by choosing a base category[12] and setting the corresponding parameter vector to zero, e.g., $\theta_1 = \{\beta_1 = 0, \gamma_1 = 0\}$. Similarly, the scale of utility is irrelevant because each utility can be multiplied by a positive constant k without changing which

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[12]We use working part-time as the base category throughout the whole analysis.

working alternative has the highest utility (Train, 2009). Scale of utility is normalized by imposing constraints on Ω: as demonstrated by Bunch (1991), in case of J alternatives, one needs to impose J constraints to account for symmetry of Ω and one more constraint to normalize scale.

5.4 Simulation of Choice Probabilities

Using the structural form of the model, probabilistic statements about the individual working decisions can be made. To give an example, the probability of working full-time given DI benefits are received is of the form:

$$
\begin{aligned}
P(y_i = 2 | D_i = 1, x_i) = {} & \frac{P(U_{i2} > U_{i1}, U_{i2} > U_{i3}, D_i^* > 0)}{P(D_i^* > 0)} \quad (4) \\
= {} & \int_{-\infty}^{x_i'\beta_2 + D_i\gamma_2} \int_{-\infty}^{x_i'(\beta_2 - \beta_3) + D_i(\gamma_2 - \gamma_3)} \phi_2(\tilde{\varepsilon}_{12}, \tilde{\varepsilon}_{32}) d\tilde{\varepsilon}_{12} d\tilde{\varepsilon}_{32} \\
& - \frac{\int_{-\infty}^{x_i'\beta_2} \int_{-\infty}^{x_i'(\beta_2 - \beta_3)} \int_{-\infty}^{-w_i\delta} \phi_3(\tilde{\varepsilon}_{12}, \tilde{\varepsilon}_{32}, v_i) d\tilde{\varepsilon}_{12} d\tilde{\varepsilon}_{32} dv_i}{\Phi(-w_i\delta)} \\
= {} & \Phi_2(x_i'\beta_2 + D_i\gamma_2, x_i'(\beta_2 - \beta_3) + D_i(\gamma_2 - \gamma_3); V_1) \\
& - \frac{\Phi_3(x_i'\beta_2, x_i'(\beta_2 - \beta_3), -w_i\delta; V)}{\Phi(-w_i\delta)}
\end{aligned}
$$

where $\phi_2(\cdot)$ and $\phi_3(\cdot)$ are the bi- and trivariate normal densities; $\Phi_2(\cdot)$ and $\Phi_3(\cdot)$ the corresponding bi- and trivariate normal *cdf*'s with the covariance matrix of differenced errors V; $V_1 \equiv \rho_{\tilde{\varepsilon}_{12}, \tilde{\varepsilon}_{23}}$ is the correlation in differenced errors of part-time to full-time and full-time to out of the labor force. Equation (4) demonstrates that the choice probabilities in the discrete ES model are multivariate integrals over subsets of the Euclidean space. The problem is that these choice probabilities cannot be expressed in closed-form. Instead, one has to use simulation methods to evaluate the integrals numerically. In this study, the GHK-algorithm is used to simulate the working choice probabilities. The GHK-algorithm is based on the observation that the choice probabilities as in (4) can be re-expressed as a sequence of conditional probabilities which can be simulated recursively. The basic principle of the algorithm is to take a predefined number of draws from the unit interval for each observation and to generate the simulated probability at each iteration step[13]. In this paper, we use the GHK-based Conditional Mixed Process Estimator[14] programmed by David Roodman (2011) to estimate the latent model parameters by maximum simulated likelihood (MSL). The corresponding simulated log-likelihood function can be found in appendix A.2.

5.5 Treatment Effects

As in most maximum likelihood framework, we estimate latent parameters which have no useful direct interpretation. To illustrate the DI benefit effects, we use the estimated coefficients to derive

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[13]For an excellent treatment of the GHK-simulator see Geweke, Keane and Runkle (1994) or Train (2009).

[14]The routine is programmed in Stata and can be installed using the command: `ssc install cmp`.

the treatment effect on treated for each labor market outcome. To give an example, the treatment effect on treated (TOT) for the outcome of working full-time is of the form[15]:

$$
\begin{aligned}
TOT_{full} &= P(y_{i1} = 2 | D_i = 1, x_i) - P(y_{i0} = 2 | D_i = 1, x_i) \qquad (5) \\
&= \Phi_2(x_i'\beta_2 + D_i\gamma_2, x_i'(\beta_2 - \beta_3) + D_i(\gamma_2 - \gamma_3); V_1) - \Phi_2(x_i'\beta_2, x_i'(\beta_2 - \beta_3); V_1)
\end{aligned}
$$

The TOT reflects the difference between the probability of working full-time given that beneficiary i received DI benefits and the probability of working full-time given that the exact same beneficiary did not receive benefits. A negative TOT therefore indicates that the DI benefit receipt decreases the probability of working full-time and vice versa for a positive TOT.

6 Results

The results section starts with an overview of the coefficient estimates of the discrete ES model. The estimates are shown for three different model specifications using the age cutoff as instrument for the benefit status. We discuss the question of the incentive effects of DI benefits on the working decision of existing beneficiaries using evidence from the distributions of the treatment effects for each labor market outcome. For the results discussed, 1'000 random draws per observation are used to simulate the working choice probabilities. To be more precise, antithetic Halton draws are used meaning that each draw is mirrored through the origin to maximize uniformity of coverage of the unit interval and therefore to achieve greater accuracy than pseudo-random draws (Train, 2009). Subsection 6.2 is then devoted to additional robustness checks: we present the coefficient estimates as the number of simulations is varied.

