How do Disability Insurance Beneficiaries Respond to Cash on Hand? New Evidence and Policy Implications*

Gregory A. Bruich

November 2014

Abstract

This paper presents new evidence on the costs and benefits of disability insurance (DI). I start by estimating the effect of unconditional transfers on the labor force participation of DI beneficiaries in Denmark. I show that a large fraction of the impact of DI benefits on labor supply can be attributed to non-distortionary income effects (i.e., making it feasible for disabled workers to "afford" not to work) rather than distortionary price effects (i.e., reducing effective wages). I then show evidence that DI beneficiaries respond very differently to cash-on-hand than do non-disabled populations. In particular, the probability of an emergency room visit increases for DI beneficiaries, but not other groups, when monthly income is received, and this response to payments is present even in the years before they were granted DI benefits. This "excess sensitivity" creates fiscal externalities and may be caused by behavioral biases. These results imply that the standard approaches to welfare analysis may need to be modified to study DI and that optimal policy may involve setting the frequency at which payments are dispersed in addition to benefit levels.

*Economics Department, Harvard University, Cambridge, Massachusetts, USA and Epidemiology Research Department, Statens Serum Insitut, Copenhagen, Denmark; e-mail: gbruich@fas.harvard.edu. I thank Raj Chetty, David Cutler, and Martin Feldstein for their time, help, and advice. I am grateful to Mads Melbye, Poul Erik Hansen, and the Statens Serum Institut for their hospitality and generosity while I was in Copenhagen and to Mette Pedersen and the Ministry of Social Affairs and Integration for answering my many questions. I thank Nete Munk Nielsen, Rainer Winkelmann, and Jan Wohlfahrt for comments on an earlier draft of the ER visit results and David Autor, Thomas Barrios, Stefano DellaVigna, Kathleen Feldstein, John Friedman, Edward Glaeser, Nate Hilger, Lawrence Katz, Brian Knight, Jessica Laird, Sendhil Mullainathan, Maja Halgren Olsen, John van Reenen, Annette Søberg Roed, Emily Sands, Mark Shepard, Jacob Simonsen, Stefanie Stantcheva, Matthew Weinzierl, participants at the Spring 2013, Fall 2013, and Spring 2014 Harvard Public Economics seminar, and the Fall 2014 Public Economics Seminar and Fiscal Policy Workshop, and many others at the Department of Epidemiology Research and the National Health Surveillance and Research Division at the Statens Serum Institut for helpful comments and conversations. Funding was provided by a NBER fellowship on the economics of an aging workforce and a research grant from Helsefonden.

1 Introduction

Over the last sixty years, modern governments have increasingly devoted resources to providing insurance against adverse events, such as disability, job loss, and illness (Gruber 2007). Of these social insurance programs, disability insurance (DI) is potentially one of the most valuable, but also one of the most costly. It is valuable because the impact of severe disabilities on income and consumption is large and long-lasting (e.g., Meyer and Mok 2013). Further, the private DI market is unlikely to provide adequate insurance coverage because of strong information asymmetry (e.g., Hendren 2013). Disability insurance is costly, because once awarded benefits, exit from the labor force tends to be permanent, so that DI becomes a lifetime annuity. In the United States, DI rolls have expanded as the generosity of the program has increased and screening stringency has been relaxed (Autor and Duggan 2006). There is now a large empirical literature which has uniformly found causal evidence that disability insurance reduces labor supply (e.g., Maestas, Mullen, and Strand 2013).[1]

However, the normative implications of this relationship are unclear. One interpretation is that these trends and causal evidence reflect that the program is very distortionary, because it reduces effective wages by imposing large implicit tax rates on earnings.[2] Alternatively, the evidence could reflect that the program is very valuable, because it makes it feasible to stop working when one's disability has made remaining in the labor force very costly. In this case, the decline in labor force participation is simply a result of providing resources to those who need it and, in fact, is desirable.[3] The welfare implications of DI and optimal benefit levels depend on quantifying the relative contributions of each of these mechanisms (Chetty 2008).

This paper makes two main contributions. First, I shed new light on the value of disability insurance by measuring the labor supply responses of DI beneficiaries to re-

[1] An exception is Campolieti (2004), but the confidence intervals are wide.

[2] For example, Maestas and Song (2010) note that SSDI imposes implicit marginal tax rate on earnings of up to 100,000 percent.

[3] Indeed, a program designed to maximize labor supply would set benefits to zero at zero hours worked.

sources that do not affect marginal incentives to earn (i.e., cash-on-hand). In particular, I measure the labor supply responses of Danish disability insurance beneficiaries to a policy change that affected resources available, but did not preclude them from working (as in Autor and Duggan 2007 and Marie and Castello 2012). I find that labor supply is very responsive to these unconditional transfers. These estimates suggest that the effect of DI on labor force participation is driven in large part by making it feasible for the disabled to stop working, rather than by reducing effective wages. The standard interpretation would be that DI is very valuable from a social welfare perspective.

The second contribution of the paper is to show that this standard approach may need to be modified in order to be applied to disability insurance, because this group's behavioral responses to income generate fiscal externalities and, perhaps, internalities. Using high frequency emergency room (ER) data, I show that the probability of an adverse health event increases for DI beneficiaries in the days after they receive income. Non-disabled groups show no such increases around payment dates. Excess sensitivity in this domain creates fiscal externalities, because ER visits are costly to the government. In a model with externalities or internalities, labor supply responses are no longer sufficient statistics for optimal disability insurance benefit levels. Optimal benefit levels could differ depending on the frequency at which payments are dispersed.

The policy implications of my results are twofold. First, disability insurance appears to be very valuable based on the labor supply evidence. Second, optimal policy may involve non-traditional policy tools such as setting pay frequency. My on-going work evaluates this proposal by testing whether smaller, more frequent payments can smooth rates of adverse health events and reduce rates of adverse health events overall using policy variation in pay frequency of the child benefit in Denmark (Bruich, Nielsen, Simonsen, and Wohlfahrt 2014).[4]

The labor supply evidence builds on a large literature measuring labor supply re-

[4]While many studies suggest using pay frequency as policy tool (e.g., Shapiro 2005, Dobkin and Puller 2007, Mastrobuoni and Weinberg 2009), there is little causal evidence on the impacts of this proposal, in part because changes to pay frequency are relatively rare. One example is Stephens and Unayama (2011) who study the effect of a change in pay frequency of Japanese pensions on consumption smoothing.

sponses to disability insurance. The estimates I present are for near-retirement age disability insurance beneficiaries, as in Maestas and Yin (2008) and Maestas and Song (2011). In the DI literature on labor supply, only Autor and Duggan (2007, 2008) and Marie and Castello (2012) emphasize the distinction between moral hazard and income effects. The literature on unemployment insurance has been much more active in separately identifying income versus substitution effects (e.g., Card, Chetty, Weber 2007, Chetty 2008, LaLumia 2013, Landais 2014). In this way, this paper presents some of the first evidence on income effects in the disability insurance context and confirms that income effects are large.

To obtain these causal estimates, I use a difference in difference research design around age 65, comparing labor supply across cohorts using a discontinuity in eligibility for a policy change by date of birth. The payments associated with this policy change did not affect marginal incentives to earn. For example, the amount was not taxed, was not reduced with income, and was designed not to affect eligibility for other resources. I focus on a sample of disability insurance beneficiaries over 60, who cannot have their benefits taken away, regardless of how much they work. I argue that these institutional features allow me to interpret these estimates as capturing only an income effect.

The evidence on ER visits has not been shown previously in Denmark, but relates to findings in other countries. This literature has found that expenditures, consumption, mortality, and hospitalizations increase in the short run after both transitory and reoccurring payments are received. As in Dobkin and Puller (2007) and Gross and Tobacman (2014), I find that drug and alcohol related ER visits increase around payment dates.[5] I also find that ER visits for head injuries, which are rarely coded as drug and alcohol related in these Danish data, but may nevertheless be due to drugs and alcohol, increase at these times.

This paper builds on that evidence in three ways. First, I document heterogeneity

[5] Dobkin and Puller (2007) show that Supplemental Security Income (SSI) beneficiaries' in-patient hospitalizations related to cocaine, heroin, and amphetamines increase when they receive payments. They also find that in-hospital mortality increases. Gross and Tobacman (2014) show that ER visits related to drugs and alcohol increased when the 2008 stimulus payments were received.

across groups and characterize *which* disability insurance beneficiaries present at the ER, similar to a recent literature on heterogeneity in consumption smoothing (e.g., Mastrobuoni and Weinberg 2009, Parker 2014). Second, I find that this response to income is exhibited by the disabled even in years before they were awarded DI benefits. This finding suggests that these increases in adverse health events are not a direct result of being on disability insurance rolls per se. Instead, these responses are predictive of receiving DI in the future.

Third, the institutional setting allows me to rule out several proposed explanations. For example, healthcare coverage is universal in Denmark and patients owe no copayments for visits to the ER. In this way, the results documented here are not likely to be driven by the ability to pay for medical care, which has been shown to be important in other contexts, such as in the Oregon Health Insurance Experiment (Taubaum et al. 2014). The results also seem inconsistent with the explanation that the increases are due to heightened activity in the general population (e.g., Evans and Moore 2011, 2012), because I find that it is largely only the disabled who present at the ER, even though over 60% of the population receives income at the same time in Denmark.[6] Instead, the evidence seems to point to models of addiction and imperfect self-control (Gruber and Koszegi 2004, Bernheim and Rangel 2004).

Finally, the paper is related to the behavioral public economics literature (Mullainathan, Schwartzstein, and Congdon 2011). The evidence I present in this paper shows that there is a subset of DI beneficiaries whose behavior and consumption choices may generate fiscal externalities and internalities. A theme in the behavioral public economics literature is that when there is a mixture of behavioral and rational agents, corrective policies are desirable even though they reduce the welfare of rational agents. Intuitively, the welfare gains from bringing behavioral agents closer to the social optimum are first order, while the welfare losses are only second order for the agents who

[6] I also find no evidence of an increase in ER visits for heart attacks or strokes, which contrasts with the finding that deaths for these reasons do increase in the United States (Evans and Moore 2011) and Sweden (Andersson, Lundborg, Vikström 2014). One possibility is that the underlying mechanisms that generate deaths and ER visits differ.

locate at the social optimum on their own. Other policies (nudges) which would have no effect on rational agents, but would change the behavior of the non-rational agents, are even more desirable. Insights from behavioral economics have been applied to the optimal design of taxes and some social insurance programs (e.g., Feldstein 1985, Gruber and Koszegi 2004, O'Donoghue and Rabin 2006). But so far this has not occurred in the disability insurance literature, which is somewhat surprising given the prevalence of mental impairments and substance abuse in this population.

The rest of the paper is organized as follows. In Section 2, I present a static extensive margin labor supply model. I derive the standard result that the optimal disability insurance benefit level can be characterized by the ratio of income effects to moral hazard effects of DI benefits on labor supply. In Section 3, I provide institutional details on disability insurance eligibility, benefit levels, the quasi experiment used to identify income effects, and payment dates. I also describe the various datasets used in the paper. In Section 4, I estimate the effect of unconditional transfers on the labor supply of disability insurance beneficiaries, which is one of the parameters in the formula presented in Section 2. In Section 5, I present the results on ER visits in three parts. First, I establish that ER visits increase nationwide in Denmark when a large fraction of the population receives income. Second, I show that, disproportionately, it is those receiving disability insurance benefits and those who will receive it in the future who are coming to the ER on these days. Third, I characterize which disability insurance beneficiaries display this excess sensitivity. Section 6 concludes by discussing the welfare and policy implications of these results.

2 Moral hazard vs. liquidity and optimal DI

In this section, I review the result that the optimal level of social insurance benefits can be characterized by the ratio of income effects to moral hazard effects of DI benefits on labor supply, as in Chetty (2008). This result provides a framework for interpreting the empirical results.

Consider a static model with a binary labor supply choice.[7] Individuals, indexed by i, all earn the same wage w if they choose to work, but have disutility of working δ_i that is distributed smoothly in the population with cumulative distribution function $F(\delta_i)$. I abstract from the issue of screening for disability because my empirical application focuses on a sample that has already been awarded disability insurance benefits. The government can observe whether i works, but not his disutility δ_i. Disability insurance is a benefit b paid when not working that is financed by a tax t paid by those who are working. Assets A are available both when in the labor force and when not working. Let $c_h = w+A-t$ denote consumption if the agent works and $c_l = A+b$ denote consumption if the agent chooses not to work. Utility is additively separable in consumption and disutility from working. Utility over consumption is concave.

An individual i will choose to work if his net utility from working exceeds his net utility when he does not work:

$$u(c_h) - \delta_i > u(c_l) \tag{1}$$

In the population, all i with δ_i above the cutoff $\overline{\delta} = u(c_h) - u(c_l)$ will choose not to work. The cutoff decreases as b and A increase and increases as $w - t$ increases. Let the fraction of workers choosing to work be denoted by $e = \int_{-\infty}^{\overline{\delta}} dF(\delta_i)$.

I show in Appendix B that the effect on welfare of increasing the disability insurance benefit by \$1 can be written as:

$$\begin{aligned} \frac{dW}{db} &= \frac{u'(c_l) - u'(c_h)}{u'(c_h)} + \frac{\varepsilon_{e,b}}{1-e} && (2) \\ &= \frac{-\frac{\partial e}{\partial A}}{\frac{\partial e}{\partial A} - \frac{\partial e}{\partial b}} + \frac{\varepsilon_{e,b}}{1-e} && (3) \end{aligned}$$

where $\varepsilon_{e,b} = \frac{de}{db}\frac{b}{e}$ is the total, uncompensated elasticity of the fraction of the population working with respect to b. The second line re-writes the gap in marginal utilities using comparative statics for the effect of wages, disability insurance benefits, and assets on the fraction of the population working ($\partial e/\partial w$, $\partial e/\partial b$, and $\partial e/\partial A$). Equation 3 shows

[7] See Golosov and Tsyvinski (2006), Low and Pistaferri (2010), and Denk and Michau (2012) for dynamic models.

that optimal benefit levels only depend on extensive margin labor supply responses to unconditional transfers (A) and state contingent benefits (b).

The first term in the formula uses revealed preferences to infer the value of b. If many workers exit the labor force in response to an increase in unconditional transfers ($\frac{\partial e}{\partial A} \ll 0$), then this implies that increasing b is very valuable, because an extra \$1 of consumption is worth much more when not working, than it is worth when working ($u'(c_l) \gg u'(c_h)$). In contrast, if labor supply does not respond to these resources, then this implies that there is little value in increasing b, because that extra \$1 of consumption is worth the same in either case ($u'(c_l) \approx u'(c_h)$). Intuitively, this must mean that agents are able to smooth consumption on their own at the current level of benefits and, therefore, that increasing disability insurance benefits further adds no value.[8,9] The second term reflects that transferring an additional \$1 requires taking more than \$1 away from workers, because fewer people work when the net wage is reduced. The two terms should exactly offset each other at the optimum.

To implement this formula, one needs to estimate two partial elasticities of labor force participation or partial marginal propensities to work ($\frac{\partial e}{\partial A}$ and $\frac{\partial e}{\partial b}$), as well as the total, uncompensated elasticity of labor force participation with respect to benefit levels ($\varepsilon_{e,b}$). In Section 4, I estimate the response to unconditional transfers ($\frac{\partial e}{\partial A}$). While this estimate alone is not sufficient to implement the formula, note that the hypothesis that $\frac{\partial e}{\partial A} = 0$ implies that increasing benefits cannot improve welfare ($\frac{dW}{db} \leq 0$). Indeed, knowledge that $\frac{\partial e}{\partial A} = 0$ for all b implies that insurance markets are complete and, therefore, optimal social insurance benefits are zero. In this way, one would logically want to determine whether $\frac{\partial e}{\partial A}$ is non-zero in order to decide whether estimates of $\frac{\partial e}{\partial b}$ and $\varepsilon_{e,b}$ are even needed to assess the welfare effects of increasing b.

The labor supply responses in Equation 3 are sufficient statistics for optimal benefit levels because these same parameters would still characterize optimal benefit levels in

[8] The consumption smoothing interpretation is from the perspective of a representative agent. From the agent's decision rule in Equation 1, an increase in A must increase $u(c_l)$ and $u(c_h)$ by the same amount in order for $\frac{\partial e}{\partial A} = 0$.

[9] This connection between the labor supply response to cash on hand and consumption smoothing is used by Card, Chetty, and Weber (2007) to distinguish between theories of intertemporal consumption.

a more general model with other choice variables and constraints. In a model with externalities or internalities, there will be an additional term added to the formula; I give an example showing this in Appendix C. The results in Section 5 show that this externality/internality term is non-zero.

3 Institutional background and data

3.1 Disability insurance system

I describe the disability insurance system that applies to the sample that I use in the labor supply analysis. Specifically, this system applies to individuals who applied for disability insurance before turning 60, but have since turned 60, and whose benefits were awarded before 2002. The quasi experiment is discussed in the next subsection.

Severity levels. Disability insurance can be awarded at three levels of disability severity, with more severe disabilities corresponding to higher monthly benefits. The level at which disability insurance benefits are awarded is based on an assessment of how an applicant's impairment impacts his ability to work; Appendix A provides a detailed example. In this sense, disability insurance eligibility in Denmark is similar to the assessment of eligibility for SSDI, described in detail, for example, in Chen and van der Klaauw (2008). However, unlike in the U.S., disability can be partial. My main analysis sample (described in more detail below) was awarded benefits at the lowest level of severity, which corresponds to a disability that only partially diminishes one's ability to work.

Benefit amounts. In contrast with the Social Security Disability Insurance (SSDI) program in the U.S., benefit levels do not depend on past earnings. There is a residency requirement, but no past work requirement. Therefore, the replacement rate can be quite large, and even infinite for those who are given benefits at age 18 without having spent time in the labor force. Individuals receive taxable, means tested benefits, as well as non-means tested benefits that are tax free.

Work incentives. Importantly, individuals can and do earn labor income while receiving disability insurance benefits. About 15% of those on disability insurance have positive labor income, both in my data (described below) and in the data studied by Geerdsen (2006). Disability insurance recipients who are over 60 cannot have their benefits taken away, regardless of how much they work.[10] However, the returns to earning labor income are very low due to the taxation of the means tested portion of their benefits as personal income, and even more so, once these benefits begin to be phased out at a 30% rate at 64,300 kr ($12,000) in 2012.[11] Appendix Figure A1 shows the combined income tax and phase out rate for disability insurance beneficiaries on the bottom two levels in 2002. The marginal tax rate on the first $1 of earnings is over 40%.

Transition to social security. Beneficiaries continue to receive disability insurance benefits until they reach retirement age. At that point, beneficiaries are transferred to the social security system. They may also become eligible to receive payouts from their private or public savings plans. Social security benefits are lower than the disability insurance amount, because they are essentially the same as the means tested benefit amounts, but do not include any of the lump sum amounts.[12]

3.2 Quasi experiment for labor supply analysis

I use policy variation in the non-taxable, non-means tested lump sum benefit amount to identify the impact of unconditional transfers on the labor force participation of

[10] Benefits can only be taken away at the request of the beneficiary. In personal communication with the Ministry of Social Affairs and Integration, I have confirmed that these rules have been constant over time. The rules for disability insurance recipients under 60 have changed over time. Currently, this younger group can also work without risk of permanently losing their benefits. However, if they work enough in any given year (earnings above 139,000 kr or around $25,000 in 2013), they may have their disability insurance benefits replaced by a lump sum, tax free amount while they work. However, this is not a sharp cutoff; the threshold may not apply for a number of reasons, described by Geerdsen (2006, footnote 3). Benefits resume at the request of the beneficiary. The amount received while working is approximately the same (228 kr more generous) as the lump sum benefit amount received while on disability insurance benefits, but does not include the means-tested part of their benefits. This contrasts with the situation for those over 60, who are not subject to these limitations. Note though that the main work disincentive in the SSDI program in the United States is the potential for permanent loss of benefits.

[11] The income level cited is for singles. Benefits are phased out at a 60% rate at higher income levels.

[12] If awarded benefits before 2002, the non-means tested benefit amounts continue until turning 67 even for those whose retirement age is 65. The extra two years does not apply to the benefits associated with the quasi experiment described below.

disability insurance beneficiaries. As shown in Figure 1, the lump sum benefit amount for the low level of disability insurance was increased in 2006 from around \$3000 per year to \$6000 per year.[13]

I argue that changes in labor supply resulting from this quasi experiment can be interpreted as being caused by only an income effect for two reasons. First, the lump sum benefit amount, which was increased in 2006, is not taxable and is not means tested. Therefore, receipt of these additional resources left marginal incentives to earn income unchanged. Note that the fact that these extra payments are untaxed is important: in a progressive income tax system, additional taxable income increases the tax rate paid on earned income.[14] Second, disability insurance recipients who are over 60 cannot have their benefits taken away, regardless of how much they work. This second point is reminiscent of the arguments made in prior studies of income effects, such as Autor and Duggan (2007) in the U.S. and Marie and Castello (2012) in Spain. For both these reasons, an estimate of the causal effect of this policy change on the fraction of disability insurance beneficiaries working provides an estimate of $\frac{\partial e}{\partial A}$.

The extra payments are only received until beneficiaries reach retirement age. As described in more detail in Section 4, my research design uses a difference in difference estimator, comparing cohorts that were affected by the policy change, with those that were ineligible for the increase in benefits because they had already reached retirement age in 2006.

3.3 Payment dates

Over 60% of the population receives income on the last business day of the month, which equals the last calendar day of the month unless that day is a weekend or public holiday, in which case the payments are made the day before. Payments received on this day include disability insurance benefits, other transfer and social insurance payments, and

[13]The higher benefit amount was announced in December 2005 and the first extra payments were received in April 2006.

[14]Note that VA disability benefits in the U.S. are also not taxed, which is an important but not emphasized feature of Autor and Duggan's (2007, 2008) research design. The basic issue is similar to the high marginal tax rates on spouses of high earners in the United States (e.g., Eissa 1995).

salaries for most wage earners.[15] Public benefits and most paychecks are deposited directly into individuals' bank accounts.[16]

3.4 Data

Labor supply analysis data. In the labor supply application, I use data on the earnings of disability insurance beneficiaries contained in the registers described in Petersson, Baadsgaard, and Thygesen (2011) and in Baadsgaard and Quitzau (2011) for years 1990 through 2011. These registers are based on tax records, pension payments, and asset holdings that are third-party reported to the tax authority. All income data are annual measures. Important for my study is that I observe information on the level at which disability insurance benefits have been granted. A limitation in the data is that I do not observe the amount of the lump sum disability insurance payments. However, I believe that compliance with the law as described above is very good.[17] I supplement these data with a data set on chronic diseases that was created to document trends in utilization by people with diabetes, cardiovascular disease, chronic lung disease, musculoskeletal disorders, and mental and behavioral disorders. The mental illnesses include schizophrenia, mood disorders, and dementia. The database is constructed by using ACT active ingredient codes for prescription drugs and ICD-10 diagnosis codes for any type of encounter with the health care system.

I select the main analysis sample as follows. I include anyone whom I observe on the low disability insurance level in the year in which they turn 60 years old. I restrict the sample to only those who were awarded benefits prior to 2002 and prior to turning 60. I make these restrictions because the transition to retirement and benefit amounts differ depending on the year and age when benefits were awarded. Further, I only include birth cohorts whom I observe turning 66 during the period over which I have data,

[15] Paydays for wage earners are determined by collective bargaining agreements between unions and employers.

[16] Taxes are withheld from paychecks and public benefits.

[17] Non-compliance would only be due to switching levels prior to the policy change, but switching is rare. In personal correspondence, I have confirmed the date of birth cutoffs with the Ministry of Social Affairs and Integration.

which limits me to individuals born in 1945 and earlier.

