Within-Year Uncertainty and Perception of Year-End Work Incentives*

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Abstract: While taxes are based on year-end income, people often make multiple labor supply decisions during the year and face uncertainty about the next month's earnings. Using a regression discontinuity approach, we show that the effects of information about the year-end tax-benefit schedule depend on the stability of earnings of Norwegian welfare recipients. Consistent with a simple model of (mis-)perceived incentives, individuals with stable earnings respond to the mid-year treatment by modifying their year-end earnings target while those with variable earnings do not display any response. We find no impact on average earnings, but observe that the information treatment caused an increase in the mass of earnings around the kink – especially for workers with stable earnings. Our findings suggest that the targeting efficiency and the value of information policies depend on the stability of the labor environment.

Keywords: labor supply; information frictions; welfare programs; disability insurance
JEL codes: H20; H31; H55; J22; J26

1 Introduction

Understanding the exact work incentives generated by nonlinear tax and benefit schedules is often difficult (e.g., Moffitt, 1990, Saez *et al.*, 2012 and Aghion *et al.*, 2017).[1] People face such challenges as having to learn about tax brackets to calculate take-home income from overtime work on a Wednesday evening or how to fine-tune work hours in June in response to a phase-out of tax credits on year-end income. These challenges are compounded when workers face uncertainty about next month's income, a natural consequence of the fluctuating job opportunities associated with hourly and contract work. This unpredictability reduces workers' abilities to forecast annual earnings and blurs incentives (see, Liebman & Zeckhauser, 2004, pp. 5). This instability, and its

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[1] Liebman & Zeckhauser (2004) discuss the general idea of inaccurately perceived pricing schedules. Chetty & Saez (2013), Chetty *et al.* (2013), and Bhargava & Manoli (2015) examine informational frictions and the EITC, Liebman & Luttmer (2012) examine misperceptions about the Social Security earnings test, Kostøl & Myhre (2021) examine informational frictions in disability insurance. Abeler & Jäger (2015) show that agents are often non-responsive to complex incentives in an experimental lab setting, and Rees-Jones & Taubinsky (2020) document that individuals tend to use the average tax to forecast annual incentives on hourly or weekly income. Stantcheva (2021) studies how people understand tax and redistribution policies.

effect on workers' perceptions of work incentives, has important implications for the design of information and tax policy. Nevertheless, little is known about how workers' understanding of – and responses to complex incentives are shaped by uncertainty about year-end income.

This paper explores the connection between perceptions of work incentives and wage instability by first developing a simple conceptual framework where a worker chooses a mid-year labor supply decision while facing uncertainty about year-end income. In the dissertation version of the seminal paper on bunching, Saez (1999) illustrates how uncertainty about year-end income smooths out kinks in the tax schedule. In his work, this randomness corresponds to unpredictable bonuses or uncertain returns (e.g., dividends, capital gains). We make the observation that to a worker with uncertain future work opportunities, *her future earnings are themselves random and unpredictable.* This uncertainty in forecasted income effectively "irons" out the tax schedule, making it flatter and less convex in the middle of the year. Importantly, this within-year wage instability makes people less sensitive to information about year-end work incentives and renders the precise location of kinks inconsequential for workers' mid-year labor supply choices.

We assess these predictions drawing on two key features from the context of the Norwegian tax-and-transfer system. First, part-time working disability insurance (DI) recipients face nonlinear budget sets: workers can earn income without losing their DI benefits up to a year-end threshold, analogous to the substantial gainful activity (SGA) level in the US Social Security Disability Insurance (SSDI) system. Once earnings exceed this threshold, benefits phase out gradually, creating a kink. This contrasts with the abrupt benefit cutoff, or 'cash cliff,' in the SSDI system. Second, the Norwegian Social Security Administration (SSA) sent out targeted information letters in June explaining that the SGA amount had recently been lowered from $USD12,000$ to $USD8,000$. To identify individuals most likely to benefit from this information, the SSA projected year-end earnings based on monthly earnings from January to May. Letters were sent to those expected to exceed the $8,000 earnings threshold by November.

We estimate the effects of the information treatment using a regression discontinuity design (RDD), leveraging variation in treatment assignment around the projected earnings threshold. We find that the information treatment increased the likelihood of individuals with stable earnings updating their year-end earnings targets. In contrast, individuals with variable earnings do not adjust their behavior in response to the information treatment. When examining actual year-end earnings, we find no evidence of an effect. However, using a complementary research design, we detect notable differences in the earnings distribution between treated and untreated workers. We find that treated workers' earnings become more concentrated around the $8,000 kink—particularly among those with stable earnings, who exhibit a reallocation of mass from the $12,000 kink to the new threshold.

Our paper advances research on studies of attention and behavioral public finance (see, e.g., Liebman & Zeckhauser, 2004). In a closely related paper, Rees-Jones & Taubinsky (2020) show that people tend to use the average annual tax when deciding on hours of work and weekly income. Our evidence is consistent with their findings, and our theoretical framework provides an alter-

nate mechanism for generating the smoothing of incentives associated with the ironing heuristic that they study. We further contribute by documenting important differences in how people with different work arrangements respond to information and offering evidence on a specific source for why non-linear incentives tend to be ironed out.[2] In related work, Chetty *et al.* (2013) and Tazhitdinova (2020) show that people respond more strongly when the taxes are more salient, and Taubinsky & Rees-Jones (2018) show that people make more accurate forecasts of incentives when stakes are high.[3] Finally, our paper builds on Kostøl & Myhre (2021) who show that information frictions account for at least two-thirds of the short-run attenuation in labor supply. We contribute by showing that informational policies in labor markets can improve targeting efficiency by accounting for the stability of the economic environment.

Our findings have important policy implications. While tax incentives typically kick in at year-end, welfare systems often calculate benefit offsets at the monthly level. The US SSDI program, for example, phases out DI payments at a monthly frequency. Our evidence speaks to the policy proposal known as the "$1 for $2 offset" that aims to stimulate increased exit from the US SSDI program by allowing recipients to keep $1 of benefits for every $2 of labor earnings above the substantial gainful activity (SGA) threshold. While Schimmel *et al.* (2011) document important inertia to the cash cliff at the SGA level, our theory and evidence suggest that administering the phase-out at monthly levels limits the misperceptions of the benefit offset rules and additional complexity from time-varying paychecks. Second, our findings have potential implications for the design of the tax system. For example, Goodman *et al.* (2022) highlight the benefits of automatic tax filing – which is especially important at the lower end of the distribution. In light of recent trends in income instability (e.g., Gottschalk & Moffitt, 2009) and growth of contract work (e.g., Abraham *et al.*, 2018), our findings indicate an important role of tax forecasting and tax simplicity for inequality (e.g., Aghion *et al.*, 2017).

The remainder of the paper is organized as follows. Section 2 describes a model where people make a mid-year choice of labor supply while faced with year-end work incentives. Section 3 describes the policy environment, the information treatment and the data. Section 4 describes the research design, 5 reports the evidence attention and Section 6 concludes.

2 A Theory of (Mis-)perceived Incentives

This section develops a model in which people are uncertain about the income yet to be earned in the remainder of the year and explores how this uncertainty interacts with their vague perceptions

[2] A large literature studies how optimization frictions affects decisions, including labor supply responses to welfare reform with adjustment frictions (Kline & Tartari, 2016), over-withholding of tax liabilities (Jones, 2012), information provision and take-up of the earned income tax credit (Chetty & Saez, 2013; Bhargava & Manoli, 2015), and labor supply of old-age retirees (Liebman & Luttmer, 2012). Hastings & Weinstein (2008) and Jensen (2010) study how information and perceptions about the returns to schooling affect behavior, Chetty *et al.* (2009) and Finkelstein (2009) document attenuated responses to non-salient taxes in consumer spending.

[3] See Cunha & Heckman (2016) for the consequences of forecastable and uncertain income components for inequality and Craig & Slemrod (2022) for welfare consequences of unequal perceptions of work incentives along the earnings distribution.

of the tax schedule. Consider a representative worker with uncertain future work opportunities faced with a mid-year labor supply problem. From this perspective, her year-end income is a sum of her theretofore accumulated income, which we normalize to 0; her short-term, *controllable*, income, z; and her future income η, which is a random variable. This setup captures the fact that due to her unpredictable future work opportunities the worker can only control her immediate, short-term, income. η is distributed according to cdf F on $[0, \bar{\eta}]$, which corresponds to continuous density f; and μ denotes the expectation of η.

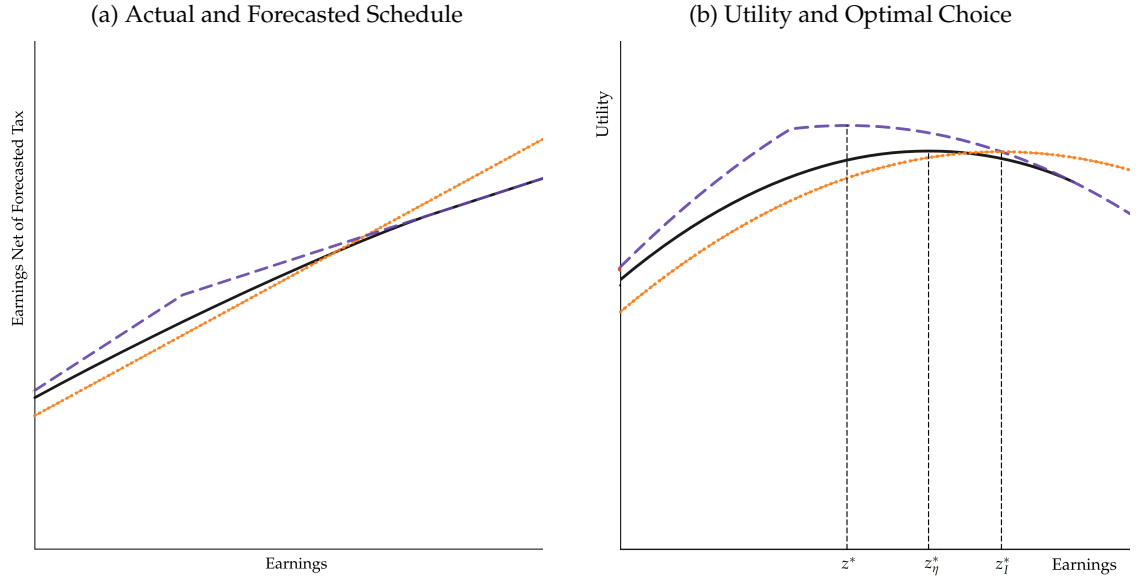
The worker's problem is to maximize utility by choosing effort and consumption while facing a tax schedule. For simplicity, she faces a linear tax with one kink: for year-end earnings y, the tax schedule is

$$\tau(y) = \begin{cases} \tau_1(y) & y \leq K \\ \tau_2(y) - K\Delta_\tau & K < y, \end{cases}$$

with $\Delta_\tau \equiv \tau_2 - \tau_1 > 0$. This specification implies that workers pay a tax rate of τ_1 on earnings less than the kink point K and τ_2 on earnings more than K. Assuming $\bar{\eta} > K$, the forecasted tax schedule faced by the mid-year worker is

$$\tilde{\tau}(z) \equiv \mathbb{E}_F[\tau(z+\eta)] = \begin{cases} \tau_1 \int_0^{K-z} (z+\eta)\, dF(\eta) + \int_{K-z}^{\bar{\eta}} [\tau_2(z+\eta) - K\Delta_\tau]\, dF(\eta) & z \leq K \\ \tau_2(z+\mu) - K\Delta_\tau & K < z. \end{cases}$$

Figure 1: The Effects of Uncertain Future Income and Ironing on the Optimal Labor Supply.