6.1 Main Results

Table (5) shows the estimated coefficients of the discrete ES model for three different model specifications. The coefficients on the benefit status are reported for the labor market outcomes of working full-time ($\hat{\gamma}_{full}$) and staying out of the labor force ($\hat{\gamma}_{oolf}$). In all models, the discontinuity in the benefit award rate above the age of 55 is used as the instrument for the benefit status and working part-time is used as the baseline category. In a *first* step, we include demographic background characteristics[16] into the model resulting in a highly significant and negative coefficient on the benefit status on the decision of working full-time. At the same time, there is no statistically significant effect of the DI benefits on the decision of staying out of the labor force. In a *second* step, we add socio-economic status indicators[17] which slightly reduces (in absolute terms) the coefficient on the

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[15] The TOT for the labor market outcomes of working part-time and out of the labor force are computed similarly.

[16] age, gender, weight (kg), height (cm), number of kids, foreigner, region dummies (base: Central Switzerland), type of community dummies (base: rural)

[17] marital status, years of schooling, logarithmized household income, life satisfaction

benefits for the decision of working full-time but does not affect the statistical significance. On the other hand, the coefficient on the benefits for the outcome of not working is increased but still far from significant. To condition on the health status of a person, we add various health indicators[18] in a *final* step to the labor supply equations. Although the standard error of the coefficient on the benefit status for the decision of working full-time more than doubles, it is still statistically significant at the 5% level. As for the coefficient on the decision of staying out of the labor force, it turns negative and remains insignificant. Note here that the coefficient estimates in this last final specification are basically unchanged if further control variables are added to the equation reinforcing the robustness of the presented findings[19].

The fact that the coefficient on the benefit status for the labor market outcome of working full-time is negative and significant in all specifications suggests, at first glance, that the DI benefits provide strong work disincentives for the existing beneficiaries. However, to appropriately address the question on the benefit effects on the labor market decision of beneficiaries, one needs to consider the treatment effects as outlined in the previous section. The treatment effects on treated (TOT) provide the relevant information on the behavioral change in the labor supply decision by comparing the working decision of a beneficiary to the working decision of the same person in the absence of the DI benefits (the counterfactual). To provide a complete picture on the labor supply responses, figures (4) to (6) present the whole distributions of the TOT for each labor market outcome separately. In addition to that, table (6) gives the relevant summary statistics for each distribution. Starting with the discussion on the benefit effects for the decision of working part-time, figure (4) shows that the TOT for all beneficiaries in the sample is positive which means that the DI benefits in general increase the probability of working in a part-time employment. From table (6) we see that the treatment effects range from about 3%-points to a maximum of about 81%-points. For beneficiaries in the upper tail of the distribution, the results suggests that the lion's share of their working decision is determined by the benefit status. Moreover, we see that on average the probability of working part-time is increased by about 41%-points. In other words, the probability of working part-time for the average beneficiary would have been about 41%-points lower in the absence of the DI benefits. Therefore, conditional on the health status, the demographic and socio-economic background of a beneficiary, the results provide strong evidence that the decision of working part-time is mainly determined by the benefit status.

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[18]number of doctor visits, number of ill-days, physical activity, health impediments, medication needed, indication for self-assessed health and dummies for depression, back problems, weariness, headaches and sleeping problems

[19]Even when controlling for additional health indicators (number of hospital days, the number of specialist visits, etc.) and parental education as a proxy for genetic endowment, the coefficient estimates are unchanged and remain stable.

As for the discussion of the treatment effects for the labor market outcome of working full-time, figure (5) shows the exact opposite picture to what we just observed: here the treatment effects are negative for all beneficiaries indicating that in general the probability of working in a full-time job is decreased by the DI benefits. To be more specific, table (6) shows that the benefit receipt on average decreases the probability of working full-time by about 42%-points. Hence the probability of working full-time would have been about 42%-points higher for the average beneficiary if she/he was not entitled to DI benefits. Furthermore, we see that the treatment effects range from about 0%-points to roughly –86%-points. In fact, for about 25% of beneficiaries the probability of working full-time is decreased by at least 75%-points meaning that their labor supply decision is basically entirely determined by the benefits. If we combine the results so far, then this leads to the conclusion that the DI benefits induce the beneficiaries to reduce their working intensity from working in a full-time job to working part-time. Following that line of thinking, the financial incentives provided by the Swiss DI system create substantial lock-in effects which at least in part might explain the low DI outflow of existing beneficiaries as observed in most developed economies (OECD, 2010).

What remains is the discussion of the benefit effects for the labor market outcome of staying out of the labor force. Figure (6) shows that the treatment effects take on both positive and negative values with a large probability mass at zero. In addition, we see from table (6) that the probability of staying out of the labor force is only weakly increased by about 3%-points for the average beneficiary. This allows for the conclusion that the decision of not participating in the labor market is hardly influenced by the benefit status. To put it differently, the decision of staying out of the labor force can be explained by many background characteristics of a beneficiary, the benefit status on the other hand is not a very valuable predictor.

