Journal of Public Economics 129 (2015) 26–40

Contents lists available at ScienceDirect

Journal of Public Economics

journal homepage: www.elsevier.com/locate/jpube

Asset accumulation and labor force participation of disability insurance applicants☆

Pian Shu

Harvard University, United States

ARTICLE INFO

Article history:
Received 12 July 2013
Received in revised form 29 May 2015
Accepted 8 June 2015
Available online 17 June 2015

JEL classification:
H55
J22
H31

Keywords:
Disability insurance
Asset accumulation
Labor force participation
Health and retirement studies (HRS)

ABSTRACT

This paper provides empirical evidence of the existence of forward-looking asset-accumulation behavior among disability-insurance applicants, previously examined only in the theoretical literature. Using panel data from the RAND Health and Retirement Study, I show that rejected applicants for Social Security Disability Insurance (SSDI) possess significantly more assets than accepted applicants immediately prior to application and exhibit lower attachment to the labor force. These empirical results are consistent with the theoretical prediction in Diamond and Mirrlees (1978) and Golosov and Tsyvinski (2006) that certain individuals with high unwillingness to work maximize utility by planning in advance for their future disability insurance application. Because the existing empirical literature on disability insurance does not account for this intertemporal channel, it may underestimate the total work-disincentive effect of SSDI.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction

Social Security Disability Insurance (SSDI), designed to protect the working population from the risk of total disability, is among the largest U.S. income transfer programs. In December 2010, SSDI paid $9.6 billion in benefits to over 9.4 million people, including 8.2 million disabled workers (Social Security Administration, 2010). To qualify for SSDI, a worker must be younger than full retirement age and must have met minimum work requirements. [1] The worker must also be screened for "total disability," which the Social Security Administration (SSA) defines as inability to work due to medical conditions expected to last at least one year or to result in death.

Prior empirical studies report two work-disincentive effects of disability insurance. First, receiving disability benefits may discourage work-capable recipients from returning to the labor force (Chen and van der Klaauw, 2008; von Wachter et al., 2011; Borghans et al., 2012; Maestas et al., 2013; French and Song, 2014; Moore, 2015). [2] Because the program is intended for workers with long-term disabilities, few beneficiaries exit by returning to work. [3] Second, the possibility of receiving disability benefits may prompt work-capable individuals to drop out of the labor force, especially when they face adverse labor-market conditions (Black et al., 2002; Autor and Duggan, 2003, 2006; Duggan et al., 2007; Duggan and Imberman, 2009; von Wachter et al., 2011). The design of the insurance, specifically the disability benefits it offers and its screening stringency, has a significant impact on labor force participation (Gruber and Kubik, 1997; Gruber, 2000; Autor and Duggan, 2003).

This paper explores a dynamic work-disincentive channel previously considered only in the theoretical literature. I develop a two-period model, similar to those of Diamond and Mirrlees (1978) and Golosov and Tsyvinski (2006), which shows that certain individuals with high unwillingness to work maximize utility by planning in advance to apply for disability insurance at a future time of their choosing, regardless of their health at that time. Such individuals find this path preferable to leaving the labor force right away because it allows time to adjust

☆ I thank David Autor for his detailed guidance. I also appreciate helpful comments from Leila Agha, Peter Diamond, JB Doyle, Amy Finkelstein, Jon Gruber, Henrik Kleven (the editor), Frank Neuhauser, Jon Skinner, Matthew Weinzierl, anonymous referees, and seminar participants at Colgate University and the Massachusetts Institute of Technology. I acknowledge support from the Kauffman Foundation.

E-mail address: pshu@hbs.edu.

[1] The employment requirements are specified by the Social Security Administration and vary from person to person.

[2] For instance, Maestas et al. (2013) and French and Song (2014) find that receiving benefits as a result of random assignment to lenient disability examiners or Administrative Law Judges has a significant and negative impact on applicants' propensity to return to work several years later.

[3] Attainment of full retirement age and death together account for 86% of exits from SSDI in 2004 (Autor and Duggan, 2006).

http://dx.doi.org/10.1016/j.jpubeco.2015.06.002
0047-2727/© 2015 Elsevier B.V. All rights reserved.

their assets accordingly. Because leaving the labor force lowers expected future income, individuals who plan in advance accumulate more assets than they would if they did not plan in advance and only decided to apply upon becoming disabled.

My empirical strategy compares the assets of rejected and accepted SSDI applicants. When disability-insurance screening is sufficiently effective, the pool of rejected applicants will include a higher proportion of planners than the pool of accepted applicants. Thus, all else equal, rejected applicants will possess more assets than accepted applicants. In the absence of planning, healthier agents—those with a lower probability of being disabled in the future—will accumulate fewer assets than less-healthy agents, since they are more likely to continue to work and have higher expected future earnings. In this case, rejected applicants, who are presumably healthier (Bound, 1989), will possess fewer assets than accepted applicants.

Using the RAND Health and Retirement Study (HRS) panel data, I examine the differences between rejected and accepted applicants who applied for SSDI between ages 44 and 65. [4] Consistent with the model, I find evidence that rejected applicants display significantly lower attachment to the labor force before applying for SSDI: they are less likely to be in the labor force and have accumulated fewer years of employment. [5] Although the two groups self-report similar health at the time of application, accepted applicants are significantly less healthy than rejected applicants in the years immediately following application, suggesting that SSDI awards are not random. I use quantile regressions to show that, conditional on a rich set of observed characteristics—including demographics, income, labor force participation, health status, and out-of-pocket medical expenses—rejected applicants possess significantly more liquid financial assets than accepted applicants at the time of application. Both the magnitude and the statistical significance of the effect increase with applicants' asset levels. The divergence in assets at the time of application is unlikely to result from unobserved differences in applicants' inherent tendency to save, since the two groups possessed very similar assets two or three years before application. These results suggest that at least some rejected applicants accumulated assets in a manner consistent with a plan to apply for SSDI regardless of their actual future health status.

My results build upon Benitez-Silva et al. (2004), which finds that rejected applicants for SSDI and SSI have higher average assets than accepted applicants, and that accepted applicants who do not self-identify as disabled on surveys have more assets than those who do. These simple mean comparisons, however, cannot be taken as clear evidence of forward-looking asset accumulation. Many observables can affect asset accumulation, and the existence of outliers in a skewed distribution of wealth is likely to have a disproportionate influence on the mean (Engen and Gruber, 2001). By contrast, my empirical analysis focuses on applicants who applied for SSDI but not SSI; it also uses quantile regressions to control for a rich set of observations and to minimize the impact of outliers. I further show that my results are robust to using a longer pre-period to compare asset accumulation patterns and to exploiting differences among applicants' self-reported disability states.

Furthermore, Benitez-Silva et al. (2004) do not distinguish between SSDI and SSI applicants, even though SSI's asset test is likely to affect the saving behavior of the latter group. As a robustness check I show that, among the SSI applicants, rejected applicants do not possess significantly different assets at the time of application. Using these applicants as a control group yields the same key finding that rejected SSDI applicants accumulate more assets than accepted SSDI applicants at the time of application but not several years before.

This paper contributes to the vast theoretical literature known collectively as New Dynamic Public Finance. This literature argues that policy instruments that distort intertemporal savings can be optimal because, in anticipation of stochastic future shocks to their skills (in this case, onset of disability), some agents will save more and exit the labor force sooner than is socially optimal (in this case, planning to drop out of the labor force and apply for disability insurance) (Golosov et al., 2003, 2006; Kocherlakota, 2005; Albanesi and Sleet, 2006; Golosov and Tsyvinski, 2007; Kocherlakota, 2010; Farhi and Werning, 2012). Consistent with this literature, I find empirical evidence of forward-looking asset-accumulation behavior. My results thus suggest that the existence of disability insurance affects not merely current but also future labor supply. Discussions of the welfare implications of disability insurance thus ought to take into account the possibility of an intertemporal work-disincentive effect.

2. A two-period model of asset accumulation and disability application

Following Diamond and Mirrlees (1978) and Golosov and Tsyvinski (2006), I develop a two-period model with Type I and Type II screening errors to capture the forward-looking asset-accumulation behavior of applicants. I then discuss the model's empirical implications. Appendix B provides all of the proofs.

2.1. Model set-up

The model consists of two periods. In the first period, all agents are able to work. In the second period, each agent faces a probability of being disabled and unable to work. Thus, the sole source of uncertainty in the model is disability status in the second period. In either period, an agent who is working will supply one unit of labor inelastically and receive wage w. All agents begin the first period with zero assets. I denote the discount rate as β and the interest rate as R. To simplify the math without loss of generality, I also assume that $\beta R = 1$.

Agents differ on two parameters: θ_i, the probability of being totally disabled in the second period, and x_i, the disutility of work in each period. Both are known to the agent. An agent derives utility $u(c_i) - x_i$ in a given period if working and $u(c_i)$ if not, where c_i is consumption in that period. Following standard assumptions, $u(\cdot)$ is increasing and concave, and $u(0) = -\infty$. As in Golosov and Tsyvinski (2006), I also assume that labor (in this case, disutility of work) and consumption enter separately into an agent's calculation of utility. By distinguishing disutility of work from probability of total disability, I conceptually distinguish *unwillingness* to work from *inability* to work. [6] Empirically, I consider the former an unobserved preference whereas the latter can be partially observed based on health.

Like SSDI, the disability-insurance program in this model exists in the second period by imposing a labor tax (τ) on the wages of the working population and transferring benefits (T) to recipients, where total transfers equal total tax payments. Because the population of disabled workers is much smaller than the working population, it is reasonable to assume that $(1-\tau)w > T$. An agent receiving disability benefits cannot work and takes the parameters (τ, T) as given.[7]

Though Diamond and Mirrlees (1978) and Golosov and Tsyvinski (2006) do not explicitly include screening in their model, screening clearly affects the labor force participation and the asset accumulation of potential applicants. To incorporate screening into the model, I assume that both Type I and Type II classification errors characterize the screening

[4] I omitted applicants for SSDI who also applied for Supplemental Security Income (SSI) because SSI imposes an assets test. SSI pays stipends to low-income individuals who are 65 or older, blind, or disabled.

[5] Giertz and Kubik (2011) find similar results using HRS data to compare the labor-force participation of rejected and accepted applicants. But they do not study asset accumulation or test a model similar to mine.

[6] For purposes of designing optimal disability insurance, Diamond and Sheshinski (1995) argue that there is no need to distinguish between the two. However, the optimal design of disability insurance is beyond the scope of this paper.

[7] Golosov and Tsyvinski (2006) point out that this may not be the optimal design of disability insurance. The purpose of this model, however, is to illustrate how individuals behave under the current program.

process. I denote $q \in [0, 1)$ as the probability that a disabled applicant is rejected (Type I error) and $p \in [0, 1]$ as the probability that an able applicant is accepted (Type II error). Like (τ, T), the parameters (p, q) are also taken as given and do not vary by agent. When $p > 0$, able agents who choose not to work in the second period will always apply for disability insurance. I further assume that decisions on applications are made instantly and that a rejected applicant earns no income in the second period. [8]

In the first period agents always work, since they begin with zero assets and have no disability; they also choose the level of assets to accumulate. During the second period, disabled agents are by definition unable to work; thus they must consume their assets and apply for disability insurance. Able agents may drop out of the labor force and apply for disability insurance if the expected utility of doing so is higher than that of working.

Let k_i be individual i's assets accumulated by the end of the first period. There are three possible states in the second period:

- The agent is able and works, in which case her utility is $u(Rk_i + (1 - \tau)w) - x_i$.
- The agent is able but applies for disability insurance, in which case her expected utility is $pu(Rk_i + T) + (1 - p)u(Rk_i)$.
- The agent is disabled and applies for disability insurance, in which case her expected utility is $(1 - q)u(Rk_i + T) + qu(Rk_i)$.

A disabled agent has no choice but to apply for disability insurance. Given the level of assets k_i chosen in the first period, an able agent will work during the second period if and only if the utility of doing so is higher, i.e., $u(Rk_i + (1 - \tau)w) - x_i \geq pu(Rk_i + T) + (1 - p)u(Rk_i)$. This is the incentive-compatibility constraint in the second period. Importantly, k_i enters into this constraint, and the agent knows how k_i influences her decision to work in the second period. Thus, by choosing how much to save in the first period, the agent is effectively deciding whether to work in the second period if not disabled.