Notes: Figure 1a illustrates the actual and foretasted tax and benefit schedule and Figure 1b the corresponding utility, where z^*_I denotes the ironing (schmeduling) worker's optimal choice of earnings, and z^*_η and z^*denote a worker's optimal choice of earnings when the future income is random variable η, and deterministic (μ), respectively. The black, solid curve is for uncertain earnings and the purple, dashed line is for agents with no uncertainty about future income (perfectly controllable). The orange, dashed/dotted figure illustrates the problem faced by a worker who irons (schmedules) à la Taubinsky & Rees-Jones (2018).

We illustrate this in Figures 1a and 1b. Both graphs contain three curves. The first graph

illustrates a worker's optimization problem in the middle of the year. The black (solid), and purple (dashed) curves depict the function $z + \mu - \tilde{\tau}(z + \eta) - \psi\left(\frac{z}{w}\right)$ for two different levels of uncertainty of η. In the first (black, solid) curve, the future income is uncertain; and in the second (purple, dashed), there is no uncertainty about future income, i.e., year-end income is perfectly controllable. In each case, the worker chooses z in order to optimize these objectives, and as the graph illustrates, this optimum decreases as η becomes less dispersed. The third curve (orange, dashed/dotted) illustrates the problem faced by a worker who irons (schmedules) à la Taubinsky & Rees-Jones (2018). Observe, that this worker also "overworks" relative to the benchmark in which the worker neither irons nor has uncertainty about future income (the purple, dashed curve). Keep in mind; however, that the worker who irons has no uncertainty about future income, it is just that she misperceives her incentives and uses a simplifying heuristic.

Though the observable effects and predictions–namely, the (apparent) overexertion in the short term–resulting from the scenarios with uncertain future income and workers who iron are virtually identical, the mechanisms behind the two results are different. The ironing worker forecasts her end-of-the-year income, backs out her average tax at this forecasted number, then uses this to choose her labor supply. This worker ignores the location of the kinks in the tax and benefits schedule. In contrast, in our setting, workers are assumed to be fully aware of the schedule's kinks and nonlinearities. Instead, the uncertainty regarding the future income effectively "irons" out the tax schedule making it flatter and less convex, as workers integrate over the η. In the next subsection, we introduce vagueness about the location of the kink and study how it interacts with the smoothing of the tax schedule engendered by a worker's uncertain future income.

Mis-specified Incentives

Now we formalize the notion that the slope and location of the kink are not perfectly understood. Suppose the true tax rate remains as given above, $\tau(y)$, but the worker has a vague estimate of the kink's location. Such a misperception could arise from a policy-induced reduction in the kink location, where the new kink point faced by the worker is lower than in the previous year. This change causes uncertainty about the location and leads workers to (weakly) overestimate the kink point due to inertia or "stickiness" in beliefs. As we will see, information about annual marginal work incentives may not be relevant if the worker has insufficient control over her income.

We stipulate that the (mid-year) worker believes that the kink is located at $K + \varepsilon$, where ε is a random variable distributed according to cdf G on $[-\bar{\varepsilon}, \bar{\varepsilon}]$ with expectation $\mu_\varepsilon \in [0, \bar{\varepsilon})$. That is, the worker is unsure of the kink's location and moreover (weakly) overestimates its location on average.[4]

Our goal is to study the interaction between this vagueness and the worker's uncertain work opportunities and their combined effect on the worker's short-term incentives to work. For sim-

[4]To ease the analysis, we also assume that ε and the uncertain future income, η, are independent. In addition, workers may also be uncertain about the tax rate. However, given our quasi-linear formulation of the worker's utility, it is without loss to assume the worker has no uncertainty along this dimension.

plicity the worker's year-end utility from consumption c and labor l is $u(c,l) = c - \psi(l)$,where ψ is smooth, strictly increasing and convex. Letting $\hat{\tau}(z) \equiv \mathbb{E}_{F,G}[\tau(z+\eta)]$ denote the worker's perceived tax, given the income and kink uncertainty, the worker maximizes

$$\mathbb{E}_{F,G}[z+\eta] - \hat{\tau}(z) - \psi\left(\frac{z}{w}\right),$$

where $w > 0$ is the worker's wage (in the short term).

Under natural, minimal, assumptions (detailed in the online appendix), the worker's objective is continuously differentiable and strictly concave (and has an interior solution) so that the first-order condition determines the optimal short-term choice of income, z^*:

$$1 = \hat{\tau}'(z^*) + \frac{1}{w}\psi'\left(\frac{z^*}{w}\right).$$

We model a hypothetical informational intervention as eliminating the worker's uncertainty about the kink's location. Formally, as a result of the intervention the worker's perceived kink point goes from the random variable given above to K with certainty. Accordingly, following the informational treatment, the worker's optimal short-term choice of income, z_T, solves

$$1 = \tilde{\tau}'(z_T) + \frac{1}{w}\psi'\left(\frac{z_T}{w}\right).$$

Our setup produces two key predictions. First, under natural conditions on the worker's distribution over forecasted income, F, a worker who does not receive the informational treatment works more than one who does.[5] The imprecise (perceived) location of the kink effectively lowers the worker's (expected) forecasted marginal tax rate, leading to her overexertion. Second, if a worker's future income is sufficiently uncertain, the treatment has a negligible effect. This unpredictability renders the worker's vague perception of the kink point inconsequential, and so informing the worker has little effect.

3 Policy Environment and Paycheck Data

Armed with the insights from our model, we turn our attention to the institutional setting and data, describing the year-end work incentives of the Norwegian Disability Insurance (DI) program, the mid-year informational treatment, and the monthly paycheck data.

3.1 Annual Work Incentives in The Norwegian DI System

The Norwegian DI program is designed to provide partial earnings replacement to all workers below retirement age who are unable to work because of an impairment that has lasted for at least a year. The level of DI benefits received is based on a worker's previous earnings, and involves

[5] For instance, this result holds if f is single peaked, with a peak at a sufficiently high value of η , a natural assumption in this setting.

calculating a worker's average indexed annual earnings (AIE). Past wages are indexed to present wages using a deflator that is equal to the average wage growth in the economy. The years with the lowest earnings are excluded from these calculations, and the proportion of income that is replaced falls with the level of previous earnings. Similar to other European DI programs, the DI system distinguishes between total disability awards and partial awards that permit beneficiaries to use their residual work capacity.

Norway implemented a change in the benefit phase-out for DI beneficiaries in 2015. Under the DI system, beneficiaries are allowed to work up to a substantial gainful activity (SGA) level. Earnings up to this point are subject to income taxation but are exempt from benefit phase-out rules. Workers remain eligible for DI benefits until their earnings exceed a threshold set to 80 percent of their previous earnings level, after which they are automatically disenrolled from the program. This SGA level was reduced from $USD12,000$ to USD8,000 in 2015, where the change equals about 10 percent of the average earnings before enrolling in the program. On average, the kink increases the effective marginal tax from 0.35 to 0.78, where the exact slope change varies with the replacement rate. By contrast, the key difference from the 2014 rules is that the old location of the SGA level was 50 percent higher.[6]

3.2 Mid-Year Informational Treatment

In June 2015, the SSA issued targeted information letters for recipients actively participating in the labor market. The primary motivation was to ensure that people were made aware of the change in the location of the SGA. However, the SSA decided to target individuals deemed likely to earn more than the annual kink by November.[7] To implement this information experiment, the SSA collected information about recipients' monthly earnings from January to May to project their annual earnings. The projected annual earnings (PAE) is defined as $PAE_i = \sum_{m=1}^{2} w_{im} + 3 \cdot \sum_{m=3}^{5} w_{im}$ where w_{it} is earnings for individual i in month m.[8]

After determining eligibility, the SSA sent the information letter by regular mail to recipients' residential address. The letter included the emblem of the SSA, as imprinted on standard payment checks; hence, recipients were likely to open and read the letter. The letter i) informed individuals about the exact location of the kink (e.g. $K = USD8,000$), ii) instructed individuals that it would always pay to work more, and iii) encouraged individuals to report to the SSA if they expect annual earnings to exceed the annual kink – either by using a web portal administered by the SSA, or by

[6] In 2014, about half of the sample faced a notch instead of the kink. The difference between a kink and a notch does not play an important role for our analysis. See Kostøl & Mogstad (2014) and Kostøl & Myhre (2021) for details.

[7] Individuals who had informed the SSA about expected annual earnings above SGA would not receive the letter. Individuals with cumulative earnings above the SGA in May 2015 were neither eligible for the information letter.

[8] In fact, the SSA effectively used only earnings in March, April and May to predict the annual earnings. As the SSA used eleven months, they targeted individuals who would reach the annual kink by the end of November. This means that individuals were able to adjust their "last" month if the information letter provided relevant information; or to the extent that their annual earnings were predictable, individuals could start the re-adjustment of annual earnings (by negotiating fixed hours contract etc.) already in July.

telephone.[9] An example of the information letter is displayed in Appendix Figure A.1.

3.3 Monthly Program and Paycheck Data

Our main data source provides us with complete information on paychecks from every employer, reported monthly and covers contracted hours, hourly wages, bonuses, and other taxable benefits provided by employers. The main outcome variable we consider measures whether a person reported a change in the target or expected year-end earnings to the SSA after receiving the letter. Crucial to our analysis is having access to whether a person received the information letter and the assignment rule the SSA used to determine eligibility for the letter.

Our administrative records allow us to combine several data sources that can be linked using anonymized identifiers for every resident and employer. Because individual employment histories and most income components are third-party reported (e.g. by employers and financial intermediaries), the coverage and reliability are rated as exceptional by international quality assessments (see e.g. Atkinson *et al.*, 1995). What is more, since administrative data are a matter of public record, there is no attrition due to non-response or non-consent by individuals or firms, and individuals can only exit these data sets due to natural attrition (i.e., death or out-migration).

4 Empirical Approach

Our target parameter is the causal effect of the information letter on perceptions of the tax and benefit system. The informational treatment provided details about the annual kink location and its slope. It also requested recipients to report any change in year-end earnings target. We will use an indicator for whether a person updates the year-end earnings target as our main outcome variable.