Summing up, the analysis of this more complex labor market decision reveals aspects which have not been captured by the existing literature which has entirely focused on simple binary working decisions (e.g. Parsons (1980), Bound (1989), Gruber (2000), Chen and van der Klaauw (2008)). Our results suggest that the working decision of existing beneficiaries is to a large part determined by their benefit status. Moreover, the findings provide evidence that DI benefits create strong lock-in effects as the beneficiaries are induced to shift their working intensity from working full-time to part-time.

6.2 Robustness Checks

In this robustness section, we present the estimated model coefficients as the number of pseudo-random draws (S) increases. Table (7) shows the discrete ES estimates for 1, 10, 100 and 1000 draws per observation, the number of iterations needed to reach convergence, the value of the pseudo log-

likelihood at the coefficient vector and the computation time in seconds[20]. Recall that for the main results discussed above, 1000 draws per observation were used to estimate the model coefficients so that column 4 in table (7) is identical to the results presented in table (5). For small numbers of draws, we know from asymptotic theory that the MSL estimator is not equivalent to the ML estimator and is inconsistent (Gouriéroux & Monfort, 1991). This is likely to be the case for the estimates corresponding to $S = 1$ and $S = 10$ draws per observation. For such small S, the significantly reduced computation time comes at the cost of inconsistent estimates. However, as the number of draws is increased to $S = 100$, the MSL estimates stabilize and remain basically unchanged with the only exception of model specification (1) for the outcome of staying out of the labor force. Other than that, table (7) suggests that estimates with as few as 100 random draws per observation produce reliable coefficient estimates that are very close to those when using $S = 1000$. This is also relevant to know from a practical point of view since the differences in computation time are considerable: for the full specification used to produce the results discussed in the last section, the computation time is roughly 2 minutes for $S = 100$ but already 17 minutes for $S = 1000$. If the number of draws is further increased above $S = 1000$[21], the coefficient estimates hardly change but again come at the cost of a much higher computational time.

7   Conclusion

Over the course of the past few decades, the number of beneficiaries and the costs of DI programs have literally exploded in most OECD countries. At the same time only a tiny fraction of those who are entitled to DI benefits ever leave the DI system and very little is known about the mechanisms related to the DI outflow. Policy makers who want to effectively improve the incentive structure of the DI system therefore need to ask the question of how the working decision of existing beneficiaries is affected by the DI benefits. This paper investigates exactly that question by analyzing the potential lock-in effects that are created by the financial incentives embodied in the Swiss DI system. We use a fuzzy RD design exploiting a discontinuity in the DI benefit award rate to instrument the individual benefit status. Specifically, we estimate discrete endogenous switching (ES) models (Miranda & Rabe-Hesketh, 2006; Roodman, 2011) to identify the benefit effects on the labor market decision of working part-time, full-time or staying out of the labor force for existing beneficiaries. Unlike the existing literature (e.g. Parsons (1980), Bound (1989), Gruber (2000), Chen and van der Klaauw (2008)), we analyze the discrete working decision of working part-time, full-time or staying out of the labor force instead of focusing only on the binary choice of working versus not working. Our results reveal interesting new aspects of the labor supply decision of existing beneficiaries and show

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[20]The simulations were ran on an Intel(R) Core(TM) i7-4500 CPU @ 2.39 GHz with 8GB RAM on Windows 8.1 pro.

[21]The specifications were also estimated for $S = 2000$ and $S = 5000$ and the results are available upon request.

that their individual working decision is considerably influenced by the DI benefits. For the average beneficiary, the DI benefits conditional on the demographic and socio-economic background and the health status increase the probability of working in a part-time employment by about 41%-points, decrease the probability of working full-time by about 42%-points and have little or no effect on the decision of staying out of the labor force. It follows that the DI benefits induce a change in the work supply of beneficiaries from working full-time to working part-time instead of forcing them completely out of the labor market. A positive interpretation of these findings would be that the DI system works in the sense that people who receive the benefits remain in the working process. A more critical interpretation on the other hand would be that the financial incentives provided by the DI system triggers beneficiaries to lower their working intensity and therefore keeps them dependent on the income transfers, which in turn adds a possible explanation for the low DI outflow as observed in many OECD countries. Overall, the results have proven to be robust against the inclusion of further control variables and variations in the number of simulation draws when estimating the model coefficients by maximum simulated likelihood.

Appendix A.1

Variable Construction

The indicator for DI benefits is constructed from the annual amount of DI pensions a person receives and equals one for individuals in the sample who receive DI benefits and zero for those who do not receive any income transfers from the Swiss DI. The discrete labor force participation variable is one for individuals who work part-time, two for those who work full-time and three for those who are unemployed or not in the labor force. The dummy variable "happy" is created from a life satisfaction variable that is scaled from "not satisfied" (0) to "completely satisfied" (10) and is coded such that it is one for individuals with a satisfaction score of at least seven and zero else. General health status ranges from "very well" (1) to "not well at all" (5) and is recoded as a dummy variable good health that takes the value one for individuals with a "very well" or "well" health status and zero, else. Physical activity is a binary variable indicating whether a person exercises for at least half an hour a week (one) or if that person remains inactive (zero). Health impediments in everyday activities and medication needed in everyday functioning are measured on a 11-point scale from "not at all" (0) to "a great deal" (10). For both of these variables I generate an indicator that is one for individuals with a value of at least 5 in terms of severity of the health impediments and medication needed for everyday functioning and zero, for all others. Depression, anxiety and blues is measured on a scale of "never" (0) to "always" (10). I construct from that information the indicator depression which equals to zero for all observations below 3 and one for the rest. The cutoff value of 3 is chosen here as the 75%-quantile in the distribution of the original depression variable. Finally, indicators for back problems, weakness and weariness, sleeping problems and headaches are dummy variables which were created in the way that they are one for observations that report that they are suffering "very much" and zero for those who are suffering "not at all" or "somewhat" from these illnesses.