Emergency room visit analysis data. To implement the emergency room visit analysis, I use data on all emergency room visits contained in the Danish National Patient Register. Lynge, Sandegaard, and Rebolj (2011) provide a detailed description. The earliest data I use are from 1994, because this is the year in which the register began classifying admissions using ICD-10 diagnosis codes. Note that the reporting of emergency room visits only became mandatory in 1995, but I include visits in 1994 in my analysis because some hospitals did report emergency room visits in this year. My results are not sensitive to including or excluding 1994.

I focus on three main groups in the emergency room visit analysis: disability insurance beneficiaries, social security beneficiaries, and wage earners. I define these groups using data on sources of income contained in the registers described for the labor supply analysis.

The hospitalization data are daily, but group affiliations are defined using annual data. For disability insurance beneficiaries and social security beneficiaries, I include individuals who receive that type of income at any point during the year. In addition, the social security sample excludes anyone whom I observe receiving disability insurance income in previous years. To define wage earners, I exclude workers 60 or over, all non-wage earners, wage earners with self-employment income, and wage earners with unemployment benefits. I define wage earners only using information from previous years, because most variables are measured at the end of the current year and wage earner status at year end is endogenous to health events occurring during the year (Cutler, Meara, and Richards-Shubik 2011). I further exclude observations that received DI at any point in the previous two years.

I also use data from Ankestyrelsen that contain up to three reasons that disability insurance benefits were awarded for disability insurance claims in 1999-2012. These data cover approximately 170,000 individuals at the end of the period. I use these data to divide my disability insurance sample into beneficiaries with mental and behavioral disorders and those with all other impairments.

4 Effects of Cash Transfers on Labor Supply

In this section, I estimate the effect of unconditional transfers on the labor supply of disability insurance beneficiaries ($\frac{\partial e}{\partial A}$) using the quasi experiment described in Section 3. I first lay out my research design in Section 4.1 and describe the sample I use to implement my design in section 4.2. Section 4.3 presents the results.

4.1 Research design

In section 3, I argued that an estimate of the causal effect of the 2006 policy change on the fraction of disability insurance beneficiaries working provides an estimate of $\frac{\partial e}{\partial A}$. To obtain this causal estimate of $\frac{\partial e}{\partial A}$, I use a difference in difference research design around age 65, comparing labor supply across cohorts using a discontinuity in eligibility for these payments by date of birth. In particular, beneficiaries who turned 65 before 2006 were ineligible for the increase in benefits, because they had already reached retirement age.[18] Beneficiaries turning 65 just before 2006, therefore, provide a control group for beneficiaries who turned 65 just after 2006 (the treatment group). These two groups differ based only on their dates of birth and were both initially assessed at the same level of disability severity (the lowest level). After age 65, both groups are transferred to the social security system, but the treatment group's income declines by \$3000 more than the control group's. Therefore, this research design identifies the effect of a \$3000 reduction in exogenous income, holding all other changes that occur at retirement age fixed. The identification assumption is similar to the common trends needed for a standard difference in difference estimate: in the absence of the 2006 policy change, the change in labor force participation at 65 would have been the same in both groups.

[18] There is also a group of disability insurance recipients on the low level of benefits who turned 67 in 2006 and received 1 to 6 months of the extra benefit, because the retirement age is 67 for those born before July 1, 1939. The retirement age is 65 for those born after this date.

My main point estimates are based on the following estimating equation:

$$y_{itg} = \alpha_i + \alpha_{gt} + \sum_{\substack{a \in [60,69], \\ a \neq 64}} \beta_a 1(age_{it} = a) + \sum_{\substack{a \in [60,69], \\ a \neq 64}} \gamma_a \left[1(age_{it} = a) \times 1(g = \text{treat})\right] + u_{igt} \tag{4}$$

where y_{itg} is labor supply for individual i in year t and group g (i.e., treatment group or control group), α_i is an individual fixed effect, and α_{gt} is a year fixed effect interacted with the treatment group indicator to allow time trends to differ in the control and treatment groups. Age a refers to age at year end. The nine β_a coefficients measure the change in labor supply at age a relative to age 64. The nine γ_a coefficients measure how this change differs for the treated group relative to the control group. The main coefficient of interest is γ_{66}, which measures the change in labor supply at age 66 (the first full year on social security) relative to labor supply at age 64 (the last full year on disability insurance) for the treatment group relative to the control group. I interpret γ_{66} to be the causal effect of the \$3000 reduction in the lump sum benefit amount on labor supply. A static labor supply model would predict $\gamma_{66} > 0$. That is, the treatment group should work more than the control group at age 66 relative to age 64. I cluster standard errors by person.

4.2 Summary statistics

Table 1 presents summary statistics for the analysis sample. There are 8,476 people in the control group (born in 1939 or 1940) and 16,312 people in the treatment group (born between 1941 and 1945). I follow each group from age 60 to 69, yielding a total of 213,074 person-year observations. In some analyses, I exclude the group born in January to June 1939, because their retirement age is 67 and not 65, leaving 192,156 person-year observations. At age 60, 11% had positive wage earnings. This number drops to 7.3% across ages 60 to 69. A little less than half had positive wage earnings two years before the first year observed on disability insurance.

As shown in Table 1, the treatment and control groups are very well balanced along observable characteristics. Four features of this sample should be kept in mind. First, the sample is comprised predominantly (about 70%) of women and the less educated, with only 6% having a college degree; about half is married at age 60 and over 90% is Danish. Second, the sample has received DI for a significant length of time when turning 65 (at least five years). The average first year observed receiving disability insurance is 1994, and this figure understates the length of time spent on DI, because I cannot determine the first year for anyone awarded benefits in 1990 or earlier in these data.[19] Third, chronic diseases are quite common in my sample: 21% has diabetes, 44% has a heart condition, 22% has a lung condition, 10% has a musculoskeletal disorder, and 25% has a mental or behavioral disorder. Fourth, the sample has very little wealth, with average non-pension assets at age 60 just under 300,000 kr ($60,000) and median wealth around 15,000 kr ($3,000).

4.3 Results

I begin with graphical evidence for the full sample. Figure 2a plots the change in labor force participation between age 64 and 66 for each birth cohort from 1935 to 1945. Cohorts born between 1941 and 1945 were eligible for the extra payment until reaching age 65, while cohorts born earlier were never eligible for the extra payments.[20] The cohorts born between 1935 and 1938 (shown in gray) have a different retirement age than the rest of the cohorts and are shown for completeness. Labor force participation is defined here as having any positive labor income. To construct this figure, I first use the pooled sample of all birth cohorts shown in the figure to estimate the following model:

$$y_{igt} = \alpha_{gt} + u_{igt} \tag{5}$$

where y_{igt} is an indicator for positive labor income and α_{gt} are year and year $\times$ treatment group fixed effects. I use the residuals $\widehat{u}_{igt}$ as the dependent variable in models of the

[19] Indeed, many other research designs would be possible if I observed the application or award date in these data.

[20] As noted earlier, some individuals in the 1939 birth cohort also received amounts, ranging from a total of $1500 to $250. However, this occurred during the year in which they turned age 67, not at age 64 or age 66 which are shown in the figure. The figure and point estimates are similar if one excludes this group.

form:

$$\widehat{u}_{igt} = \alpha_i + \sum_{\substack{a\in[60,69], \\ a\neq 64}} \theta_a 1(age_{it} = a) + \upsilon_{igt} \tag{6}$$

estimated separately by birth cohort, where α_i is an individual fixed effect. The figure plots the $\widehat{\theta}_{66}$ coefficient for each cohort, which measures the change in labor force participation across age 64 and 66. The graphs show that the change in labor force participation is smaller for cohorts born between 1941 and 1945 than those born between 1940 and 1939. This evidence is consistent with the decline in the labor supply being attenuated by the loss of $3000 between ages 64 and 66 for the treatment group.

Figure 2b presents the data by age to assess whether labor force participation was trending along the same path prior to age 65 in the treatment group and the control group. To construct this figure, I estimate models of the form:

$$y_{it} = \alpha_i + \alpha_t + \sum_{\substack{a\in[60,69], \\ a\neq 64}} \theta_a 1(age_{it} = a) + u_{it} \tag{7}$$

separately for the birth cohorts born between 1940 and July 1939 and for the birth cohorts born between 1941 and 1945, where α_i are individual fixed effects and α_t are year fixed effects. The figure plots the $\widehat{\theta}_a$ coefficients, with y-axis scaled so that the average of the nine $\widehat{\theta}_a$ coefficient estimates and $\theta_{64} = 0$ equals the sample average of the dependent variable for each group. The figure shows that labor supply declines with age for both groups. The two series appear to be parallel until a break at age 65 (perhaps starting at 64) for the control group. There is no break for the treatment group. This figure indicates that there was a relative increase in labor supply in the treatment group when its income decreased at age 65. Under the identifying assumption that the change in labor force participation at 65 would have been the same in both groups in the absence of the 2006 policy change, this relative increase is the effect of losing $3000 on labor force participation.

To assess the robustness of the results illustrated in Figure 2, I present estimates from Equation 4 in Table 2, defining labor force participation as any positive labor income (columns 1-4) and as labor income above 2,000 real 2013 kr (columns 5-8). The table also reports the mean of the dependent variable to help judge the magnitudes of the regression coefficients. The excluded age is 64 so each coefficient measures the change in labor force participation relative to age 64. The coefficient of interest is $\widehat{\gamma}_{66}$ on the treatment $\times$ age 66 indicator variable. The first column includes year and year $\times$ treatment group fixed effects, but no other controls. The second column adds the following individual level covariates: indicators for marital status, Danish nationality, gender, college education, living in Copenhagen, and white-collar occupation at age 60. The third column adds controls for the chronic diseases that I observe in these data. The fourth column adds individual fixed effects, which additionally control for any other time-invariant omitted variables. The estimates in columns 1-3 imply that labor force participation increased in the treatment group relative to the control group between ages 64 and 66 by 3 to 4 percentage points, which is 40% to 60% of the mean in the treatment group across the entire 60-69 age range. Adding fixed effects in column 4 reduces the point estimate to 1.7 percentage points (or 23% relative to the treatment group mean). All these estimates are statistically significant at the 5% or 1% level. Using the 2000 kr cutoff as the dependent variable in columns 5-8 yields slightly smaller point estimates.

Table 3 focuses on the subset of disability insurance recipients with recent work experience, which I define as having positive labor income at age 60. There are 2,530 observations that meet this condition. The columns of this table are organized in exactly the same way as in Table 2. The regressions in this table only include individuals from ages 61 to 69, since earnings at age 60 are used to define the sample. Average labor force participation for this group is 46% overall between ages 61 and 69, 49% in the treatment group, and 39% in the control group. The point estimates in this table are an order of magnitude larger than those in Table 2, but are similar to those for the full sample when expressed as a percentage of the mean (22% for the model with fixed effects to 54% for the other columns). This relative change is shown in Figure 3.

Taken together, these estimates reject the hypothesis that $\frac{\partial e}{\partial A} = 0$. Economically, the magnitude is large, both as a percentage of mean labor force participation and relative to the \$3000 used as identifying variation. My estimates of $\frac{\partial e}{\partial A}$ from Table 2 are a 1 percentage point to 0.57 percentage point decline in labor force participation per \$1000. As a point of comparison, note that Maestas, Mullen, and Strand (2013) find that SSDI reduces labor force participation by 28 percentage points. The average yearly SSDI benefit amount is \$13,752 in 2014. Scaling Maestas, Mullen, and Strand's (2013) point estimate by the average annual value of benefits yields a ratio of 2 percentage points per \$1000, and this would include both income and work disincentive effects of SSDI benefits. My estimates are of course from a very different setting and my research design uses a very different source of identifying variation. Nevertheless, the evidence shows that this relatively small change in income had a large effect on labor force participation of the elderly disabled.

4.4 Estimates by demographics, disease, and asset holdings

This section presents estimates for different subgroups, defined based on demographics, impairments, and assets. The results are summarized in Figure 3, which presents the point estimates as a percentage of the mean labor force participation rate in each subgroup, along with 95% confidence interval bands.

Table 4 and Figure 3 explore heterogeneity by gender and marital status (panel a), chronic disease (panel b), and assets (panel c). The table reports the $\widehat{\gamma}_{66}$ estimates of the change in labor force participation between age 64 and 66 for the treatment group relative to the control group. The table also reports average labor force participation for each subgroup. In panel (a), note that labor force participation is twice as high at 10% for men as for women, while the estimated treatment effect is almost four times as large for men as it is for women. Therefore, the larger treatment effect estimates can be partially explained by the higher labor force participation for men. The next two columns present estimates for groups divided by marital status. The point estimate is larger for single disability insurance beneficiaries, while the mean labor force participation is higher for those who are married (6.5% compared to 8%).

Panel (b) reports estimates for each of the six chronic diseases. Mean labor force participation is about 7% for each disease category, except for the mental and behavioral disorder subgroup, which is slightly lower at 6%. The treatment effect estimates suggest that the subgroups with musculoskeletal and mental and behavioral disorders are less sensitive than other groups to loss of income, although the confidence intervals are wide for these groups.

Panel (c) reports estimates by assets measured at age 60. I divide each year of birth cohort into two groups (above and below median assets) to maintain balance of the sample. The group with below median wealth has 6000 kr on average in assets, while the group with above median wealth has 574,000 kr in assets. One may expect that there should be larger responses by those with less liquid wealth, but the treatment effect estimates in columns 1 and 2 appear to run counter to this intuition. However, note that mean labor force participation is much higher for the group with above median assets (9% compared to 5.4%). To make the comparisons as clear as possible, columns 3 and 4 restrict the sample to those with recent work experience, as in Table 3. I re-define median wealth for these subgroups. Mean labor force participation is still higher for the group with more wealth, but the difference is small (43% compared to 48%). In this more comparable subgroup, the treatment effect is similar across wealth categories. The apparent unimportance of assets contrasts with the evidence for unemployment insurance recipients in the U.S. presented by Chetty (2008). One aspect of the research design that could explain this difference is that many pension assets may become accessible at retirement age. Therefore, liquid assets may be less important here simply because of the nature of the identification strategy. Unfortunately, I do not observe pension assets in these data.

The estimates described above show that the difference in labor supply responses across groups defined by demographics, chronic diseases, and asset holdings is small. In contrast, the results in the next section show that there is much heterogeneity in their high frequency responses to receipt of payments.

5 Timing of Cash Transfers and ER visits

I now turn to describing the results on the *timing* of payment disbursements and emergency room (ER) visits. The emphasis in this part of the paper is on heterogeneity: even though over 60% of the population receives income on the same day each month, it is, disproportionately, disability insurance beneficiaries and those who will be disability insurance beneficiaries in the future who present at the ER. While the previous section showed large labor supply responses to unconditional transfers, this section shows that other behaviors also display excess sensitivity to income at a much higher frequency. Further, excess sensitivity in this domain creates fiscal externalities because ER visits are costly to the government. It is difficult to reconcile the evidence with a rational model, suggesting that there could additionally be internalities because of self-control problems. In a model with externalities or internalities, labor supply responses are no longer sufficient statistics for optimal disability insurance benefit levels. Instead, there is an additional externality/internality term that would enter the formula in Equation 3. The results described below suggest that this extra term is non-zero. In section 4.1, I first discuss my empirical strategy for measuring excess sensitivity in ER visits. Section 4.2 presents the main results, section 4.3 shows robustness checks, and section 4.4 provides a discussion.

5.1 Empirical framework

The statistic that I use to characterize the increase in ER visits is the mean number of people (per 100,000) who visit the ER on the day after the last business day of the month, relative to the day before the last business day of the month. I adjust these averages for fluctuations in the number of ER visits that occur across day of week, months, years, and on nineteen holidays and other reoccurring special dates listed in Appendix Table A3. In this way, the results reported here can be interpreted as how many more people can be expected to visit the ER beyond normal weekly, seasonal, and yearly patterns.[21]

In particular, let $y_{id} = 1$ if individual i visits the ER on date d and 0 otherwise. Let t index days relative to the last business day of the month, so that $t = 0$ on that date, $t < 0$ on dates before the last business day of the month, and $t > 0$ on dates after the last business day of the month. I restrict my sample to the twenty-eight days spanning $t = -13$ to $t = 14$ so that I have a balanced sample of 215 twenty-eight day months across 1994 to 2011.

I collapse the data to daily averages $\overline{y}_d$ and regress:

$$\overline{y}_d \times 100000 = \alpha + \sum\nolimits_{s=-13}^{-1} \beta_s 1(t_d = s) + \sum\nolimits_{s=1}^{14} \beta_s 1(t_d = s) + \gamma X_d + \overline{u}_d \qquad (8)$$

where I weight each observation by the number of people in my sample on date d.[22] In Equation 8, 1() is an indicator function that equals 1 if the statement in parentheses is true for date d and 0 otherwise. X includes a vector of indicator variables to allow the mean of the dependent variable to differ by day of the week, month, year, and on holidays and other reoccurring special dates.[23] Throughout, I report standard errors that allow serial correlation across days within a twenty-eight day month.

The twenty-seven $\widehat{\beta}_s$ coefficient estimates measure the difference in the average number of people (per 100,000) who visit the ER on dates where $t = s$, relative to days where $t = 0$. The coefficients can be interpreted as changes in the probability that an individual will visit the ER at $t = s$ relative to $t = 0$. The standard errors on these coefficients test whether this difference is statistically significant. The difference between $\widehat{\beta}_1$ and $\widehat{\beta}_{-1}$ measures the mean number of people (per 100,000) who visit the ER on the day after the last business day of the month, relative to the day before the last business day of the month. In the figures that follow, I plot the twenty-seven $\widehat{\beta}_s$ coefficients and $\beta_0 = 0$, but I scale the left y-axis so that the average of the twenty-eight points equals

[21] I measure people instead of number of visits for two reasons. First, multiple ER visits by the same person that occur on the same day are likely to be related to the same adverse health event. Second, multiple ER visits listed for the same person on the same day may be due to data entry errors.

[22] Because I weight each observation by the number of people in my sample on date d, this regression is equivalent to a regression using y_{id} instead of $\overline{y}_d$.

[23] I control for twelve "synthetic" months in the terminology of Evans and Moore (2012), instead of calendar months. Each synthetic month is a twenty-eight day period from $t = -13$ to $t = 14$.

the average of the dependent variable.

In robustness checks, I also include indicators for the days before and after each of the holidays and other reoccurring special dates. I consider the impact of excluding the twenty-eight day months containing New Year's, which is a very busy day in the emergency room as shown in column 3 of Appendix Table A3. Because about 40 percent of the paydays occur on a Friday (as seen in Appendix Figure A3), I also consider a robustness check where I exclude these twenty-eight day months from my sample. In addition, all the results shown here have been estimated by including acute in-patient admissions with ER visits. In all these cases, my basic results remain unchanged relative to the more restrictive model and sample criteria. As another robustness check, I find that defining $t = 0$ as the last calendar day of the month, instead of the last business day of the month, changes the results in a predictable way. Because the last business day of the month always precedes the last calendar day of the month in this analysis, an increase in rates of ER visits is visible before $t = 0$ and is smaller than estimates using the last business day of the month.

5.2 Results

Figure 4 plots the average number of people receiving income (panel a) and visiting the emergency room (panel b) over the two weeks before and two weeks after the last business day of the month. Panel (b) of the figure is constructed by replacing the dependent variable in Equation (8) with the sum of y_{id} on date d. Panel (a) shows that 3 million people receive income at the same time, while the point estimate $\widehat{\beta}_1 - \widehat{\beta}_{-1}$ $= 79.83$ in panel (b) shows that about 80 more people visit the ER.[24] About 2,500 people visit the emergency room each day, on average.

Figure 5 disaggregates the series in Figure 4b using the diagnosis codes associated with each visit. I focus on drug and alcohol related visits and visits for head injuries.[25]

[24] Appendix Figure A2 shows the total and average payment amounts.

[25] I define a visit to be drug and alcohol related if any of the diagnosis codes associated with that visit matches an ICD-10 diagnosis code that is drug or alcohol related. My codes are similar to the ICD-9 codes used by Gross and Tobacman (2014) and are listed in the notes to Figure 5. I define a visit to be for a head injury if the primary diagnosis code associated with that visit matches the ICD-10 diagnosis

While not mutually exclusive by construction, very few head injuries (less than 1%) are coded also as drug and alcohol related.[26] The results for drugs and alcohol are shown in panel (a) and the results for head injuries are shown in panel (c). There are about 9.5 more people who visit the ER for drugs and alcohol on the day after the last business day of the month, relative to the day before the last business day of the month, which is a 30% increase relative to the average daily rate. The number of ER visits for drugs and alcohol gradually declines over the 14 days after the last business day of the month. The pattern for head injuries in panel (c) is somewhat different. Here, there is a spike in people visiting the emergency room that only remains elevated for the three or four days after $t = 0$. The combined increase for drugs and alcohol and head injuries is about 38% relative to the overall increase shown in Figure 4 (and ignoring the small overlap between these categories).

Panels (b) and (d) show that the timing of the increases in drug and alcohol related visits and head injuries are consistent with a behavioral response to receipt of income during the day on the last business day of the month. The figures divide the series in panels (a) and (c) by six hour intervals. The payments are posted at $t = -1$, while the increase in emergency room visits occurs at $t = 0$ in the afternoon and evening, but at $t = 1$ during the after-midnight hours. The intuition here is that simply receiving the income should not, by itself, cause people to go to the emergency room. Consistent with this reasoning, the increases in emergency room visits occurs with a lag, which would be expected if emergency room visits are due to changes in consumption and behavior.

These aggregate results are for the whole population. I turn now to findings that disaggregate the data. I organize the rest of the results as four key lessons that can be learned from combining the ER visit data with administrative data containing in-

codes for head injuries.

[26] I focus on alcohol and drug related visits and head injuries because the literature on hospitalizations and mortality from the United States has focused on external causes of death and hospitalizations for and deaths from drugs and alcohol. An interesting question is what categories of emergency room visits do not increase. Many do not. An example is heart attacks where I find no increase (not reported), which contrasts with the findings of Evans and Moore (2011) and Andersson, Lundborg, Vikström (2014) in mortality data.

formation on sources of income, assets, and information from disability insurance case files.

- Result 1: *It is the disabled who drive the increase in emergency room visits—not wage earners and not social security recipients, even though all three groups receive income on the same day.*

Figure 6 present estimates from Equation 8 for the disability insurance beneficiary (shown in diamonds), social security beneficiary (shown in squares), and wage earner samples (shown in triangles).

Note first the difference in average daily rates across these groups. The average daily rate of emergency room visits is highest among disability insurance recipients, with about 72 people visiting the ER a day per 100,000 people. For social security beneficiaries and workers, average daily rates are around 50 and 40 people per 100,000 people.[27] Rates for drug and alcohol related visits are an order of magnitude larger for the DI sample compared with the other groups. Daily rates for head injuries in the DI sample are about double the rates for all other groups.

The change in the number of people who visit the ER around $t = 0$ is striking for the disability insurance sample, while no comparable increases are visible for the other groups. Relative to the base rate for the DI sample, the change in probability of visiting the ER is 11% for all ER visits, 41% for drug and alcohol related ER visits, and 37% for ER visits for head injuries.

Expressing the point estimates as a percentage of the aggregate estimates, the increase among the disabled is 25% for ER visits overall, 42% for drug and alcohol related ER visits, and 25% for ER visits for head injuries. These estimates are precise enough that using the lower bound on the 95% confidence interval only lowers these percentages to 20.9%, 34.9%, and 20.7%, respectively.

[27] Appendix Figure A4 divides the series for wage earners by lagged earnings quartile, using earnings averaged across the previous two years. Average daily rates for wage earners are progressively lower for each higher quartile of the (lagged) earnings distribution, reflecting a health-wealth gradient.