Mathematically, the agent solves the following utility-maximization problem:

$$V = \max_{k_i} u(w-k_i)-x_i + \beta \max\left\{V_2^W(k_i), V_2^{NW}(k_i)\right\}, \text{where}$$
$$V_2^W(k_i) = (1-\theta_i)[u(w(1-\tau)+Rk_i)-x_i] + \theta_i[(1-q)u(Rk_i+T)+qu(Rk_i)], \text{ and}$$
$$V_2^{NW}(k_i) = (1-\theta_i)[pu(Rk_i+T)+(1-p)u(Rk_i)] + \theta_i[(1-q)u(Rk_i+T)+qu(Rk_i)]$$

represent the utilities in the second period of the working and non-working paths.

The agent can solve this problem in two steps. First, she finds k_i^α and k_i^β which maximize respectively the utilities of working and not working in the second period. Second, she chooses k_i^α and the working path over k_i^β and the non-working path if and only if $u(w - k_i^\alpha) + \beta V_2^W(k_i^\alpha) \geq u(w - k_i^\beta) + \beta V_2^{NW}(k_i^\beta)$.

Proposition 1. *Given θ, there exists a cutoff $\tilde{x}$ such that, for all $x_i \leq \tilde{x}$, the agent will work during the second period if able ("the working path") and will accumulate $k_i^* = k^\alpha$. For all $x_i > \tilde{x}$, the agent will not work in the second period ("the non-working path") and will accumulate $k_i^* = k^\beta$. The levels of assets, k^α and k^β, solve the following first-order conditions and satisfy the following incentive-compatibility constraints:*

$$u'(w-k^\alpha) = (1-\theta)\left(u'\left(w(1-\tau)+Rk^\alpha\right)\right) + \theta(1-q)u'(Rk^\alpha+T) + \theta q u'(Rk^\alpha), \tag{1}$$

$$\tilde{x} \leq u\left(w(1-\tau)+Rk^\alpha\right) - \left(pu(Rk^\alpha+T)+(1-p)u(Rk^\alpha)\right), \tag{2}$$

$$\text{and } u'\left(w-k^\beta\right) = (\theta(1-q)+(1-\theta)p)u'\left(Rk^\beta+T\right) + ((1-\theta)(1-p)+\theta q)u'\left(Rk^\beta\right), \tag{3}$$

$$\tilde{x} \geq u\left(w(1-\tau)+Rk^\beta\right) - \left(pu\left(Rk^\beta+T\right)+(1-p)u\left(Rk^\beta\right)\right). \tag{4}$$

Proposition 2. *$k^\alpha < k^\beta$ if $\theta < 1$; $k^\alpha = k^\beta$ if $\theta = 1$.*

Given the probability of being disabled in the second period, forward-looking agents with a sufficiently high disutility of work will decide in the first period that they will not work in the second period. Instead, they will apply for disability insurance regardless of their actual disability status at that time. Since they will earn less by not working, they will accumulate more assets in the first period than they would if they planned to work (if able) in the second period. By contrast, agents with relatively low disutility of work will apply for disability insurance only if they become disabled. Decisions about asset accumulation and labor supply are made jointly, because agents are forward-looking and the incentive-compatibility constraints are clear: they know how they will react to actual disability shock in the second period given their accumulation of assets.

If an agent's optimal level of assets, k_i^*, maximizes the utility of working in the second period and satisfies the incentive-compatibility constraint, she cannot find another level of assets that will make not working in the second period more attractive than working. As a counterexample, suppose an agent saves k^α with the intention of working in the second period, but her disutility of work is sufficiently high that $V_2^W(k^\alpha) < V_2^{NW}(k^\alpha)$ and she would be better off not working in the second period. Eq. (3) implies that she would have gained greater overall utility by saving k^β instead of k^α. Therefore, accumulating k^α and choosing the non-working path (or, alternatively, accumulating k^β and choosing the working path) cannot be optimal.

Fig. 1 provides a graphic illustration of Propositions 1 and 2 using the logarithmic utility function $(u(c_i) = \log(c_i))$ and a sample set of values for parameters w, R, β, τ, and T. Panel A assumes no screening, where $p = 1$ and $q = 0$. Panel B uses Type I and Type II error rates derived by Benitez-Silva et al. (2006), where a disabled applicant has a 22-percent possibility of being rejected (q) and an able applicant has a 62-percent probability of being accepted (p). [9] Panel C uses Type I and Type II error rates derived by Low and Pistaferri (2015) for workers aged 45 and above, where $p = 0.18$ and $q = 0.37$. [10] Panel D assumes perfect screening without classification errors, so p and q are both zero. Within a panel, each line plots the optimal level of assets, k_i^*, against the disutility of work, x_i, for a given value of θ_i.

All four panels illustrate similar patterns. Agents with a sufficiently low disutility of work will choose the working path and accumulate non-zero assets to insure against the risk of disability in the second period. Those with a sufficiently high disutility of work will choose the non-working path and accumulate even more assets, since they will not earn wages in the second period. Because the disutility of work, x_i, enters the utility function separately from consumption, it does not enter the first-order conditions; thus, k_i^α and k_i^β do not vary with x_i. The cutoff $\tilde{x}$ is decreasing in θ, suggesting that as the risk of becoming disabled increases the non-working path becomes more attractive. The difference between the two levels of assets, $k^\beta - k^\alpha$, is also decreasing in θ. The intuition is that as the probability of becoming disabled increases, the difference between expected earnings on the working and

[8] The latter assumption is consistent with the requirement that an applicant must be out of the labor force for at least five months before applying for disability insurance and for the duration of the application, which can take many years due to appeal and re-application (French and Song, 2014). Thus rejected applicants may have difficulty returning to the labor force even if they are work-capable (Parsons, 1991).

[9] See footnote 7 of Benitez-Silva et al. (2006) on page 3.

[10] See Section 5.6.1 of Low and Pistaferri (2015).

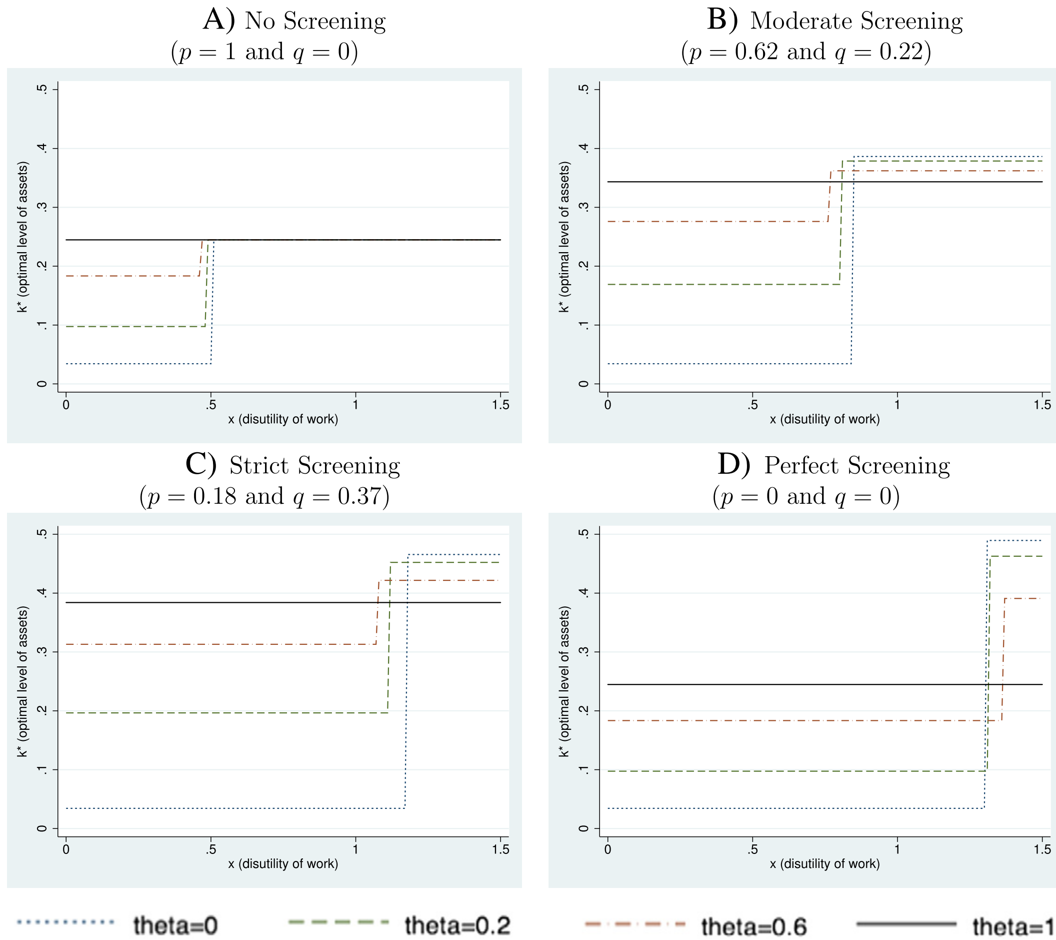


Fig. 1. Simulated values of the optimal asset level k_i^*. *Notes*: This figure plots simulated values of the optimal level of asset, k_i^*, against x_i for four values of θ_i and four levels of screening stringency. The assumptions are: $u = \log(c)$; $w = 1$; $R = 1.043$; $\beta = 1/R$; $\tau = 0.07$; $T = 0.5$.

non-working paths decreases. In the extreme case where $\theta = 1$—that is, where an agent will definitely become disabled—there are no differences between the working and non-working paths.

2.2. Screening and optimal asset levels

Eqs (1) and (3) imply that the classification errors, p and q, influence the optimal level of assets. To understand the impact of screening, it is helpful to distinguish between screening *quality* and screening *stringency*. A superior screening mechanism lowers both types of classification errors. A stricter screening mechanism decreases p at the cost of increasing q, in which case the probabilities of receiving benefits decrease for both able and disabled applicants. Improving screening quality is difficult in the face of resource constraints, and policy makers usually encounter a tradeoff between the two types of classification errors at the margin (Autor and Duggan, 2006; Kleven and Kopczuk, 2011).

Proposition 3. $\frac{\partial k^\alpha}{\partial p} = 0$; $\frac{\partial k^\alpha}{\partial q} > 0$; $\frac{\partial k^\beta}{\partial p} < 0$; and $\frac{\partial k^\beta}{\partial q} > 0$.

Proposition 3 suggests that the optimal levels of asset accumulation for the working and non-working paths are higher when screening is stricter (i.e., lower p and higher q) because, for both paths, expected earnings in the second period decrease as the probabilities of receiving benefits decrease. By contrast, a superior screening mechanism (i.e., lower p and lower q) decreases the probability of receiving disability benefits for an able agent but increases the probability of receiving disability benefits for a disabled agent. Thus, it increases expected earnings in the second period for the working path and has an ambiguous effect for the non-working path. The comparisons across the panels in Fig. 1 are consistent with Proposition 3.

Proposition 3 also implies that given θ, $k^\beta - k^\alpha$ is decreasing in p. Intuitively, increasing the probability of Type II errors increases expected earnings in the second period for the non-working path but does not affect the working path. Thus the difference in the assets accumulated by agents who choose the working and non-working paths respectively would decrease. It is not clear how $k^\beta - k^\alpha$ varies with q, since a higher Type I error rate decreases expected earnings in the second period for both the working and non-working paths, and thus increases the optimal asset levels for both paths.

Proposition 4. $\frac{d\tilde{x}}{dp} < 0$, and $\frac{d\tilde{x}}{dq} < 0$.

The two types of classification errors have similar effects on the attractiveness of the working and non-working paths. As the likelihood of receiving disability benefits without being disabled (p) increases, the expected utility in the second period of the non-working path increases; that of the working path does not change. Thus, individuals who were previously undecided between the two paths now have incentives to choose the non-working path. Expected utility in the second period increases for both the working and non-working paths as the likelihood of receiving disability benefits when disabled $(1 - q)$ increases. However, the marginal impact on expected utility in the second period is higher for the working path, since such agents accumulate fewer assets and the utility function is concave. So individuals who were indifferent before have an incentive to choose the working path. Therefore, a stricter screening mechanism (lower p and higher q) will not always encourage more agents to choose the working path, but a superior screening mechanism (lower p and lower q) will. Fig. 1 shows that given θ, $\tilde{x}$ is highest in the scenario of perfect screening and lowest in the scenario of no screening.