4.1 Regression Discontinuity Design

The institutional design of the intervention provides a natural setting to estimate the average treatment effect using a regression discontinuity (RD) design – comparing the reporting behavior of individuals who received additional information about the new tax (Y^T) to a control group with baseline knowledge (Y^B). Specifically, we will estimate the differences in means,

$$\Delta Y = E[Y_i^T - Y_i^B \mid PAE_i = K], \tag{1}$$

where PAE is the SSA's projected annual earnings of individual i. We invoke the standard assumption that individuals are unable to precisely manipulate the assignment variable PAE (and thereby affect the treatment assignment) and that our outcome is continuous, without any other

[9] The social security administration also surveyed recipients about reading the letter. 81 percent recall receiving the first information letter by the end of 2014, suggesting that letters from SSA are received and opened. In the empirical analysis we proxy for whether the content of the letter was understood by whether the person reported any expected change in annual earnings.

confounders at the threshold. When these assumptions are satisfied the variation in treatment near the threshold is as good as random.

Our empirical approach is to exploit the discontinuous assignment of information letters, where only individuals who were likely to earn more than the annual kink by December would receive the information letter in June 2015. Specifically, we implement a fuzzy RD design following the two-equation system described in Dahl *et al.* (2014). Our baseline specification is a local linear relationship on either side of the threshold with triangular weights that assign more weight to observations close to it. We can estimate the change in the share receiving the information letter in a first stage RD regression and the two stage least squares (2SLS) estimate of the impact of the information letter on our outcome of interest.

We choose the optimally selected bandwidth following Calonico *et al.* (2014) for the combined sample.[10] Next, we pool observations on monthly earnings from July to December and estimate heteroskedasticity-robust standard errors. Finally, we discuss robustness to alternative bandwidth choices below. Online appendix Table A.1 shows that the density and demographics for people with earnings on either side of the cutoff are not statistically significant, lending support to our empirical design.

4.2 Empirical Samples

Our target population consists of DI recipients engaged in the labor market from January to May 2015. We exclude those aged above 66 due to eligibility for old-age retirement benefits beginning at age 67, and focus on individuals deemed fully disabled by the SSA before January 1, 2015. This restriction is due to a lack of information on the exact location of the kink among the partially disabled and because recipients awarded benefits in 2015 faced a different set of work incentives.[11] Panel A of Table 1 presents summary statistics for DI recipients with any earnings from January to May. The average person has spent nearly 14 years on the DI program, receives benefits replacing about 62 percent of his previous earnings, and earned about half of the SGA amount in 2014.

Our baseline measure of peoples' abilities to forecast year-end earnings is based on variability in monthly paychecks. We use monthly earnings as the sum of all monthly paychecks and compute the standard deviation of individual earnings using data from January to May 2015. Next, we compute the coefficient of variation among part-time working DI recipients and for the overall population. As expected, part-time working DI recipients exhibit more variability in monthly paychecks than the overall population. About one-sixth have constant monthly earnings, while more than a quarter of the overall population have no changes in monthly paychecks (i.e., a coefficient of variation equal to zero). We illustrate the distribution of variability in Appendix Figure

[10] While different outcomes may have different optimal bandwidths, the optimal bandwidth for our two main outcomes is $2,912 for reporting a change in target earnings to the SSA and $2,815 for monthly earnings, respectively. As these bandwidths are almost identical, we use the lowest of these as our baseline bandwidth for consistency and simplicity. We nevertheless show how our estimates change for different choices of bandwidth in Appendix Figures A.5 and A.6.

[11] If a person has already exceeded the annual kink by May, the person is not eligible for the information treatment. Our estimation sample excludes these individuals.

A.4. Our baseline definition of "Stable Earnings" means having a coefficient of variation below the median in our sample and the remaining workers as "Variable Earnings." We also split the sample into more fine-grained groups and used qualitative information about the type of work contracts as alternative measures of variability. Note that only one percent of our sample has any income from self-employment, making this form of control over income less relevant in our setting.

Table 1 reports summary statistics. Panel A reports summary statistics for all working DI recipients, and Panel B focuses on two samples we will use for the regression analysis. Column 2 reports summary statistics for the empirical sample using optimal bandwidths, Column 3 reports observable characteristics for the stable earnings sample, and Column 4 shows the same variables for the variable earnings sample. We see clear differences in observable characteristics across the variable and stable earnings groups – most notably in age and time on the DI program. We also see a larger fraction of cohabiting DI recipients with children. In Section 5, we examine whether our findings hold if we instead use the type of wage employers report, such as regular or hourly.

Table 1: Summary statistics: Regression Discontinuity Sample

Sample:	A. All working DI recipients	B. RD Sample Full sample	Stable Earnings	Variable Earnings
Column:	(1)	(2)	(3)	(4)
Earnings	mean	mean	mean	mean
Earnings Jan-May in 2015 ($)	2,619	3,283	3,326	3,219
Annual earnings in 2014 ($)	6,537	8,059	8,011	8,129
DI information				
Age at DI award	35.79	37.03	33.85	41.64
Years on DI	14.36	14.21	15.48	12.38
Uncapped annual DI benefits ($)	35,286	35,095	34,714	35,647
Annual indexed earnings ($)	56,333	56,103	55,067	57,604
Characteristics				
Age on January 1st, 2015	49.73	50.84	48.89	53.67
Fraction females	.53	.51	.50	.53
Fraction cohabitants	.43	.48	.42	.58
Years of Schooling	10.21	10.32	10.07	10.68
Number of Children	1.43	1.59	1.34	1.96
Observations	39,071	7,443	4,403	3,040

Notes: The sample of working DI recipients includes all fully disabled recipients awarded DI before the 1st of January 2015 with some earnings during January-May 2015. The RD sample includes the individuals from the sample of working recipients eligible to receive the information treatment and had projected annual earnings (PAE) within $2,815 of the cutoff. Round numbers (in multiples of NOK 1,000 of PAE) are excluded. The stable (variable) earnings samples include individuals whose earnings variability measure is below (above) the sample median, where earnings variability is defined as the individual level SD/mean in January-May 2015. Annual indexed earnings summarize earnings history before the disability onset. All variables are measured in 2015 dollars (NOK/USD = 7.5).

5 Empirical Findings

A virtue of the RD design is that it provides a transparent way of showing how we identify the effects of the information treatment. We begin our graphical analysis by documenting a discrete change in receipt of the information letter at the threshold before turning to regression results and robustness. At the end of the section, we use a complementary research design to examine how the information letter affected the distribution of earnings.

5.1 Regression Discontinuity Evidence

Figures 2a and 2b show the fraction of individuals receiving of the letter for different values of the assignment variable, collapsed into $133 (NOK 1,000) bins on either side of the cutoff and normalized at the annual kink.[12] They demonstrate a large discrete jumps around 60 percent in both samples. They also illustrate a key feature of the setting where employers could update their employees' monthly wage reports for a given calendar year until the tax return was filed in April the following year. This lag in reporting resulted in attenuation in the information letter assignment – generating a fuzzy discontinuity at the cutoff.

Turning to changes in target earnings, Figure 2c plots the fraction of individuals in the stable earnings sample who report a change in target year-end earnings to the SSA. We observe a discrete jump at the cutoff, clearly indicating that the letter caused a change in the expected annual earnings. The dashed lines correspond to 95 percent confidence intervals and show that the two confidence intervals do not overlap. Consistent with the theoretical framework, Figure 2d reveals no clear sign of changes in reporting in the variable earnings sample.

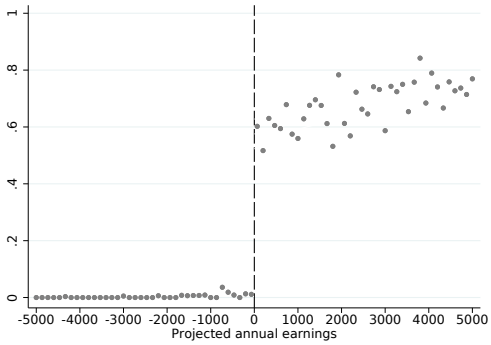
While our theory makes stark predictions about the perception of incentives, the expected impacts of correcting misperceptions depend on the bias of beliefs and their distribution. As the SGA was moved from 12 to 8 thousand per year, we expect belief updating, on average, to reduce average earnings if people primarily lower their earnings targets.[13] The average impacts also depend on whether workers have the needed hours flexibility to adjust labor supply. The evidence from Figures 2e and 2f show no statistically or economically significant impact on average earnings – even though the sign appears negative in both samples. As discussed above, one possible explanation is that more binding hours frictions and a higher ability to forecast year-end earnings offset each other and attenuate the real earnings responses to learning about incentives. Other potential explanations are that our research design is underpowered and that average impacts miss distributional effects of the informational treatment.

[12] Note that we use the year-end earnings information, where all employers have reported earnings.

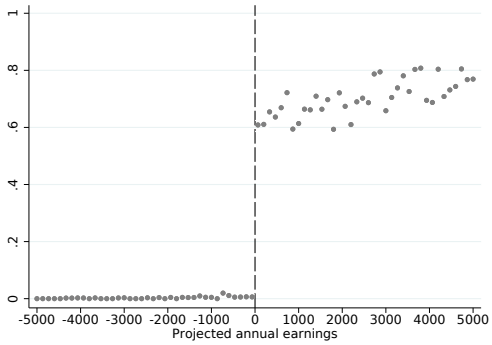
[13] However, we have no prior on the direction of perceptions of the marginal tax rate above the kink. The bias may be positive and negative, rendering the average impacts ambiguous.

Figure 2: Graphical Evidence

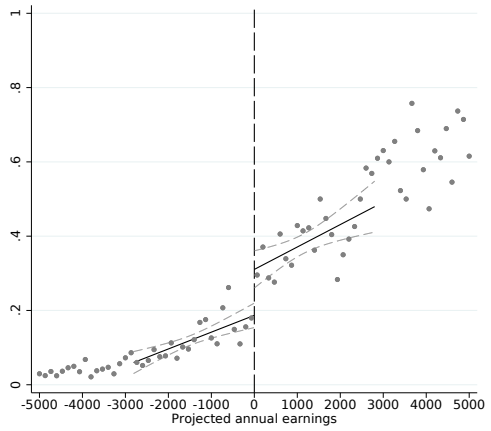
(a) Stable: Receipt



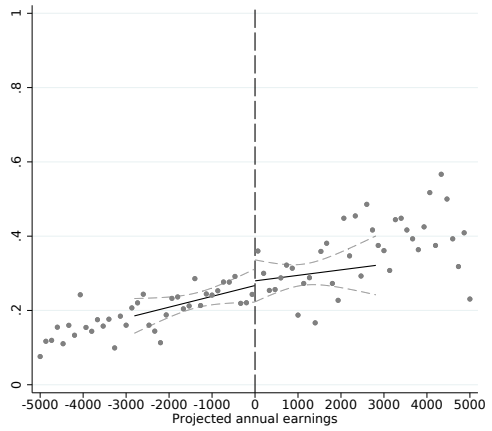
(b) Variable: Receipt



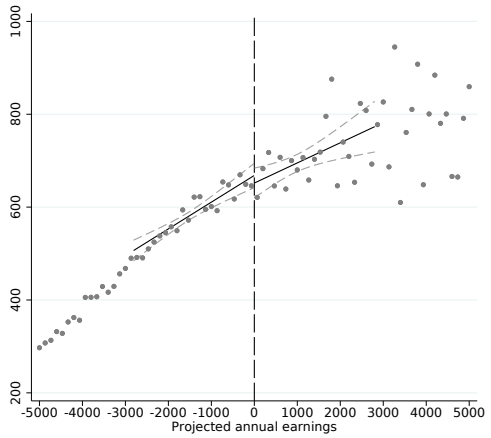
(c) Stable: Report Earnings Change



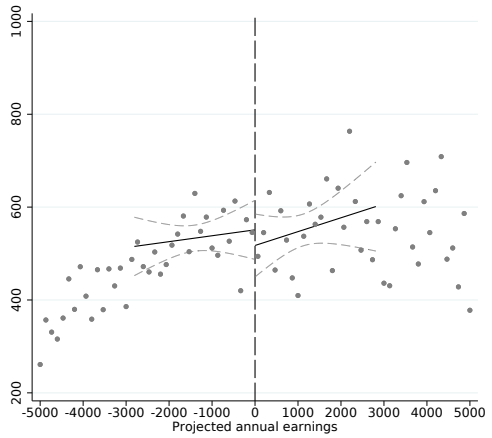
(d) Variable: Report Earnings Change



(e) Stable: Monthly Earnings ($)