These three groups are very different sizes. The disability insurance sample, at around 250,000 people on average over time, is about 40% of the size of the social security sample and 13.1% of the size of the wage earner sample. However, accounting for the difference in sizes of the groups does not change the conclusion that the aggregate increases are driven by the disabled, which is surprising given that the DI sample is only about 4.5% of the full population of Denmark.

- *Result 2:* *The disabled exhibit increases in emergency room visits on the last business day of the month even in years before receiving benefits.*

This result is shown in Figures 7 and 8. In Figure 7, I present two sets of estimates. The top line (in triangles) is for disability insurance recipients during years in which they receive disability insurance benefits. The bottom line (in diamonds) plots rates for these same people in prior years. I restrict the sample to people for whom I observe at least one year before receiving disability insurance income and one year while receiving the benefits. I use years 1994-2010 for the pre-DI sample and years 1995-2011 for the post-DI sample.

In Figure 8, I study the time path of the increase in ER visits around $t = 0$ leading up to the first year that individuals are observed on DI for this same sample. The figure plots the increase around $t = 0$ relative to the base rate in three year bins by time relative to the first year on DI, along with 95% confidence interval bands. Because the last business day of the month is such a common payday, it is likely that these individuals receive income on that day even in years before receiving disability insurance benefits.

The average daily rate of emergency room visits is higher during years when disability insurance benefits are received, with about 73 people visiting the ER per 100,000 compared with 56.2 people visiting the ER per 100,000 in the earlier years. Similarly, the daily rates for drug and alcohol related ER visits are 4 people per 100,000 in years while receiving the benefits and 2.1 people per 100,000 for years before. For ER visits for head injuries, the corresponding rates are 6.1 people per 100,000 and 5 people per 100,000. That the overall rates of ER visits are higher while on disability insurance is perhaps not surprising if individuals are healthier on average prior to being awarded disability.

While the levels are higher while receiving benefits, Figure 7 shows that the probability of visiting the ER increases around the last business day of the month even in the prior years. Figure 8 shows that this increase is present even 9 years before the first year observed receiving DI. The change in probability of an ER visit around $t = 0$ relative to the base rate increases slightly over time, peaking right before the first year observed while on DI for all ER visits and ER visits for head injuries, but peaking at three years after for alcohol and drug related ER visits.

These findings suggest that the increase in the probability of an adverse health event around payment dates is not a direct result of being on disability insurance rolls per se. Instead, these patterns appear to be explained by persistent individual characteristics that pre-date award of DI.

- <u>*Result 3:*</u> *The increase in emergency room visits is driven by the poorest disability insurance recipients.*

Figure 9 divides the disability insurance sample into three equal sized groups (terciles) on the basis of their net asset holdings, averaged across the previous two years. In all three panels, the average daily rate of ER visits is higher for the bottom tercile (shown in diamonds) and the middle tercile (shown in triangles), compared to the rate for top tercile (shown in squares). Together, these differences in levels across asset terciles reflect a health-wealth gradient within the disability insurance population.

The figures also clearly show that the probability of visiting the ER increases around $t = 0$ only for individuals in the bottom two terciles of asset holdings. As a percentage of the average daily rate, the magnitude of the increase in all ER visits is decreasing with wealth, at 16.2% in the bottom tercile, 9.5% in the middle tercile, and 5% in the top tercile. For drug and alcohol related visits, the increases for the bottom two asset terciles are essentially equal (39.8% and 40.4%), while the increase for the top asset tercile is significantly smaller at 12.6%. Similarly, the increases for head injuries for the bottom two asset terciles are very close at 44.1% and 41.7%. The increase is again significantly smaller for the top tercile at only 8%.

These results using assets are consistent with the hypothesis that liquidity constraints play a role in the increase in ER visits around dates of payment. However, the results are also consistent with other explanations, including behavioral biases and addiction, either of which could plausibly cause individuals to have low asset holdings and, in addition, to cause them to engage in behaviors that increase the probability of needing to visit the emergency room after receiving income.

- *Result 4: The largest increases in ER visits are for disability insurance beneficiaries with mental and behavioral impairments.*

Figure 10 uses the impairments data to separately plot event studies by reason that disability insurance benefits were granted. I divide the sample into disability insurance beneficiaries with mental and behavioral disorders (triangles) and with other disorders (squares).

The mental and behavioral disorders sample is uniformly higher in both average daily rates and in the change in probability of visiting the ER around $t = 0$. The increase as a percentage of the base rate is 13.7% for all ER visits, 37% for drug and alcohol related ER visits, and 31.9% for ER visits for head injuries. No comparable increases are visible for the residual group without mental and behavioral disorders.

In Appendix Figure A5, I restrict attention to those with any mention of drug or alcohol dependence among the reasons that disability was awarded to them. The average daily rates of all kinds of ER visits are about double that of the full DI sample. The daily rates for drug and alcohol related visits are almost four times as large as those for the overall group. The daily rates for head injuries are over three times as large as those for the overall group. The changes in the probability of visiting the ER around $t = 0$ as a percentage of the mean are 27.3% for all ER visits, 49.8% for drug and alcohol related ER visits, and 39.8% for head injuries.[28]

[28] Note that most head injuries are not coded as drug or alcohol related in these data. In this way,

These results show that mental and behavioral disorders and addiction play an important role in explaining why the probability of an adverse health event increases when income is received.

5.3 Robustness Checks

This section presents additional results that show that the results described above are robust to alternative samples and controls.

A fully interacted version of Equation 8 would be non-parametric in the sense that the conditional expectation function would necessarily be linear. While all the covariates in Equation 8 are binary, I do not fully interact them. In this way, I place certain restrictions on the relationship between means on certain days. For example, by not interacting the $t = s$ indicators with the day of the week indicators, I am restricting the change in the mean at $t = 0$ to be the same for every weekday. In Appendix Figure A6, I assess whether the increases in ER visits found around the last business day of the month are different on different days of the week. In each panel of Figure A6, I plot coefficients estimated from Equation 8 in the same way as before. However, here, I estimate Equation 8 five times, where each time I restrict the sample to exclude the twenty-eight day months where $t = 0$ occurs on a particular day of the week. The figures in the first column are for the full population. The figures in the second column are for the disability insurance sample. Overall, the five lines line up quite closely, with the possible exception being the series plotted in triangles that excludes the twenty-eight day months where $t = 0$ occurs on a Friday. For the full population, this series is lower in levels than the four other series, but for the disability insurance sample, the difference is much smaller. The results are similar no matter which weekday payments are made. The increase around the last business day of the month is not driven by Fridays or any other day of the week.

In Appendix Figure A7, I assess in what ways changes to the vector of controls

these results illustrate the difficulty in inferring health conditions when one is restricted to diagnosis codes available in hospitalization data.

affect my results. The figures in the first column are for the full population. The figures in the second column are for the disability insurance sample. In each panel, I plot the coefficients from the basic regression model as a reference in diamonds. I then re-estimate the model, adding the days before and after each holiday and interactions of the month and year indicators to the vector of controls. Coefficients from this expanded model are plotted in small squares. I re-estimate the model also where I include these additional controls and exclude the twenty-eight day months during which the New Year's holiday occurs. Coefficients from this third model are plotted in larger squares. While there are small differences in the three series, it is remarkable how closely the lines and points lie on top of each other. The results here are not sensitive to the controls used and are not driven by the New Year's holiday, which always occurs a few days after the final payment of each year.

Lastly, I address the concern that heterogeneity within payment dates could obscure the results for the non-disabled groups. In Appendix Figure A8, I restrict the sample to narrow industries and occupations, where payment dates should be more homogeneous. In panel (a), I plot estimates of Equation 8 for teachers (diamonds), the military (triangles), and nurses (squares) using occupation classification codes for the prior year. The results in this figure are similar to those for the wage earner sample overall. I repeat these estimates again in panel (b), but measure time relative to the last calendar day of the month instead of the last business day of the month. Again, these results are very similar to those in the base set of results for wage earners.

5.4 Discussion

Prior evidence on adverse health events around payment dates has been in the context and institutional setting of the United States.[29] It is noteworthy then that emergency room visits increase around payment dates even in Denmark, a country with universal healthcare coverage. Patients in the United States are often asked to pay their insurance

[29] Andersson, Lundborg, Vikström (2014) have recently presented evidence on mortality in Sweden for government employees around payment dates.

copayments before leaving the emergency room. In this way, one interpretation of the evidence in the United States is that patients go to the emergency room after receiving income, because that is when they can afford to pay for medical care. Evidence from the Oregon Health Insurance Experiment suggests that this explanation could be very important in the United States among low income households (Taubaum et al. 2014). However, in Denmark, this effect is much less likely to be driving the results. Instead, it seems more plausible that changes in the composition of consumption are the causal channel through which the results are manifested.

While the underlying mechanisms that generate deaths and ER visits could differ, the results documented here do not support the argument made in the literature on mortality (e.g., Evans and Moore 2011, Andersson, Lundborg, Vikström 2014) that increases in rates of adverse health events around payment dates are caused by increased activity in the general population. Instead, I find that the increase in rates of ER visits is largely limited to those who receive disability insurance income or those who will receive it in the future. While activity likely does increase when income is received, my results show clearly that an across the board increase in activity is not what is driving the increase in emergency room visits around the last business day of the month in Denmark. Instead, my results could suggest that either disability insurance beneficiaries engage in high risk behaviors when they receive income, or, that their impairments are so severe that even low risk behaviors are potentially dangerous.

One question is whether the results are driven by supply side responses, which could be especially important here, because more than 60% of the population receives income at once. For example, is there greater availability of drugs and alcohol at these times of the month? It would certainly be interesting to provide additional evidence along these lines. However, one would not expect to find that the increase in ER visits is limited to DI beneficiaries if supply side factors are extremely important.

The results also have implications for what the eligibility criteria should be for disability insurance. For example, the United States eliminated eligibility for disability insurance programs on basis of drug and alcohol abuse in 1996 (Chatterji and Meara

2010). However, Result 2 shows that rates of ER visits increase around the last business day of the month, even in years before receiving disability insurance. Therefore, my results call into question whether eliminating coverage is the right policy to deal with addiction, since other kinds of income, such as wages or other transfer payments, seem to produce the same effect as disability insurance income for a subset of the population.[30] Other policies, such as those tested by Schilbach (2014), may be more effective.[31]

6 Conclusions

This paper has presented new evidence from Denmark to quantify the costs and benefits of disability insurance. The first set of results shows that disability insurance is very valuable because the labor supply of disability insurance beneficiaries is sensitive to unconditional transfers. These estimates suggest that the effect of DI on labor force participation is driven in large part by making it feasible for the disabled to stop working, rather than by reducing effective wages. In a standard model, optimal benefits are increasing in the ratio between these two responses. However, the second set of results implies that welfare analysis in this setting may need to be modified because behavioral responses in this population generate fiscal externalities and, perhaps, internalities.

This evidence shows that a subset of disability insurance beneficiaries, who tend to have mental and behavioral disorders and low assets, respond very differently to the timing of payments than do non-disabled populations and other DI beneficiaries. These responses result in increases in the rate of ER visits in the days after payments are received. Although these people respond to income in the same way even before they were awarded DI, the externalities (and internalities) generated by their behavioral responses must still be taken into account when setting optimal DI benefit levels. In the formula in Equation 3, these results imply that there is an additional term which

[30] Autor and Duggan (2006) make a more general critique of the efficacy of eliminating coverage for particular disorders based on the evidence that most of the beneficiaries whose benefits were terminated in 1996 eventually were granted benefits under a different impairment.

[31] Recently, Georgia passed legislation to require drug tests as part of food stamp eligibility. However, Georgia has been prohibited from implementing this law.

much be estimated to set benefit levels. In this way, the evidence shows that there are unique challenges to designing a disability insurance system that may not be present for other social insurance programs. For example, the optimal DI benefit amount may differ depending on how disability insurance benefits are dispersed.

An important conclusion from the evidence presented here is that even though the disabled make up a relatively small group, they are the most relevant group to study in order to understand why adverse events increase on the last business day of the month and the group for which alternative program designs should be considered. Many studies suggest using pay frequency as a potential policy tool (e.g., Shapiro 2005, Dobkin and Puller 2007, Mastrobuoni and Weinberg 2009).[32] However, there is little causal evidence on the impacts of proposals of this type. There are two potential research questions with regard to pay frequency. The first question is whether smaller, more frequent payments can smooth rates of adverse events. The second question is whether smaller, more frequent payments can reduce rates of adverse events overall.

My on-going work presents quasi experimental evidence on pay frequency to address these two questions (Bruich, Nielsen, Simonsen, and Wohlfahrt 2014). We use variation in payment frequency of the child benefit in Denmark. Each family with a child receives a cash payment per child until the child turns 18. Benefits are paid out on the 20th of the first month of each quarter for families with children under 14. Benefits for families with children between 15 and 17 were paid out quarterly until 2011, when benefits began to be paid out monthly. Preliminary evidence suggests that the smaller, more frequent payments both smoothed and reduced rates of adverse health events overall for families with children in the affected age range, relative to the families with younger children.

The results suggest five directions for future research. First, estimates of the labor supply responses to net wages or state contingent benefits, combined with the estimates

[32] One could also change the form of benefits from cash to in-kind or stagger the timing of payments. As an example of the latter, many states have recently staggered Supplemental Nutrition Assistance Program (SNAP) benefits so that different beneficiaries receive income at different times (see e.g., Bruich 2014 for examples). Dobkin and Puller (2007) present quasi-experimental evidence on this type of policy. If one thinks that the evidence on ER visits is driven by social interactions or congestion, this might be another viable alternative payment scheme.

in the first part of the paper, would allow one to determine whether increasing benefits further in Denmark would increase welfare using Equation 3. Second, implementing a version of this formula that corrects for externalities is also needed based on the evidence in the second part of this paper. Third, experimental or quasi experimental evidence of alternative payment policies affecting the disability insurance population directly would be most valuable, since this group is the sample that displays the most excess sensitivity to the timing of payments. Fourth, it would be useful to develop a theory of optimal pay frequency. Fifth, it would be interesting to provide analogs of the ER visit figures for other outcomes such as crime, traffic accidents, consumption, and expenditures around the last business day of the month. While the overall rate of adverse events is the relevant outcome to guide policy in the case of ER visits, crime, and traffic accidents, in the case of consumption, it is the time path that is most relevant both for policy and for distinguishing between theories of intertemporal behavior.

References

Andersson, Elvira, Petter Lundborg, and Johan Vikström (2014) "Income Receipt and Mortality: Evidence from Swedish Public Sector Employees," mimeo.

Allcott, Hunt, and Dmitry Taubinsky (2014). "The Lightbulb Paradox: Evidence from Two Randomized Experiments," mimeo.

Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky (2014). "Energy policy with externalities and internalities," *Journal of Public Economics* 112 (2014) 72–88.

Autor, David H. and Mark G. Duggan (2003). "The Rise In The Disability Rolls And The Decline In Unemployment," *Quarterly Journal of Economics*, 118(1): 157-205.

Autor, David H. and Mark G. Duggan. (2006). "The Growth in the Social Security Disability Rolls: A Fiscal Crisis Unfolding," *Journal of Economic Perspectives*, 20(3): 71-96.

Autor, David H. and Mark G. Duggan (2007). "Distinguishing Income from Substitution Effects in Disability Insurance," *American Economic Reivew Papers and Proceedings*, 97(2): 103-105, May.

Autor, David H. and Mark G. Duggan (2008). "The Effect of Transfer Income on Labor Force Participiation and Enrollment in Federal Benefits Programs: Evidence from the Veterans Disability Compensation Program," mimeo.

Autor, David H., Nicole Maestas, Kathleen Mullen and Alexander Strand (2011) "Does Delay Cause Decay? The Effect of Administrative Decision Time on the Labor Force Participation and Earnings of Disability Applicants." MRRC Working Paper #2011-258, September 2011.

Baadsgaard, Mikkel and Jarl Quitzau (2011) "Danish registers on personal income and transfer payments," *Scandinavian Journal of Public Health*, 39(7): 103-105, July.

Bernheim, B. Douglas and Antonio Rangel (2009) "Addiction and Cue-Triggered Decision Processes," *American Economic Review* 94(5): 1558-1590.

Black, Dan, Kermit Daniel and Seth Sanders. (2002). "The Impact of Economic Conditions on Participation in Disability Programs: Evidence from the Coal Boom and Bust," *American Economic Review*, 92(1): 27-50, March.

Borghans, Lex, Anne C. Gielen, Erzo F.P. Luttmer (2014) "Social Support Substitution and the Earnings Rebound: Evidence from a Regression Discontinuity in Disability Insurance Reform," forthcoming *American Economic Journal: Economic Policy.*

Bound, John. (1989) "The Health and Earnings of Rejected Disability Insurance Applicants" *American Economic Review*, 79(3): 482-503, June.

Bound, John and Richard V. Burkhauser. (1999). "Economic Analysis of Transfer Programs Targeted on People with Disabilities," Chapter 51 in Vol. 3 *Handbook of Labor Economics*, eds. Orley Ashenfelter and David Card, Amsterdam: Elsevier Science, pp.

3417–3528.

Bruich, Gregory A. (2014) "The effect of SNAP benefits on household expenditures and consumption: New evidence from scanner data and the November 2013 benefit cuts," mimeo.

Bruich, Gregory A., Nete Munk Nielsen, Jacob Simonsen, and Jan Wohlfahrt (2014) "The causal effect of pay frequency on adverse health outcomes," research in progress.

Campolieti, Michele (2004). "Disability Insurance Benefits and Labor Supply: Some Additional Evidence" *Journal of Labor Economics* 22(4): 863-889, October.

Card, David, Raj Chetty, and Andrea Weber (2007). "Cash-on-Hand and Competing Models of Intertemporal Behavior: New Evidence from the Labor Market," *Quarterly Journal of Economics* 122 (4): 1511-1560.

Chatterji, Pinka and Ellen Meara (2010) "Consequences of eliminating federal disability benefits for substance abusers," *Journal of Health Economics* 29(2): 226-240, March.

Chen, Susan and Wilbert van der Klaauw. (2008). "The work disincentive effects of the disability insurance program in the 1990s," *Journal of Econometrics* 142: 757–784.

Chetty, Raj (2006a) "A General Formula for the Optimal Level of Social Insurance," *Journal of Public Economics* 90: 1879-1901.

Chetty, Raj (2006b) "A New Method of Estimating Risk Aversion" *American Economic Review*, 96(5), 1821-1834, December 2006.

Chetty, Raj (2008) "Moral Hazard vs. Liquidity and Optimal Unemployment Insurance," *Journal of Political Economy* 116(2): 173-234.

Chetty, Raj (2009) "Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods," *Annual Review of Economics* 1: 451-488, 2009.

Cutler, David M., Ellen Meara, and Seth Richards-Shubik (2011). "Health Shocks and Disability Transitions Among Near-elderly Workers," Harvard University Working Paper.

Denk, Oliver and Jean-Baptiste Michau (2012). "Optimal Social Security with Imperfect Tagging," working paper.

Dobkin, Carlos and Steven L. Puller. (2006) "The Effects of Government Transfers on Monthly Cycles in Drug Abuse, Crime and Mortality," mimeo.

Dobkin, Carlos and Steven L. Puller. (2007) "The effects of government transfers on monthly cycles in drug abuse, hospitalization and mortality," *Journal of Public Economics* 91: 2137–2157.

Duggan, Mark G. and Scott A. Imberman (2009). "Why Are the Disability Rolls Skyrocketing? The Contribution of Population Characteristics, Economic Conditions, and Program Generosity," in *Health at Older Ages: The Causes and Consequences of Declining Disability among the Elderly*, National Bureau of Economic Research, Inc.

Duggan, Mark G., Perry Singelton, and Jae Song (2007) "Aching to Retire? The Rise in the Full Retirement Age and it's Impact on the Disability Rolls," *Journal of Public Economics* 91(7): 1327-50, August.

Eissa, Nada O. (1995) "Taxation and Labor Supply of Married Women: The Tax Reform Act of 1986 as a Natural Experiment," NBER Working Paper No. 5023, February.

Evans, William N. and Timothy J. Moore (2011) "The Short-Term Mortality Consequences of Income Receipt," *Journal of Public Economics*, 95(11): 1410-1424.

Evans, William N. and Timothy J. Moore (2012) "Liquidity, Economic Activity, Mortality," *Review of Economics and Statistics* 94(2): 400-418, May.

Feldstein, Martin S. (1985) "The Optimal Level of Social Security Benefits," *Quarterly Journal of Economics*, 10(2): 303-320, May.

Foley, C. Fritz. (2011) "Welfare Payments and Crime," *Review of Economics and Statistics*, 93(1): 97-112, February.

French, Eric, and Jae Song. (2014). "The Effect of Disability Insurance Receipt on Labor Supply," *American Economic Journal: Economic Policy*, 6(2): 291-337.

Geerdsen, Peter Pico (2006). "Førtidspensionister og arbejdsmarkedet," Socialforskningsinstituttet working paper.

Gelman, Michael, Shachar Kariv, Matthew D. Shapiro, Dan Silverman, and Steven Tadelis (2014) "Harnessing Naturally-Occurring Data to Measure the Response of Spending to Income," *Science* 345(6193): 212-215.

Golosov, Mikhail and Aleh Tsyvinski (2006) "Designing Optimal Disability Insurance: A Case for Asset Testing," *Journal of Political Economy* 114(2): 257-279, April.

Gross, Tal and Jeremy Tobacman (2014) "Dangerous Liquidity and the Demand for Health Care: Evidence from the 2008 Stimulus Payments," *Journal of Human Resources* 49(2): 424-445, Spring.

Gruber, Jonathan. (2000). "Disability Insurance Benefits and Labor Supply," *Journal of Political Economy* 108, 1162-1183.

Gruber, Jonathan (2007) *Public Finance and Public Policy*, Third Edition. New York: Worth Publishers.

Gruber, Jonathan and Botond Koszegi (2001) "Is Addiction 'Rational'? Theory And Evidence," *Quarterly Journal of Economics* 116(4): 1261-1303, November.

Gruber, Jonathan and Jeffrey D. Kubik. (2002). "Health Insurance Coverage and the Disability Insurance Application Decision," NBER Working Paper No. 9148, September.

Gruber, Jonathan and Jeffrey D. Kubik. (1997). "Disability insurance rejection rates and the labor supply of older workers," *Journal of Public Economics* 64(1): 1–23, April.

Hastings, Justine and Ebonya Washington (2010) "The First of the Month Effect: Consumer Behavior and Store Responses," *American Economic Journal: Economic Policy*

2(2): 142-62, May.

Hansen, Hans (2006) *Public Pension Schemes in Seven European Countries: A Micro-Simulation Approach.* New York: Nova Science Publishers, Inc.

Hendren, Nathaniel (2013) "Private Information and Insurance Rejections," *Econometrica* 81(5): 1713-1762.

Johnson, David S., Jonathan A. Parker, and Nicholas S. Souleles. (2006). "Household Expenditure and the Income Tax Rebates of 2001." *American Economic Review*, 96(5): 1589-1610.

Kostøl, Andreas Ravndal and Magne Mogstad. (2014). "How Financial Incentives Induce Disability Insurance Recipients to Return to Work," *American Economic Review* 2014, 104(2): 624–655.

LaLumia, Sara. (2013). "The EITC, Tax Refunds, and Unemployment Spells," *American Economic Journal: Economic Policy*, 5(2): 188-221.

Landais, Camille (2014). "Assessing the welfare effects of unemployment insurance using the regression kink design," forthcoming *American Economic Journal: Economic Policy.*

Low, Hamish and Luigi Pistaferri (2010). "Disability Risk, Disability Insurance and Life Cycle Behavior," NBER Working Paper No. 15962, May.