Appendix A.2

Simulated Log-Likelihood

The vector of model parameters $\theta_j \equiv \{\beta_j, \gamma_j\}$ and Ω are estimated by maximizing a simulated log-likelihood function of the form,

$$SLL(\theta, \Omega; x, y) = \sum_{j=1}^{3} \sum_{n=1}^{N} d_{ij} D_i log(\tilde{P}(y_i = j | D_i = 1))$$

$$+ \sum_{j=1}^{3} \sum_{n=1}^{N} d_{ij}(1 - D_i) log(\tilde{P}(y_i = j | D_i = 0)) \tag{6}$$

where d_{ij} is an indicator for the choice taken by individual i, D_i is the indicator for the DI benefits and $\tilde{P}(\cdot)$ is the simulated (conditional) choice probability.

Tables and Figures

Table 1: Degree of Disability and Pensions

Degree of disability	Type of pension	Minimum	Maximum
Less than 40%	No pension	-	-
40-49%	quarter pension	277 CHF	553 CHF
50-59%	half pension	553 CHF	1105 CHF
60-69%	three quarter pension	829 CHF	1658 CHF
More than 70%	full pension	1105 CHF	2210 CHF

Note: Source: Federal Social Insurance Office (2014). The minimum and maximum pensions are monthly benefits adjusted for inflation in Swiss Francs of 2007.

Table 2: Descriptive Statistics:

Beneficiaries versus Non-Beneficiaries

Difference in means t-tests

| | Full sample | | |
	Beneficiaries	**Non-Beneficiaries**	**Difference**
Age	49.64	43.35	6.29***
Female	0.54	0.55	-0.01
Weight (kg)	76.07	71.70	4.37***
Height (cm)	169.84	171.33	-1.49**
Number of kids	0.41	0.63	-0.22***
Foreigner	0.12	0.10	0.02
Married	0.47	0.56	-0.08**
Education	11.99	13.44	-1.45***
Household Income (CHF)	104'538	149'016	-44'479***
Happy	0.64	0.90	-0.26***
Number of doctor visits	14.73	4.79	9.94***
Number of ill-days	86.82	8.43	78.39***
Physical activity	0.54	0.80	-0.26***
Impediments	0.73	0.16	0.56***
Medication needed	0.66	0.16	0.51***
Good health	0.48	0.86	-0.38***
Depressed	0.49	0.20	0.29***
Back problems	0.29	0.09	0.20***
Weariness	0.29	0.09	0.21***
Insomnia	0.22	0.08	0.14***
Headache	0.11	0.07	0.04**

Notes: The first and second columns show the average value for a selection of demographic, socio-economic and health related indicators. Column three displays the t-test for the null of no difference in means: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Table 3: First Stage Regression Results

First Stage Effects		
Dependent Variable: DI Benefits		
$I(age > 55)$	0.044***	0.042**
	(0.016)	(0.019)
Control Variables	No	Yes
Number of Observations	3'873	3'873
R^2	0.05	0.166
Cragg-Donald Wald F-stats	10.60	6.87

Notes: First stage regression results using the indicator for DI benefits as dependent variable. The set of exogenous controls variables includes all the demographic, socio-economic and health related variables as described in the data section 4. The instrumental variable is the indicator for the discontinuity in the benefit award rate above the age of 55. Age is centered at 56. Standard errors clustered at the household level: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Table 4: Validity checks:

Differences in Baseline Covariates

Difference in Means t-tests

	Full sample			Window: ± 1 years		
	Below	**Above**	**Difference**	**Below**	**Above**	**Difference**
Benefit Receipt	0.03	0.07	-0.04***	0.04	0.09	-0.04**
Annual Benefits (CHF)	20'857.00	22'507.80	-1650.80**	24'320	20'012.50	4307.50
Number of Doctor Visits	5.07	5.74	-0.67*	5.12	6.25	-1.13
Number of Ill-Days	9.72	15.55	-5.83***	12.28	13.79	-1.51
Physical Activity	0.80	0.77	0.03**	0.78	0.77	0.01
Depression	0.20	0.24	-0.04***	0.27	0.29	-0.01
Back Problems	0.09	0.13	-0.04***	0.12	0.16	-0.04
Weariness	0.10	0.10	0.00	0.09	0.12	-0.03
Insomnia	0.08	0.11	-0.03***	0.12	0.15	-0.03
Headaches	0.08	0.06	0.02*	0.06	0.10	-0.03
Female	0.52	0.52	0.01	0.49	0.51	-0.02
Weight (kg)	71.60	72.81	-1.21***	74.12	73.21	0.91
Height (cm)	171.84	169.56	2.28***	171.43	169.70	1.73*
Number of Kids	0.76	0.07	0.69***	0.22	0.16	0.06
Share of Foreigners	0.12	0.10	0.03***	0.15	0.12	0.03
Married	0.50	0.74	-0.24***	0.75	0.73	0.01
Years of Schooling	13.19	13.05	0.14	13.27	13.12	0.14
Life Satisfaction	0.89	0.88	0.01	0.88	0.86	0.03

Notes: t-tests for the null of no difference in means below and above the age cutoff at 56 for a selection of baseline covariates: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$..