(f) Variable: Monthly Earnings ($)



Notes: Figures 2a and 2b show the fraction of recipients who received the information letter from SSA in June 2015, Figures 2c and 2d show the fraction of individuals reporting changes in earnings to the SSA, and Figures 2e and 2f show the monthly earnings during July-December 2015 for the stable and variable earnings samples. The black solid lines represent the predicted values of local linear regressions on each side of the cut-off using a bandwidth of $2,815 and a triangular kernel, and the dashed lines represent 95% confidence intervals. Sample definitions are described in Table 1.

5.1.1 Regression Evidence

Next, we perform a regression-based analysis and report our first stage and second stage estimates in Table 2. Panel A reports our findings for individuals with stable earnings, and Panel B reports findings for individuals with variable earnings, for our baseline definition of variability of earnings. The first columns present estimates of the first stage and the second two columns the second stage estimates.

Table 2: 2SLS Estimates of Impact on Reported Changes in Earnings and Earnings

	A. Stable: Below Median Variability			B. Variable: Above Median Variability		
	(1)	(2)	(3)	(1)	(2)	(3)
	First stage	Change Target Earnings	Actual Earnings ($)	First stage	Change Target Earnings	Actual Earnings ($)
Estimate	.562***	.220***	-29	.684***	.018	-49
	(.027)	(.056)	(38)	(.029)	(.054)	(69)
Dependent mean	.013	.184	669	.003	.267	551
p-value	<.001	<.001	.437	<.001	.733	.476
Observations	4,403	4,403	26,418	3,040	3,040	18,240

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Standard errors (in parentheses) are clustered at the individual level and are robust to heteroskedasticity.

Notes: This table presents the average impacts of the information letter on an indicator for whether the person reports a change in year-end target earnings to the SSA as well as monthly earnings during July-December 2015. The first column shows the first-stage regressions, while the second and third present the 2SLS estimates for each outcome. We use a local linear regression using a triangular kernel density and a bandwidth of $2,815 on each side of the cutoff. Sample definitions are described in Table 1.

The first stage estimates in Panel A show that the assignment rule caused a 56 percentage point increase in the likelihood of receiving the information letter in the stable earnings sample.Similarly, Panel B documents a 68 percentage point increase among individuals with variable earnings. Our second-stage estimates are obtained using the jumps from Figures 2c and 2d, scaled with the inverse of the corresponding first-stage estimates. We find that the letter caused more than a 100 percent increase in the likelihood of reporting a new earnings target. The estimates are highly statistically significant. In contrast, the impact on reporting for the workers with variable income is indistinguishable from zero but relatively imprecisely estimated. We interpret the impacts on reporting in the stable earnings sample as a response to the information provided in the letter – indicating that it updated peoples' perceptions of the location and slope of the kink. The differences in effects from Table 2 are statistically significant and are consistent with the conceptual framework, where larger uncertainty about future realizations reduces the likelihood of reacting to the information about the tax-benefit schedule.

Regarding the information letter's effects on realized earnings, column 3 of Panel A shows that people may have reduced labor supply in response to the information, but estimates are very imprecise. As discussed above, this may reflect that misperceptions vary, both in terms of the location of the kink and over and under-estimating its slope, and it may reflect more binding

hours constraints in this subsample. In Panel B, we show a similar and imprecisely estimated impact of the letter on the likelihood of working more than the threshold among individuals with more unstable earnings.

In sum, our results indicate that targeting information letters may yield important benefits. At the same time, the ability to forecast year-end earnings and simultaneously adjust work hours may interact in non-trivial ways. Understanding the role of hours constraints is beyond the scope of this paper but appears to be a fruitful avenue for future research.

5.1.2 Specification Checks

The validity of our evidence hinges on the assumption that individuals are unable to perfectly manipulate the assignment variable. Online appendix Figure A.3 shows that after we exclude round numbers in the assignment variable, the distribution of our assignment variable is smooth around the cutoff. We perform a formal test for bunching at either side of the cutoff and do not reject the null of no bunching – consistent with the notion that individuals did not strategically manipulate their earnings to become eligible for the letter. We have performed a series of balancing tests in Online appendix Table A.1, showing we are unable to reject the null hypothesis for any of the covariates separately nor jointly, and Online appendix Figure A.2 shows a smooth evolution of all characteristics – including earnings in 2014 – on either side of the cutoff.

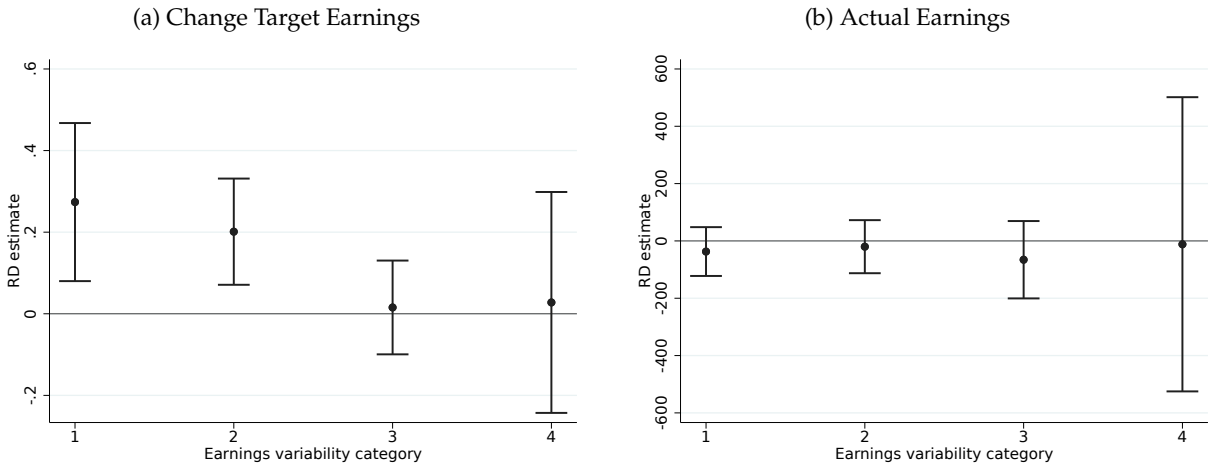
Finally, we validate that our main results in Table 2 are robust to the usual specification checks performed in RD studies. In Panel A of Online appendix Table A.2, we show that including all the characteristics from Table 1 barely moves our point estimates for the stable earnings sample. We further validate that our conclusions remain significant if we implement the bias-corrected and robust standard errors proposed by Calonico *et al.* (2014) and if we follow the suggestion by Lee & Lemieux (2010) to deviate from the optimal bandwidth. Online appendix Figures A.5 and A.6 extend this exercise by plotting 2SLS estimates and confidence intervals over a wider range of bandwidths, illustrating that our main results are highly robust to bandwidth selection. Finally, we demonstrate the stability of the estimates while including round numbers of the assignment variable and applying rectangular weights. Panel B repeats the sensitivity checks for the sample of recipients with unstable earnings. As the baseline estimates are less precise, the specification checks reflect a higher sensitivity to the particular specification used. The various specifications across column (2) suggest that treated individuals are more likely to report change in target earnings than the control group. While the average impact of information letters appears to be broadly positive across specifications, we are never able to reject the null hypothesis of no impact.

5.1.3 Alternative Measures of Variability

Our conclusions may also depend on the exact definitions of variability in income. We begin our assessment of the sensitivity of our grouping by dividing the sample into finer sub-groups. One group has no variability in monthly earnings, i.e., fixed salary; another has no stability, i.e., working one month from January to May, and then there are two intermediary groups of relatively high

stability and high variability (above and below the sample median, respectively). We redo our analysis using these definitions and plot the sub-group evidence for reporting and realized earnings in Figures 3a and 3b. The point estimates, standard errors, and sample sizes are reported in the Appendix Table A.3. Consistent with the model's predictions, we see the strongest response on reporting among the people with perfect foresight of year-end earnings. In terms of actual earnings, we see no clear pattern. We also report similar evidence using complementary measures of variability and exploiting some of the qualitative information from the data, such as whether compensation consists of variable and fixed pay. These results are quantitatively similar and qualitatively the same and are reported in the Appendix Table A.4.