Lynge, Elsebeth, Jakob Lynge Sandegaard, and Materjka Rebolj (2011) "The Danish National Patient Register," *Scandinavian Journal of Public Health*, 39(7): 30-33, July.

Maestas, Nicole and Jae Song. (2011) "The Labor Supply Effects of Disability Insurance: Evidence from Automatic Conversion Using Administrative Data." MRRC Working Paper #2010-247.

Maestas, Nicole and Na Yin (2008) "The Labor Supply Effects of Disability Insurance Work Disincentives: Evidence from the Automatic Conversion to Retirement Benefits at Full Retirement Age." MRRC Working Paper #194.

Maestas, Nicole, Kathleen J. Mullen, and Alexander Strand (2013). "Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt," *American Economic Review*, 103(5): 1797-1829.

Marie, Olivier and Judit Vall Castello (2012) "Measuring the (income) effect of disability insurance generosity on labour market participation," *Journal of Public Economics* 96(1–2): 198–210, February.

Mastrobuoni, Giovanni, and Matthew Weinberg (2009). "Heterogeneity in Intra-monthly Consumption Patterns, Self-Control, and Savings at Retirement" *American Economic Journal: Economic Policy*, 1(2): 163-89.

Meyer, Bruce D. and Wallace K.C. Mok (2013) "Disability, Earnings, Income and Consumption" NBER Working Paper No. 18869, March.

Moore, Timothy J. (2014) "The Employment Effect of Terminating Disability Benefits," NBER Working Paper No. 19793, January.

Mueller, Andreas I., Jesse Rothstein, Till M. von Wachter (2014) "Unemployment Insurance and Disability Insurance in the Great Recession," forthcoming, *Journal of Labor Economics*.

Mullainathan, Sendhil, Joshua Schwartzstein, and William J. Congdon (2012) "A Reduced Form Approach to Behavioral Public Finance," *Annual Review of Economics* 4: 511-540.

O'Donoghue, Ted and Matthew Rabin (2006) "Optimal sin taxes," *Journal of Public Economics*, 90(10-11): 1825-1849, November.

Parker, Jonathan A. (1999). "The Reaction of Household Consumption to Predictable Changes in Social Security Taxes," *American Economic Review* 89(4): 959-973, September.

Parker, Jonathan A. (2014). "Why Don't Households Smooth Consumption? Evidence from a 25 million dollar experiment," MIT working paper.

Parsons, Donald O. (1980). "The Decline in Male Labor Force Participation," *Journal of Political Economy* 88(1): 117-134.

Parsons, Donald O. (1991). "The Health and Earnings of Rejected Disability Insurance Applicants: Comment," *American Economic Review* 81(5): 1419-1426, December.

Petersson, Flemming, Mikkel Baadsgaard, and Lau Caspar Thygesen (2011) "Danish registers on personal labor market affiliation," *Scandinavian Journal of Public Healt*h, 39(7): 95-98, July.

Schilbach, Frank (2014) "Alcohol Myopia, Self-Control, and Intertemporal Choice: A Field Experiment in India" mimeo.

Shapiro, Jesse M., (2005). "Is there a daily discount rate? Evidence from the food stamp nutrition cycle," *Journal of Public Economics* 89(2-3): 303-325, February.

Shapiro, Matthew D and Slemrod, Joel (1995) "Consumer Response to the Timing of Income: Evidence from a Change in Tax Withholding," *American Economic Review*, 85(1): 274-83, March.

Spinnewijn, Johannes (2014) "Unemployed but Optimistic: Optimal Insurance Design with Biased Beliefs," forthcoming *Journal of the European Economic Association.*

Stephens, Melvin, Jr. (2003) "3rd of tha Month: Do Social Security Recipients Smooth Consumption between Checks?" *American Economic Review*, 93(1): 406-422, March.

Stephens, Melvin, Jr. (2006) "Paycheque Receipt and the Timing of Consumption," *Economic Journal* 116(513): 680-701.

Stephens, Melvin, Jr. and Takashi Unayama (2011) "The Consumption Response to Seasonal Income: Evidence from Japanese Public Pension Benefits," *American Eco-*

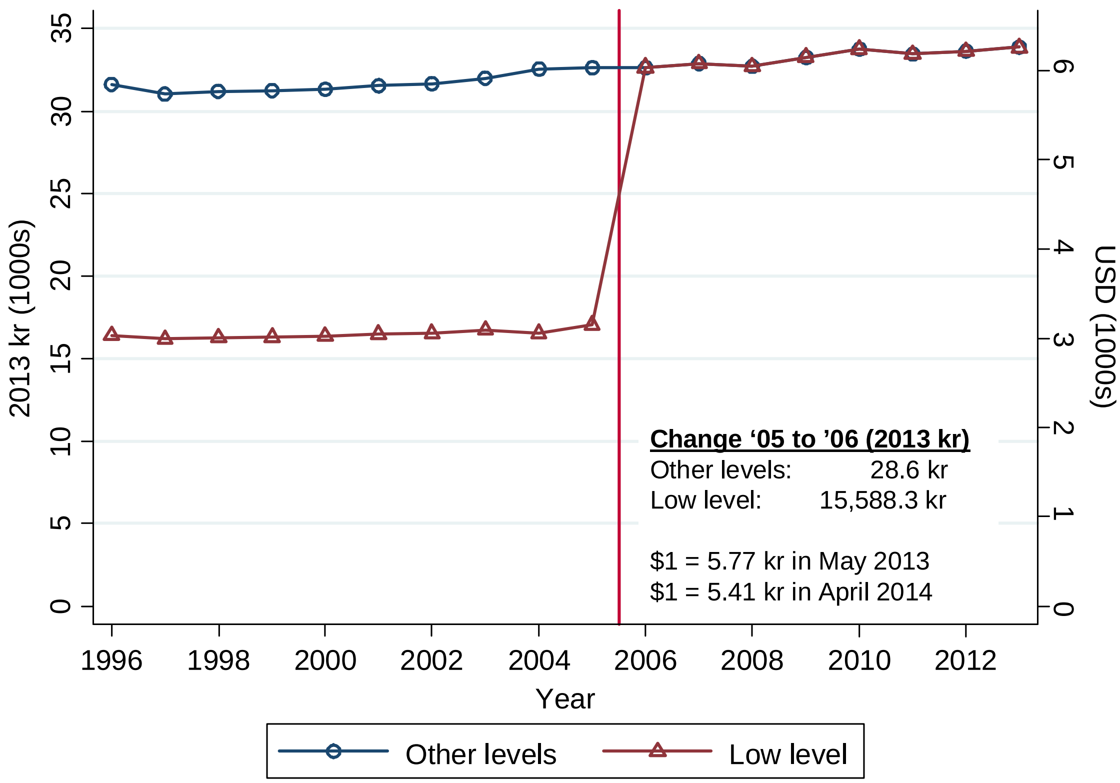
nomic Journal: Applied Economics 3(4): 86-118, October.

Taubman, Sarah, Heidi Allen, Bill Wright, Katherine Baicker, Amy Finkelstein, and the Oregon Health Study Group (2014) "Medicaid Increases Emergency Department Use: Evidence from Oregon's Health Insurance Experiment," *Science*, 343(6168): 263-268, January.

von Wachter, Till M., Jae Song, and Joyce Manchester (2011) "Trends in Employment and Earnings of Allowed and Rejected Applicants to the Social Security Disability Insurance Program" *American Economic Review*, 101(7): 3308-29.

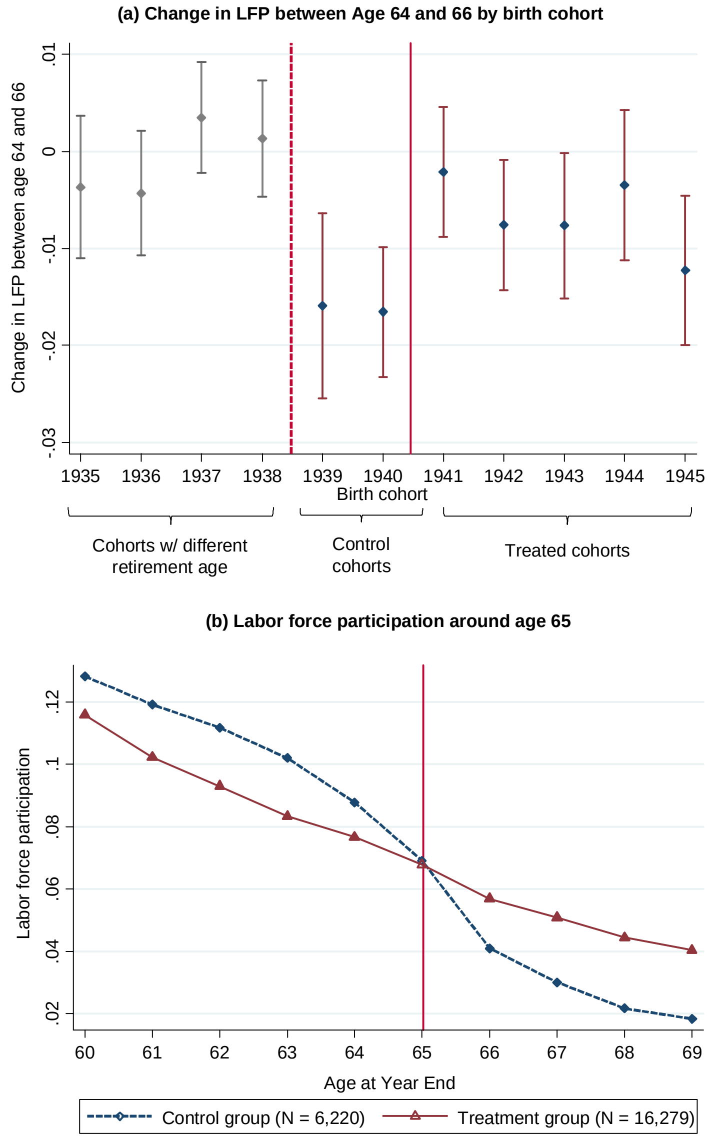
FIGURE 1

Policy Variation in the Tax Free, Lump Sum Disability Insurance Benefit Amount



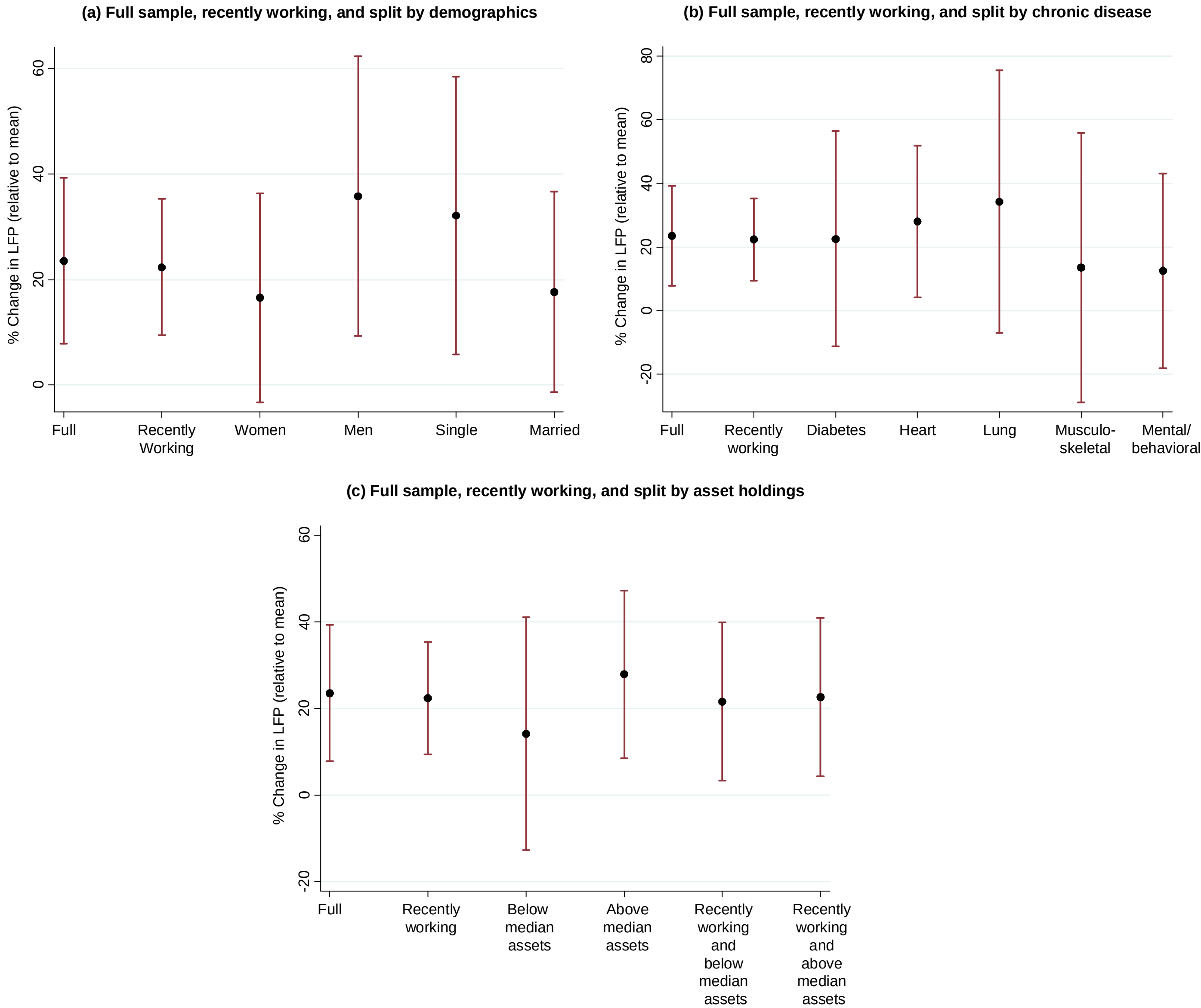
NOTE—This figure plots the yearly lump sum disability insurance benefit amount for beneficiaries on the low (triangles) and higher disability levels (circles). The left y-axis shows the yearly benefit amount in 2013 kroner and the right y-axis shows the amount in dollars using the $1 = 5.41 kroner exchange rate in April 2014.

FIGURE 2
The Effect of Unconditional Cash Transfers on Labor Force Participation



NOTE–This figure plots the change in labor force participation between ages 64 and 66 by birth cohort (panel a) and by age for the treatment group and the control group (panel b). To construct panel (a), I first use the pooled sample of all birth cohorts shown in the figure to estimate a model with year fixed effects and year × treatment group fixed effects. The figure plots the change in labor force participation for each cohort separately using the residuals from this pooled regression as the dependent variable in a model with individual fixed effects. To construct panel (b), I estimate linear probability models separately for the birth cohorts born between 1940 and July 1939 and for the birth cohorts born between 1941 and 1945, where each model includes individual fixed effects and year fixed effects. The figure plots the age coefficients, with y-axis scaled so that the average of the coefficient estimates equals the sample average of the dependent variable for each group.

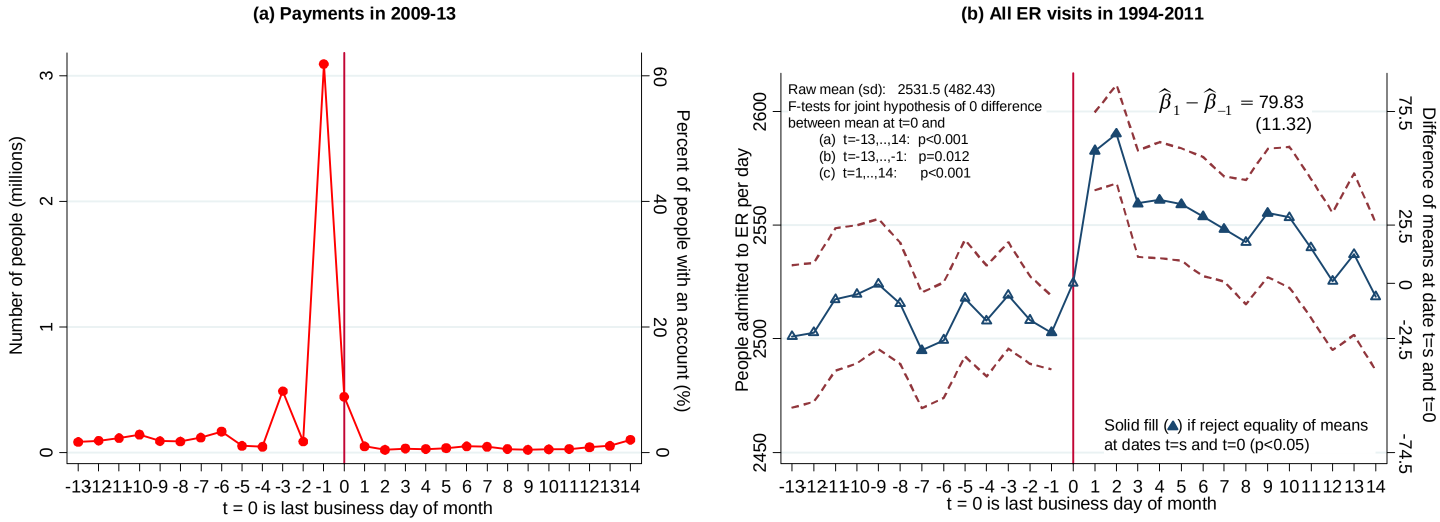
FIGURE 3
Heterogeneity in the Effect of Unconditional Cash Transfers on LFP



NOTE–This figure plots the change in labor force participation between ages 64 and 66 in the treatment group relative to the control group for the full sample, the recently working subsample, and by demographics (panel a), chronic disease (panel b), and asset holdings (panel c). The treatment effect is expressed as a percentage of the mean labor force participation in the treatment group.

FIGURE 4

Event Studies of Payments and ER visits around Last Business Day of Month

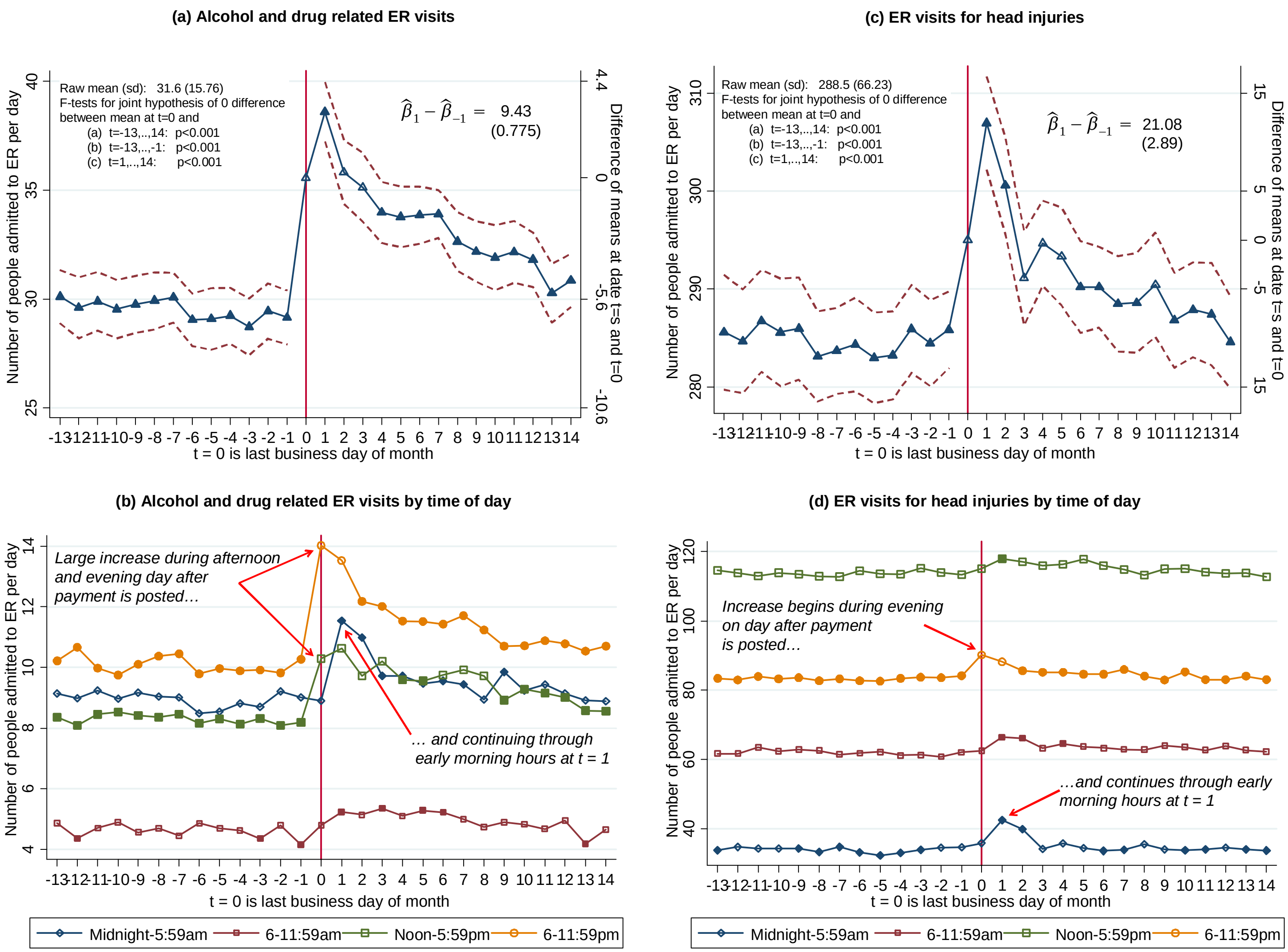


NOTE–This figure plots event studies of the number of people receiving payments (panel a) and the number of people visiting the ER (panel b) around the last business day of the month ($t = 0$). Panel A shows the average number of people each day who receive a payment to their NemKonto bank account in 2009-2013 for the 28-day window around $t = 0$. The figure includes payments from any of the 850 government authorities in Denmark, including transfer and social insurance program payments, tax refunds, and wages for government employees. The right y-axis expresses the number of people receiving a payment as a percentage of the total number of people with a NemKonto bank account, which was 4,927,626 on average from 2009 to 2013. Panel B plots the average number of people who visit the ER per day in 1994-2011 for the 28-day window around $t = 0$. The means are adjusted for day of the week, synthetic month, year, and nineteen holidays and other reoccurring special dates by regressing the number of people admitted to the ER on date d on indicators for each date $t = -13, \ldots, 14$ and indicators for each control variable:

$$\sum_i y_{id} = \alpha + \sum_{s=-13}^{-1} \beta_s I(t_d = s) + \sum_{s=1}^{14} \beta_s I(t_d = s) + \gamma X_d + \widetilde{u}_d$$

where y_{id} is an indicator for whether person i visited the ER on date d. The points in the figure are $\beta_0 = 0$ and the twenty-seven $\widehat{\beta}_s$ coefficients. The dashed lines show a 0.95 confidence interval for $\widehat{\beta}_s$, which equals the difference between means at date $t = 0$ and date $t = s$. Standard errors are clustered by 28-day month. The y-axis along the left-hand side of the figure is scaled so that the mean of the twenty-eight points equals the sample average of the dependent variable. The nineteen reoccurring dates are listed in Appendix Table A3.