Table 5: Discrete Endogenous Switching Model Coefficient Estimates

DI Benefit Effects			
Dependent Variable: Working Status	(1)	(2)	(3)
$\hat{\gamma}_{full}$	-3.08***	-2.96***	-2.61**
	(0.42)	(0.54)	(1.30)
$\hat{\gamma}_{oolf}$	0.17	0.67	-0.23
	(0.95)	(1.03)	(1.63)
Background 1: Demographics	Yes	Yes	Yes
Background 2: Socio-Economic Status	No	Yes	Yes
Background 3: Health	No	No	Yes
Number of Observations	3'531	3'531	3'531
Number of Iterations	9	7	8
Pseudo Log-likelihood	-2'515.17	-2'363.16	-1'781.40
Computation time (sec)	1'266.41	1'003.55	1'021.41

Notes: Discrete ES coefficient estimates on the DI benefit status for the labor market outcomes working full-time and out of the labor force (base category: working part-time) based on 1'000 GHK draws. Coefficients on all background variables are not shown. Standard errors clustered at the household level: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Background 1: Age, gender, weight (kg), height (cm), number of kids, foreigner, region dummies (base: Central Switzerland), type of community dummies (base: rural);

Background 2: Marital status, years of schooling, logarithmized household income, life satisfaction

Background 3: Number of doctor visits, number of ill-days, physical activity, health impediments, medication needed, indication for self-assessed health and dummies for depression, back problems, weariness, headaches and sleeping problems.

Table 6: Summary Statistics:

Average Treatment Effects on Treated (ATT)

Labor Market Outcome	Mean	S.D.	Minimum	Maximum
Working part-time	0.412	0.260	0.031	0.807
Working full-time	-0.416	0.315	-0.862	-0.000
Out of the labor force	0.032	0.068	-0.056	0.444

Notes: Summary statistics of the treatment effects on treated for the labor market outcomes working part-time, full-time and out of the labor force. The TOTs' are based on the coefficient estimates from the discrete ES model as outlined in specification (3) in table (4).

Table 7: Robustness Checks:

Varying the Number of Simulation Draws

Number of Draws	S = 1			S = 10			S = 100			S = 1000		
$\hat{\gamma}_{full}$	-2.87***	-2.68***	-1.78**	-2.99***	-2.84***	-2.64***	-3.06***	-2.92***	-2.60**	-3.08***	-2.96***	-2.61**
	(0.33)	(0.39)	(0.79)	(0.33)	(0.38)	(0.72)	(0.46)	(0.49)	(1.28)	(0.42)	(0.54)	(1.30)
$\hat{\gamma}_{oolf}$	1.00	0.63	-0.31	0.82	0.70	0.37	0.60	0.70	-0.24	0.17	0.67	-0.23
	(0.30)	(0.42)	(1.58)	(0.82)	(0.79)	(1.60)	(1.49)	(0.79)	(1.63)	(0.95)	(1.03)	(1.63)
Background 1: Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Background 2: Socio-Economic Status	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Background 3: Health	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Number of Iterations	5	6	5	6	7	8	8	7	8	9	7	8
Pseudo Log-likelihood	-2'519.01	-2'365.04	-1'781.10	-2'515.00	-2'362.32	-1'780.70	-2'515.67	-2'363.34	-1'781.43	-2515.17	-2363.16	-1781.40
Computation time (sec)	4.90	5.75	4.78	9.36	10.66	11.31	304'58	126.85	141.06	1'266.41	1'003.55	1'021.41

Notes: Discrete ES coefficient estimates using different numbers of simulation draws (S). The simulations were ran on an Intel(R) Core(TM) i7-4500 CPU @ 2.39 GHz with 8GB RAM on Windows 8.1 pro.