Figure 3: RD Evidence by Sub Groups



Notes: Figures 3a shows the RD estimates of the impacts of the information letter on reporting and 3b show the RD estimates of the impacts of the information letter on monthly earnings from July to December 2015. Spikes represent 95% confidence intervals, where standard errors are clustered at the individual level and are robust to heteroskedasticity. Sample definitions are described in Table 1

The interpretation of our findings also depend on other factors determining income variability. For example, Table 1 documented that people are similar in terms of prior income and education, but differ in terms of time on the program and age. We implement a parametric difference in regression discontinuity design to examine whether these characteristics may confound our conclusions about income variability. This specification subtracts the treatment effect for the variable earnings sample, δ^{variable}, from the treatment effect for the stable earnings δ^{stable}, i.e., $\delta^{\text{DRD}} = \delta^{\text{stable}} - \delta^{\text{variable}}$, and allows us to perform inference on the difference as well as examine how the inclusion of controls relate to the difference in treatment effects. Comparing across the rows i) to iii) in Appendix Table A.5 shows that the differences remain statistically significant at conventional levels – indicating that observable differences in characteristics do alter our main result.[14]

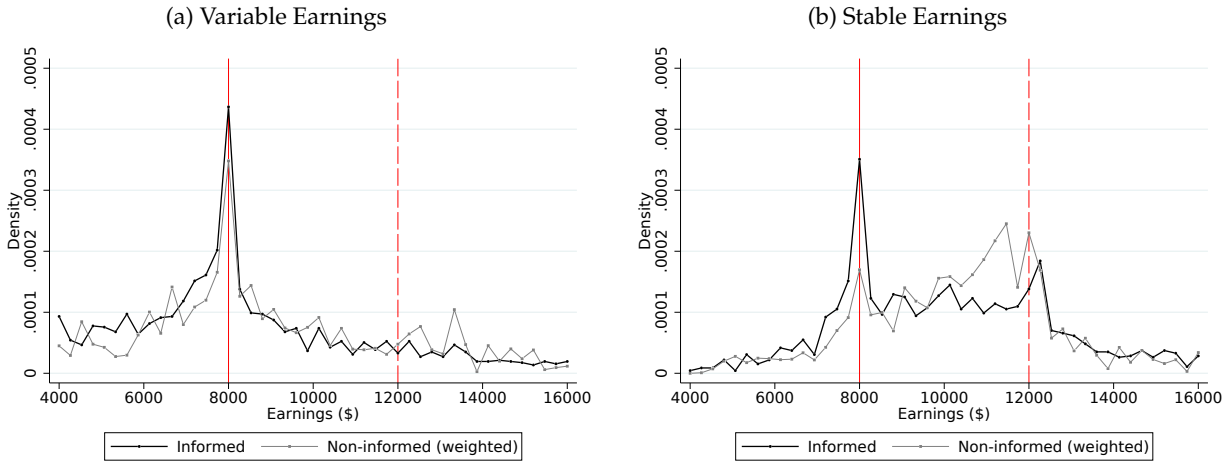
[14]Of course, there may be unobservable confounders. Addressing this possibility would require administering a field experiment and randomizing the level of uncertainty in income – which is beyond the scope of this paper.

5.2 Distributional Effects

Until now, we have focused on the mean impacts of the information letter. Since our simple labor supply theory suggests that these mean impacts might average together negative and positive labor supply responses to misperceptions, we focus on the distributional effects of the information policy. A quantile treatment effects analysis using the regression discontinuity design is not feasible since the number of workers at different earnings bins becomes too few. Instead, we leverage the differences in treatment among the eligible, i.e., those with projected earnings above the cutoff, and use a reweighing approach to correct for observable differences between treated and non-treated workers. Following Kline (2011), this approach uses the observable characteristics to predict whether a worker will receive the letter using logistic regression and uses the estimated propensity to reweigh the earnings distribution among the untreated.

To interpret our differences in distributions between treated and non-treated as a causal response, we must assume that conditional on the observable differences, the information letter was as good as randomly assigned. Kostøl & Myhre (2021) provide supportive evidence of this assumption by showing that the two groups' earnings distributions in 2014 are statistically indistinguishable and that the two groups followed similar pre-trends before the information intervention.

Figure 4: Conditional Earnings Distributions

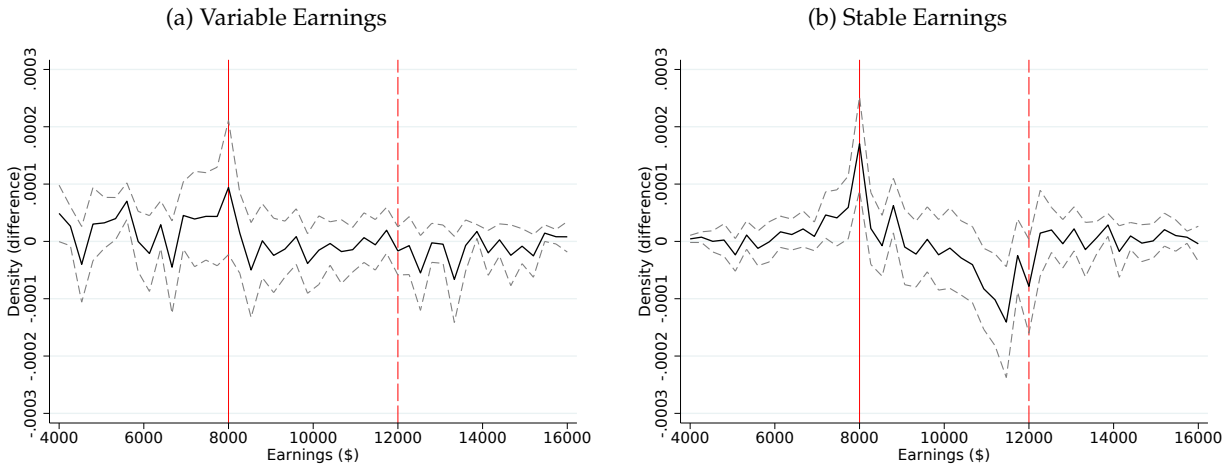


Notes: The figures present earnings histograms for the sample of workers eligible to receive the information treatment (PAE above the cutoff), separately for treated individuals (received information letter in June 2015) and untreated recipients (did not receive information letter). Figure 4a (4b) illustrates the distributions for individuals whose earnings variability measure is above (below) the sample median, where earnings variability is defined as the individual level SD/mean in January-May 2015. Non-treated recipients are reweighed using propensity score weights $w(x) = \frac{P(I=1|x)}{P(I=1)} \frac{1-P(I=1)}{1-P(I=1|x)}$, where $P(I=1)$ denotes the probability of receiving the information letter in June 2015 and $P(I=1|x)$ is estimated by a logit on characteristics in Table 1 and occupation fixed effects.

We begin by plotting histograms of annual earnings for the variable and stable subgroups in Figure 4. The left panel shows the earnings distributions for the treated and untreated with variable earnings, and the right panel shows the same distributions for the sample with stable earnings. It is apparent from both figures that the mass at the kink is higher in the treated group. However,

we also see that the increase in mass due to the information letter is the largest among stable workers. Next, we estimate the differences in mass at each earnings bin and calculate bootstrapped standard errors to account for uncertainty in the estimated propensity scores. Figure 5 plots the estimated differences and 95 percent confidence intervals. We see that where treated workers are statistically significantly more likely to locate their earnings on the new kink among the stable earnings group, we see no statistically significant differences in the variable subgroup. Moreover, we also see that the stable earnings group is much more likely to reduce their earnings around or below the old kink at USD 12,000 when they receive the letter. We interpret these findings as broadly consistent with the theory outlined in Section 2, suggesting that uncertainty in earnings restricts the response to the possible adjustment amount as uncertainty about year-end earnings clears. Moreover, the evidence indicates that belief updating and inertia among people with stable earnings can be potential mechanisms behind the labor supply responses.

Figure 5: Differences in Earnings Distributions



Notes: The figures present differences between earnings histograms among treated individuals (received information letter in June 2015) and untreated recipients (did not receive information letter). Figure 5a (5b) illustrates estimated differences and bootstrapped 95 % confidence intervals using 500 bootstrap repetitions. See Figure 4 for details on sample and reweighing approach.

6 Conclusion

The central thesis of this paper is that employees often decide how much to work without knowing the minute details of tax and benefit schedules, which affects the value of information. The increasing prevalence of time-varying work arrangements suggests that understanding the details of year-end incentives may have become increasingly difficult, with important implications for the aggregate response to tax and benefit system changes. We have made some progress in understanding whether the strength of informational barriers depends on the stability of the work environment and how well workers can forecast year-end earnings.

Our paper has studied how the stability of work environments shapes the response to person-

alized information about work incentives. We formulated a model in which workers with unpredictable annual earnings choose their short-term labor supply. In this framework, we argued that correcting misperceptions about the tax schedule has little effect when workers' future earnings are sufficiently uncertain. Guided by the insights from our model, we explored an information policy targeting part-time working disability insurance recipients in Norway. The unique combination of a regression discontinuity design and detailed data on reporting and monthly earnings allowed us to examine the responses to the information treatment and how it varied with the stability of monthly earnings. We uncovered important heterogeneity in reactions to the informational treatment.

A natural question is whether tax reforms primarily affect earnings at the end of the calendar year as uncertainty about year-end earnings clears. Moreover, how do different work arrangements shape the elasticity of taxable income? Does responding to tax changes may become increasingly hard as the number of people working as contractors without fixed contracts increases? While this paper has only scratched the surface of these important but difficult questions, these are interesting avenues for future research. It would also be useful to explore how income instability shapes labor supply in more general settings and design a lab- or field experiment to control uncertainty more directly.

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Online Appendix

A Additional Tables and Figures

Table A.1: Smoothness of Density and Predetermined Covariates

Dependent variable:	Full sample	Stable earnings	Variable earnings
	(1)	(2)	(3)
Density	-.061	-.029	-.090
	(.058)	(.074)	(.084)
Earnings Jan-May in 2015 ($)	-36	3	-79
	(33)	(16)	(73)
Annual earnings in 2014 ($)	-226	66	-573
	(313)	(247)	(647)
Uncapped annual DI benefits ($)	163	187	127
	(302)	(382)	(485)
Annual indexed earnings ($)	-1,058	-2,223	509
	(922)	(1,230)	(1,386)
Age on January 1st, 2015	-.043	-.496	.694
	(.546)	(.723)	(.816)
Years on DI	-.276	-.041	-.621
	(.547)	(.746)	(.783)
Fraction females	.016	.012	.025
	(.027)	(.036)	(.041)
Fraction cohabitants	-.031	-.057	.008
	(.027)	(.036)	(.041)
Years of Schooling	.144	.034	.311
	(.125)	(.161)	(.195)
Number of Children	.027	-.045	.140
	(.074)	(.097)	(.113)
Joint F-test [p-value]	.464	.514	.677
Observations	7,443	4,403	3,040

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Standard errors (in parentheses) are clustered at the individual level and are robust to heteroskedasticity.

Notes: The table shows results from local linear regressions with a triangular kernel density and a bandwidth of $2,815 on each pre-determined covariate, except for the density of our running variable where we follow the optimal bandwidth calculation of McCrary (2008) ($2,470 for the full sample). The full sample includes fully disabled recipients awarded DI before the 1st of January 2015 with some earnings during January-May 2015 who were eligible to receive the information treatment (Column 1). Round numbers (in multiples of NOK 1,000 of PAE) are excluded. The stable (variable) earnings samples include individuals whose earnings variability measure is below (above) the sample median, where earnings variability is defined as the individual level SD/mean in January-May 2015. Maximum DI benefits are the initial DI benefits before being earnings tested. Annual indexed earnings summarizes earnings history before the disability onset. All variables are measured in 2015 dollars (NOK/USD = 7.5).

Table A.2: Specification checks

Sample	A. Stable Earnings				B. Variable Earnings			
	First stage	Report change	Earnings ($)	Obs	First stage	Report change	Earnings ($)	Obs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
i: Baseline RD estimate	.562***	.220***	-29	26,418	.684***	.018	-49	18,240
	(.027)	(.056)	(38)		(.029)	(.054)	(69)	
ii: With controls	.564***	.219***	-31	26,418	.682***	.022	-43	18,240
	(.026)	(.054)	(37)		(.028)	(.053)	(69)	
iii: Bias-corrected, robust	.557***	.247***	-12	26,418	.689***	.115	10	18,240
	(.037)	(.078)	(54)		(.042)	(.077)	(94)	
iv: With round numbers	.563***	.212***	-31	28,746	.685***	.071	42	20,298
	(.027)	(.054)	(36)		(.028)	(.051)	(66)	
v: Rectangular kernel	.564***	.197***	-38	26,418	.675***	-.025	-72	18,240
	(.025)	(.050)	(33)		(.027)	(.050)	(64)	

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Standard errors (in parentheses) are robust to heteroskedasticity.