The model suggests that decreasing the quality of screening has a clear work-disincentive effect. As classification error rates increase, more individuals switch from the working path (applying if disabled) to the non-working path (applying regardless of disability status). In other words, a disability-insurance program with imperfect screening may encourage forward-looking agents with high disutility of work to plan their exit from the labor force in advance.

2.3. Comparing asset levels of rejected versus accepted applicants

Empirically, we do not observe whether an applicant has chosen the working or non-working path, but we do observe whether he or she is accepted or rejected. Able agents on the working path will always work during the second period and will not apply for disability insurance. Thus, the applicant pool consists of three groups: disabled agents on the working path, disabled agents on the non-working path, and able agents on the non-working path. Under imperfect screening, both rejected and accepted applicants will include members of all three groups. Given θ, let $F_\theta(x)$ be the conditional cumulative distribution function of x, and $\tilde{x}$ be the cutoff in Proposition 1.

Proposition 5. *Given $\theta \in (0, 1)$, $E(k|\theta, rejected) - E(k|\theta, accepted) > 0$ if and only if $1 - p > q$ and $F_\theta(\tilde{x}) \in (0, 1)$.*

Proposition 5 suggests that the expected assets of a rejected applicant will be higher than those of an accepted applicant as long as (a) there are agents pursuing both paths, and (b) screening is sufficiently effective to be more likely to reject an able applicant than a disabled applicant. The first requirement is straightforward: if all agents take the same path, their asset level will be identical conditional on θ. The second requirement implies that, compared to accepted applicants, rejected applicants will include a higher proportion of agents who have chosen the non-working path.

Empirically testing for this proposition is challenging, since wealth is highly skewed; the existence of outliers is likely to bias the estimates from standard mean regressions (Engen and Gruber, 2001). Therefore, I use quantile regressions as my preferred specifications in Section 5.

Proposition 6. *Given $\theta \in (0, 1)$, let $Q_k(\lambda|\theta, rejected)$ be the λth conditional quantile of k. There exist λ_1 and λ_2 such that*

$$Q_k(\lambda|\theta, rejected) - Q_k(\lambda|\theta, accepted) = \begin{cases} k^\beta - k^\alpha & \text{for } \lambda_2 < \lambda < \lambda_1; \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

if and only if $1 - p > q$ and $F_\theta(\tilde{x}) \in (0, 1)$. And,

$$\lambda_1 = \frac{\theta(1-q)F_\theta(\tilde{x})}{\theta(1-q) + p(1-\theta)(1-F_\theta(\tilde{x}))}; \quad \lambda_2 = \frac{\theta q F_\theta(\tilde{x})}{\theta q + (1-p)(1-\theta)(1-F_\theta(\tilde{x}))}.$$

As in the case of Proposition 5, when there are agents pursuing both paths and screening is sufficiently effective, agents on the non-working path will represent a lower portion of accepted applicants than of rejected applicants. Thus, rejected and accepted applicants in the lowest and highest quantiles will possess similar assets, but in the middle quantile rejected applicants will have higher assets.

Screening quality has two opposing effects on the composition of rejected and accepted applicants. Proposition 4 suggests that as classification errors (p and q) increase, $\tilde{x}$ and $F_\theta(\tilde{x})$ decrease; thus more agents are choosing the non-working path and applying for disability insurance without being disabled. On the other hand, more classification errors are likely to increase similarity between rejected and accepted applicants. Where p is as high as $1 - q$ (that is, where the probability of receiving benefits is identical for able and disabled applicants), $\lambda_1 - \lambda_2 = 0$, and rejected and accepted applicants will exhibit the same mixture of the able and the disabled. The two groups will also exhibit the same distributions of asset levels.

The model thus suggests that, for the empirical exercise to be informative, classification errors need to be sufficiently low that differences are detectable between rejected and accepted applicants. If they are too low, however, it is possible that few agents will choose the non-working path and there will thus be few able applicants. Whether this happens empirically depends on the distribution of disutility of work, which is unobserved. Importantly, as Panel D in Fig. 1 shows, agents with a sufficiently high disutility of work will still choose the non-working path even when screening is perfect. They will apply for disability insurance as long as p is positive.

Fig. 2 plots simulated distributions of the assets accumulated by rejected and accepted applicants using two sets of classification errors, estimated by Benitez-Silva et al. (2006) ($(p, q) = (0.62, 0.22)$; Panel A) and by Low and Pistaferri (2015) ($(p, q) = (0.18, 0.37)$; Panel B). Both panels assume the same utility function and parameters as in Fig. 1, $\theta = 0.2$, and uniformly distributed disutility of work (x) between 0 and 1.5. In both scenarios, rejected applicants include a higher proportion of able agents who have chosen the non-working path. When screening is moderate, rejected and accepted applicants have similar distributions of asset levels, differing only between the 13th and 22nd percentiles. When screening is strict, the asset levels of the two groups differ between the 23rd and 57th percentiles.

2.4. Empirical implications

The key takeaway from this theoretical exercise is the prediction that if rejected applicants are more likely to have planned their applications in advance, then they are also likely to have accumulated more assets than accepted applicants. To test this prediction, I compare the asset accumulation of rejected applicants to that of accepted applicants. The main goal of the empirical exercises is to test the existence of forward-looking asset-accumulation behavior. It is difficult to use the model to predict the magnitudes or quantiles of differences in the asset levels of rejected and accepted applicants, since doing so requires making strong assumptions about the distribution of disutility of work, the distribution of probability of disability, and classification errors. Furthermore, many other factors affect asset accumulation, such as unobserved risk preferences, which the model does not account for. Since the model is not intended to capture all of the behavior of applicants, it is worthwhile to clarify the assumptions and limitations of the model.

First, Propositions 5 and 6 assume that θ is known, but empirically we observe health imperfectly. In the absence of the non-working path, i.e., $F_\theta(\tilde{x}) = 1$, rejected and accepted applicants with the same θ should possess the same level of assets, k^α. Since k^α is increasing in θ (Eq. (1) and Fig. 1), and since rejected applicants are expected to be healthier (i.e., with lower θ) than accepted applicants (Bound, 1989), rejected applicants should have lower levels of assets in the absence of the non-working path: if the expected alternative to receiving disability insurance is to work, rejected applicants should have higher expected income in the second period than accepted applicants. Thus, observing health imperfectly should bias against finding a positive correlation between rejection and asset level at the time of application in the absence of the non-working path. A similar argument applies in the case where rejected applicants expect a lower probability of receiving disability benefits (i.e., a higher rate of rejection) than accepted applicants.

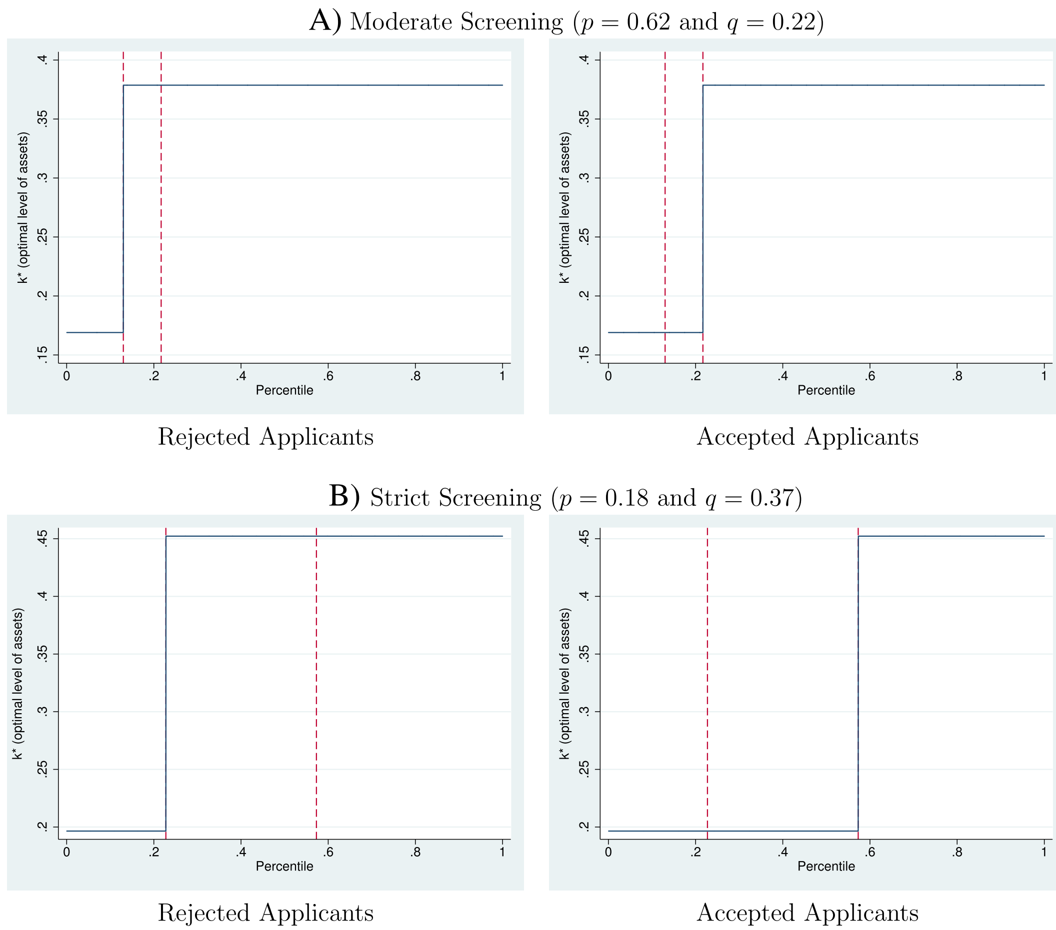


Fig. 2. Simulated distributions of rejected and accepted applicants' assets with moderate or strict screening. *Notes*: This figure plots simulated distributions of applicants' assets for rejected applicants (on the left) and accepted applicants (on the right) with moderate screening (Panel A) or strict screening (Panel B). The assumptions are: $u = \log(c)$; $w = 1$; $R = 1.043$; $\beta = 1/R$; $\tau = 0.07$; $T = 0.5$; $\theta = 0.2$; and x uniformly distributed between [0, 1.5]. The red dashed lines indicate simulated values of λ_1 and λ_2 defined in Eq. (5).

Second, in this simple model, rejected applicants are either disabled or have decided to withdraw from the labor force. Empirically, this is unlikely to be true of all rejected applicants; studies have shown that a non-zero proportion of rejected applicants return to work (von Wachter et al., 2011; Maestas et al., 2013; French and Song, 2014). However, the existence of such applicants should again bias against finding a positive correlation between rejection and accumulation of more assets, since the expectation of returning to work diminishes incentives to save. Though the model could be generalized to include the probability of returning to work after rejection, doing so would not affect its key prediction.

Third, other non-health-related shocks, such as unemployment, could lead to applications from work-capable applicants (Autor and Duggan, 2003). Hence, it is possible that rejected applicants accumulate more assets than accepted applicants to self-insure against a higher risk of unemployment (von Wachter et al., 2011). This reasoning is consistent with the interpretation that some applicants are forward-looking and that rejected applicants plan their application in advance for non-health-related reasons.

Finally, rejected and accepted applicants may differ systematically on certain unobserved determinants of assets, such as risk preferences. To test whether this is true, I compare rejected and accepted applicants not merely at the time of application but also a few years earlier. Measurement errors in wealth as the dependent variable would bias against finding significant differences, but there is no reason to believe that measurement errors would vary over time.

3. Data construction

For my empirical analysis, I use the RAND Health and Retirement Studies dataset, [11] which allows me to observe the timing and outcome of SSDI application as well as applicants' path of asset accumulation. In addition to disability insurance application and wealth, the dataset provides information on demographics, health, employment, retirement, and income. It follows five cohorts of individuals born between 1931 and 1953, with observations every two years beginning in 1992.

Previous studies that used the HRS do not distinguish between SSDI and SSI applicants (Benitez-Silva et al., 1999, 2004, 2006; Giertz and Kubik, 2011). SSDI does not have an asset test, but many applicants also apply for Supplemental Security Income (SSI), which imposes a limit on "countable resources" such as cash and bank accounts. [12] Such an asset test is likely to suppress variation in the asset levels of SSI applicants. The HRS began distinguishing between SSDI and SSI applicants in 2000. Of the 3352 individuals in the RAND HRS data who applied for SSDI or SSI between ages 44 and 65, 1323 applied only for SSDI, 189 only for SSI, and 635 for both. Information is lacking on the remaining 1205 applicants. My main analysis focuses on individuals who applied for SSDI but not SSI. I use the remaining applicants as a comparison group for robustness checks.