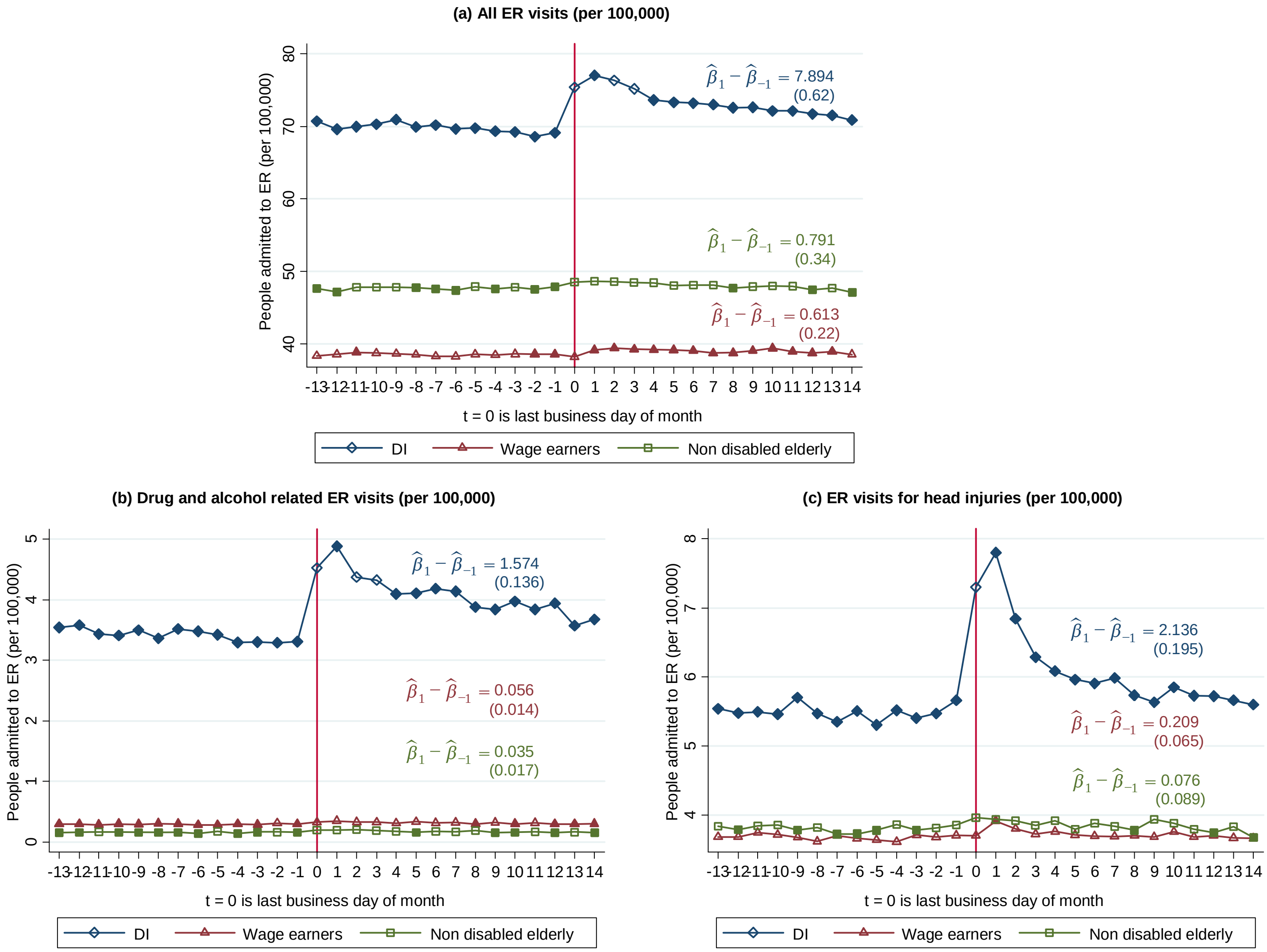
FIGURE 5
Event Studies of ER visits around Last Business Day of Month: Full Population



NOTE–This figure plots the average number of people who visit the ER per day over the 28-day window around the last business day of the month ($t = 0$) in 1994-2011 and whose diagnosis code is either alcohol and drug related (panels a and b) or for a head injury (panels c and d) . The means are adjusted for day of the week, synthetic month, year, and nineteen reoccurring dates in the same way as in Figure 4. A visit is defined as alcohol and drug related if any of the ICD-10 diagnosis codes associated with that visit are for drugs and alcohol (ICD-10 codes T40, T436, T510, and those starting with F10 to F19, but excluding F17). A visit is defined as being for a head injury if the primary diagnosis code is for a head injury (ICD-10 codes starting with S00 to S09). Panels (b) and (d) show the number of people visiting the ER per day divided into four 6-hour intervals: midnight to 5:59 am (diamonds), 6 am to 11:59 am (small squares), noon to 5:59 pm (larger squares), and 6 pm to 11:59 pm (circles). There are $T = 215 \times 28 = 6020$ days in my sample.

FIGURE 6

Event Studies of ER visits around Last Business Day of Month by Group

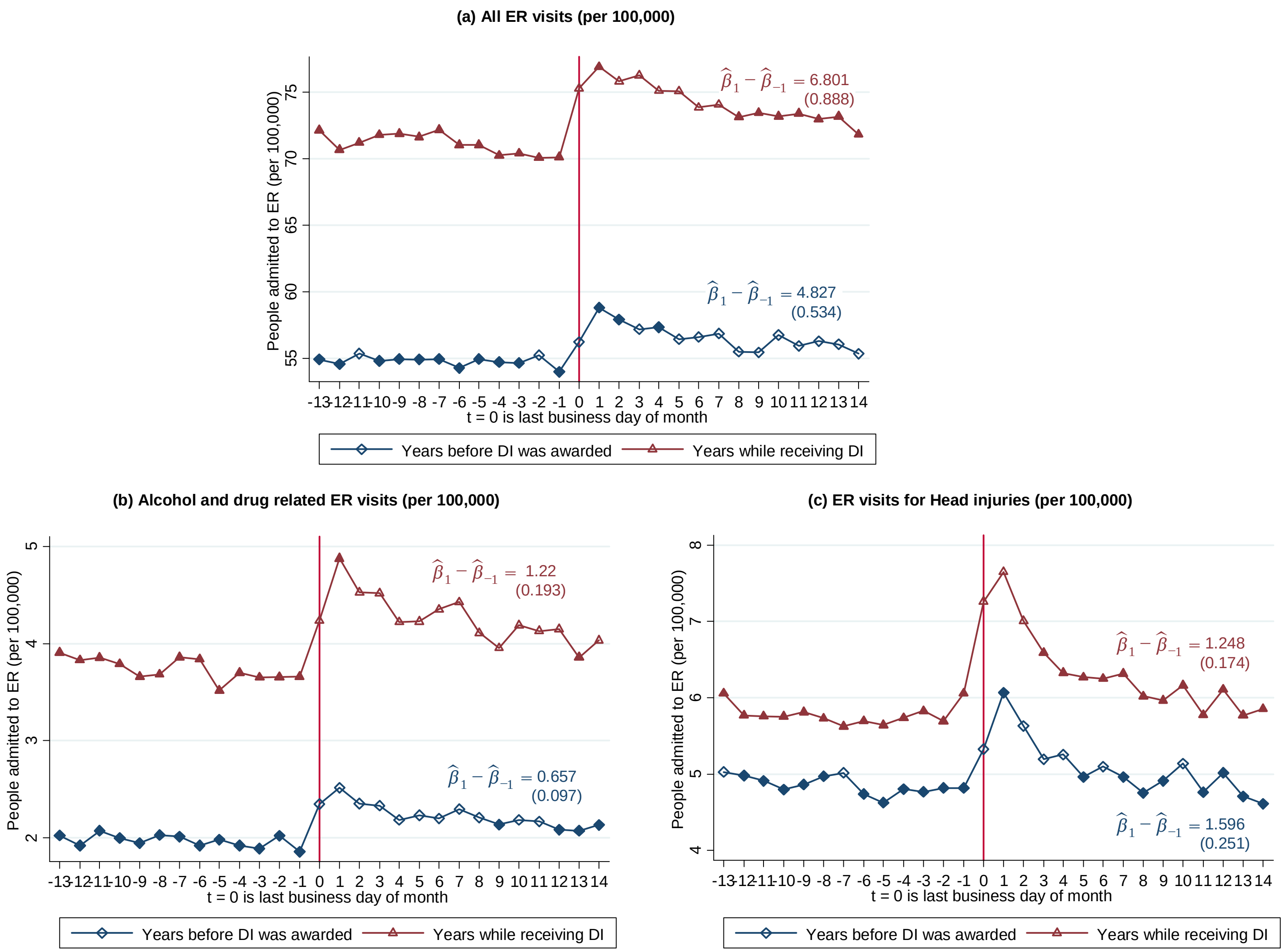


NOTE–This figure plots the average number of people per 100,000 who visit the ER per day over the 28-day window around the last business day of the month ($t = 0$) in 1994-2011. The graph shows three samples: those who receive disability insurance during the year in which $t = 0$ falls (blue diamonds), wage earners (red triangles), and non-disabled elderly who receive social security income during the year in which $t = 0$ falls. The figures are drawn for all ER visits (panel a), for ER visits that have at least one diagnosis code that is alcohol and drug related (panel b), and for ER visits whose primary diagnosis code is for a head injury (panel c). The means are adjusted for day of the week, synthetic month, year, and holidays and other reoccurring special dates, by regressing the number of people admitted to the ER per 100,000 on date d on indicators for each date $t = -13, \ldots, 14$ and indicators for each control variable:

$$\bar{y}_d \times 100000 = \alpha + \sum_{s=-13}^{-1} \beta_s I(t_d = s) + \sum_{s=1}^{14} \beta_s I(t_d = s) + \gamma X_d + \bar{u}_d$$

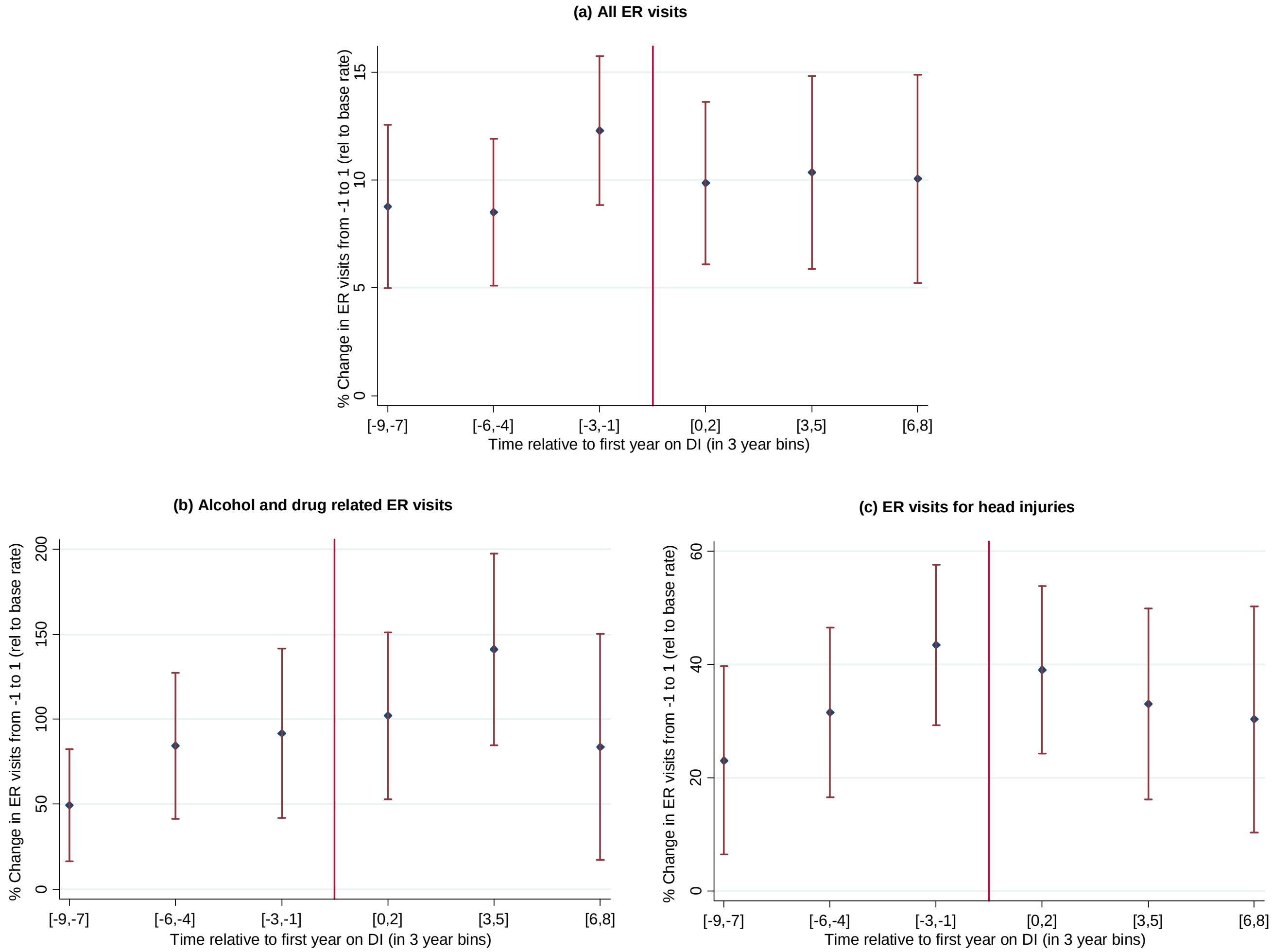
where each observation is weighted by the number of people in the sample on date d. The twenty-seven β_s coefficients can be interpreted as the difference in the probability of visiting the ER on date $t = s$ relative to date $t = 0$. There are $T = 215 \times 28 = 6020$ days in my sample.

FIGURE 7
Event Studies of ER visits for Years Before and After DI was Awarded



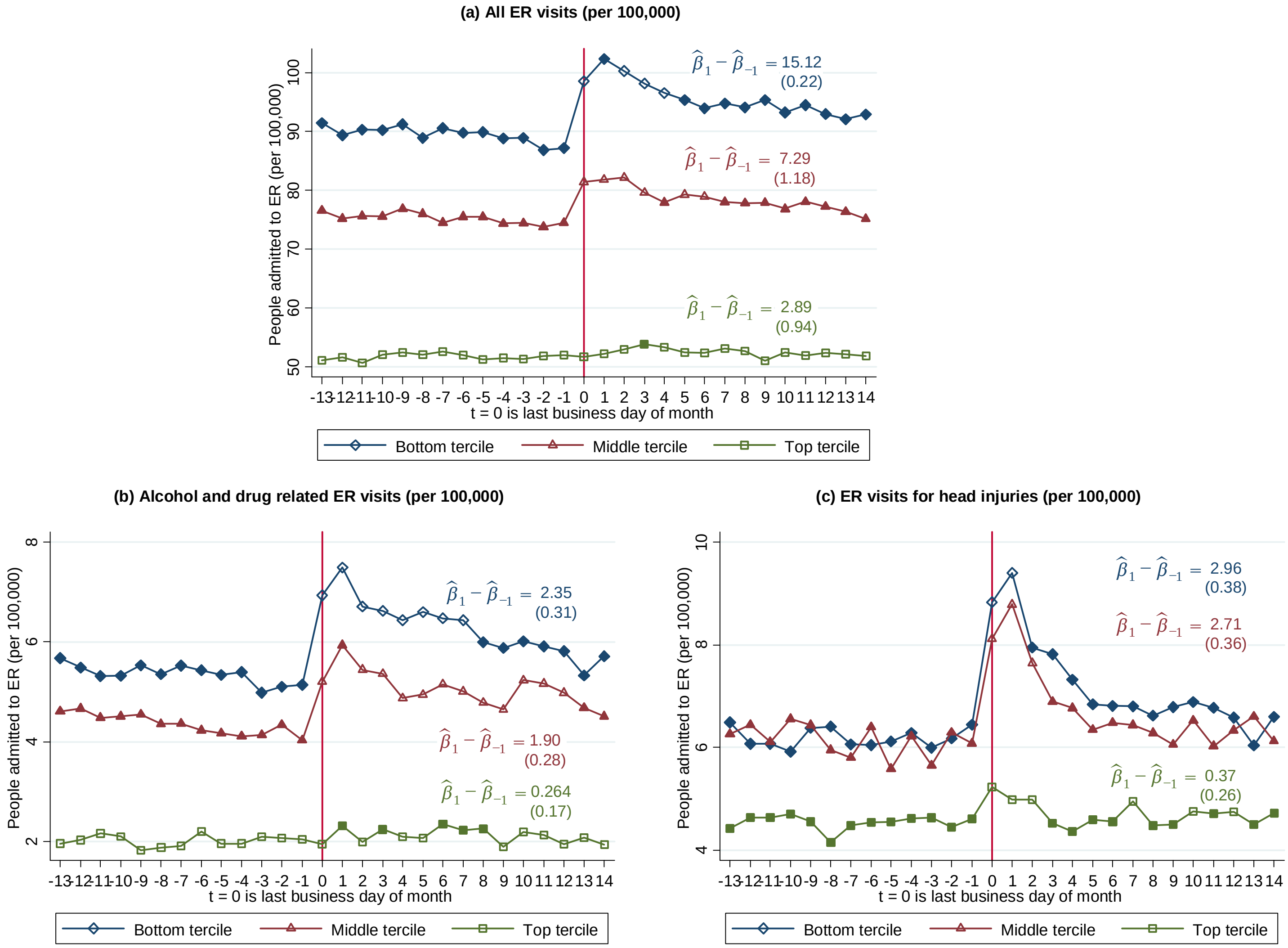
NOTE–This figure plots the average number of people per 100,000 who visit the ER per day over the 28-day window around the last business day of the month ($t = 0$) in 1994-2011. The sample is restricted to those who receive disability insurance income at some point in the sample. I then follow the same procedure as in Figure 6, but I estimate the model twice, first using the years before person i was awarded DI and, second, using the years after. The figures are drawn for all ER visits (panel a), for ER visits that have at least one diagnosis code that is alcohol and drug related (panel b), and for ER visits whose primary diagnosis code is for a head injury (panel c).

FIGURE 8
Change in ER visits around t=0 by Time Relative to Award of DI



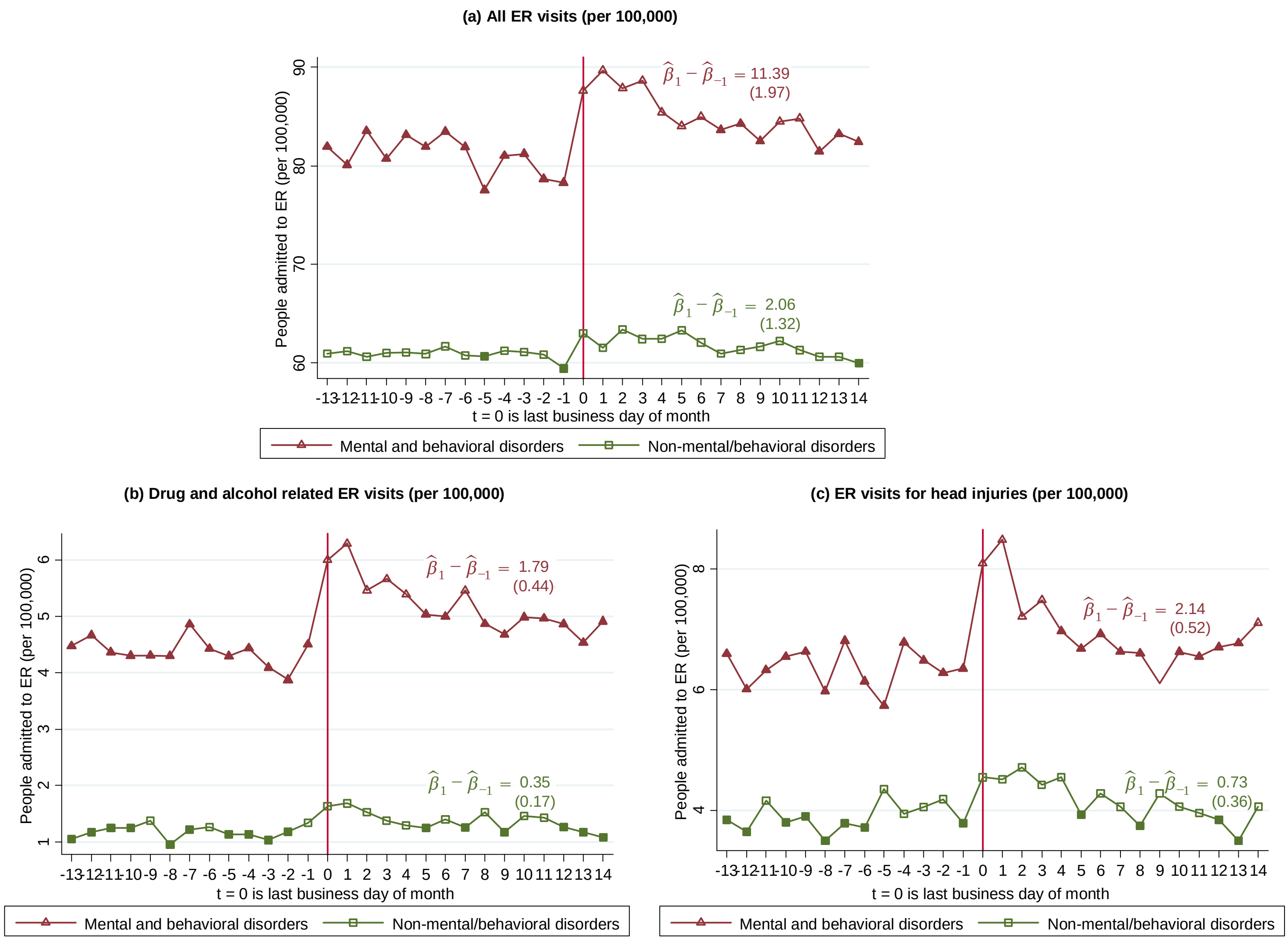
NOTE–This figure plots estimates of $\widehat{\beta}_1 - \widehat{\beta}_{-1}$, the change in probability of visiting the ER on the day after the last business day of the month relative to the day before, as a percentage of the base rate. The x-axis is time relative to the first year observed on DI (divided into three year bins). The figures are drawn for all ER visits (panel a), for ER visits that have at least one diagnosis code that is alcohol and drug related (panel b), and for ER visits whose primary diagnosis code is for a head injury (panel c).

FIGURE 9
Event Studies by Lagged Net Asset Tercile: DI population



NOTE–This figure plots the average number of people per 100,000 who visit the ER per day in 1998-2011. The sample is restricted to those receiving disability insurance income during the year in which $t = 0$ falls. I divide the sample by net asset terciles, averaged over the previous two years. The bottom tercile is plotted in diamonds (top line), the middle tercile is plotted in triangles (middle line), and the top tercile is plotted in squares (bottom line). The figures are drawn for all ER visits (panel a), for ER visits that have at least one diagnosis code that is alcohol and drug related (panel b), and for ER visits whose primary diagnosis code is for a head injury (panel c). Please see the notes to Figure 6 for more details on the construction of these figures.

FIGURE 10
Event Studies of ER visits by Reason Awarded Disability Insurance



NOTE–This figure plots the average number of people per 100,000 who visit the ER per day over the 28-day window around the last business day of the month ($t = 0$) in 1999-2013. The sample is restricted to those who were awarded disability insurance benefits. I divide the sample by reason that disability insurance was awarded: mental and behavioral disorders (in triangles, top line) and other diagnoses that exclude mental and behavioral disorders (in squares, bottom line). The figures are drawn for all ER visits (panel a), for ER visits that have at least one diagnosis code that is alcohol and drug related (panel b), and for ER visits whose primary diagnosis code is for a head injury (panel c).