Notes: This table presents the results of first stage regressions and 2SLS estimates for reporting changes in earnings to the SSA in 2015 using different regression specifications. All specifications use a bandwidth of $2,815, and all specifications use a triangular kernel except specification (v) which uses a rectangular kernel. The specification with controls includes the covariates included in Table 1. The specification with bias corrected estimates and robust standard errors follows Calonico *et al.*, 2014. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 who were eligible to receive the information treatment. Round numbers (in multiples of NOK 1,000 of PAE) are excluded except specification (iv). The stable (variable) earnings samples include individuals whose earnings variability measure is below (above) the sample median, where earnings variability is defined as the individual level SD/mean in January-May 2015.

Table A.3: Variability quantiles

	First stage (1)	Change Target Earnings (2)	Actual Earnings ($) (3)	Obs (4)
i: Fully stable	.728***	.274***	-37	5,988
	(.057)	(.099)	(43)	
ii: Relatively stable	.525***	.201***	-20	20,430
	(.031)	(.066)	(47)	
iii: Relatively variable	.680***	.016	-66	15,678
	(.031)	(.059)	(69)	
iv: Fully variable	.716***	.028	-12	2,562
	(.082)	(.138)	(262)	

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Standard errors (in parentheses) are robust to heteroskedasticity.

Notes: This table presents the results of first stage regressions and 2SLS estimates for reporting changes in target earnings to the SSA in 2015 using different regression specifications. All specifications use a bandwidth of $2,815, and all specifications use a triangular kernel except specification (v) which uses a rectangular kernel. The specification with controls includes the covariates included in Table 1. The specification with bias corrected estimates and robust standard errors follows Calonico *et al.*, 2014. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 who were eligible to receive the information treatment. Round numbers (in multiples of NOK 1,000 of PAE) are excluded except specification (iv). The stable (variable) earnings samples include individuals whose earnings variability measure is below (above) the sample median, where earnings variability is defined as the individual level SD/mean in January-May 2015.

Table A.4: 2SLS Estimates Using Alternative Measures of Variability

	A. Stable: Some wage reported as regular			B. Variable: All wage reported as variable		
	(1) First stage	(2) Change Target Earnings	(3) Actual Earnings ($)	(1) First stage	(2) Change Target Earnings	(3) Actual Earnings ($)
Estimate	.666***	.173***	-108*	.625***	.096*	39
	(.035)	(.066)	(61)	(.028)	(.056)	(52)
Dependent mean	.016	.218	686	.006	.252	570
p-value	<.001	.009	.076	<.001	.086	.451
Observations	2,091	2,091	12,546	3,559	3,559	21,354

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Standard errors (in parentheses) are clustered at the individual level and are robust to heteroskedasticity.

Notes: This table presents the average impacts of the information letter on an indicator for whether the person reports any expected changes in year-end earnings to the SSA as well as monthly earnings during July-December 2015. The first column shows the first-stage regressions, while the second and third present the 2SLS estimates for each outcome. We use a local linear regression using a triangular kernel density and a bandwidth of $2,815 on each side of the cutoff. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 with some earnings during January-May 2015 who were eligible to receive the information treatment. Round numbers (in multiples of NOK 1,000 of PAE) are excluded.

Table A.5: Differential Impact of Information Treatment Effects

	First stage	RD-DID Estimates: Change Target Earnings	RD-DID Estimates: Actual Earnings ($)	Obs
	(1)	(2)	(3)	(4)
i: Baseline model	-.122***	.202***	20	44,658
	(.040)	(.078)	(79)	
ii: With controls	-.118***	.205***	15	44,658
	(.038)	(.076)	(78)	
iii: With controls,	-.118***	.199***	12	44,658
industry & occupation FE	(.038)	(.076)	(78)	

*** significant at 1% level, ** significant at 5% level, * significant at 10% level

Standard errors (in parentheses) are clustered at the individual level and are robust to heteroskedasticity.

Notes: This table presents the differences in treatment effects using a differences in regression discontinuity design. See Table 2 for details of samples and variable definitions. Row (i) implements a parametric difference in regression discontinuity design, where we estimate a standard RD-DID model using the stable earnings sample as the treated individuals, where the variable earnings sample is the baseline sample. Row (ii) reports results using the covariates included in Table 1 as control variables, and row (iii) also includes 10 categories of industry and occupation fixed effects as controls.

Figure A.1: Information letter



Returadresse,
NAV HAUGESUND POSTBOKS 353 5501 HAUGESUND

Dato: 11. juni 2015

NAV har mottatt opplysninger om inntekten din

Fødselsnummer: Saksreferanse:

Opplysninger fra arbeidsgiver viser at den årlige arbeidsinntekten din kan bli høyere enn inntekten vi brukte til å beregne utbetalingen av uføretrygden din.

Dersom inntekten din i år overstiger 174 926 kroner skal utbetalingen av uføretrygden reduseres. Det lønner seg likevel å jobbe, fordi inntekt og uføretrygd vil være høyere enn uføretrygd alene. Selv om vi reduserer uføretrygden din, beholder du uføregraden du har fått innvilget.

Dette kan du gjøre

Vi sender deg dette brevet slik at du så tidlig som mulig kan melde fra om eventuell ny årlig forventet inntekt.

Forventer du at inntekten din i år ikke overstiger 174 926 kroner, trenger du ikke gjøre noe.

Dersom du forventer at inntekten i år overstiger 174 926 kroner, må du melde fra om den nye inntekten din. Dette kan du gjøre under menyvalget «Uføretrygd» når du logger deg inn på nav.no. Det er viktig at du melder fra om ny årlig inntekt slik at du får riktig utbetaling av uføretrygd.

NAV Forvaltning

Postadresse: NAV HAUGESUND // POSTBOKS 353 // 5501 HAUGESUND
Besøksadresse: ØVREGATA 126 // 5527 HAUGESUND
Tel: 55 55 33 33
nav.no

PE_UT_04_908

Dette kan NAV gjøre

Dersom opplysninger fra arbeidsgiver på et senere tidspunkt viser at inntekten din har oversteget 174 926 kroner, reduserer vi uføretrygden. Dette kan imidlertid være for sent til at du får riktig årlig utbetaling av uføretrygden din.

Du vil motta vedtaksbrev fra NAV dersom vi justerer uføretrygden din på grunn av endret inntekt.

Dersom du har fått for lite eller for mye utbetalt i uføretrygd, foretar vi et etteroppgjør. Dette gjør vi på høsten når likningen for året før er klar.

Har du spørsmål?

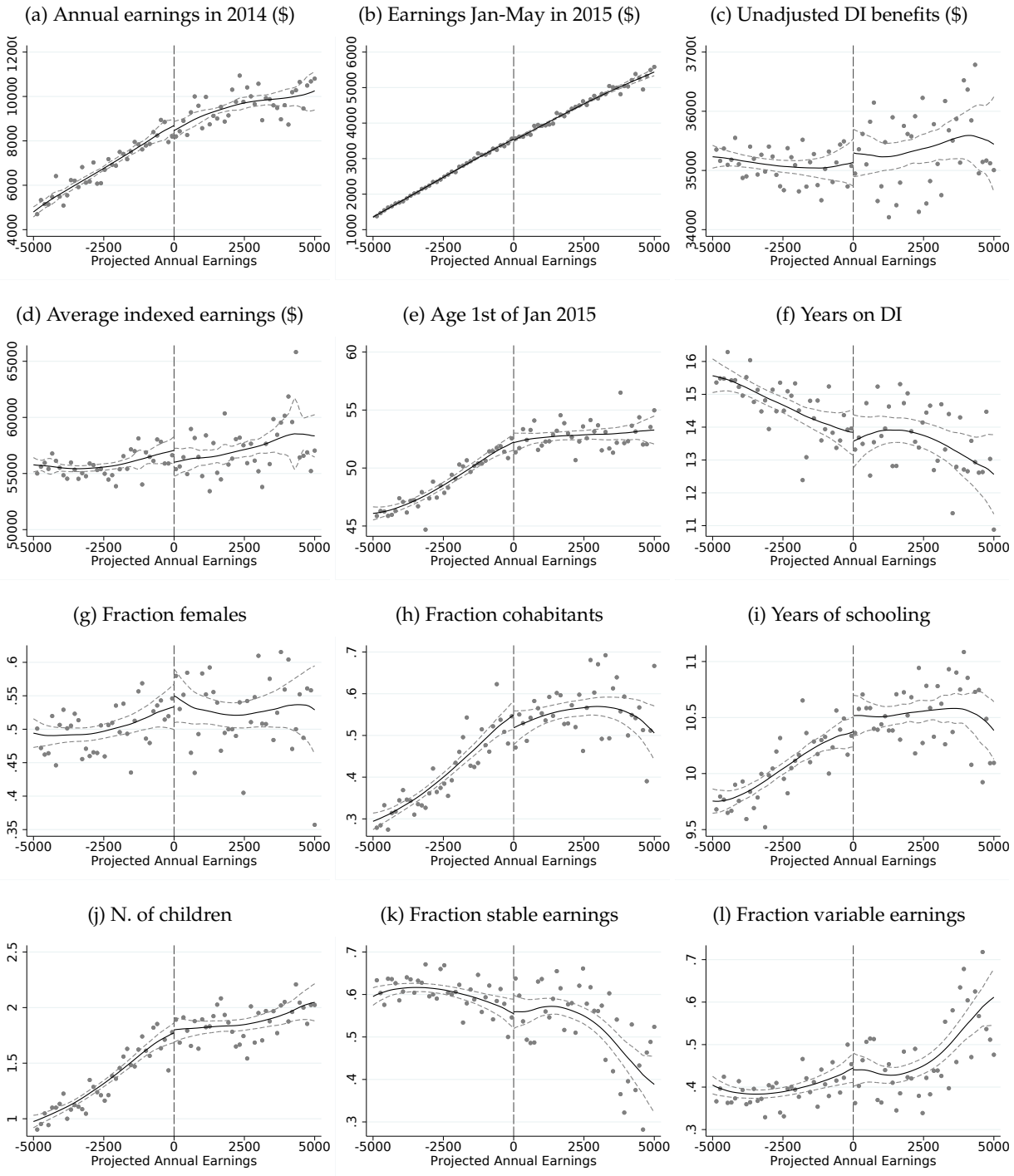
Kontakt oss gjerne på telefon 55 55 33 33. Du må alltid oppgi fødselsnummeret ditt når du tar kontakt med NAV. Da kan vi lettere gi deg rask og god hjelp.