See notes from table (4) for a description of the background characteristics used in each specification. Standard errors clustered at the household level: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Figure 1: Share of DI Beneficiaries
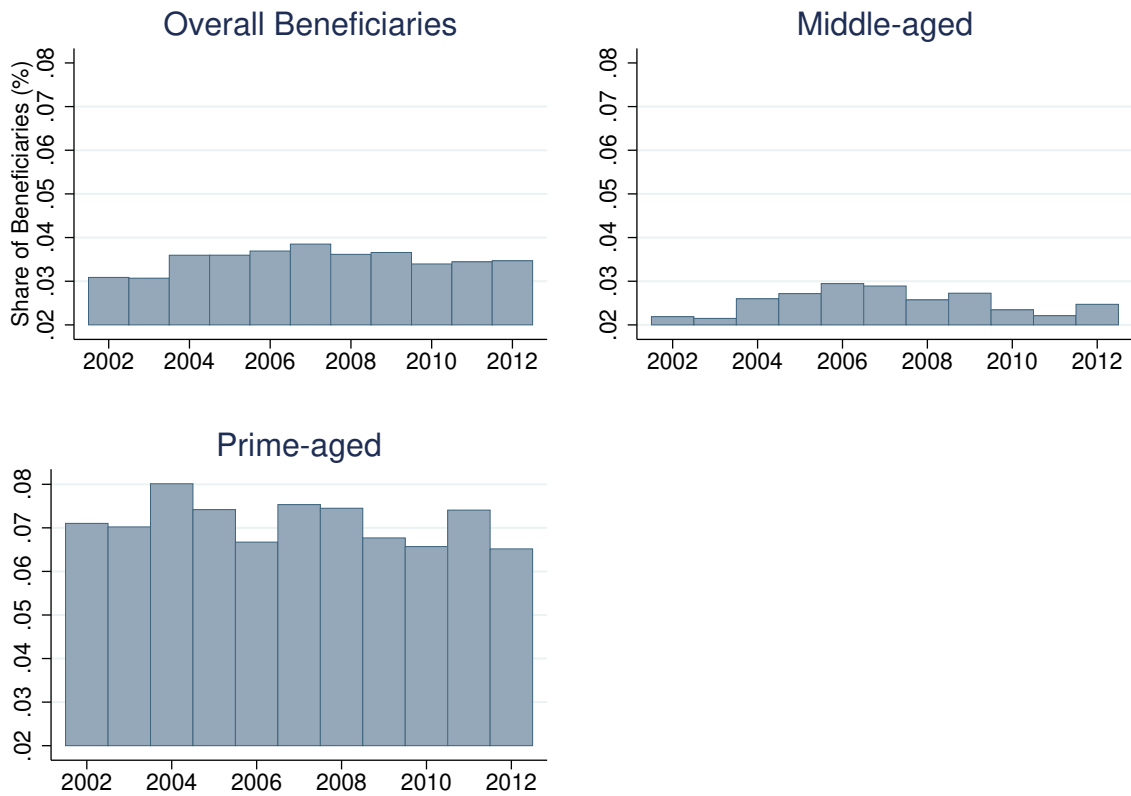
Notes: The panels show the share of beneficiaries from 2002-2012. The top left panel shows the overall share of beneficiaries which is at a level of about 3.5% within this timeframe. The top right panel shows the share of beneficiaries for the middle-aged (ages 20-54) subpopulation (average: 2.5%). The bottom left panel finally shows the percentage of DI beneficiaries between the ages of 55-65 with an average share of about 7.1%.

Figure 2: Discontinuity in the Benefit Award Rate

Notes: Figure 2 displays the discontinuity in the benefit award rate overlaid with the fitted line from a local polynomial regression along with the corresponding 95% confidence band (bins of half-years of age).

Figure 3: Density of the Forcing Variable:

McCrary Test
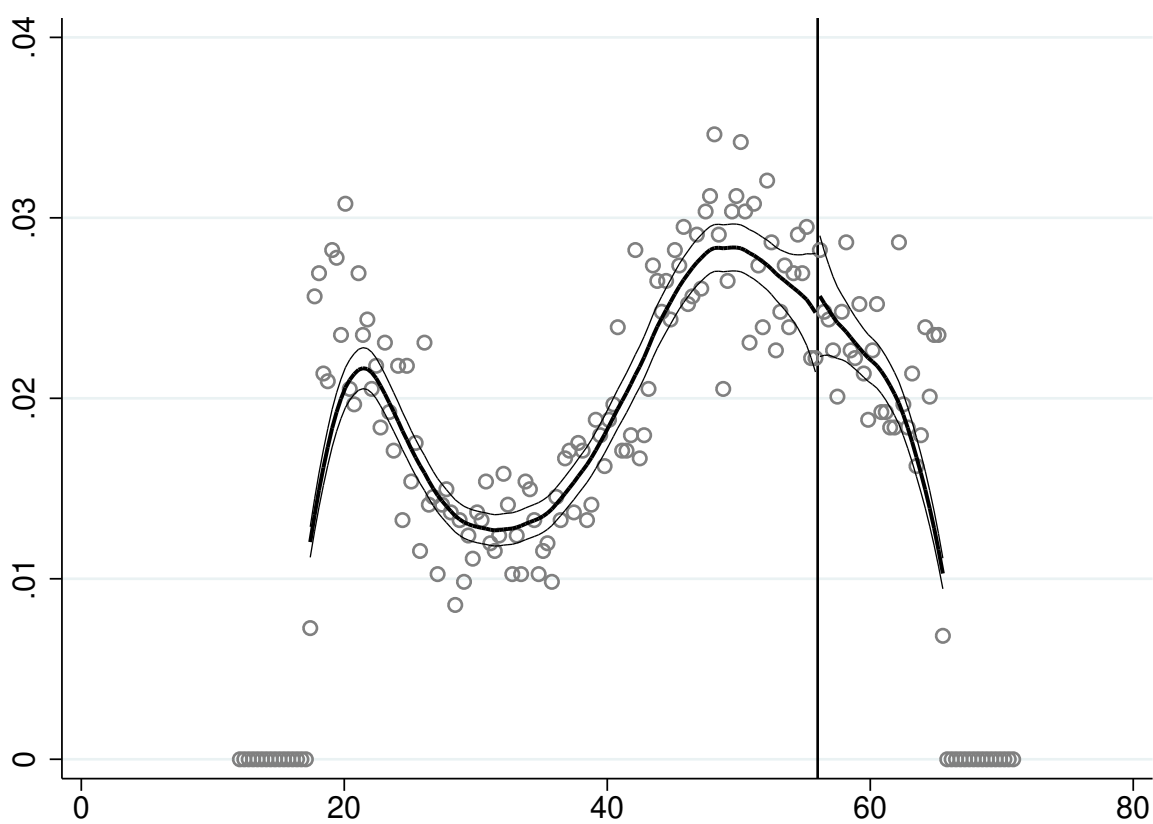
Notes: Figure 3 shows the density estimate based on the two-step procedure proposed by McCrary(2008). The graph shows no evidence for a discontinuity at the age cutoff reinforcing local random assignment.