TABLE 1

Summary Statistics for Labor Supply Analysis Sample

			Combined	Control group	Treatment group
			(1)	(2)	(3)
1.	Year of birth		1939-1945	1939-1940	1941-1945
2.	First year observed on DI		1994	1994	1994
			(3.39)	(2.97)	(3.55)
3.	Male		0.288	0.269	0.298
4.	Married at age 60		0.481	0.506	0.468
5.	Lives in Copenhagen at age 60		0.137	0.135	0.138
6.	College educated		0.0599	0.0582	0.0608
7.	Danish nationality		0.910	0.915	0.907
8.	Characteristics 2 yrs prior to 1st year on DI				
	Fraction with wage income > 0		0.464	0.483	0.455
	White-collar occupation		0.133	0.136	0.131
	Wage income		81,185	89,838	77,053
			(123,310)	(125,975)	(121,806)
9.	Chronic health conditions				
	Diabetes		0.208	0.205	0.210
	Heart conditions		0.436	0.445	0.432
	Lung conditions		0.218	0.214	0.221
	Musculoskeletal disorders		0.100	0.108	0.0959
	Mental and behavioral disorders		0.246	0.239	0.250
10.	Fraction with wage income > 0 at age 60		0.114	0.127	0.108
11.	Fraction with wage income > 0 at ages 60-69		0.0733	0.0735	0.0731
12.	Wage income at ages 60-69		4,174	3,348	4,656
			(26,469)	(21,234)	(29,077)
13.	Wage income at 60-69 conditional on positive		56,970	45,558	63,649
			(80,960)	(64,912)	(88,343)
14.	Non-pension assets at age 60	Mean:	289,815	271,623	299,279
		SD:	(797,459)	(646,674)	(865,441)
		Median:	15,297	15,553	15,172
15.	Transfer payments at ages 60-69		152,708	148,630	155,084
			(58,450)	(56,623)	(59,359)
16.	Number of people at age 60		24,788	8,476	16,312
17.	Person-year observations (ages 60-69)		213,074	78,439	134,635

NOTE -- Table reports means with standard deviations in parentheses unless otherwise noted. All financial data in real 2013 kroner. Pre-DI data excludes observations not observed in the data at least two years before the first year on DI. There are 16,834 observations with non-missing pre-DI data.

TABLE 2

Effect of Unconditional Cash Transfers on Labor Force Participation

Dependent variable:	1 if labor income > 0				1 if labor income > 2000 kr			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment group x Age 60	**-0.00929**	**-0.0259**	**-0.0265**	**0.0186**	**-0.0139**	**-0.0286**	**-0.0291**	**0.00749**
	(0.0282)	(0.0280)	(0.0280)	(0.0158)	(0.0255)	(0.0253)	(0.0253)	(0.0138)
Treatment group x Age 61	**-0.0121**	**-0.0245**	**-0.0249**	**0.00909**	**-0.0116**	**-0.0226**	**-0.0230**	**0.00473**
	(0.0212)	(0.0210)	(0.0210)	(0.0112)	(0.0192)	(0.0191)	(0.0191)	(0.0100)
Treatment group x Age 62	**-0.0118**	**-0.0201**	**-0.0204**	**0.00226**	**-0.0121**	**-0.0195**	**-0.0197**	**-0.00117**
	(0.0141)	(0.0140)	(0.0140)	(0.00745)	(0.0128)	(0.0128)	(0.0128)	(0.00673)
Treatment group x Age 63	**-0.00960**	**-0.0138***	**-0.0139***	**-0.00263**	**-0.00674**	**-0.0105**	**-0.0106**	**-0.00130**
	(0.00723)	(0.00717)	(0.00717)	(0.00419)	(0.00665)	(0.00662)	(0.00662)	(0.00379)
Treatment group x Age 65	**0.0118***	**0.0160****	**0.0161****	**0.00494**	**0.00851**	**0.0122***	**0.0123***	**0.00312**
	(0.00688)	(0.00685)	(0.00685)	(0.00391)	(0.00633)	(0.00632)	(0.00631)	(0.00352)
Treatment group x Age 66	**0.0309****	**0.0393*****	**0.0395*****	**0.0172*****	**0.0212***	**0.0286****	**0.0289****	**0.0105***
	(0.0124)	(0.0123)	(0.0123)	(0.00586)	(0.0115)	(0.0115)	(0.0115)	(0.00538)
Treatment group x Age 67	**0.0378****	**0.0504*****	**0.0508*****	**0.0171****	**0.0303***	**0.0414*****	**0.0418*****	**0.0141****
	(0.0172)	(0.0172)	(0.0171)	(0.00736)	(0.0160)	(0.0160)	(0.0160)	(0.00658)
Treatment group x Age 68	**0.0416***	**0.0584*****	**0.0589*****	**0.0141**	**0.0288**	**0.0436****	**0.0441****	**0.00726**
	(0.0216)	(0.0216)	(0.0215)	(0.00870)	(0.0202)	(0.0202)	(0.0202)	(0.00779)
Treatment group x Age 69	**0.0426***	**0.0635****	**0.0642****	**0.00845**	**0.0296**	**0.0481****	**0.0487****	**0.00296**
	(0.0257)	(0.0257)	(0.0256)	(0.0106)	(0.0242)	(0.0242)	(0.0242)	(0.00946)
Year x treatment group f.e.'s	x	x	x	x	x	x	x	x
Controls for demographics		x	x			x	x	
Controls for chronic diseases			x				x	
Individual fixed effects				x				x
Mean of dep. var in treat group	0.0731	0.0731	0.0731	0.0731	0.0630	0.0630	0.0630	0.0630
Mean of dep. var in control group	0.0729	0.0729	0.0729	0.0729	0.0591	0.0591	0.0591	0.0591
Mean of dep. Var overall	0.0731	0.0731	0.0731	0.0731	0.0618	0.0618	0.0618	0.0618
Number of people	22,499	22,499	22,499	22,499	22,499	22,499	22,499	22,499
Person-year observations	192,156	192,156	192,156	192,156	192,156	192,156	192,156	192,156

NOTE -- Each column reports results from OLS regressions where the dependent variable is an indicator variable for having positive labor earnings (columns 1-4) or having labor earnings above 2000 kr (columns 5-8). Standard errors are clustered by individual and are reported in parentheses below each coefficient estimate. Age 64 is the excluded age. The sample includes disability insurance beneficiaries observed on the low severity level at age 60 who were born in July 1939 through the end of 1945. Individuals are included from ages 60 to 69. Demographic controls consist of indicator variables for marital status, Danish nationality, gender, college education, living in Copenhagen, and white-collar occupation at age 60. Chronic disease controls consist of indicators for diabetes, heart conditions, lung conditions, musculoskeletal disorders, and mental or behavioral disorders (which include schizophrenia, mood disorders, and dementia). *** p<0.01, ** p<0.05, * p<0.1

TABLE 3

Effect of Unconditional Cash Transfers on Labor Force Participation for Recently Working Sample

Dependent variable:	1 if labor income > 0				1 if labor income > 2000 kr			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment group x Age 61	**-0.286*** **	**-0.287*** **	**-0.280*** **	**-0.0553**	**-0.282*** **	**-0.285*** **	**-0.278*** **	**-0.105**
	(0.101)	(0.0996)	(0.0994)	(0.0848)	(0.102)	(0.101)	(0.101)	(0.0810)
Treatment group x Age 62	**-0.179** **	**-0.180** **	**-0.175** **	**-0.0252**	**-0.180*** **	**-0.183*** **	**-0.178** **	**-0.0613**
	(0.0706)	(0.0699)	(0.0698)	(0.0572)	(0.0698)	(0.0696)	(0.0693)	(0.0544)
Treatment group x Age 63	**-0.103*** **	**-0.104*** **	**-0.101*** **	**-0.0264**	**-0.0850** **	**-0.0863** **	**-0.0838** **	**-0.0256**
	(0.0381)	(0.0378)	(0.0377)	(0.0301)	(0.0371)	(0.0369)	(0.0368)	(0.0283)
Treatment group x Age 65	**0.115*** **	**0.115*** **	**0.113*** **	**0.0378**	**0.0920*** **	**0.0932*** **	**0.0907** **	**0.0325**
	(0.0371)	(0.0369)	(0.0368)	(0.0240)	(0.0355)	(0.0354)	(0.0353)	(0.0220)
Treatment group x Age 66	**0.264*** **	**0.265*** **	**0.260*** **	**0.109*** **	**0.189*** **	**0.191*** **	**0.186*** **	**0.0686** **
	(0.0662)	(0.0656)	(0.0654)	(0.0322)	(0.0643)	(0.0641)	(0.0638)	(0.0301)
Treatment group x Age 67	**0.331*** **	**0.332*** **	**0.325*** **	**0.0971*** **	**0.263*** **	**0.267*** **	**0.259*** **	**0.0825*** **
	(0.0921)	(0.0912)	(0.0906)	(0.0314)	(0.0894)	(0.0891)	(0.0884)	(0.0291)
Treatment group x Age 68	**0.378*** **	**0.379*** **	**0.370*** **	**0.0659*** **	**0.290*** **	**0.295*** **	**0.285** **	**0.0493** **
	(0.115)	(0.114)	(0.113)	(0.0209)	(0.112)	(0.112)	(0.111)	(0.0192)
Treatment group x Age 69	**0.388*** **	**0.389*** **	**0.378*** **		**0.299** **	**0.306** **	**0.293** **	
	(0.138)	(0.137)	(0.136)		(0.135)	(0.135)	(0.134)	
Year x treatment group f.e.'s	x	x	x	x	x	x	x	x
Controls for demographics		x	x			x	x	
Controls for chronic diseases			x				x	
Individual fixed effects				x				x
Mean of dep. var in treat group	0.488	0.488	0.488	0.488	0.433	0.433	0.433	0.433
Mean of dep. var in control group	0.392	0.392	0.392	0.392	0.328	0.328	0.328	0.328
Mean of dep. var overall	0.456	0.456	0.456	0.456	0.398	0.398	0.398	0.398
Number of people	2,530	2,530	2,530	2,530	2,530	2,530	2,530	2,530
Person-year observations	19,909	19,909	19,909	19,909	19,909	19,909	19,909	19,909

NOTE -- Each column reports results from OLS regressions where the dependent variable is an indicator variable for having positive labor earnings (columns 1-4) or having labor earnings above 2000 kr (columns 5-8). Standard errors are clustered by individual and are reported in parentheses below each coefficient estimate. Age 64 is the excluded age. The sample includes disability insurance beneficiaries observed on the low severity level at age 60 who were born in July 1939 through the end of 1945. The sample is restricted to the subset of observations that had postive labor income at age 60. Individuals are included from ages 61 to 69. Demographic controls consist of indicator variables for marital status, Danish nationality, gender, college education, living in Copenhagen, and white-collar occupation at age 60. Chronic disease controls consist of indicators for diabetes, heart conditions, lung conditions, musculoskeletal disorders, and mental or behavioral disorders (which include schizophrenia, mood disorders, and dementia). *** p<0.01, ** p<0.05, * p<0.1

TABLE 4

Heterogeneity in Labor Force Participation Responses to Unconditional Cash Transfers

Panel A: Gender and marital status

Sample:	Women	Men	Single	Married
	(1)	(2)	(3)	(4)
Treatment group x Age 66	**0.00994**	**0.0376*****	**0.0207****	**0.0145***
	(0.00608)	(0.0142)	(0.00866)	(0.00798)
Mean of dep. var in treat group	0.0601	0.105	0.0644	0.0823
Mean of dep. var in control group	0.0606	0.107	0.0685	0.0769
Mean of dep. var overall	0.0602	0.106	0.0656	0.0806
Number of people	15,915	6,584	11,714	10,785
Person-year observations	137,702	54,454	96,467	95,689

Panel B: Chronic diseases

Condition:	Diabetes	Heart Conditions	Lung Conditions	Musculo-skeletal	Mental/ behavioral
	(1)	(2)	(3)	(5)	(6)
Treatment group x Age 66	**0.0158**	**0.0202****	**0.0229**	**0.00891**	**0.00768**
	(0.0121)	(0.00879)	(0.0141)	(0.0142)	(0.00956)
Mean of dep. var in treat group	0.0701	0.0722	0.0669	0.0657	0.0613
Mean of dep. var in control group	0.0638	0.0739	0.0761	0.0863	0.0575
Mean of dep. var overall	0.0682	0.0727	0.0696	0.0723	0.0602
Number of people	4,708	9,801	4,932	2,215	5,550
Person-year observations	43,024	89,887	45,043	20,450	50,462

Panel C: Assets at age 60

			Working at 60	
Assets above or below median:	Below	Above	Below	Above
	(1)	(2)	(3)	(4)
Treatment group x Age 66	**0.00757**	**0.0256*****	**0.101****	**0.115****
	(0.00734)	(0.00906)	(0.0437)	(0.0474)
Mean assets at age 60 (2013 kr)	6,021	573,656	122,734	947,008
Median assets at age 60 (2013 kr)	6,150	187,700	9,749	623,520
Mean of dep. var in treat group	0.0535	0.0919	0.468	0.508
Mean of dep. var in control group	0.0541	0.0912	0.378	0.406
Mean of dep. var overall	0.0537	0.0917	0.437	0.475
Number of people	11,275	11,200	1,273	1,257
Person-year observations	94,128	97,904	9,906	10,003

NOTE -- Each cell reports the treatment group x age 66 coefficient from separate OLS regressions where the dependent variable is an indicator variable for having positive labor earnings. Each regression includes year, year x treatment group, and individual fixed effects (as in Column 4 of Table 2). Standard errors are clustered by individual and are reported in parentheses below each coefficient estimate. Age 64 is the excluded age. The sample includes disability insurance beneficiaries observed on the low severity level at age 60 who were born in July 1939 through the end of 1945. In panel C, each birth cohort is divided separately into two groups (above or below median assets for that birth cohort at age 60). Columns 3 and 4 restrict the sample to those working at age 60; median assets in these columns are re-defined for this recently working subgroup, instead of the pooled sample. *** p<0.01, ** p<0.05, * p<0.1

TABLE A1
Examples from Literature on Effect of Disability Insurance on Labor Supply

Focus:	Entry into the program	Rejected and accepted applicants	Policies affecting those receiving DI
	(1)	(2)	(3)
	Parsons 1980	Bound 1989	Maestas and Yin 2008
	Gruber and Kubik 1997, 2002	Parsons 1991	Maestas and Song 2011
	Gruber 2000 *	Chen and van der Klaauw 2008	Marie and Castello 2012 *
	Black, Daniel and Sanders 2002	von Wachter, Song, and Manchester 2011	Kostøl and Mogstad 2014 *
	Autor and Duggan 2003, 2007, 2008	Autor, Maestas, Mullen and Strand 2011	Borghans, Gielen, and Luttmer 2014 *
	Campolieti 2004 *	Maestas, Mullen, and Strand 2013	Moore 2014
	Duggan, Singelton and Song 2007	French and Song 2014	
	Duggan and Imberman 2009		
	Mueller, Rothstein, and von Wachter 2014		

NOTE -- Table provides examples of papers on disability insurance and labor supply. There are many other important contributions not listed; see Bound and Burkhauser (1999) for additional references. The papers are divided into three categories. The first category estimates the effect of program parameters and other factors, such as economic conditions, on entry into the program. The second category follows Bound (1989) in using the labor supply of rejected disability insurance applicants to infer the labor supply of accepted disability insurance applicants had their claims not been accepted. Parsons (1991) and Autor, Maestas, Mullen and Strand (2011) can be read as providing evidence that caution must be taken in using this approach. The third category studies the labor supply responses of those receiving disability insurance to changes in program parameters. Papers with asterisks use non-US data.

TABLE A2

Examples of Recent Evidence on Excess Sensitivity to Timing of Payments

	Expenditures and consumption	Mortality	Hospitalizations	Crime
	(1)	(2)	(3)	(4)
(a) Reoccurring payments	Stephens 2003 Shapiro 2005 Stephens 2006 * Mastrobuoni and Weinberg 2009 Hastings and Washington 2010 Stephens and Unayama 2011 * Gelman, Kariv, Shapiro, Silverman, and Tadelis 2014	Dobkin and Puller 2007 Evans and Moore 2011 Evans and Moore 2012 Andersson, Lundborg, and Vikström 2014 *	Dobkin and Puller 2007	Dobkin and Puller 2006 Foley 2011
(b) One time payments	Johnson, Parker, and Souleles 2006 Parker 2014	Evans and Moore 2011 Evans and Moore 2012	Gross and Tobacman 2014	

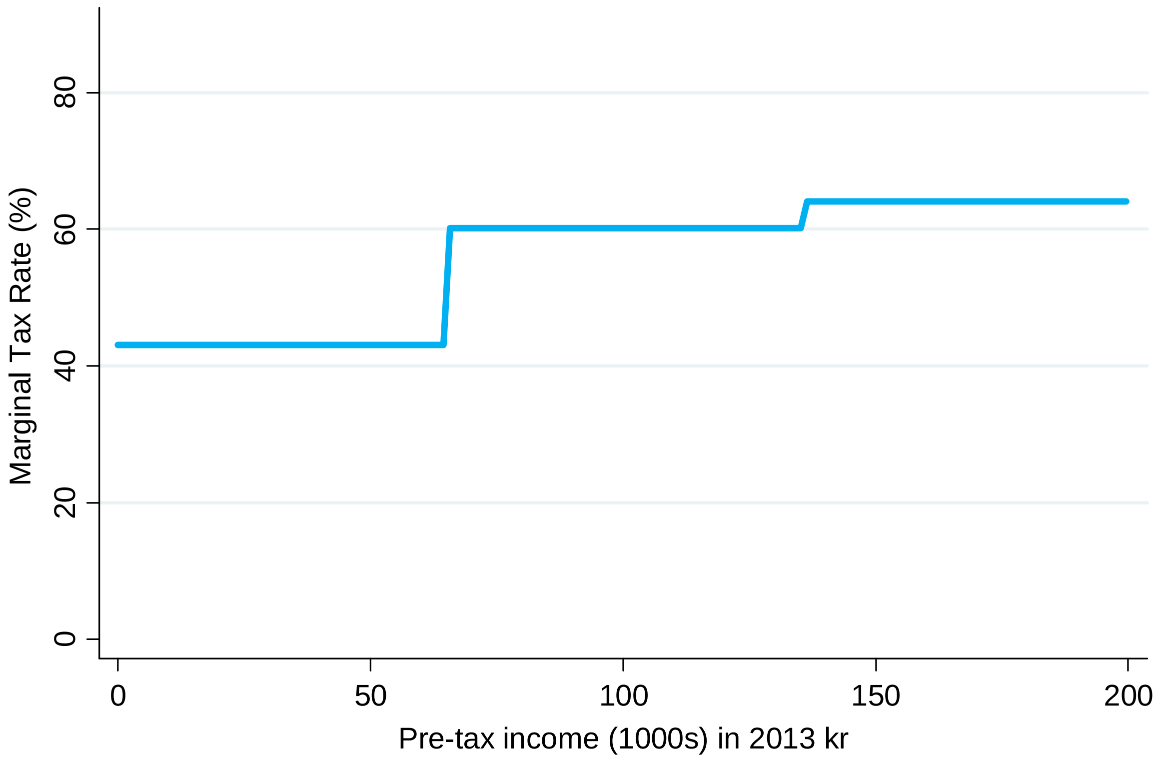
NOTE -- Table provides recent examples of papers showing excess sensitivity of various outcomes to timing of income payments. The table is divided into two categories: reoccurring payments (e.g., monthly SNAP benefits) and one time payments (e.g., stimulus payments). The table excludes many important papers that are related (e.g., consumption responses to predictable changes in income in Shapiro and Slemrod 1995 and Parker 1999). Evans and Moore (2012) also present evidence on various other outcomes as measures of activity (e.g., baseball game attendance). Papers with asterisks use non-US data.

TABLE A3
Control Vector in Main Specificiation

	Description (1)	Dates (2)	Coef. (3)	S.E. (4)
Panel A. Holidays and other special days				
1.	New Years Day	January 1	657.9	(121.8)
2.	Fastelavn	February/March	-100.9	(101.5)
3.	Palm Sunday	March/April	-28.66	(104.5)
4.	Maundy Thursday	March/April	-123.7	(99.46)
5.	Good Friday	March/April	61.51	(114.3)
6.	Easter Sunday	March/April	-24.61	(100.5)
7.	Easter Monday	March/April	-143.8	(105.3)
8.	Prayer Day	April/May	56.01	(98.62)
9.	May Day	May 1	182.1	(107.8)
10.	Ascension Day	May/June	-26.00	(102.9)
11.	Whit Sunday	May/June	408.9	(116.6)
12.	Whit Monday	May/June	146.9	(111.2)
13.	Constitution Day	June 5	255	(110.0)
14.	Christmas Eve	December 24	-867.9	(75.23)
15.	Christmas	December 25	-518.4	(89.22)
16.	Day after Christmas	December 26	-482.7	(88.16)
17.	New Years Eve	December 31	-762.2	(69.66)
18. and 19.	Midsommerfesten	June 24	221.2	(113.5)
		June 25	367.8	(127.9)
20. and 21.	Longest night of the year	December 13	-109.6	(113.2)
		December 14	-184	(92.28)
	Constant		2,533	(22.25)
	F test: p<0.001			
Panel B. Days of week				
1.	Monday		2,675	(23.71)
2.	Tuesday		2,503	(22.75)
3.	Wednesday		2,482	(22.54)
4.	Thursday		2,480	(22.51)
5.	Friday		2,506	(22.33)
6.	Saturday		2,479	(23.06)
7.	Sunday		2,590	(24.09)
	F test for equality of means: p<0.001			

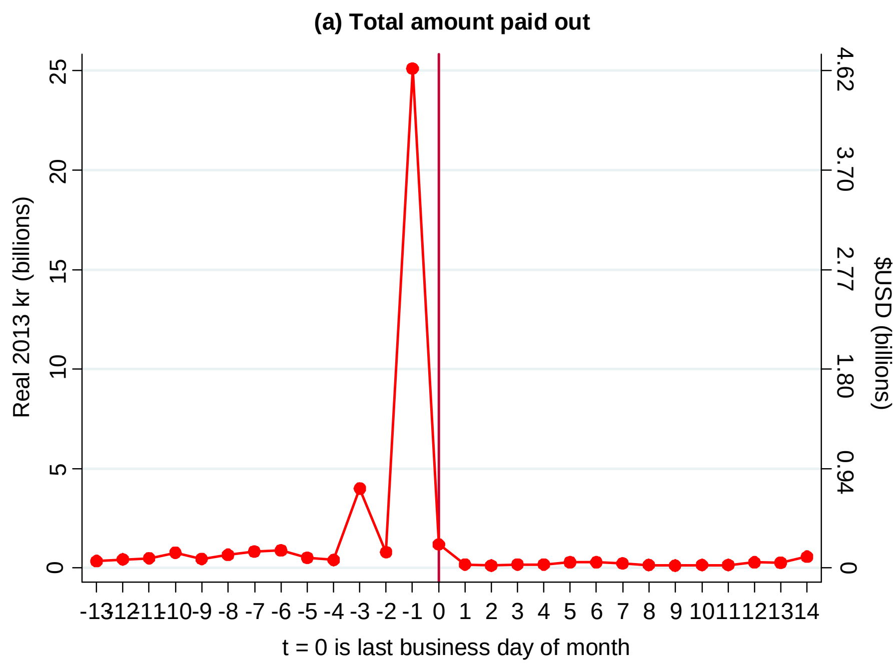
Notes: Table lists the controls for reoccuring special days and days of week that are included in the main specification. Columns 3 reports coefficients from a regression of the number of people visiting the ER on the indicator variables listed in that panel. The regression in panel B excludes the constant. Column 4 reports Newey-West standard errors with 15 lags. There are T=6,574 observations in each regression.