Med vennlig hilsen
NAV Forvaltning

Side 2 av 2

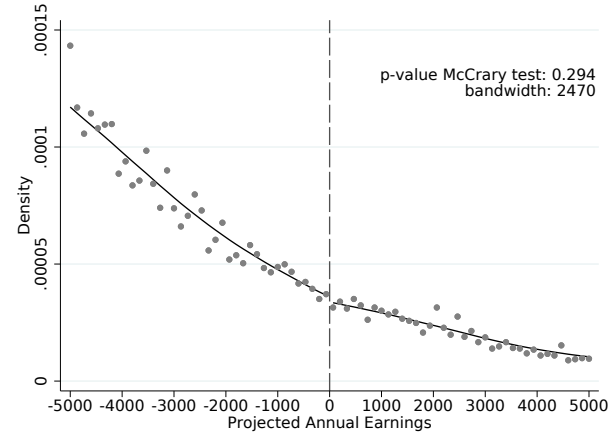
Notes: This is an example of an anonymized letter (in Norwegian) for a recipient working part time. **"NAV/SSA has received information about your income".** Personal identifier (removed), Case file (removed). 1st paragraph: The information from your employer shows that the annualized labor earnings can be higher than the earnings we used to calculate your benefit level. Second paragraph: If your earnings this year exceed X kroner, your benefit payments will be reduced. It still pays to work more, as earnings and benefits are higher than benefits alone. Even if we reduce your benefits, you will keep the disability rating you were awarded. **"This is what you can do"**. We send you this letter so you can prepare, and notify us as soon as you expect your annual income to increase. Fourth paragraph: If you do not expect your annual earnings to exceed X, you do not need to do anything. Fifth paragraph: If you expect earnings to exceed X kroner, you will have to report your new earnings. You can do this under the choice "disability benefits" when logging in to nav.no. It is important that you report your expected annual earnings to receive the correct amount of benefits. Page 2, first paragraph: **"This is what NAV can do"**. If the information provided by your employer at a later date shows that your earnings exceeded X, we will reduce your benefit payments. It may be too late to make sure the annual payment is correct. Second paragraph: You will receive a letter from NAV if we reduce your benefits due to the changes in the level of earnings. Third paragraph: If you have received too much or too low benefits, we will make a settlement later. **"Do you have any questions?"** Contact us at phone number Y. You will have to provide your personal identifier when contacting NAV. That way we can provide good and fast assistance.

Figure A.2: Characteristics at Cutoff



Notes: The figures show the unconditional means of each pre-determined covariate in $133 (NOK 1,000) bins as a function of distance to cutoff, and the estimated regression lines of local linear regressions with triangular kernel densities on each side of the cutoff using a bandwidth of $2,815 represented by the solid black lines. The dashed lines represent 95 percent confidence intervals. Uncapped DI benefits are the initial DI benefits before being earnings tested. Annual indexed earnings summarizes earnings history before the disability onset. The stable (variable) earnings samples include individuals whose earnings variability measure is below (above) the sample median, where earnings variability is defined as the individual level SD/mean in January-May 2015. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 with some earnings during January-May 2015 who were eligible to receive the information treatment. Round numbers (in multiples of NOK 1,000 of PAE) are excluded. All variables are measured in 2015 dollars (NOK/USD = 7.5).

Figure A.3: Distribution of the Assignment Variable and the McCrary Test

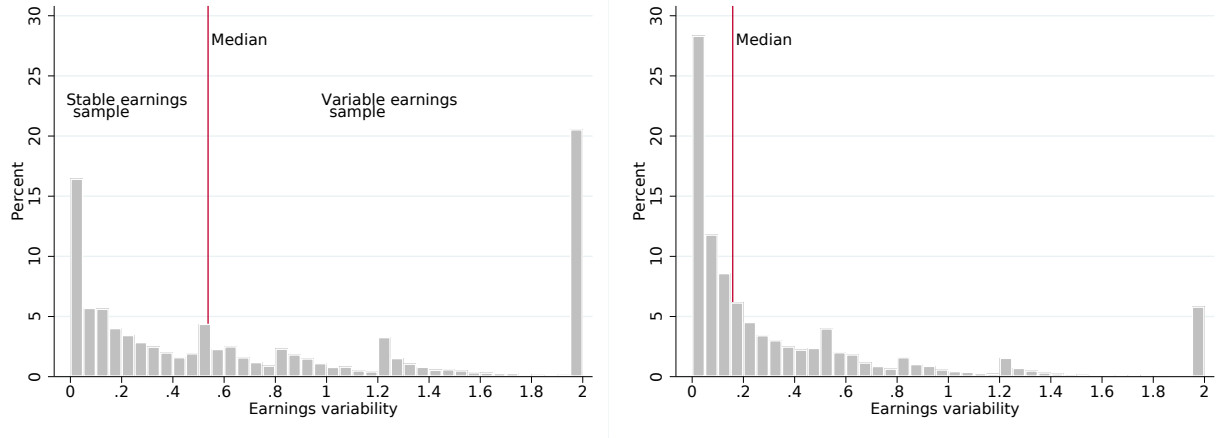


Notes: The figure shows the distribution of PAE in $133 (NOK 1,000) bins around the cutoff, and a smoothed density using a local linear regression with a triangular kernel density following the optimal bandwidth calculation of McCrary (2008) represented by the black solid line. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 with some earnings during January-May 2015 who were eligible to receive the information treatment. Round numbers (in multiples of NOK 1,000 of PAE) are excluded.

Figure A.4: Distribution of Earnings Variability January-May

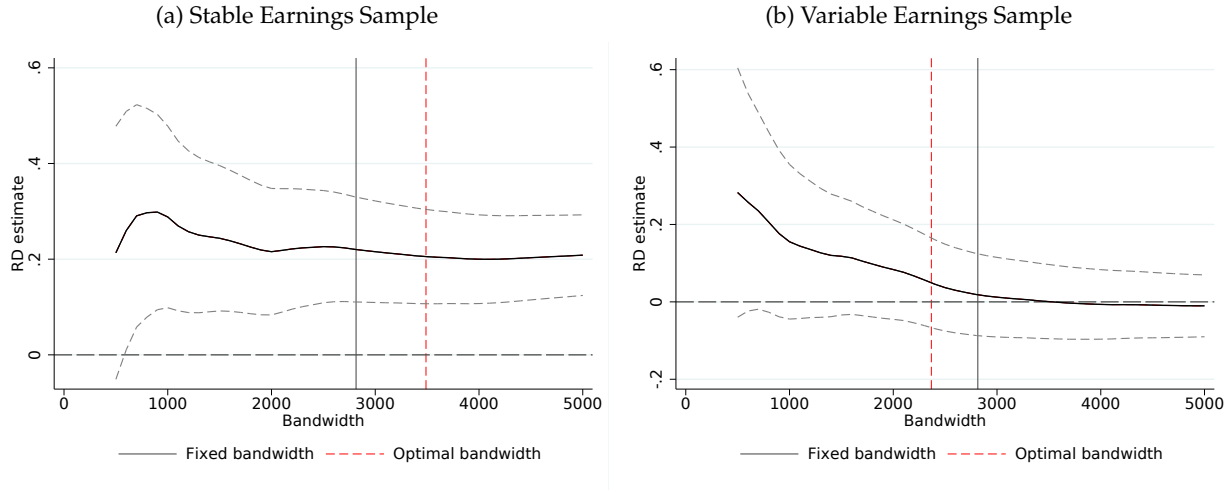
(a) Working DI Recipients

(b) Overall Population



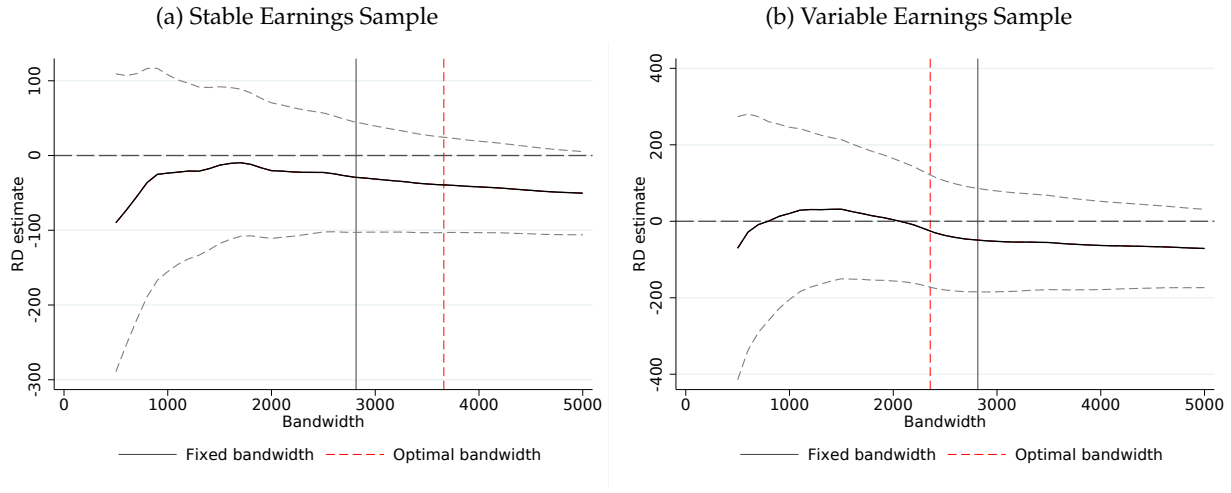
Notes: The figures show the distribution of earnings variability (coefficient of variation) defined as SD/mean (calculated at the individual level) in earnings January-May 2015 for the baseline estimation sample of employed DI recipients and the overall population.

Figure A.5: RD Estimates and Bandwidth Selection: Report Change in Target Earnings



Notes: The figures show the separate 2SLS estimates of individuals reporting changes in target earnings to the SSA in 2015 using a local linear regression with a triangular kernel density on each side of the cutoff for different choices of bandwidth (indicated on the horizontal axis). The grey solid line indicates the baseline bandwidth used in the main analyses, and the red dashed line indicates the optimal bandwidth for each sample following Calonico *et al.* (2014). The dashed lines represent 95% confidence intervals. The sample consists of fully disabled recipients awarded DI before 1st of January 2015 who were eligible to receive information treatment. The stable (variable) earnings samples include individuals whose earnings variability measure is below (above) the sample median, where earnings variability is defined as the individual level SD/mean in January-May 2015. Round numbers (in multiples of NOK 1,000 of PAE) are excluded.

Figure A.6: RD Estimates and Bandwidth Selection: Monthly Earnings ($)



Notes: The figures show the separate 2SLS estimates of monthly earnings (in $) during July-December 2015 using a local linear regression with a triangular kernel density on each side of the cutoff for different choices of bandwidth (indicated on the horizontal axis). The grey solid line indicates the baseline bandwidth used in the main analyses, and the red dashed line indicates the optimal bandwidth for each sample following Calonico *et al.* (2014). The dashed lines represent 95% confidence intervals. The sample consists of fully disabled recipients awarded DI before 1st of January 2015 who were eligible to receive information treatment. The stable (variable) earnings samples include individuals whose earnings variability measure is below (above) the sample median, where earnings variability is defined as the individual level SD/mean in January-May 2015. Round numbers (in multiples of NOK 1,000 of PAE) are excluded.