[11] RAND (2011) describes construction of the data used in this paper.

[12] As of 2015, the limit is $2000 for an individual and $3000 for a couple (SSA, 2015).

Table 1
Comparison of rejected and accepted SSDI applicants: Demographics and labor force participation at the time of application.

	Rejected (N = 152)	Accepted (N = 400)	|t|
Panel A: Demographics			
Male	0.414	0.435	0.43
White	0.612	0.693	1.80*
Black	0.211	0.185	0.68
Hispanic	0.151	0.100	1.70*
College or above	0.303	0.300	0.06
Years of education	11.68	11.88	0.70
Year of birth	1943.0	1942.2	1.52
Age at application	58.01	58.38	1.01
Religion: Protestant/Catholic	0.888	0.920	1.17
Veteran	0.197	0.185	0.33
Married	0.691	0.738	1.10
Household size	2.730	2.478	2.02**
At least one living parent (N = 537)	0.440	0.406	0.72
Region: Northeast	0.132	0.170	1.10
Region: Midwest	0.224	0.253	0.70
Region: South	0.487	0.430	1.20
Region: West	0.158	0.148	0.30
Financial-planning horizon: ≥ 3 years (N = 384)	0.327	0.343	0.29
Panel B: Labor force participation			
Considers self partly/completely retired	0.392	0.339	1.13
In the labor force	0.408	0.598	4.05***
Currently working for pay	0.351	0.540	4.01***
$\frac{Self-reported\ total\ years\ working}{Eligible\ working\ years}$	0.779	0.841	2.23**
Hours worked per week (if employed, N = 268)	34.10	38.18	2.10**
Weeks worked per year (if employed, N = 262)	49.96	49.98	0.02
Self-employed (if employed, N = 269)	0.208	0.157	0.87
Blue-collar occupation (N = 518)	0.362	0.355	0.13
Manufacturing occupation (N = 519)	0.273	0.234	0.91

Notes: This table reports mean statistics on the individual characteristics of rejected and accepted SSDI applicants. Here |*t*| is the t-statistic from a two-sample *t*-test for equal means; the superscripts *, **, and *** signify $p < 0.10$, $p < 0.05$, and $p < 0.01$ respectively. *Married*, *Household size*, *At least one living parent*, *Region* dummies, *Financial-planning horizon*, and variables in Panel B are determined in the year of application or one year earlier; *Eligible working years* is calculated as (age − years of education − 6); *Blue-collar occupation* and *Manufacturing occupation* refer to the longest-duration occupation; *Financial planning horizon* is surveyed in the 1992 and 1998–2006 waves.

Table 2
Comparison of rejected and accepted SSDI applicants: health.

	Rejected	Accepted	|t|
Panel A: Zero/one year before application			
Self-reported health: fair or poor	0.572	0.550	0.47
Change in self-reported health	0.520	0.506	0.12
Self-reported change: somewhat/much worse	0.566	0.525	0.86
Health-related work limitation	0.684	0.603	1.77*
Number of doctor-diagnosed conditions	2.053	2.143	0.73
Overnight hospital stay in the last 2 years	0.428	0.413	0.32
Doctor visit in last 2 years	0.960	0.980	1.28
Out-of-pocket medical expenses	$3418	$3888	0.65
N	152	400	
Panel B: One/two years after application			
Self-reported health: fair or poor	0.594	0.691	2.07**
Change in self-reported health	0.022	0.338	2.81***
Self-reported change: somewhat/much worse	0.464	0.564	2.04**
Health-related work limitation	0.899	0.946	1.92**
Number of doctor-diagnosed conditions	2.401	2.615	1.58
Overnight hospital stay in the last 2 years	0.442	0.526	1.69*
Doctor visit in last 2 years	0.941	0.979	2.22**
Out-of-pocket medical expenses	$6096	$9582	0.63
N	138	388	

Notes: This table reports mean statistics on the health-related variables of rejected and accepted SSDI applicants. Here |*t*| is the t-statistic from a two-sample *t*-test for equal means; the superscripts *, **, and *** signify $p < 0.10$, $p < 0.05$, and $p < 0.01$ respectively. *Self-reported health* is an integer between one (excellent) and five (poor). *Self-reported health: fair or poor* is a 0/1 indicator variable for fair to poor self-reported health. *Change in self-reported health* is the first difference in *Self-reported health*. *Self-reported health change: somewhat/much worse* is a 0/1 indicator variable for self-reported deteriorating health. *Health-related work limitation* is a 0/1 indicator variable for whether the applicant self-reports a health-related limitation on the kind or amount of paid work. *Number of doctor-diagnosed conditions* is the sum of eight indicator variables for whether a doctor has ever diagnosed (1) high blood pressure or hypertension; (2) diabetes or high blood sugar; (3) cancer or a malignant tumor except skin cancer; (4) chronic lung disease except asthma; (5) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems; (6) stroke or transient ischemic attack; (7) emotional, nervous, or psychiatric problems; and (8) arthritis or rheumatism. *Out-of-pocket medical expenses* is in real year-2000 dollars.

I use two additional criteria to select my sample of applicants. Like Giertz and Kubik (2011), I define an accepted applicant as an individual who reports having received approval of his or her application or reapplication by a certain year, in this case 2010. I drop 44 individuals who applied in 2009 and 2010, some of whom may still be awaiting a decision in 2010. I assume that the remaining applicants are rejected if they do not receive approval by the time of the 2010 survey. [13]

Finally, I include only individuals whose asset data is complete for the period ending the year of application and beginning three years earlier. Applicants with missing asset data are dropped; these observations also tend to have missing values on other important variables, such as health and employment. I also exclude those who applied before the HRS study period, since we do not observe their characteristics at the time of application. Since the HRS survey takes place in even-numbered years, I observe applicants either zero and two years before application or one and three years before application. (Thus I define the time of application as either zero or one year before application.) I use observations two and three years before application to test whether there are unobserved differences in rejected and accepted applicants' tendency to accumulate assets during a time period when they are unlikely to have begun planning to apply for SSDI. Having at least two observations for each applicant ensures a balanced panel that compares the same groups over time. Because some of the applicants' asset information is missing for earlier periods, constructing a balanced panel with a longer time span would require dropping those applicants and decreasing the power for analysis. As a robustness check, I show that using a longer pre-period does not change the central results.

My resulting main sample consists of 400 accepted applicants and 152 rejected applicants who applied for SSDI but not SSI between 1994 and 2008. The overall acceptance rate is around 72.5%, [14] comparable to other studies that use the HRS to study SSDI and SSI applicants (Benitez-Silva et al., 1999, 2004, 2006; Giertz and Kubik, 2011).

A power analysis suggests that, given the number of accepted and rejected applicants, the minimum detectable effect size for the two-sample mean comparison with $power = 0.80$ is 0.237σ for $alpha = 0.10$, where σ^2 is the sample variance. To see whether the minimum detectable effect size is theoretically feasible, Fig. A.1 in Appendix A simulates the model in Section 2 and plots the range of (p, q)—the classification errors in the screening process—that would yield sufficiently large $\frac{E(k|\theta,rejected)-E(k|\theta,accepted)}{\sqrt{Var(k|\theta,applicant)}}$ under a set of assumptions. Low and Pistaferri (2015) estimate the Type I error rate (q) as 0.37 and the Type II error rate (p) as 0.18, which fall within the desirable ranges plotted in Fig. A.1. The main point estimates of (p, q) in Benitez-Silva et al. (2006) are (0.62, 0.22) and slightly outside of the ranges. However, their alternative estimates using less strict assumptions include $(p,q) = (0.55, 0.21)$ and $(p,q) = (0.42, 0.19)$, [15] both of which are within reasonable ranges. It is also noteworthy that the classification-error

[13] A few may eventually receive approval, in which case my data may underestimate the differences between accepted and rejected applicants.

[14] The proportion of accepted applicants is slightly higher for applicants in odd-numbered years than in even-numbered years, but the difference is not significant in a two-sample *T* test.

[15] See Table 5 in Benitez-Silva et al. (2006).

Table 3
Comparison of rejected and accepted SSDI applicants: income and wealth.

	Rejected (N = 152)		Accepted (N = 400)	
	Mean	Median	Mean	Median
Panel A: Zero/one year before application				
Household non-housing financial assets	34.696	2.089	28.590	1.314
Prior year's personal earnings	15.113	2.791	20.226	15.073
Prior year's household capital income	10.746	0.034	10.068	0.029
Prior year's household total income	47.989	32.921	54.902	38.451
Panel B: Two/three years before application				
Household non-housing financial assets	52.460	2.115	43.147	2.797
Prior year's personal earnings	21.644	12.105	23.835	19.134
Prior year's household capital income	7.184	0.029	9.960	0.040
Prior year's household total income	50.179	37.319	54.503	39.203

Notes: This table reports mean and median statistics on wealth-related variables for rejected and accepted SSDI applicants. Here $|t|$ is the t-statistic from a two-sample t-test for equal means; the superscripts *, **, and *** signify $p < 0.10$, $p < 0.05$, and $p < 0.01$ respectively. *Household non-housing financial assets* accounts for debt and excludes the value of retirement savings, real estate, vehicles, and businesses. All variables are in thousands of real year-2000 dollars.

rates estimated by Benitez-Silva et al. (2006) and Low and Pistaferri (2015) apply to both SSDI and SSI applicants. It is unclear how classification errors differ between SSDI and SSI.

To establish that my data have sufficient power to test the model and that screening is effective, I need to provide evidence that rejected applicants are likely to have a higher disutility of work than accepted applicants and that they are less likely to be disabled when their application outcomes are determined. I will discuss the results comparing the mean characteristics of rejected and accepted applicants in Section 4, and present the regression analysis in Section 5.

4. Mean comparisons

This section compares rejected and accepted applicants in three areas: demographics and labor force participation, health before and after disability application, and income and wealth.

4.1. Demographics and labor force participation

Table 1, Panel A, compares the demographics of rejected and accepted applicants and reports the t-statistics from a two-sample T-test of equal means. The demographics of the two groups are largely similar. The only variable significant at the 5-percent level in a t-test is household size at the time of application, which is larger for rejected applicants. Rejected applicants are less likely to be white and more likely to be Hispanic (significant at the 10-percent level). On average, rejected applicants are less likely to be male, Protestant/Catholic, and married; they are more likely to have at least one living parent at the time of application. Geographically, rejected applicants are more likely to live in the south and west and less likely to live in the northeast and midwest. None of these mean differences, however, are statistically significant. The two groups are similar in education, age, and veteran status. In the subsample of those who reported their financial planning horizon at the time of application, rejected applicants are slightly less likely to have a long planning horizon (three years or more) but the difference is not significant. Most applicants have a planning horizon shorter than three years.

Like Giertz and Kubik (2011) and von Wachter et al. (2011), I find that rejected applicants show significantly less attachment to the labor force immediately before application. According to Table 1, about 39% of rejected applicants report being at least partially retired at the time of application, compared to only 34% of accepted applicants. Only 41% of rejected applicants are in the labor force; only 35% work for pay. By contrast, almost 60% of accepted applicants are in the labor force and 54% are working for pay. The differences in both variables are large and significant. Rejected applicants are not just less likely to be working at the time of application; they have also worked significantly fewer of their eligible working years (calculated as age minus the sum of six and years of education). Given that the average number of eligible working years is around 40, the 6-percentage-point difference in the means is equivalent to 2.5 years of employment. Conditional on employment during the year of application or the prior year, rejected applicants on average work four fewer hours per week, though the two groups work a similar number of weeks.