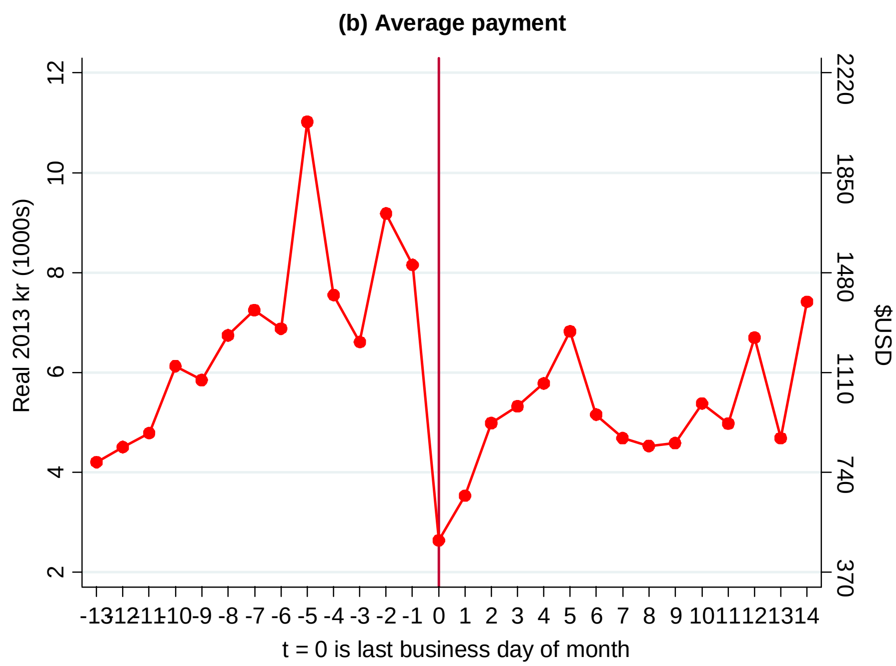
APPENDIX FIGURE A1
Implied Marginal Tax Rate on Earnings in 2002



NOTE–This figure plots the marginal tax rate on labor income implied by the income tax system and phase out of disability insurance benefits for a single disability insurance beneficiary who is over 60 and has been awarded benefits at either the middle or low disability insurance level. I use the law in place in 2002, drawing on Hansen (2006, Appendix 1) and <http://tax.dk/beregn/skat02.htm>, assuming that the disability insurance beneficiary has no income other than that shown along the x-axis.

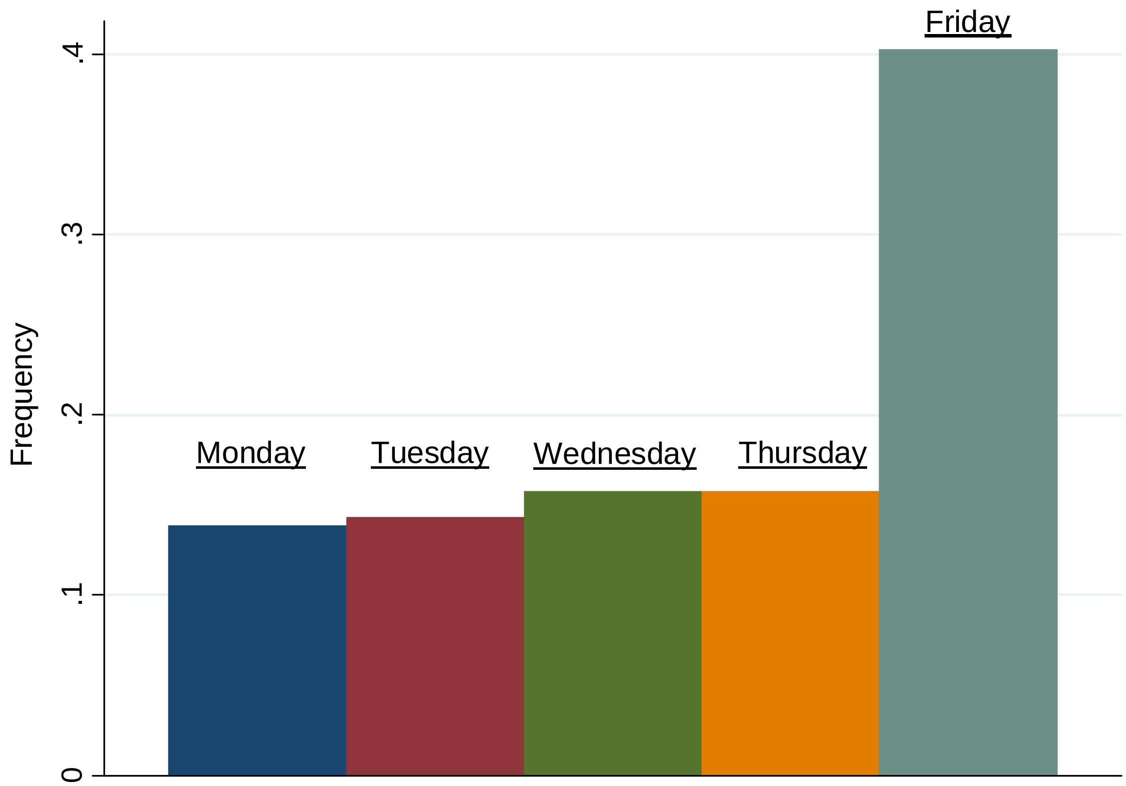
APPENDIX FIGURE A2
Event Study of Payments around Last Business Day of Month: 2009-2013





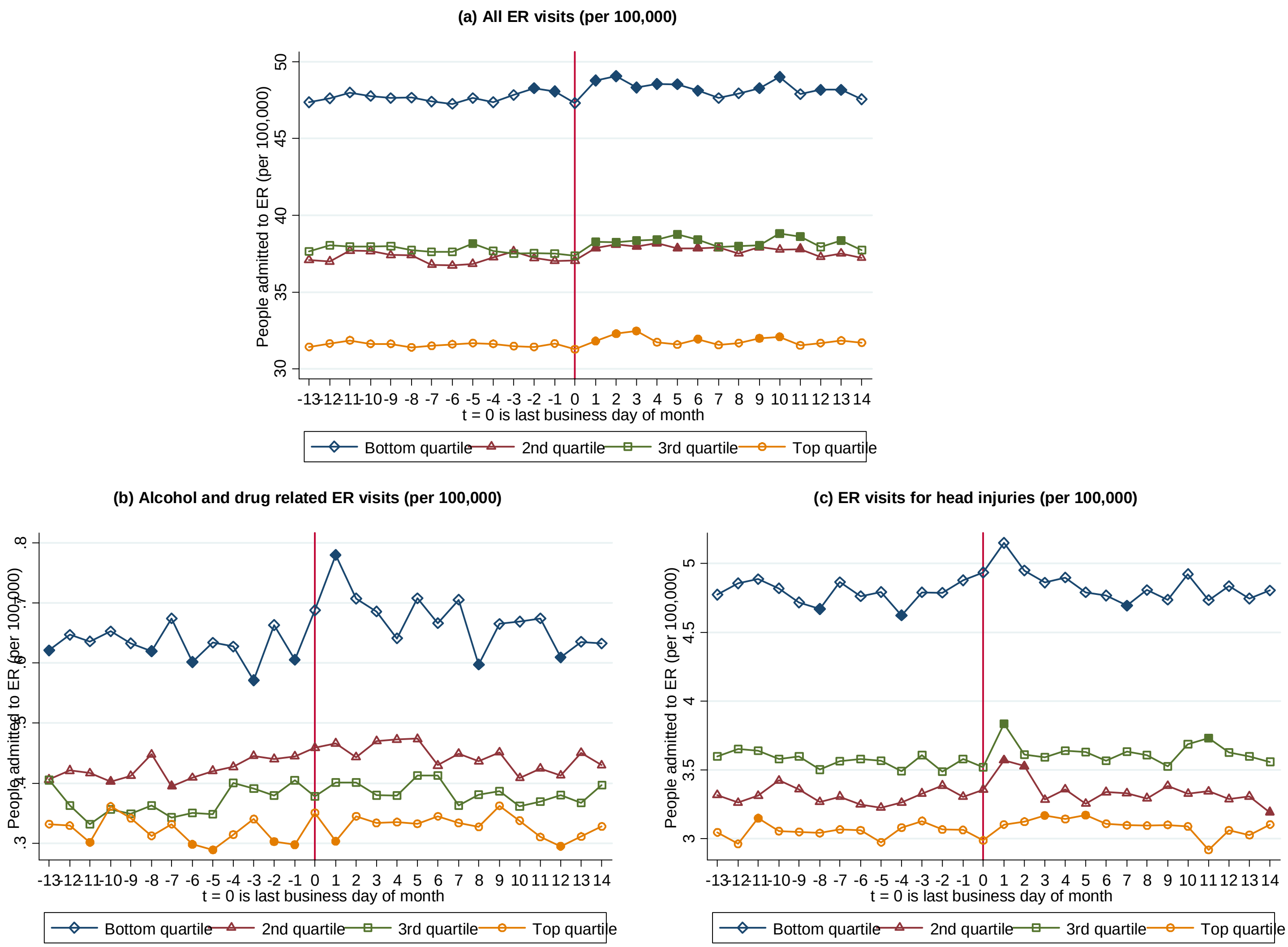
NOTE–This figure plots the dollar amount of payments received in 2009-2013 for the 28-day window around the last business day of the month ($t = 0$). Panel A plots the average daily total across all NemKonto accounts, while Panel B plots the average payment per person conditional on receiving a payment. The left y-axis plots these amounts in real 2013 kroner. The right y-axis converts to USD using the 5.41 kr to $1 exchange rate in April 2014.

APPENDIX FIGURE A3
Frequency of last business day of the month by weekday: 1994-2011



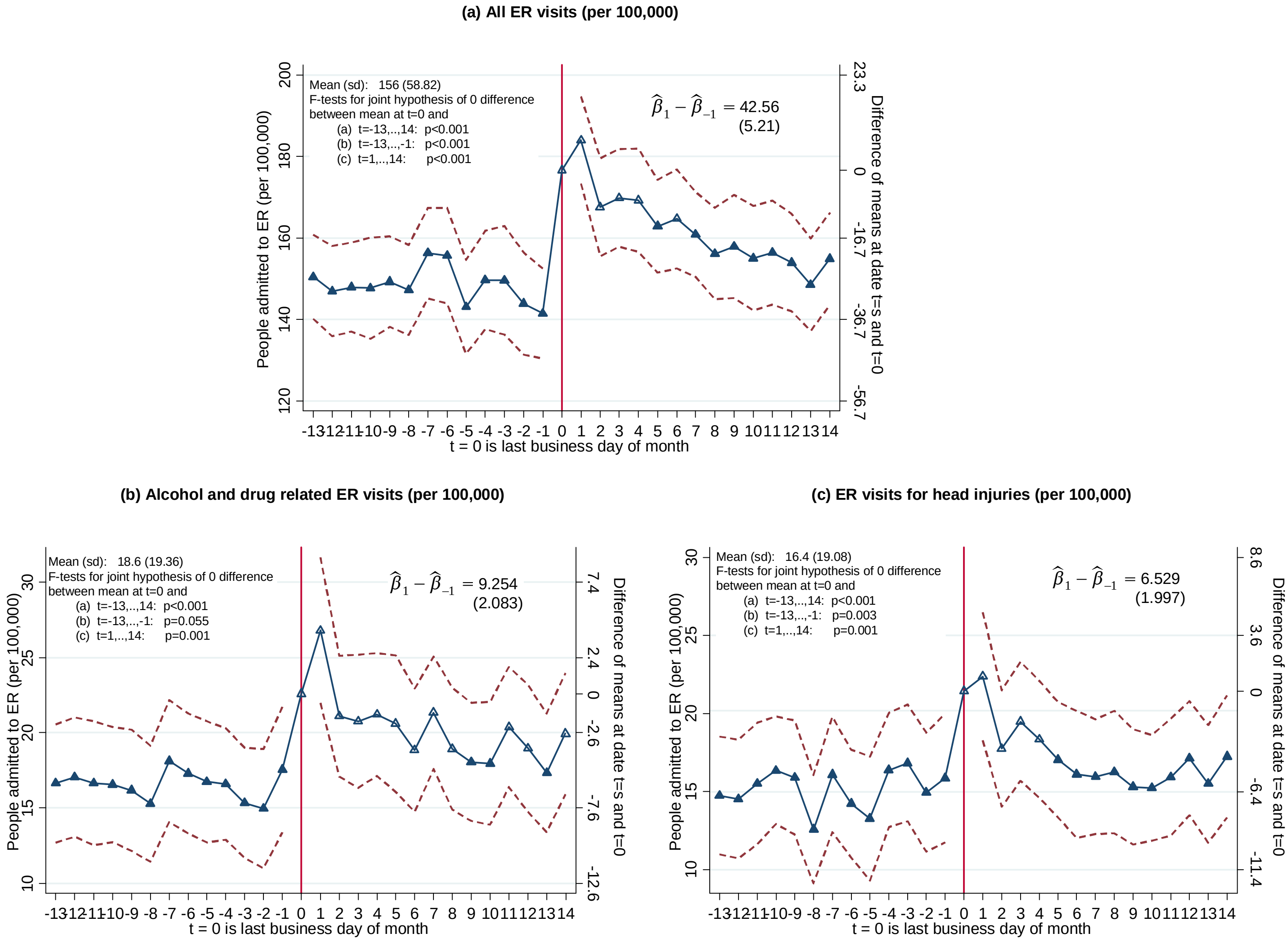
NOTE–This figure shows the days of the week on which the last business day of the month fell in 1994-2011.

FIGURE A4
Event Studies around Last Business Day of Month: Wage Earners



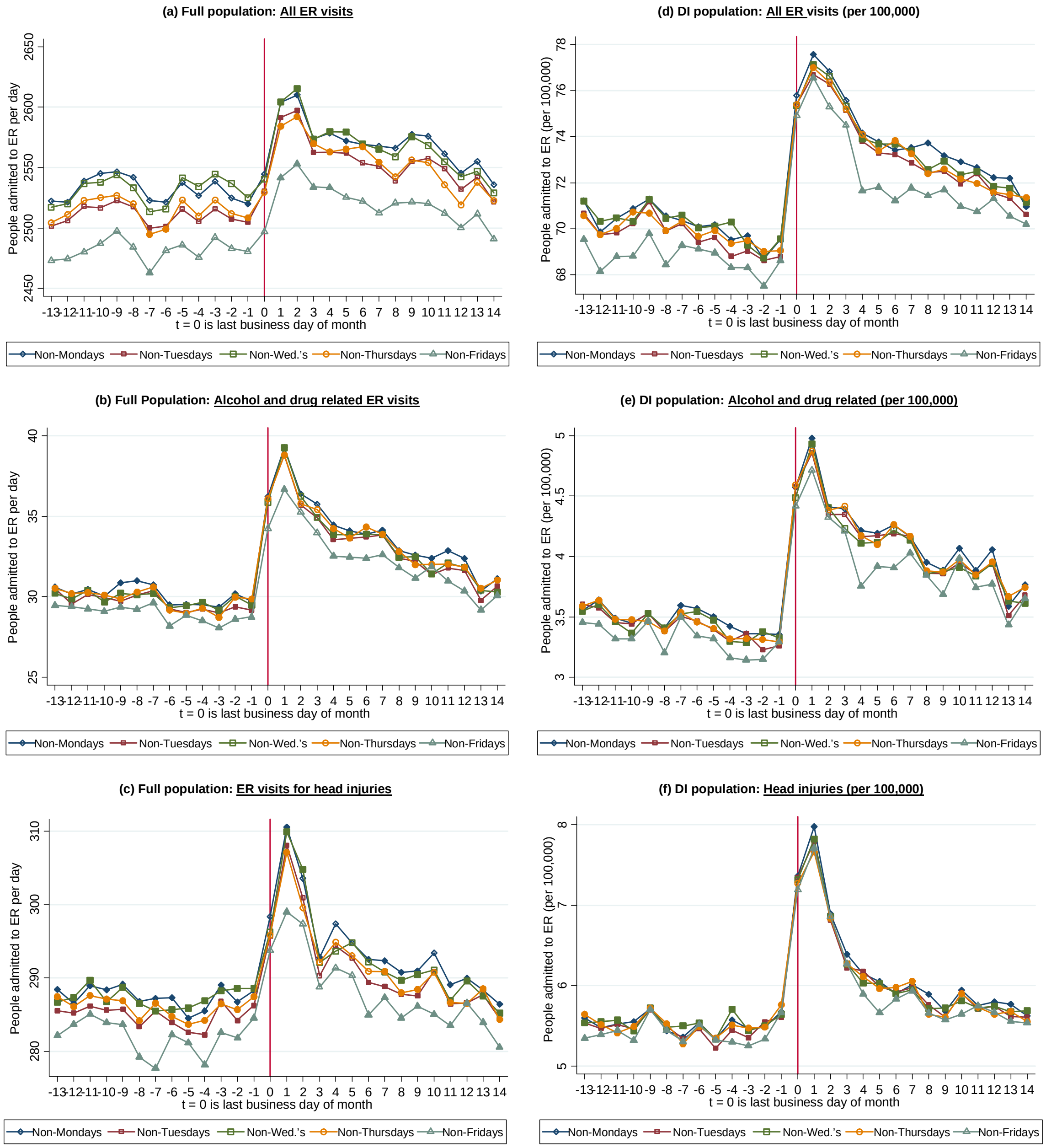
NOTE–This figure plots the average number of people per 100,000 who visit the ER per day over the 28-day window around the last business day of the month ($t = 0$) in 1994-2011. The sample is restricted to wage earners. I divide the sample by lagged earned income quartiles. The bottom quartile is plotted in diamonds, the next highest quartile is plotted in triangles, the third highest quartile is plotted in squares, and the top quartile is plotted in circles. The figures are drawn for all ER visits (panel a), for ER visits that have at least one diagnosis code that is alcohol and drug related (panel b), and for ER visits whose primary diagnosis code is for a head injury (panel c). The average number of people in each quartile is about 477,000. Please see the notes to Figure 6 for more details on the construction of these figures.

FIGURE A5
Event Studies by Reason Awarded DI: Drug or Alcohol Dependent



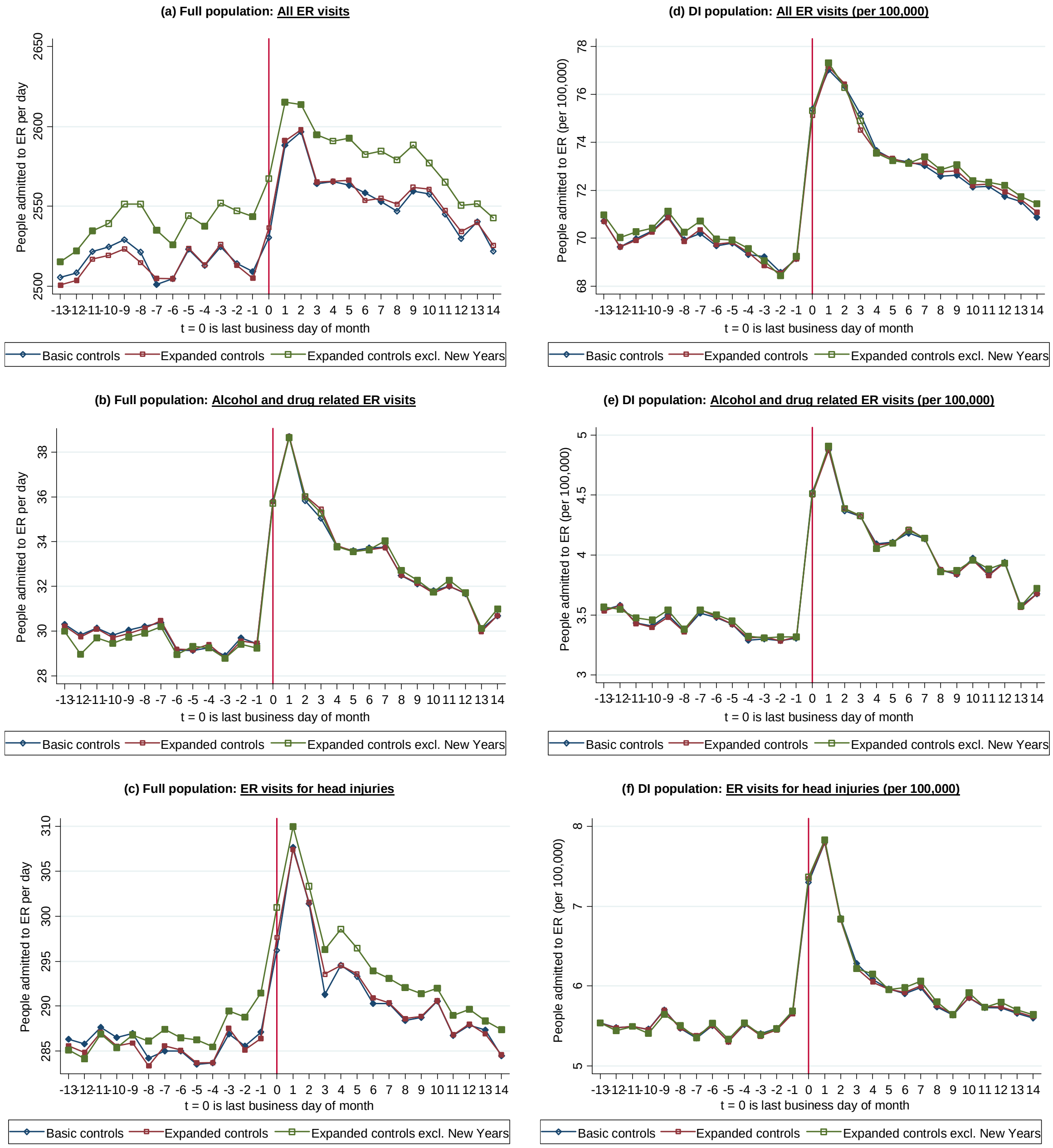
NOTE–This figure plots the average number of people per 100,000 who visit the ER per day in 1999-2013. I restrict the sample to those who were awarded disability insurance benefits and that had mention of drug or alcohol dependence in the reasons that disability was awarded. The figures are drawn for all ER visits (panel a), for ER visits that have at least one diagnosis code that is alcohol and drug related (panel b), and for ER visits whose primary diagnosis code is for a head injury (panel c). Please see the notes to Figure 6 for more details on the construction of these figures.

APPENDIX FIGURE A6
Robustness Checks: Payment Dates vs. Day of the Week Effects



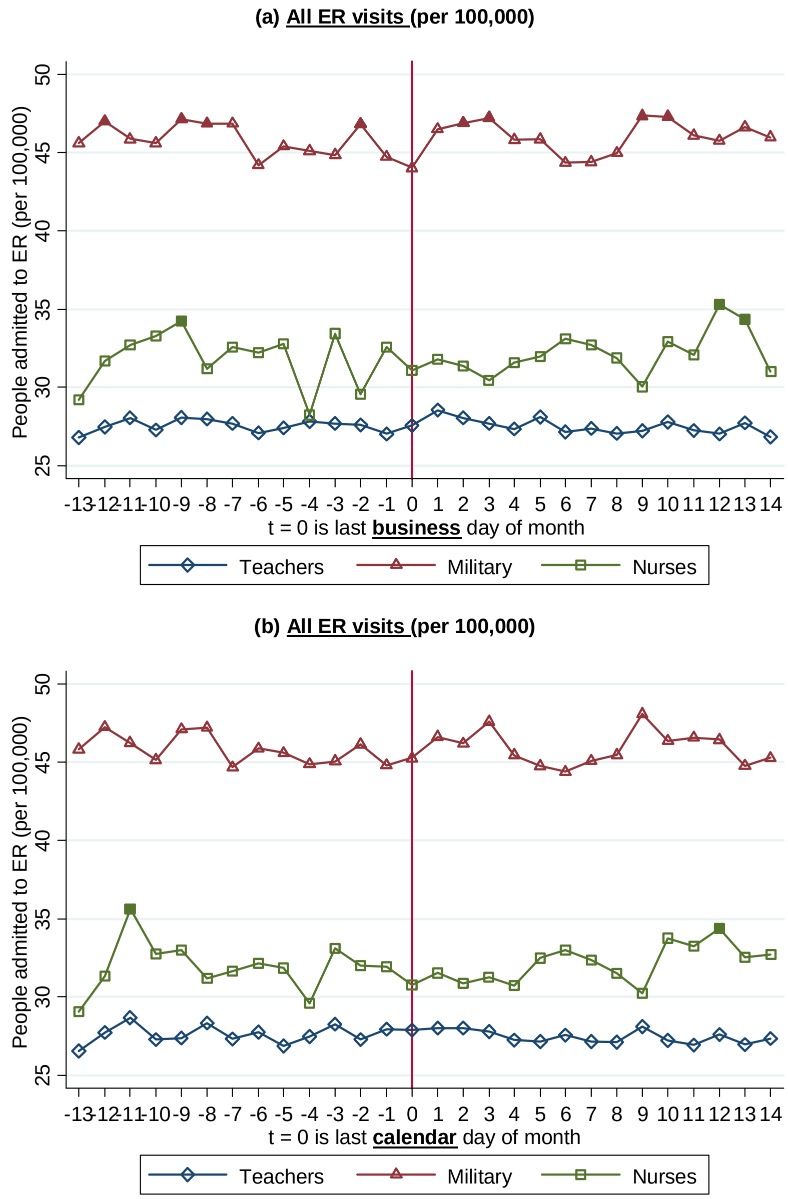
NOTE–This figure reproduces the ER visit event studies for the full population in panel (a), panels (b), and (c), and for the DI sample in panels (d), (e), and (f). In each panel, I exclude the 28-day months where $t = 0$ is a Monday (diamonds), where $t = 0$ is a Tuesday (small squares), where $t = 0$ is a Wednesday (larger squares), where $t = 0$ is a Thursday (circles), and where $t = 0$ is a Friday (triangles).