Figure 4: Distribution of the Treatment Effects on Treated (TOT)
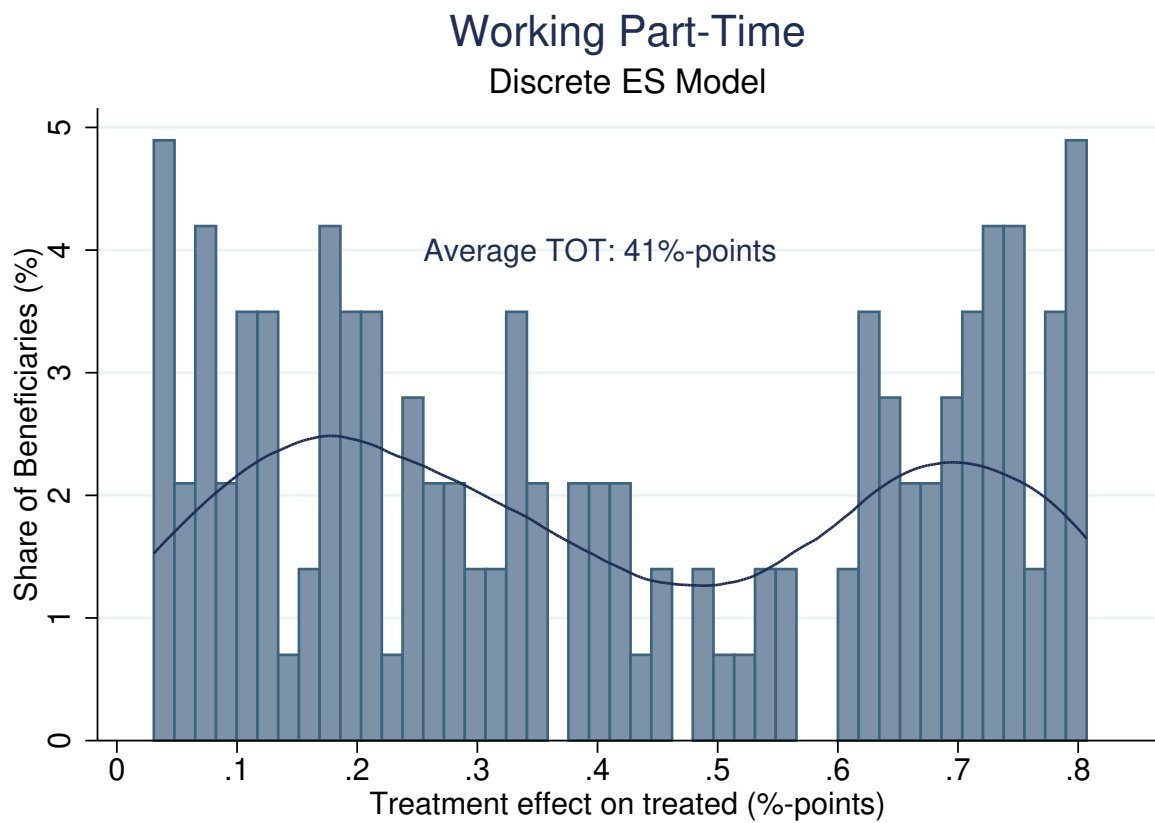
Notes: Figure 4 shows the distribution of the treatment effect on treated (TOT) for the labor market outcome of working part-time overlaid with a kernel density estimate. A positive (negative) sign on the TOT indicates an increase (decrease) in the probability of working part-time.

Figure 5: Distribution of the Treatment Effects on Treated (TOT)