These results are consistent with what Giertz and Kubik (2011) find using an earlier sample of SSDI and SSI applicants from the HRS data: rejected applicants have a lower labor force participation rate, and the difference is persistent over the decade preceding application. The two possible explanations are not mutually exclusive: rejected applicants face worse labor-market conditions or they have a higher disutility of work. Rejected applicants are more likely to be self-employed and to have worked predominantly in manufacturing or a blue-collar occupation (e.g., construction), but the differences are relatively small and

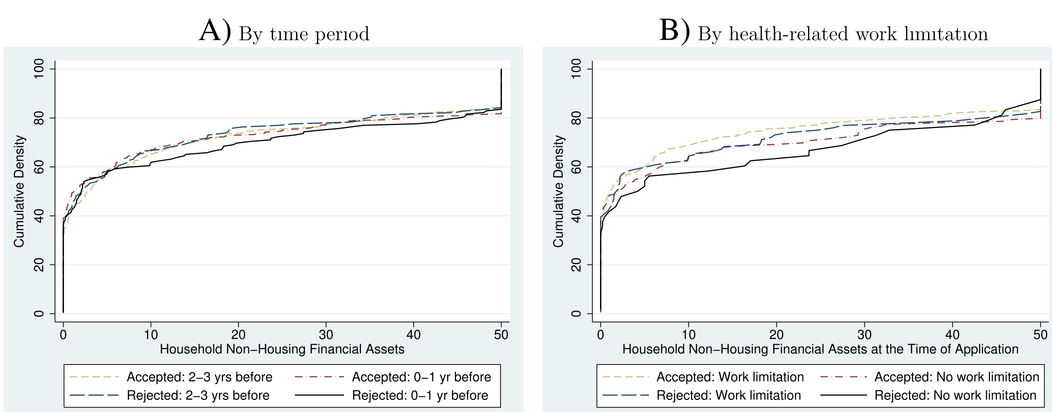


Fig. 3. Comparison of rejected and accepted SSDI applicants: household non-housing financial assets. *Notes*: This figure plots the cumulative distribution functions of the household non-housing financial assets of rejected and accepted SSDI applicants. Panel A plots the assets at 0 or 1 year before application and at 2 or 3 years before application. Panel B plots the assets at 0 or 1 year before application by health-related work limitation, which is a 0/1 indicator variable for self-report of an impairment or health problem that limits the applicant's kind or amount of paid work. Household non-housing financial assets are in thousands of real year-2000 dollars. Observations with less than 0 or more than $50,000 in financial assets are censored.

Table 4
OLS estimates of differences between rejected and accepted applicants (Dependent variable = Household non-housing financial assets).

Sample	Full		Excluding top 5%		Excluding top & bottom 5%	
	(1)	(2)	(3)	(4)	(5)	(6)
Rejected × (0 or 1 yr before)	4.180	9.594	5.624*	8.921*	2.007**	4.577**
	(8.053)	(9.730)	(1.957)	(3.231)	(0.574)	(0.919)
Rejected × (2 or 3 yrs before)	20.198**	12.244***	4.438	3.987	0.969	2.182
	(5.279)	(1.604)	(2.947)	(3.098)	(2.218)	(3.169)
Household Income	0.797**	0.731**	0.328**	0.283**	0.323**	0.277**
	(0.142)	(0.132)	(0.067)	(0.073)	(0.068)	(0.079)
Controls	No	Yes	No	Yes	No	Yes
N	1104	1104	1048	1048	994	994

Notes: This table reports OLS regression estimates. The dependent variable is the amount of household non-housing financial assets in thousands of real year-2000 dollars. Standard errors are robust and clustered by the number of years until application. The superscripts *, **, and *** signify $p < 0.10$, $p < 0.05$, and $p < 0.01$ respectively. The sample "*Excluding top 5%*" excludes individuals whose mean household non-housing financial assets across both observations exceed $225,000. The sample "*Excluding top & bottom 5%*" excludes individuals whose mean household non-housing financial assets across both observations are above $225,000 or below −$15,000. The controls include variables for gender; age; race dummies; indicator variables for college education or more, being Protestant/Catholic, being a veteran, and being married; household size; geographic-region dummies; an indicator variable for being in the labor force; indicator variables for self-reported fair or poor health, self-reported deteriorating health, and health-related work limitation; out-of-pocket medical expenses in the prior two years in 2000 dollars; survey-year dummies; and years-to-application dummies.

not statistically significant. Rejected and accepted applicants also exhibit the same education levels and largely similar demographics and geographic distributions. Adverse labor-market conditions alone are unlikely to account for the stark differences in the two groups' attachment to the labor force, both at the time of application and over their lifetimes. Since attitudes toward working are unobserved, these results are suggestive evidence that rejected applicants dislike work more than accepted applicants.

4.2. Health before and after application

Table 2 compares the health of rejected and accepted applicants at the time of application (Panel A) and shortly thereafter (Panel B), using subjective and objective measures. The subjective measures are self-reported health status, the first difference in self-reported health (i.e., the change in self-reported health since the last survey), self-reported health change, and whether poor health limits the applicant's type or amount of paid work. The objective measures are the number of doctor-diagnosed health conditions, whether one has had an overnight hospital stay in the previous two years, whether one has had a doctor visit in the previous two years, and out-of-pocket medical expenses over the previous two years (in real year-2000 dollars).

Table 5
Quantile regression estimates of differences between rejected and accepted applicants (Dependent variable = Household non-housing financial assets).

Quantile	(1) 50%	(2) 50%	(3) 25%	(3) 60%	(4) 75%
Rejected × ($T = 0, 1$)	2.395**	3.211	0.751	5.983**	8.732**
	(1.177)	(2.034)	(1.174)	(2.438)	(3.657)
Rejected × ($T = 2, 3$)	0.746	1.044	0.286	0.714	−0.201
	(1.383)	(1.472)	(1.090)	(2.332)	(4.745)
Household Income	0.291***	0.318***	0.092***	0.470***	0.843***
	(0.060)	(0.068)	(0.035)	(0.126)	(0.097)
Controls	No	Yes	Yes	Yes	Yes
N	1104	1104	1104	1104	1104

Notes: This table reports quantile regression estimates. The dependent variable is household non-housing financial assets in thousands of real year-2000 dollars. Standard errors are bootstrapped with 2000 repetitions. The superscripts *, **, and *** signify $p < 0.10$, $p < 0.05$, and $p < 0.01$ respectively. T is the number of years until SSDI application. The controls include variables for gender; age; race dummies; indicator variables for college education or more, being Protestant/Catholic, being a veteran, and being married; household size; geographic-region dummies; an indicator variable for being in the labor force; indicator variables for self-reported fair or poor health, self-reported deteriorating health, and health-related work limitations; out-of-pocket medical expenses in the prior two years in year-2000 dollars; survey-year dummies; and years-to-application dummies.

In the year of application or the prior year, the average health of rejected applicants appears worse than that of accepted applicants according to subjective measures. Around 68% of rejected applicants report a health-based work limitation at the time of application, approximately 8% more than the comparable proportion of accepted applicants; the difference is significant at the 10-percent level. Objective measures, however, show the health of rejected applicants to be comparable or better: they have fewer doctor-diagnosed health conditions, are less likely to have visited a doctor in the prior two years, and spend less on out-of-pocket medical expenses, but these differences are not statistically significant. Table A.1 in Appendix A displays similar results at two or three years before application: rejected applicants are more likely to report work limitations, and appear to have slightly worse health by subjective measures; the objective measures suggest that their average health status is comparable or better.

One or two years after application, rejected applicants are significantly healthier by both subjective and objective measures. They are significantly less likely to report fair or poor health or a change for the worse. Now 5-percentage-point fewer rejected applicants than accepted applicants report limitations on work for reasons of health, as compared to 8-percentage-point more at the time of application. Rejected applicants are also significantly less likely to self-report deteriorating health, a hospital stay, or a doctor visit in the preceding two years. They have fewer doctor-diagnosed conditions and spend less on out-of-pocket medical expenses.

These results suggest that the screening process distinguishes between healthier and less healthy applicants at least by the time of the decision, as the application-review process can take a few years. Rejected applicants may become healthier after application, resulting in rejection; alternatively, they may understate their health status to the HRS at the time of application, either to justify their application or because they doubt the study's confidentiality. For purposes of this study, it is unnecessary to distinguish between these hypotheses, since both suggest that the screening process is fairly effective.

Table A.2 in Appendix A shows that accepted applicants are significantly more likely to have been diagnosed with heart problems and cancer; rejected applicants are significantly more likely to have back pain. [16] Autor and Duggan (2003) and Autor and Duggan (2006) find that the expansion of SSDI since 1984—particularly rapid growth in

[16] Autor and Duggan (2006) show that heart disease, cancers, mental impairments, and musculoskeletal disorders (typically, back pain and arthritis) are the four largest categories of diagnoses, accounting for around 70% of all awards.

awards for back pain and mental illness, which are difficult to verify and entail low mortality—has prompted applications from individuals whose unwillingness to work is high and/or who face adverse labor-market conditions. Thus the differences observed here are consistent with higher disutility of work on the part of rejected applicants.

Following Benitez-Silva et al. (2004), Benitez-Silva et al. (2006), and Low and Pistaferri (2015), I use self-reported work limitation due to health as a proxy for disability status. I consider this measure relative, however, and not absolute; that is, I do not assume that everyone who reports work limitation is disabled. The explanation is twofold. First, HRS's definition of the variable "whether an impairment or health problem limits the kind or amount of paid work" includes partial disability, and is far less extreme than SSA's definition of disability, "inability to work due to medical conditions that are expected to result in death or to last for at least one year." Second, Table 2 suggests possible discrepancies between self-reported disability status and objective measures of health at the time of application. Instead, I assume that, within each group of rejected or accepted applicants, those who report health-limited work at the time of application are more likely than others to be disabled.

4.3. Income and wealth

Table 3 compares the wealth and income of accepted and rejected applicants. I use applicants' household non-housing financial assets to measure asset levels. This measure includes the value of liquid financial assets, such as stocks, mutual funds, bonds, checking and saving accounts, and debt. Following Engen and Gruber (2001), I exclude less-liquid assets, such as IRAs and Keogh plans, and assets that have direct consumption value, such as real estate and vehicles. Both mean and median are reported in Table 3. Panel A shows the comparison at the time of application; Panel B reports the same statistics two or three years before application. Overall, accepted applicants have higher personal earnings and total household income, consistent with the observation that they work significantly more than rejected applicants. Accepted applicants have higher median liquid assets two or three years before application, but rejected applicants' median asset level surpasses that of accepted applicants zero or one year before application.

Panel A in Fig. 3 plots the cumulative density functions of non-housing financial assets of rejected and accepted applicants, at the time of application and two or three years earlier. I censor values below 0 and above 50 so that the graphs will focus on the 20th to 80th percentiles. Two or three years before application, accepted applicants have slightly higher assets at most percentiles, though the differences are small. This is unsurprising in that accepted applicants have higher earnings. Zero or one year before application, rejected applicants have higher assets at most percentiles between the 40th and 80th percentiles, even though they are more likely to be out of the labor force and to have lower earnings. These differences are primarily due to increases in rejected applicants' asset levels, not decreases in those of accepted applicants. Panel B in Fig. 3 shows that the differences in asset levels of rejected and accepted applicants at the time of application are mainly driven by rejected applicants without health-related work limitations. Because many factors could affect asset accumulation, I use regression analysis to control for observables and to estimate the difference in asset accumulation between rejected and accepted applicants.

5. Regression analysis

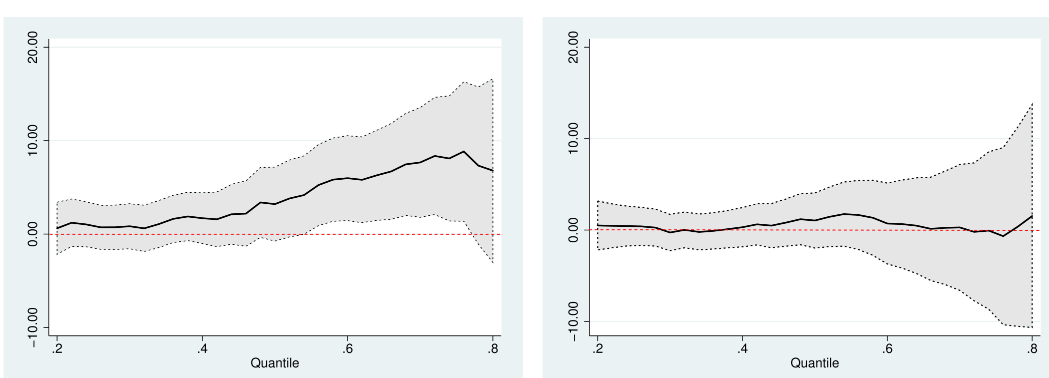
My main specification is

$$A_{iT} = \alpha + \beta_1 Rej_i \times (T = 0, 1) + \beta_2 Rej_i \times (T = 2, 3) + \beta_3 I_{iT} + \Phi \cdot \Sigma_{iT} + \varepsilon_{iT}, \tag{6}$$

where i denotes an applicant; T denotes the time period (i.e., the number of years before SSDI application); A_{iT} is person i's household liquid-asset level at time T; Rej_i is 1 if the applicant is ultimately rejected and 0 otherwise; I_{iT} is the household's total income during the last calendar year; and Σ_{iT} includes a set of variables controlling for demographics, labor force participation, health, out-of-pocket medical expenses, calendar-year dummies, and years-to-application dummies.