APPENDIX FIGURE A7
Robustness Checks: Impact of Additional Controls



NOTE–This figure reproduces the ER visit event studies for the full population in panel (a), panels (b), and (c), and for the DI sample in panels (d), (e), and (f). In each panel, I plot the coefficients from a regression of the basic specifications in those earlier figures (in diamonds), the coefficients from a regression where I add, as additional controls, interactions of the month and year controls as well as indicators for the day before and day after the special days listed in Appendix Table A1 (in small squares), and the coefficients from a regression that includes these additional controls and excludes all the 28-day months where $t = 0$ occurs right before New Years (in larger squares).

APPENDIX FIGURE A8
Event Studies for Wage Earners by Occupation



NOTE–This figure reproduces the wage earner event studies of ER visits by occupation code in the previous year. Panel (a) defines event time relative to the last business day of the month. Panel (b) defines event time relative to the last calendar day of the month. Teachers include ISCO codes 234100 and 234120 in 2010 and 23300, 23310, 23311, 23312 in 1993-2009. Military include ISCO code 011000 in 1993-2009 and 010000, 011000, 020000, 021000, 030000, 031000 in 2010. Nurses include ISCO codes starting with 2230 in 1993-2009 and 222 in 2010. The average number of teachers in the sample is 57,499, the average number of members of the military is 20,374, and the average number of nurses is 10,626.

Appendix A: Determination of severity

The level at which disability insurance benefits are awarded is based on an assessment of how an applicant's impairment impacts his ability to work. In this sense, disability insurance eligibility in Denmark is similar to the assessment of eligibility for SSDI, described in detail, for example, in Chen and van der Klaauw (2008). However, unlike in the U.S., disability can be partial. Therefore, it is useful to consider an example to illustrate how these three severity levels are determined. I focus on cardiovascular disease because over 40% of my analysis sample (described in Section 3 and 4) has a heart condition. Municipality caseworkers assess both subjective criteria (e.g., chest pain, shortness of breath) and objective criteria (e.g., cardiogram, stress test). The following vignettes are from the rating guide used by caseworkers who assess disability.[33]

The highest level of disability is quite severe. The manual describes a 28 year old male truck driver with heart disease (cardiomyopathy), right-heart failure, shortness of breath (nocturnal dyspnea), and poor circulation. This individual was assessed at the highest level of disability because of clear medical evidence of cardiac insufficiency (heart failure). The rating guide notes that his occupation is physically demanding.

The middle level of disability is also quite severe. The manual describes a 54 year old male bricklayer with a history of cardiac symptoms requiring hospitalization. It notes evidence of pathological changes in his electrocardiogram (EKG), moderate angina pectoris (1-2 episodes of chest pain per day), but no signs of heart failure. Therefore, the guide reports that this individual was assessed at the medium level of disability because his heart condition is not likely to reduce working capacity, even for physical work like his.

For the lowest level of disability, the manual describes a 49 year old divorced woman who is an office worker. She has a history of blood clots and recently had a heart attack. She has mild angina pectoris (1 episode of chest pain per day) and only mild pathological changes in her EKG. The manual states that she was assessed at the lowest

[33] I am grateful to the Copenhagen municipality for providing me with this rating guide. The information in this section is my translation of the original in Danish.

level of disability because her cardiac disorder would not prevent her from working part-time in an office setting. A second example is a 57 year old male artist and church cantor with a recent history of coronary artery occlusion and long history of cardiac symptoms. He has mild angina pectoris (1 episode of chest pain per day), mild pathological changes in his EKG, and no recent deterioration in his condition. The manual states that his disability is assessed at the lowest level because their judgment is that he should still be able to continue his work.

Appendix B

This appendix derives the standard liquidity vs. moral hazard representation of the socially optimal social insurance benefit level. Note that the model can be recast as one in which a representative agent chooses the fraction of the population working e to maximize total private surplus:

$$\begin{aligned} V &= \max_e \int_{-\infty}^{\overline{\delta}} \{u(c_h) - d_i\} dF(\delta_i) + \int_{\overline{\delta}}^{\infty} u(c_l) dF(\delta_i) &\quad (9) \\ &= \max_e eu(c_h) + (1-e)u(c_l) - \psi(e) &\quad (10) \end{aligned}$$

where $\psi(e) \equiv \int_{-\infty}^{\overline{\delta}} \delta_i dF(\delta_i)$ integrates the disutilities of labor over all agents with $\delta_i < \overline{\delta}$. The representative agent's first order condition is:

$$u(c_h) - u(c_l) = \psi'(e) \qquad (IC_e)$$

Intuitively, the representative agent increases the fraction working until the marginal worker is indifferent between exiting the labor force and continuing to work. Written this way, the expected utility and first order condition for the representative agent are exactly the same as in the standard social insurance set up (e.g., in Chetty 2009).

The government's objective is to design a disability insurance system that pays a benefit b to those who do not work. The benefit is financed by a tax t paid by workers:

$$et = (1-e)b \qquad (11)$$

The government chooses b and t to maximize the representative agent's indirect utility:

$$\max_{b,t} V(t,b) \tag{12}$$

subject to the budget constraint for t and the incentive compatibility constraint for e.

At the optimum, a small change db must have no effect on utility:

$$\frac{dV}{db} = \frac{\partial V}{\partial b} + \frac{\partial V}{\partial t}\frac{dt}{db} + \frac{\partial V}{\partial e}\frac{de}{db} = 0 \tag{13}$$

There is an envelope condition for e because the representative agent has chosen it to maximize utility: $\frac{\partial V}{\partial e} = 0$. Intuitively, the agent on the margin between working and not working is indifferent $(u(c_h) - u(c_l) = \delta_i)$. Therefore, changing b to induce him to exit the labor force has no effect on social welfare. Hence, all the terms that involve $\frac{de}{db}$ in dV/db can be ignored:

$$\frac{dV}{db} = \frac{\partial V}{\partial b} + \frac{\partial V}{\partial t}\frac{dt}{db} = (1-e)u'(c_l) - eu'(c_h)\frac{dt}{db} \tag{14}$$

The only behavioral responses that matter here are those in the $\frac{dt}{db}$ term that directly affect the government's budget constraint. $\frac{dt}{db}$ measures how much the tax must be increased to finance a \$1 increase in b because of behavioral responses, which is equal to:

$$\frac{dt}{db} = \frac{1-e}{e}\{1 - \frac{1}{1-e}\varepsilon_{e,b}\} \tag{15}$$

where $\varepsilon_{e,b} = \frac{de}{db}\frac{b}{e}$ is the total, uncompensated elasticity of the fraction of the population working with respect to b.

To obtain a money metric, define dW/db to be the change in welfare from increasing b by \$1, $\frac{dV}{db}/(1-e)$, scaled by the change in welfare from increasing the wage by \$1, $\frac{dV}{dw}/e$:

$$\frac{dW}{db} = \frac{\frac{dV}{db}/(1-e)}{\frac{dV}{dw}/e} = \frac{u'(c_l) - u'(c_h)}{u'(c_h)} + \frac{1}{1-e}\varepsilon_{e,b} \tag{16}$$

The intuition for this expression is as follows. The first term is the marginal benefit of increasing b by \$1: smoother consumption from the perspective of the representative agent. The second term is the marginal cost of increasing b, which depends on the labor supply response to the benefit level. A larger behavioral response requires a larger increase in t to finance that increase in b. At the optimum $dW/db = 0$ so these two terms must offset each other.[34]

A disability insurance version of the Chetty (2008) liquidity vs. moral hazard formula would then re-write the gap in marginal utilities using comparative statics for the effect of wages, disability insurance benefits, and assets on the fraction of the population working ($\partial e/\partial w$, $\partial e/\partial b$, and $\partial e/\partial A$). From the representative agent's first order condition, we have:

$$\frac{\partial e}{\partial A} = \frac{u'(c_h) - u'(c_l)}{\psi''(e)} \leq 0 \tag{17}$$

$$\frac{\partial e}{\partial w} = \frac{u'(c_h)}{\psi''(e)} > 0 \tag{18}$$

and combining these yields:

$$\frac{\partial e}{\partial b} = -\frac{u'(c_l)}{\psi''(e)} = \frac{\partial e}{\partial A} - \frac{\partial e}{\partial w} \leq 0 \tag{19}$$

The gap in marginal utilities can therefore be written as:

$$\frac{u'(c_l) - u'(c_h)}{u'(c_h)} = \frac{-\frac{\partial e}{\partial A}}{\frac{\partial e}{\partial w}} = \frac{-\frac{\partial e}{\partial A}}{\frac{\partial e}{\partial A} - \frac{\partial e}{\partial b}} \tag{20}$$

so that the formula for b^* becomes:

$$\frac{dW}{db} = \frac{-\frac{\partial e}{\partial A}}{\frac{\partial e}{\partial A} - \frac{\partial e}{\partial b}} + \varepsilon_{e,b} \frac{1}{1-e} \tag{21}$$

which only depends on the extensive margin labor supply responses to unconditional transfers (A) and state contingent benefits (b).

Appendix C

In this appendix, I extend the formula in Appendix B to an example where the agent's decision utility differs from his experienced utility, similar to the models in Feldstein (1985), O'Donoghue and Rabin (2006), or Spinnewijn (2014). This creates an

[34] Meyer and Mok (2013) implement this formula using the consumption based formula in Chetty (2006a).

additional term that is akin to a fiscal externality, but here is an "internality" in the terminology of Allcott, Mullainathan, and Taubinsky (2014) and Alcott and Taubinsky (2014).

Suppose that there are two consumption goods, x and y, so that $c_h = (x_h, y_h)$ and $c_l = (x_l, y_l)$, where the price of y is normalized to 1 and the price of x is p (which is fixed). I consider the case where both decision and experienced utility over consumption are additive. Further, I only allow the agent's utility function for decision making and his experienced utility function to diverge with respect to his subutility function for x. Experienced utility from consumption of x and y is

$$u(x, y) = \phi(x) + \upsilon(y) \tag{22}$$

while decision utility is

$$\widehat{u}(x, y) = \widehat{\phi}(x) + \upsilon(y) \tag{23}$$

For example, y could be consumption today and x consumption tomorrow. Agents may be impatient, with $\widehat{\phi}(x) = \beta\phi(x)$ and $\beta < 1$, so that the agent puts too little weight on future consumption. Alternatively, x could be a good that has future adverse health consequences that are underweighted, as in O'Donoghue and Rabin (2006).

The representative agent chooses e and consumption to maximize his decision utility:

$$\widehat{V}(b, t) = \max_{e, x_l, x_h} e\{\widehat{\phi}(x_h) + \upsilon(A + w - t - px_h)\} + (1 - e)\{\widehat{\phi}(x_l) + \upsilon(A + b - px_l)\} - \psi(e) \tag{24}$$

There are three first order conditions:

$$\begin{aligned} \widehat{\phi}(x_h) + \upsilon(y_l) - \widehat{\phi}(x_l) - \upsilon(y_l) - \psi'(e) &= 0 && (IC_e) \\ \widehat{\phi}'(x_h) - p\upsilon'(y_h) &= 0 && (IC_{x_h}) \\ \widehat{\phi}'(x_l) - p\upsilon'(y_l) &= 0 && (IC_{x_l}) \end{aligned}$$

The government chooses b and t to maximize the representative agent's experienced utility $V(b, t)$, but is constrained by his choices derived from his decision utility. Its problem is:

$$\max_{b,t} V(b,t) = e\{\phi(x_h)+\upsilon(A+w-t-px_h)\}+(1-e)\{\phi(x_l)+\upsilon(A+b-px_l)\}-\psi(e)\} \quad (25)$$

subject to IC_e, IC_{x_h}, IC_{x_l}, and the balanced budget constraint

$$t(b) = \frac{e}{1-e}b \quad (26)$$

At the optimum, a small change in b and t must leave experienced utility unchanged:

$$\frac{dV}{db} = 0 \quad (27)$$

which implies that:

$$\begin{aligned} \frac{\partial V}{\partial b} + \frac{\partial V}{\partial t}\frac{dt}{db} + \frac{\partial V}{\partial x_h}\frac{dx_h}{dt}\frac{dt}{db} + \frac{\partial V}{\partial x_l}\frac{dx_l}{db} + \frac{\partial V}{\partial e}\frac{de}{db} &= 0 \quad (28) \\ \Rightarrow \frac{\partial V}{\partial b} + \frac{dt}{db}\left[\frac{\partial V}{\partial t} + \frac{\partial V}{\partial x_h}\frac{dx_h}{dt}\right] + \frac{\partial V}{\partial x_l}\frac{dx_l}{db} + \frac{\partial V}{\partial e}\frac{de}{db} &= 0 \quad (29) \end{aligned}$$

where the last three terms in the first line cannot be dropped, since e, x_l, and x_h were chosen to maximize decision utility and not experienced utility $V(b,t)$. Note that the third term in the first line would be zero if the tax were held fixed, because b only affects resources available when not working. But the tax increase needed to finance the higher b will change x_h and this will lead to a first order effect on welfare since x_h is not at the optimum.

In appendix D, I rewrite each of these terms using the agent's first order conditions from maximizing his decision utility, leading to the following expression for optimal DI benefit levels:

$$\frac{dV}{db}\frac{1}{(1-e)\,v'(y_h)} = \frac{\varepsilon_{e,b}}{1-e}(1+\Omega_2) + \frac{-\frac{\partial e}{\partial A}}{\frac{\partial e}{\partial A}-\frac{\partial e}{\partial b}} + \Omega_1 \quad (30)$$

where

$$\Omega_1 = \frac{[\phi'(x_l)-\widehat{\phi}'(x_l)]\frac{dx_l}{dA}\frac{1}{(1-e)}}{v'(y_h)} - \frac{[\phi'(x_h)-\widehat{\phi}'(x_h)]\frac{dx_h}{dA}\frac{1}{e}}{v'(y_h)} \quad (31)$$

and

$$\Omega_2 = \frac{[\phi'(x_h)-\widehat{\phi}'(x_h)]\frac{dx_h}{dA}\frac{1}{e}}{v'(y_h)} + \frac{[\{\phi(x_h)-\widehat{\phi}(x_h)\}-\{\phi(x_l)-\widehat{\phi}(x_l)\}]}{v'(y_h)}\frac{e}{b} \quad (32)$$

This equation shows that the Chetty (2008) moral hazard versus liquidity formula still holds if we add these correction factors. The $\phi' - \widehat{\phi}'$ terms are the difference between the social and perceived private marginal value of consumption of x, while $\frac{dx}{dA}$ is the marginal propensity to consume x out of income. Note that if $\phi = \widehat{\phi}$, then $\Omega_1 = \Omega_2 = 0$, and the formula collapses to the standard formula.

Appendix D

Note that

$$\begin{aligned}
\frac{\partial V}{\partial x_l}\frac{dx_l}{db} &= [\phi'(x_l) - p\upsilon'(y_l)]\frac{dx_l}{db} && (33)\\
&= [\phi'(x_l) - \widehat{\phi}'(x_l)]\frac{dx_l}{db} && (34)\\
&= [\phi'(x_l) - \widehat{\phi}'(x_l)]\frac{dx_l}{dA} && (35)\\
\frac{\partial V}{\partial x_h}\frac{dx_h}{dt}\frac{dt}{db} &= [\phi'(x_h) - p\upsilon'(y_h)]\frac{dx_h}{dt}\frac{dt}{db} && (36)\\
&= [\phi'(x_h) - \widehat{\phi}'(x_h)]\frac{dx_h}{dt}\frac{dt}{db} && (37)\\
&= -[\phi'(x_h) - \widehat{\phi}'(x_h)]\frac{dx_h}{dA}\frac{dt}{db} && (38)
\end{aligned}$$

where I substitute for $p\upsilon'(y_l)$ and $p\upsilon'(y_h)$ using IC_{x_l} and IC_{x_h}. This term is a function of the degree to which the agent's marginal utility from consuming another unit of x differs across the decision utility function and experienced utility function. If these two functions simply differ by a constant (e.g., $\widehat{\phi}(x) = \phi(x) + k$), then this term is zero. Now for the last behavioral term:

$$\begin{aligned}
\frac{\partial V}{\partial e}\frac{de}{db} &= [\phi(x_h) + \upsilon(y_l) - \phi(x_l) - \upsilon(y_l) - \psi'(e)]\frac{de}{db} && (39)\\
&= [\{\phi(x_h) - \widehat{\phi}(x_h)\} - \{\phi(x_l) - \widehat{\phi}(x_l)\}]\frac{de}{db} && (40)
\end{aligned}$$

substituting in for $\psi'(e)$ from IC_e. This condition measures how the level of utility from consuming x differs across the decision utility function and experienced utility function, which drives a wedge between his actual choice of e and the choice of e that he wishes he would have chosen. Again, if two functions simply differ by a constant, then this term is zero (as long as the constant is same whether he works or not).

The two remaining terms are the direct effect of increasing benefits on welfare:

$$\frac{\partial V}{\partial b} = (1-e)v'(y_l) \tag{41}$$

and the direct effect of the required tax increase on welfare:

$$\begin{aligned}
\frac{\partial V}{\partial t}\frac{dt}{db} &= [-ev'(y_h)]\frac{dt}{db} && (42)\\
&= [-ev'(y_h)]\frac{1-e}{e}\{1-\varepsilon_{e,b}\frac{1}{1-e}\} && (43)\\
&= -(1-e)\,v'(y_h)\{1-\varepsilon_{e,b}\frac{1}{1-e}\} && (44)
\end{aligned}$$

using the balanced budget constraint for $\frac{dt}{db}$. These are the standard terms which would combine to form an exact formula for optimal benefit levels. Notice that these two terms exclusively depend on v', the marginal utility of y, and not on the marginal utility of x. This is a special case of Chetty's (2006b) result that any subcomponent of the consumption vector can be used to infer the consumption smoothing benefits of social insurance.

Simply re-writing these terms leads to:

$$\frac{dV}{db} = -(1-e)\,v'(y_h)\{1-\varepsilon_{e,b}\frac{1}{1-e}\} + (1-e)v'(y_l) + (1-e)\,v'(y_h)\Omega \tag{45}$$

where the behavioral terms are included in $\Omega = (\frac{\partial V}{\partial e}\frac{de}{db} + \frac{\partial V}{\partial x_l}\frac{dx_l}{db} + \frac{\partial V}{\partial x_h}\frac{dx_h}{dt}\frac{dt}{db})/\,(1-e)\,v'(y_h)$.

I can show using IC_e, IC_{x_h}, and IC_{x_l} that the Chetty (2008) decomposition of the gap in marginal utilities still holds with the subutility function for y replacing $u(c)$. Recall the representative agent's first order condition for e:

$$\widehat{\phi}(x_h) + v(A+w-t-px_h) - \widehat{\phi}(x_l) - v(A+b-px_l) - \psi'(e) = 0 \tag{IC_e}$$

Consider a change in the wage rate ($\frac{\partial x_l}{\partial w} = 0$ because w only affects the budget constraint if he works):

$$\widehat{\phi}'(x_h)\frac{\partial x_h}{\partial w} + [\frac{\partial w}{\partial w} - p\frac{\partial x_h}{\partial w}]\upsilon'(y_h) = \psi''(e)\frac{\partial e}{\partial w} \quad (46)$$

$$\Rightarrow \frac{\partial x_h}{\partial w}\left[\widehat{\phi}'(x_h) - p\upsilon'(y_h)\right] + \upsilon'(y_h) = \psi''(e)\frac{\partial e}{\partial w} \quad (47)$$

Consider a change in the benefit (t is fixed and $\frac{\partial x_h}{\partial b} = 0$ because b only affects the budget constraint if he does not work):

$$\widehat{\phi}'(x_l)\frac{\partial x_l}{\partial b} + [\frac{\partial b}{\partial b} - p\frac{\partial x_l}{\partial b}]\upsilon'(y_l) = \psi''(e)\frac{\partial e}{\partial b} \quad (48)$$

$$\Rightarrow \frac{\partial x_l}{\partial b}\left[\widehat{\phi}'(x_l) - p\upsilon'(y_l)\right] + \upsilon'(y_l) = \psi''(e)\frac{\partial e}{\partial b} \quad (49)$$

Consider a change in assets:

$$\widehat{\phi}'(x_h)\frac{\partial x_h}{\partial A} + [1 - p\frac{\partial x_h}{\partial A}]\upsilon'(y_h) - \widehat{\phi}'(x_l)\frac{\partial x_l}{\partial A} - [1 - p\frac{\partial x_l}{\partial A}]\upsilon'(y_l) = \psi''(e)\frac{\partial e}{\partial A} \quad (50)$$

$$\Rightarrow \frac{\partial x_h}{\partial A}\left[\widehat{\phi}'(x_h) - p\upsilon'(y_h)\right] + \frac{\partial x_l}{\partial A}\left[\widehat{\phi}'(x_l) - p\upsilon'(y_l)\right] + \upsilon'(y_h) - \upsilon'(y_l) = \psi''(e)\frac{\partial e}{\partial A} \quad (51)$$

Note that the first order conditions for x_h and x_l are:

$$\widehat{\phi}'(x_h) = p\upsilon'(y_h) \quad (IC_{x_h})$$

$$\widehat{\phi}'(x_l) = p\upsilon'(y_l) \quad (IC_{x_l})$$

so that the terms in large square brackets are zero, leading to:

$$\upsilon'(y_h) = \psi''(e)\frac{\partial e}{\partial w} \Rightarrow \frac{\partial e}{\partial w} = \frac{\upsilon'(y_h)}{\psi''(e)} \quad (52)$$

$$\upsilon'(y_l) = \psi''(e)\frac{\partial e}{\partial b} \Rightarrow \frac{\partial e}{\partial b} = \frac{\upsilon'(y_l)}{\psi''(e)} \quad (53)$$

Similarly, for the change in assets term:

$$\upsilon'(y_h) - \upsilon'(y_l) = \psi''(e)\frac{\partial e}{\partial A} \Rightarrow \frac{\partial e}{\partial A} = \frac{\upsilon'(y_h) - \upsilon'(y_l)}{\psi''(e)} \quad (54)$$