Working Full-Time
Discrete ES Model

Average TOT: -42%-points
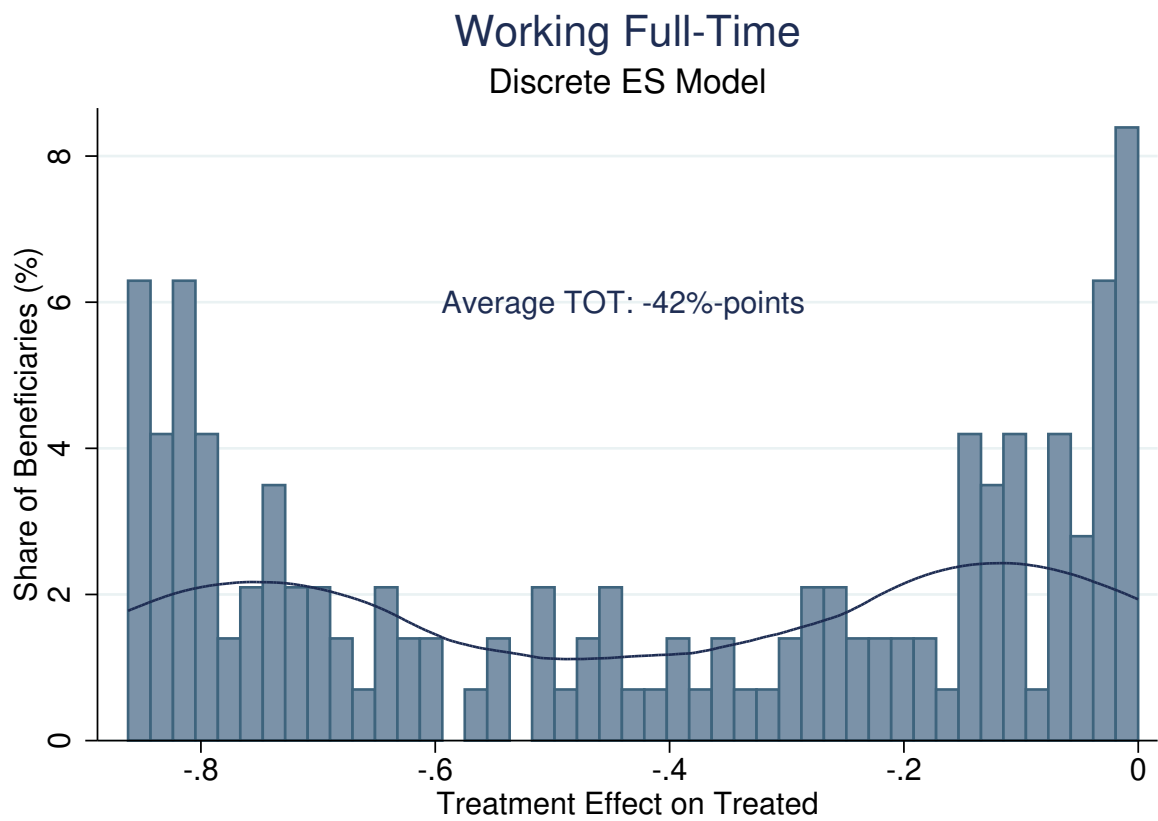
Notes: Figure 5 displays the distribution of the treatment effect on treated (TOT) for the labor market outcome of working full-time overlaid with a kernel density estimate. A positive (negative) sign on the TOT indicates an increase (decrease) in the probability of working full-time.

Figure 6: Distribution of the Treatment Effects on Treated (TOT)

Out of the Labor Force
Discrete ES Model

Average TOT: 3%-points
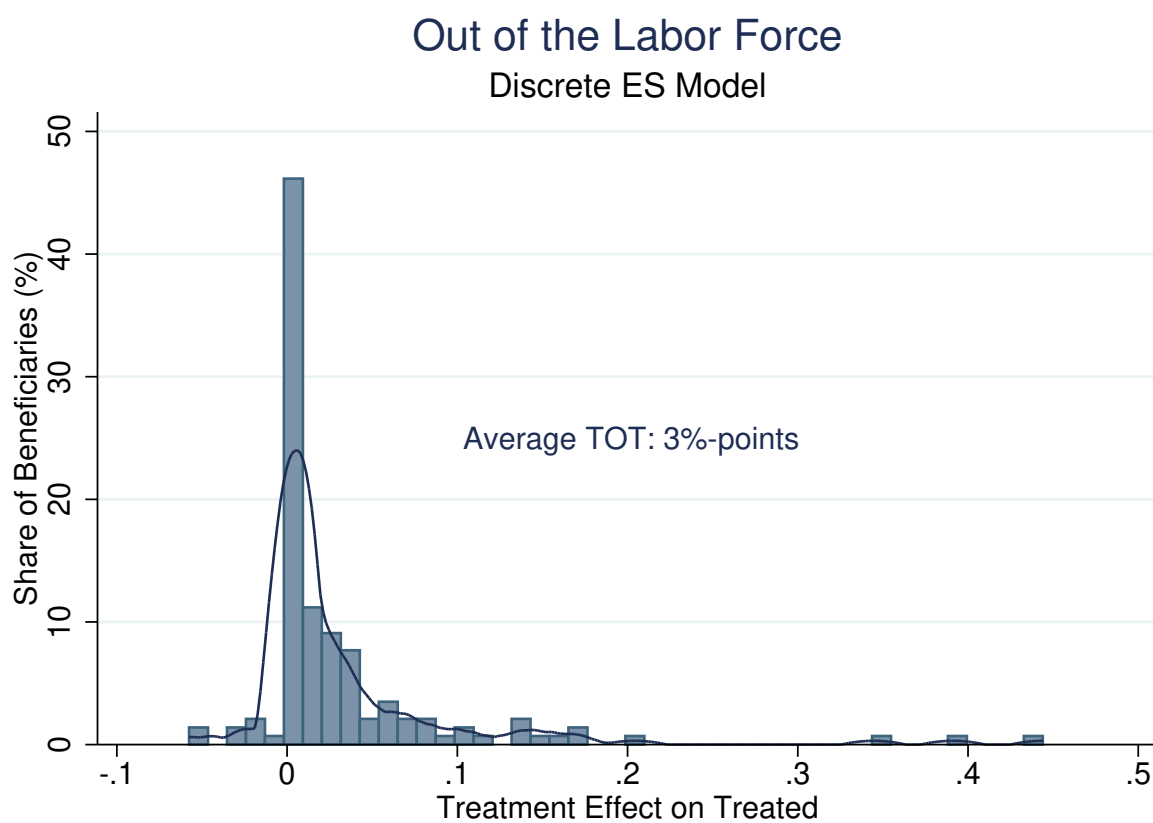
Notes: Figure 6 displays the histogram of the treatment effect on treated (TOT) for the labor market outcome of staying out of the labor force overlaid with a kernel density estimate. A positive (negative) sign on the TOT indicates an increase (decrease) in the probability to stay away from the labor market.

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