The coefficients β_1 and β_2 do not represent the causal impact of rejection on asset accumulation but capture differences in applicants' asset levels conditional on other observables. Since my sample construction ensures a balanced panel, each applicant has two observations. I separately estimate the difference between rejected and accepted applications at zero or one year before application and at two or three years before application.

Table 4 reports the OLS estimates of Eq. (6). The results are sensitive to inclusion of outliers, or individuals with extremely high or low assets. Excluding outliers, Columns (5) and (6) suggest that rejected applicants have accumulated significantly more liquid assets than accepted applicants at the time of application. The difference is smaller and statistically insignificant at two or three years before application. Controlling for



β_1: Rejected $\times(T = 0, 1)$ β_2: Rejected $\times(T = 2, 3)$

Fig. 4. Quantile regression estimates of differences in asset levels by application status. *Notes*: This figure plots the quantile regression estimates from Eq. (6) between the 20% and 80% quantiles. Standard errors are bootstrapped with 2000 repetitions. The left-hand figure plots the coefficient estimates and 95% confidence intervals of being a rejected applicant interacted with a 0/1 indicator variable for the time being zero/one year before application. The right-hand figure plots the coefficient estimates and 95% confidence intervals of being a rejected applicant interacted with a 0/1 indicator variable for the time being two/three years before application.

observables, rejected applicants accumulate around \$4600 more in mean liquid assets than accepted applicants (Column (6)).

Because the distribution of assets is highly skewed, I use quantile regressions to estimate Eq. (6), bootstrapping the standard errors with 2000 repetitions. Table 5 reports the magnitudes of the estimates at the 25%, 50%, 60%, and 75% quantiles. Controlling for income and a rich set of observables, rejected applicants possess around \$3200 more in median liquid assets than accepted applicants at the time of application, though the estimate is not statistically significant. The difference is economically meaningful, however, since the median liquid-asset levels of rejected and accepted applicants are around \$2100 and \$1300 respectively. The differences are even larger at the 60% and 75% quantiles and statistically significant at the 5% level. The difference at the 25% quantile is positive but insignificant, unsurprising given that these applicants have scant assets. Fig. 4 plots the coefficient estimates of β_1 and β_2 and the 95-percent confidence intervals for all even percentiles between 20% and 80% using bootstrapped standard errors. The coefficient estimates of β_1 increase with the applicants' asset level and are especially large and significant after the 60% quantile. In stark contrast, all the estimates of β_2 are close to zero and statistically insignificant.

Overall, I find that rejected applicants accumulate significantly more liquid financial assets than accepted applicants by the time of application. The magnitude and statistical significance of the differences increase with asset levels. Such differences do not appear at two or three years before application, suggesting that the two groups are unlikely to have unobserved differences in the tendency to save.

5.1. Robustness checks

I present three sets of robustness checks. First I include observations up to six or seven years before application. Fig. 5 plots the quantile estimates of β_1 and β_2 from Eq. (6) using a balanced sample consisting of 117 rejected applicants and 297 accepted applicants. Each applicant has four observations of non-missing asset levels between zero/one year before application and six/seven years before application. Since there are fewer applicants, the estimates are noisier. But the key results hold: positive and large differences in asset levels between rejected and accepted applicants at the time of application, but not several years earlier.

Second, I explore differences among applicants' self-reported health-related work limitations and estimate

$$\begin{aligned} A_{iT} = \alpha &+ \beta_{11} Rej_i \times (H_i = 0) \times (T = 0,1) + \beta_{21} Rej_i \times (H_i = 0) \times (T = 2,3) \\ &+ \beta_{12} Rej_i \times (H_i = 1) \times (T = 0,1) + \beta_{22} Rej_i \times (H_i = 1) \times (T = 2,3) \\ &+ \beta_{13} (H_i = 0) \times (T = 0,1) + \beta_{23} (H_i = 0) \times (T = 2,3) \\ &+ \beta_3 I_{iT} + \Phi \cdot \Sigma_{iT} + \varepsilon_{iT}, \end{aligned} \tag{7}$$

where H_i is whether applicant i self-reports health-related work limitation at the time of application.

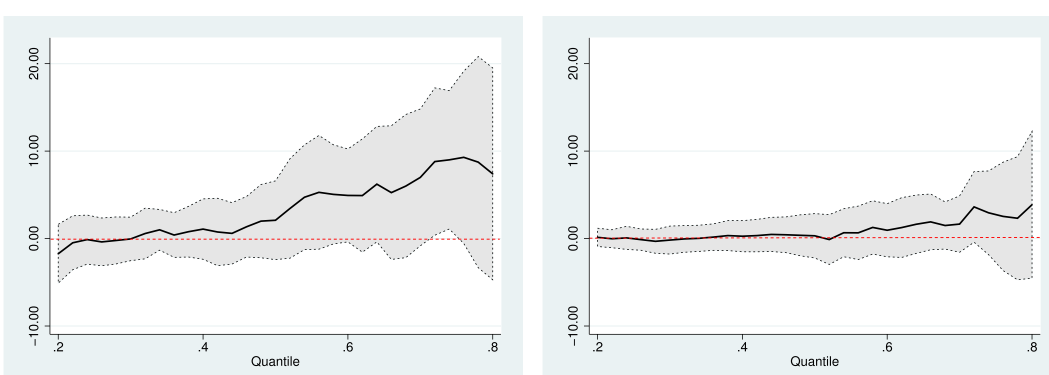
Fig. 6 plots the quantile regression estimates of $\beta_{11}, \beta_{21}, \beta_{12}, \beta_{22}, \beta_{13}$ and β_{23}. The base group here is accepted applicants who report work limitation at the time of application. Consistent with Fig. 3, rejected applicants without work limitations differ most from the base group at the time of application, though the estimates are somewhat noisy. Rejected applicants with work limitations also possess significantly more assets than the base group in some quantiles, but the magnitudes of the differences are smaller. There are no differences in asset levels between accepted applicants without limitations and the base group at the time of application. Differences among the asset levels of the four groups two or three years before application are minimal.

Third, I use other applicants likely to have applied to SSI between ages 44 and 65 as a comparison group and estimate

$$\begin{aligned} A_{iT} = \alpha &+ \beta_{11} Rej_i \times SSDI_i \times (T = 0,1) + \beta_{21} Rej_i \times SSDI_i \times (T = 2,3) \\ &+ \beta_{12} Rej_i \times (T = 0,1) + \beta_{22} Rej_i \times (T = 2,3) + \beta_3 I_{iT} + \Phi \cdot \Sigma_{iT} + \varepsilon_{iT}, \end{aligned} \tag{8}$$

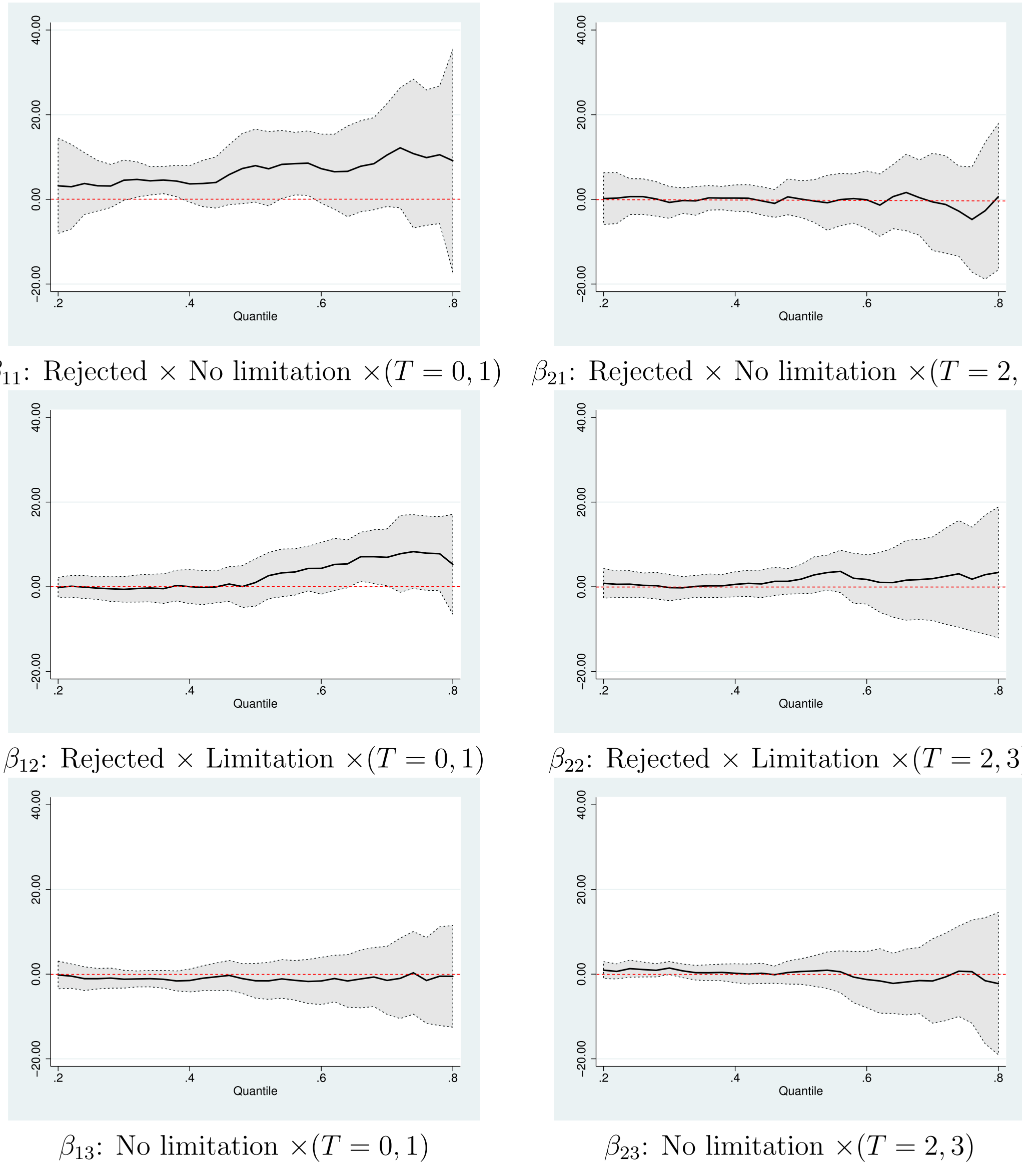
where $SSDI_i = 1$ if the applicants applied only to SSDI (my main sample). The comparison sample includes 273 accepted applicants and 206 rejected applicants who belong to one of three categories: (1) applicants to SSI but not SSDI, (2) applicants to both, or (3) those whose application patterns are unclear. Like the applicants in my main sample, those in the comparison sample applied between ages 44 and 65 and have non-missing asset information between zero/one year before application and two/three years before application. I report the characteristics of rejected and accepted applicants in the comparison sample in Appendix B.

Eq. (8) uses the disability applicants in the comparison sample to control for differences between rejected and accepted applicants in each time period. Fig. 7 plots the quantile estimates of $\beta_{11}, \beta_{21}, \beta_{12},$



β_1: Rejected $\times (T = 0, 1)$ β_2: Rejected $\times (T \in [2, 7])$

Fig. 5. Robustness checks: Quantile regression estimates of differences in asset levels by application status with a longer time horizon. *Notes*: This figure plots the quantile regression estimates from Eq. (6) between the 20% and 80% quantiles. Standard errors are bootstrapped with 2000 repetitions. The left-hand figure plots the coefficient estimates and 95% confidence intervals of being a rejected applicant interacted with a 0/1 indicator variable for the time being zero/one year before application. The right-hand figure plots the coefficient estimates and 95% confidence intervals of being a rejected applicant interacted with a 0/1 indicator variable for the time being between two and seven years before application. The sample includes 117 rejected applicants and 297 accepted applicants who satisfy the following criteria: (a) applied to SSDI but not SSI between ages 44 and 65, (b) applied before 2009, and (c) does not have any missing asset data between zero/one year before application and six/seven years before application.



β_{11}: Rejected × No limitation ×($T = 0, 1$) β_{21}: Rejected × No limitation ×($T = 2, 3$)

β_{12}: Rejected × Limitation ×($T = 0, 1$) β_{22}: Rejected × Limitation ×($T = 2, 3$)

β_{13}: No limitation ×($T = 0, 1$) β_{23}: No limitation ×($T = 2, 3$)

Fig. 6. Robustness checks: Quantile regression estimates of differences in asset levels by application status and health-related work limitation. *Notes*: This figure plots the estimates and 95% confidence intervals of the quantile regression coefficients from Eq. (7) between the 20% and 80% quantiles. Standard errors are bootstrapped with 2000 repetitions. *Health-related work limitation* is a 0/1 indicator variable for self-report of an impairment or health problem that limits the applicant's kind or amount of paid work. *T* is the number of years until SSDI application.

and β_{22}. Because SSI is means-tested, it is unsurprising that rejected and accepted SSDI/SSI applicants do not possess significantly different assets at the time of application. As in the results without the comparison sample, rejected SSDI applicants have accumulated significantly more assets than accepted applicants at the time of application but not two or three years before application. As such applicants' asset levels increase, the magnitude and statistical significance of the differences at the time of application also increase.

5.2. Discussion

Together with Section 4, the regression results suggest that at least some rejected applicants planned a couple of years in advance to apply for disability insurance and saved accordingly. One could argue that rejected applicants accumulate more assets because they are healthier and/or expect a higher probability of being rejected. If all rejected applicants had taken the working path, their asset levels would have been *lower* than accepted applicants', conditional on their earnings. This is the case because healthier agents have higher expected incomes if they decide to work. Thus any unobserved differences in health should drive rejected applicants to possess fewer assets than accepted applicants rather than more.

An alternative explanation is that rejected applicants possess more assets because they face worse labor-market conditions and self-insure against the risk of unemployment. But rejected applicants tend toward less labor force participation and lower earnings for many years—up to a decade—before application (Giertz and Kubik, 2011; von Wachter et al., 2011). If they face persistently worse labor-market conditions over time, they should accumulate more assets than accepted applicants several years before application, which I do not observe. Also, self-insuring against unemployment risk is consistent with the prediction that some applicants planned their application for non-health-related reasons.

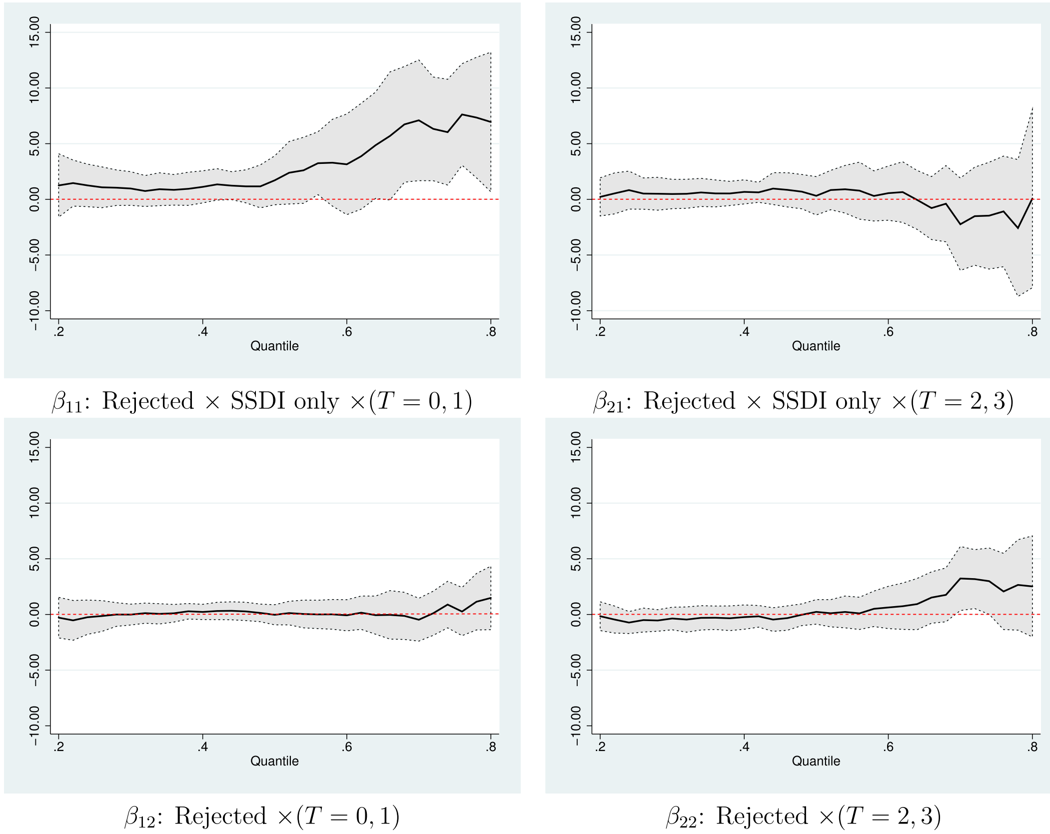


Fig. 7. Robustness checks: Quantile regression estimates of differences in asset levels by application status using SSDI/SSI applicants as a comparison group. *Notes*: This figure plots the estimates and 95% confidence intervals of the quantile regression coefficients from Eq. (8) between the 20% and 80% quantiles. Standard errors are bootstrapped with 2000 repetitions. The sample includes individuals who satisfy the following criteria: (a) applied to SSDI and/or SSI between ages 44 and 65, (b) applied before 2009, and (c) has non-missing asset data between zero/one year before application and two/three years before application. *SSDI only* is a 0/1 indicator variable that equals 1 if it is clear that the applicant applied only to SSDI. *T* is the number of years until SSDI application.

Another possible explanation is that a positive wealth shock, such as a large severance package or inheritance, could have prompted a relatively healthy agent to drop out of the labor force and apply for disability insurance. It is difficult to test this mechanism directly, but large wealth shocks are low-probability events. Given that rejected applicants hold relatively low-income jobs and are persistently less likely to be in the labor force, large severance packages are apt to be rare. Table 1 shows that 44% and 40.6% of rejected and accepted applicants respectively have at least one living parent at the time of application. Two or three years before application, the probabilities of having at least one living parent are 51.7% for the rejected applicants and 47.6% for accepted applicants. Both groups experienced a 7-percentage-point drop; thus a large inheritance is also unlikely to drive the observed differences between rejected and accepted applicants.

6. Conclusion

This paper links the theoretical literature on optimal saving distortions with the empirical literature examining the work-disincentive effects of disability-insurance programs. It presents and empirically tests a model that predicts the asset accumulation and labor force participation of SSDI applicants: if an applicant who strongly dislikes work plans to apply for disability insurance in the future even if still capable of working at that time, he or she will have accumulated more assets at the time of application than if the decision to apply were made only when truly disabled. I use the RAND HRS data to show that rejected applicants exhibit weaker attachment to the labor force and appear to be healthier at the time their applications are decided on. Although the assets of rejected and accepted applicants do not differ several years before application, rejected applicants possess more liquid assets at the time of application. These findings provide empirical support for the existence of forward-looking asset-accumulation behavior. Though the current screening system is not effective enough to deter those individuals from applying, it can detect at least some work-capable applicants who plan in advance even without relying on assets as a criterion. Thus it is unclear to what degree imposing an asset-based criterion on the current system, as suggested by Golosov and Tsyvinski (2006), would increase the efficacy of screening.

Prior studies have used rejected applicants' post-application labor force participation rate as an upper bound of accepted applicants' counterfactual labor force participation rate (Bound, 1989; von Wachter et al., 2011). My results suggest that rejected and accepted applicants differ on other dimensions besides health, and particularly on their unobserved preferences. Because rejected applicants may dislike work more than accepted applicants, it is unclear whether the former are a proper comparison group for the latter when studying labor force participation.

Disability insurance functions as long-term unemployment insurance for some individuals facing adverse labor-market conditions (Autor and Duggan, 2003, 2006); in addition, it is also possible that individuals with high unwillingness to work view SSDI as an alternative form of Social Security before they are eligible for retirement benefits (Duggan et al., 2007). Since disability insurance affects future labor supply, the empirical literature on the contemporaneous impact of disability insurance on labor force participation may underestimate the magnitude of the total work-disincentive effect. However, given suggestive evidence of rejected applicants' high disutility of work, it is unclear what proportion of them would stay in the labor force longer in the absence of a disability-insurance program. Quantifying the magnitude of the dynamic work-disincentive effect is a promising direction for future research.

Appendix A. Additional tables and figures

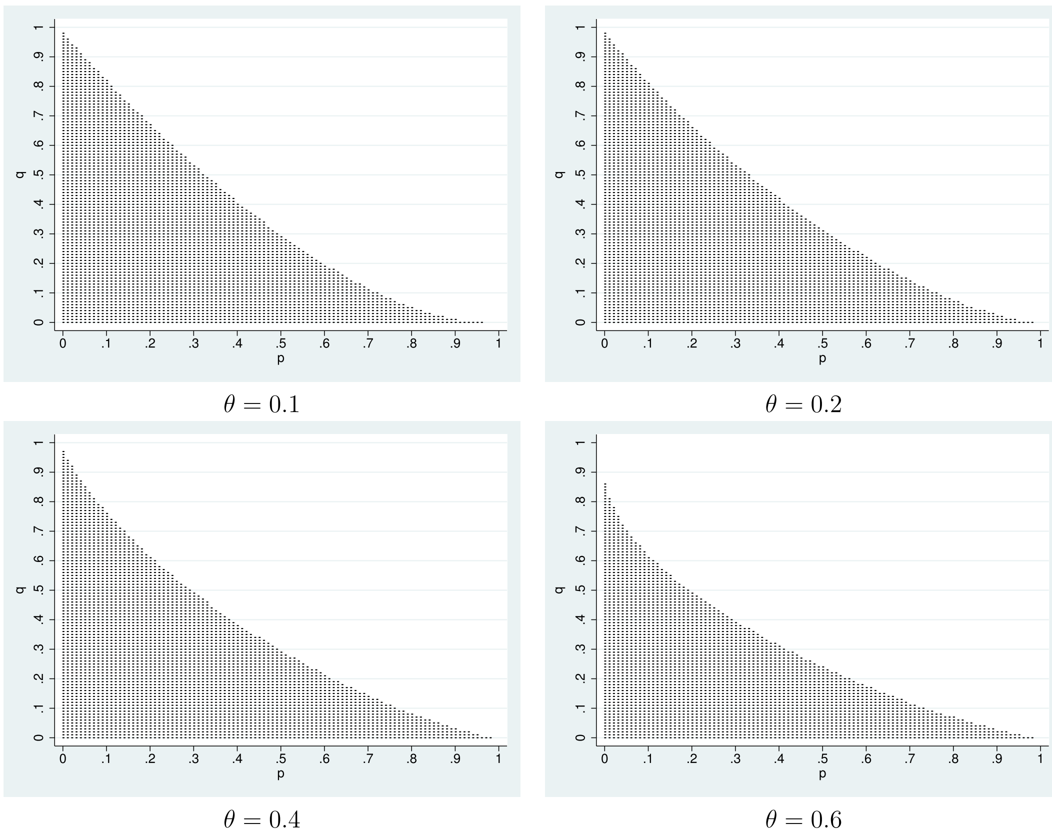


Fig. A.1. Power analysis: range of (p, q) for minimum detectable effect size. *Notes*: This figure plots the range of p and q that would yield $\frac{E(k|\theta,rejected)-E(k|\theta,accepted)}{\sqrt{Var(k|\theta,applicant)}}$ greater than the minimum detectable effect size with 400 accepted applicants and 152 rejected applicants, $power = 0.80$, and $alpha = 0.10$. The simulations use the model from Section 2.2 and assume $u = \log(c)$; $w = 1$; $R = 1.043$; $\beta = 1/R$; $\tau = 0.07$; $T = 0.5$; x uniformly distributed between [0, 1.5]. Each panel assumes a different θ.

Table A.1
Comparison of rejected and accepted SSDI applicants: health two or three years before application.

	Rejected (N = 152)	Accepted (N = 400)	$\lvert t \rvert$
Self-reported health: fair or poor	0.355	0.298	1.31
Change in self-reported health	0.036	0.092	0.54
Self-reported change: somewhat/much worse	0.368	0.355	0.29
Health-related work limitation	0.318	0.234	2.00**
Number of doctor-diagnosed conditions	1.593	1.718	1.06
Overnight hospital stay in the last 2 years	0.204	0.260	1.37
Doctor visit in last 2 years	0.913	0.914	0.04
Out-of-pocket medical expenses	$2607	$2957	0.65

Notes: This table reports mean statistics on the health-related variables of rejected and accepted SSDI applicants at two or three years before their application. Here $|t|$ is the t-statistic from a two-sample t-test for equal means; the superscripts *, **, and *** signify $p < 0.10$, $p < 0.05$, and $p < 0.01$ respectively. *Self-reported health* is an integer between one (excellent) and five (poor). *Self-reported health: fair or poor* is a 0/1 indicator variable for fair to poor self-reported health. *Change in self-reported health* is the first difference in *Self-reported health*. *Self-reported health change: somewhat/much worse* is a 0/1 indicator variable for self-reported deteriorating health. *Health-related work limitation* is a 0/1 indicator variable for whether the applicant self-reports a health-related limitation on the kind or amount of paid work. *Number of doctor-diagnosed conditions* is the sum of eight indicator variables for whether a doctor has ever diagnosed (1) high blood pressure or hypertension; (2) diabetes or high blood sugar; (3) cancer or a malignant tumor except skin cancer; (4) chronic lung disease except asthma; (5) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems; (6) stroke or transient ischemic attack; (7) emotional, nervous, or psychiatric problems; and (8) arthritis or rheumatism. *Out-of-pocket medical expenses* is in real year-2000 dollars.

Table A.2
Comparison of rejected and accepted SSDI applicants: health conditions.

	Rejected	Accepted	$\|t\|$
Panel A: Zero/one year before application			
Back pain (N = 323)	0.535	0.506	0.45
CESD score (N = 519)	2.793	2.471	1.37
Doctor-diagnosed: high-blood pressure	0.550	0.534	0.33
Doctor-diagnosed: diabetes	0.232	0.246	0.34
Doctor-diagnosed: cancer	0.093	0.123	0.99
Doctor-diagnosed: lung disease	0.113	0.128	0.48
Doctor-diagnosed: heart problems	0.166	0.243	1.96*
Doctor-diagnosed: stroke	0.113	0.068	1.73*
Doctor-diagnosed: psychological problems	0.238	0.183	1.46
Doctor-diagnosed: arthritics	0.550	0.619	1.48
N	399	151	
Panel B: One/two years after application			
Back pain (N = 279)	0.654	0.530	1.90*
CESD score (N = 495)	2.570	2.621	0.21
Doctor-diagnosed: high-blood pressure	0.606	0.599	0.13
Doctor-diagnosed: diabetes	0.277	0.287	0.21
Doctor-diagnosed: cancer	0.117	0.183	1.80*
Doctor-diagnosed: lung disease	0.124	0.165	1.15
Doctor-diagnosed: heart problems	0.197	0.313	2.59***
Doctor-diagnosed: stroke	0.146	0.121	0.74
Doctor-diagnosed: psychological problems	0.285	0.251	0.78
Doctor-diagnosed: arthritics	0.650	0.695	0.98
N	387	137	

Notes: This table reports mean statistics on health problems for rejected and accepted SSDI applicants. Here $|t|$ is the t-statistic from a two-sample t-test for equal means; the superscripts *, **, and *** signify $p < 0.10$, $p < 0.05$, and $p < 0.01$ respectively. Back pain is surveyed every other wave. *CESD score* is a score on the Center for Epidemiologic Studies Depression scale that measures the respondent's feelings in the previous week using the sum of five negative indicators minus two positive indicators; a higher score indicates more negative feelings. For the eight doctor-diagnosed health conditions, the sample includes only respondents who answer all eight questions. The conditions are: (1) high blood pressure or hypertension; (2) diabetes or high blood sugar; (3) cancer or a malignant tumor except skin cancer; (4) chronic lung disease except asthma; (5) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems; (6) stroke or transient ischemic attack; (7) emotional, nervous, or psychiatric problems; and (8) arthritis or rheumatism.

Appendix B. Supplementary materials

Supplementary materials to this article can be found online at http://dx.doi.org/10.1016/j.jpubeco.2015.06.002.

References

Albanesi, S., Sleet, C., 2006. Dynamic optimal taxation with private information. Rev. Econ. Stud. 73, 1–30. http://dx.doi.org/10.1111/j.1467-937X.2006.00367.x (URL: http://restud.oxfordjournals.org/content/73/1/1).

Autor, D., Duggan, M., 2003. The rise in the disability rolls and the decline in unemployment. Q. J. Econ. 118, 157–206.

Autor, D., Duggan, M., 2006. The growth in the social security disability rolls: a fiscal crisis unfolding. J. Econ. Perspect. 20, 71–96.

Benitez-Silva, H., Buchinsky, M., Chan, H.M., Rust, J., Sheidvasser, S., 1999. An empirical analysis of the social security disability application, appeal, and award process. Labour Econ. 6, 147–178.

Benitez-Silva, H., Buchinsky, M., Chan, H.M., Cheidvasser, S., Rust, J., 2004. How large is the bias is self-reported disability? J. Appl. Econ. 19, 649–670.

Benitez-Silva, H., Buchinsky, M., Rust, J., 2006. How large are the classification errors in the social security disability award process? NBER Working Paper No. 10219 (URL: http://www.nber.org/papers/w10219)

Black, D., Daniel, K., Sanders, S., 2002. The impact of economic conditions on participation in disability programs: evidence from the coal boom and bust. Am. Econ. Rev. 92, 27–50.

Borghans, L., Gielen, A.C., Luttmer, E.F.P., 2012. Social support substitution and the earnings rebound: evidence from a regression discontinuity in disability insurance reform. NBER Working Paper No.18261 (URL: http://www.nber.org/papers/w18261).

Bound, J., 1989. The health and earnings of rejected disability insurance applicants. Am. Econ. Rev. 79, 482–503.

Chen, S., van der Klaauw, W., 2008. The work disincentive effects of the disability insurance program in the 1990s. J. Econ. 142, 757–784.

Diamond, P., Mirrlees, J., 1978. A model of social insurance with variable retirement. J. Public Econ. 10, 295–336. http://dx.doi.org/10.1016/0047-2727(78)90050-6 (URL: http://www.sciencedirect.com/science/article/pii/0047272778900506).

Diamond, P., Sheshinski, E., 1995. Economic aspects of optimal disability benefits. J. Public Econ. 57, 1–23. http://dx.doi.org/10.1016/0047-2727(94)01435-Q (URL: http://www.sciencedirect.com/science/article/pii/004727279401435Q).

Duggan, M., Imberman, S.A., 2009. Why are the disability rolls skyrocketing? The contribution of population characteristics, economic conditions, and program generosity. Health at Older Ages: The Causes and Consequences of Declining Disability among the Elderly. University of Chicago Press, pp. 337–379 (URL: http://www.nber.org/chapters/c11119).

Duggan, M., Singleton, P., Song, J., 2007. Aching to retire? The rise in the full retirement age and its impact on the social security disability rolls. J. Public Econ. 91, 1327–1350. http://dx.doi.org/10.1016/j.jpubeco.2006.12.007 (URL: http://www.sciencedirect.com/science/article/pii/S0047272707000023).

Engen, E.M., Gruber, J., 2001. Unemployment insurance and precautionary saving. J. Monet. Econ. 47, 545–579 (URL: http://www.sciencedirect.com/science/article/pii/S0304393201000514).

Farhi, E., Werning, I., 2012. Capital taxation: quantitative explorations of the inverse Euler equation. J. Polit. Econ. 120, 398–445 (URL: http://www.jstor.org/stable/10.1086/666747).

French, E., Song, J., 2014. The effect of disability insurance receipt on labor supply. Am. Econ. J. Econ. Policy 6, 291–337. http://dx.doi.org/10.1257/pol.6.2.291 (URL: http://www.aeaweb.org/articles.php?).

Giertz, S., Kubik, J., 2011. The disability screening process and the labor market behavior of accepted and rejected applicants: evidence from the health and retirement study. J. Lab. Res. 32, 237–253. http://dx.doi.org/10.1007/s12122-011-9110-0 (URL: http://www.springerlink.com/content/v42p8765574792k6/abstract/).

Golosov, M., Tsyvinski, A., 2006. Designing optimal disability insurance: a case for asset testing. J. Polit. Econ. 114, 257–279.

Golosov, M., Tsyvinski, A., 2007. Optimal taxation with endogenous insurance markets. Q. J. Econ. 122, 487–534 (URL: http://qje.oxfordjournals.org/content/122/2/487).

Golosov, M., Kocherlakota, N., Tsyvinski, A., 2003. Optimal indirect and capital taxation. Rev. Econ. Stud. 70, 569–587 (URL: http://restud.oxfordjournals.org/content/70/3/569).

Golosov, M., Tsyvinski, A., Werning, I., 2006. New dynamic public finance: a user's guide. NBER Macroeconomics Annual 2006 vol. 21. National Bureau of Economic Research, Inc., pp. 317–388 (URL: https://ideas.repec.org/h/nbr/nberch/11181.html).

Gruber, J., 2000. Disability insurance benefits and labor supply. J. Polit. Econ. 108 (URL: http://moya.bus.miami.edu/probins/DI-Canada-Gruber.pdf).

Gruber, J., Kubik, J.D., 1997. Disability insurance rejection rates and the labor supply of older workers. J. Public Econ. 64, 1–23. http://dx.doi.org/10.1016/S0047-2727(96)01590-3 (URL: http://www.sciencedirect.com/science/article/pii/S0047272796015903).

Kleven, H.J., Kopczuk, W., 2011. Transfer program complexity and the take-up of social benefits. Am. Econ. J. Econ. Policy 3, 54–90. http://dx.doi.org/10.1257/pol.3.1.54 (URL: https://www.aeaweb.org/articles.php?).

Kocherlakota, N.R., 2005. Zero expected wealth taxes: a Mirrlees approach to dynamic optimal taxation. Econometrica 73, 1587–1621 (URL: http://www.jstor.org/stable/3598884).

Kocherlakota, N.R., 2010. The New Dynamic Public Finance. Princeton University Press.

Low, H., Pistaferri, L., 2015. Disability insurance and the dynamics of the incentive-insurance tradeoff. Am. Econ. Rev. Forthcoming (URL: http://web.stanford.edu/~pista/LP_FINAL.pdf).

Maestas, N., Mullen, K.J., Strand, A., 2013. Does disability insurance receipt discourage work? Using examiner assignment to estimate causal effects of SSDI receipt. Am. Econ. Rev. 103, 1797–1829. http://dx.doi.org/10.1257/aer.103.5.1797.

Moore, T.J., 2015. The employment effects of terminating disability benefits. J. Public Econ. 124, 30–43. http://dx.doi.org/10.1016/j.jpubeco.2015.02.004 (URL: http://www.sciencedirect.com/science/article/pii/S0047272715000171).

Parsons, D.O., 1991. The health and earnings of rejected disability insurance applicants: comment. Am. Econ. Rev. 81, 1419–1426 (URL: http://ideas.repec.org/a/aea/aecrev/v81y1991i5p1419-26.html).

RAND, 2011. RAND HRS Data, Version L. (URL: http://www.rand.org/content/dam/rand/www/external/labor/aging/dataprod/randhrsL.pdf).

Social Security Administration, 2010. Annual statistical report on the social security disability insurance program. http://www.ssa.gov/policy/docs/statcomps/di_asr/2010/index.html.

Social Security Administration, 2015. Understanding supplemental security income. http://www.ssa.gov/ssi/text-resources-ussi.htm.

von Wachter, T., Song, J., Manchester, J., 2011. Trends in employment and earnings of allowed and rejected applicants to the social security disability insurance program. Am. Econ. Rev. 101, 3308–3329.