B Theory Appendix

The purpose of this appendix is to examine the effect of ambiguity about the tax schedule when a worker has an uncertain--from the current perspective, uncontrollable--future income. Recall that the worker's year end income is the sum of her choice, z; and the exogenous random variable $\eta \sim F[0, \bar{\eta}]$. The worker believes the kink in the tax schedule is located at $K + \varepsilon$, where $\varepsilon \sim G[-\bar{\varepsilon}, \bar{\varepsilon}]$ is a mean $\mu_\varepsilon \in [0, \bar{\varepsilon})$ random variable.

The worker's utility is of the quasi-linear form given in the text: $u(c, l) = c - \psi(l)$. She solves

$$\max_z \left\{ \mathbb{E}_{F,G}[z + \eta] - \hat{\tau}(z) - \psi\left(\frac{z}{w}\right) \right\},$$

where

$$\hat{\tau}(z) \equiv \mathbb{E}_{F,G}[\tau(z + \eta)] = \begin{cases} \Phi_1(z) & 0 < z \leq K - \bar{\varepsilon} \\ \Phi_2(z) & K - \bar{\varepsilon} < z \leq K + \bar{\varepsilon} \\ \tau_2(z + \mu) - K\Delta_\tau & K + \bar{\varepsilon} < z, \end{cases}$$

and where

$$\begin{aligned} \Phi_1(z) \equiv \tau_1 &\left[\int_{K-\bar{\varepsilon}-z}^{K+\bar{\varepsilon}-z} (\eta + z)(1 - G(z + \eta - K))\, dF(\eta) + \int_0^{K-\bar{\varepsilon}-z} (\eta + z)\, dF(\eta) \right] \\ &+ \tau_2 \left[\int_{K-\bar{\varepsilon}-z}^{K+\bar{\varepsilon}-z} (\eta + z)\, G(z + \eta - K)\, dF(\eta) + \int_{K+\bar{\varepsilon}-z}^{\bar{\eta}} (\eta + z)\, dF(\eta) \right] \\ &- \Delta_\tau \int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} (K + \varepsilon)(1 - F(K + \varepsilon - z))\, dG(\varepsilon), \end{aligned}$$

and

$$\begin{aligned} \Phi_2(z) \equiv \tau_1 &\int_0^{K+\bar{\varepsilon}-z} (\eta + z)(1 - G(z + \eta - K))\, dF(\eta) \\ &+ \tau_2 \left[\int_0^{K+\bar{\varepsilon}-z} (\eta + z)\, G(z + \eta - K)\, dF(\eta) + \int_{K+\bar{\varepsilon}-z}^{\bar{\eta}} (\eta + z)\, dF(\eta) \right] \\ &- \Delta_\tau \left[\int_{z-K}^{\bar{\varepsilon}} (K + \varepsilon)(1 - F(K + \varepsilon - z))\, dG(\varepsilon) + \int_{-\bar{\varepsilon}}^{z-K} (K + \varepsilon)\, dG(\varepsilon) \right], \end{aligned}$$

It is easy to check that $\hat{\tau}(\cdot)$ is continuously differentiable and strictly concave. Accordingly, the optimal choice, z^*, is pinned down by the first derivative of the objective. Differentiating the objective, we have

$$1 - \hat{\tau}'(z) - \frac{1}{w}\psi'\left(\frac{z}{w}\right),$$

Moreover,

$$\hat{\tau}'(z) = \begin{cases} \Phi_1'(z) & 0 < z \leq K - \bar{\varepsilon} \\ \Phi_2'(z), & K - \bar{\varepsilon} < z \leq K + \bar{\varepsilon} \\ \tau_2 & K + \bar{\varepsilon} < z, \end{cases}$$

where

$$\Phi_1'(z) = \tau_1 \int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} F(K+\varepsilon-z)\, dG(\varepsilon) + \tau_2 \left(1 - \int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} F(K+\varepsilon-z)\, dG(\varepsilon\right)$$

and

$$\Phi_2'(z) = \tau_1 \int_{z-K}^{\bar{\varepsilon}} F(K+\varepsilon-z)\, dG(\varepsilon) + \tau_2 \left(1 - \int_{z-K}^{\bar{\varepsilon}} F(K+\varepsilon-z)\, dG(\varepsilon\right).$$

We assume i. $\tau_2 < 1$, ii. $1 - \tau_2 - \frac{1}{w}\psi'(0) > 0$, and iii. $1 - \tau_2 - \frac{1}{w}\psi'\left(\frac{K-\bar{\varepsilon}}{w}\right) + \Delta_\tau \int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} F(\varepsilon+\bar{\varepsilon})\, dG(\varepsilon) < 0$. These conditions guarantee that there is an interior solution $z^* \in (0, K-\bar{\varepsilon})$ to the consumer's maximization problem. These assumptions are the economically natural ones: the first captures the obvious fact that the marginal tax rate when it is steepest should not be greater than 1; the second means that it is very cheap for the worker to work a little (if given the opportunity), and is a necessary condition for the problem to have a non-trivial solution (in which the worker works at all); and the third represents the notion that the worker's controllable labor is minute in relation to her aggregate rest-of-the-year uncertainty.

The first-order condition, which defines the worker's optimal labor z^* implicitly, is

$$1 - \tau_2 = \frac{1}{w}\psi'\left(\frac{z^*}{w}\right) - \Delta_\tau \int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} F(K+\varepsilon-z^*)\, dG(\varepsilon). \tag{2}$$

Giving the worker the informational treatment and making her aware of the kink's location yields the first-order condition

$$1 - \tau_2 = \frac{1}{w}\psi'\left(\frac{z_T}{w}\right) - \Delta_\tau F(K - z_T), \tag{3}$$

where the subscript T is a mnemonic for treatment. Our final, and main, result of this appendix is to establish that when the future income is sufficiently uncertain, the informational treatment has a negligible effect on the worker's choice of z. Before doing so, we establish a pair of other results. First, we relate the shape of the distribution over uncertain future income to over-or-under-supply of short-term labor. Defining the interval $S_F \equiv [K - \bar{\varepsilon} - z^*, K + \bar{\varepsilon} - z^*]$, where z^* is the solution to (4), we have

Proposition 1. *If F is convex on S_F, z^* is greater than z_T.*

Proof. By Jensen's inequality,

$$\frac{1}{w}\psi'\left(\frac{z^*}{w}\right) - \Delta_\tau \int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} F(K+\varepsilon-z^*)\, dG(\varepsilon) \leq \frac{1}{w}\psi'\left(\frac{z^*}{w}\right) - \Delta_\tau F(K+\mu_\varepsilon-z^*) \leq \frac{1}{w}\psi'\left(\frac{z^*}{w}\right) - \Delta_\tau F(K-z^*)$$

if F is convex (concave). This, plus the observation that the right-hand side of this is strictly increasing in z^*, establish the result. □

An easy sufficient condition for $z^* \geq z_T$ is for the density f to be single peaked, with the peak at some point greater than $K + \bar{\varepsilon}$. Note that if the average upward bias of η, μ_ε, equals 0 we have the result that a concave F (e.g., one with a single-troughed density) begets a smaller z^*as a result of the vagueness. However, if η's upward bias is strictly positive, this need no longer be so.

Our next result compares the worker's choice of z^* for a pair of distributions over future incomes F and $\hat{F}$. Letting $\hat{z}^*$ be the solution to (4) when the distribution is $\hat{F}$,

Proposition 2. *Let $\hat{F}$ be dominated by F in the mean-preserving rotation order, with rotation point $a \geq K - \bar{\varepsilon}$. Then $\hat{z}^* \geq z^*$.*

Proof. By definition

$$-\int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} F\left(K + \varepsilon - z^*\right) dG\left(\varepsilon\right) \geq -\int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} \hat{F}\left(K + \varepsilon - z^*\right) dG\left(\varepsilon\right),$$

and the monotonicity of the right-hand side of (4) completes the result. □

In short, a worker with more uncertain future income chooses to work more in the current, controllable period. We now state and prove our main result: if the uncertainty about future earnings is sufficiently large, correcting the misperception about the kink has little effect.

Proposition 3. *For any $\rho > 0$, there exists an $\alpha > 0$ such that if $F\left(K + \bar{\varepsilon} - z^*\right) - F\left(K - \bar{\varepsilon} - z^*\right) < \alpha$ (where z^* is the solution to (4) and z_T is the solution to (5)), $|z_T - z^*| < \rho$.*

Proof. By the monotonicity of F,

$$F\left(K - \bar{\varepsilon} - z\right) - F\left(K - z\right) \leq \int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} F\left(K + \varepsilon - z\right) dG\left(\varepsilon\right) - F\left(K - z\right) \leq F\left(K + \bar{\varepsilon} - z\right) - F\left(K - z\right).$$

Consequently, for any $\beta > 0$, there exists an $\alpha > 0$ such that if $F\left(K + \bar{\varepsilon} - z^*\right) - F\left(K - \bar{\varepsilon} - z^*\right) < \alpha$, $\left|\int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} F\left(K + \varepsilon - z^*\right) dG\left(\varepsilon\right) - F\left(K - z^*\right)\right| < \beta$.

By the FOCs,

$$\frac{1}{w}\psi'\left(\frac{z^*}{w}\right) - \Delta_\tau \int_{-\bar{\varepsilon}}^{\bar{\varepsilon}} F\left(K + \varepsilon - z^*\right) dG\left(\varepsilon\right) + \Delta_\tau F\left(K - z^*\right) = \frac{1}{w}\psi'\left(\frac{z_T}{w}\right) - \Delta_\tau F\left(K - z_T\right) + \Delta_\tau F\left(K - z^*\right).$$

Consequently, for any $\beta > 0$, there exists an $\alpha > 0$ such that if $F\left(K + \bar{\varepsilon} - z^*\right) - F\left(K - \bar{\varepsilon} - z^*\right) < \alpha$,

$$\left|\frac{1}{w}\psi'\left(\frac{z^*}{w}\right) - \Delta_\tau F\left(K - z^*\right) - \left(\frac{1}{w}\psi'\left(\frac{z_T}{w}\right) - \Delta_\tau F\left(K - z_T\right)\right)\right| < \beta.$$

By the continuity and strict monotonicity of $\frac{1}{w}\psi'\left(\frac{\cdot}{w}\right) - \Delta_\tau F\left(K - \cdot\right)$, for any $\rho > 0$, there exists a $\hat{\beta} > 0$ such that if $\beta < \hat{\beta}$, $|z_T - z^*| < \rho$. □

Because the binary distribution with support $\{0, \bar{v}\}$ and mean μ is a mean-preserving spread of all distributions supported on $[0, \bar{v}]$ with mean μ, we immediately have the following corollary.

Corollary 1. *If the distribution over future future earnings is sufficiently dispersed, the effect of the information treatment on labor is negligible.*

Proof. This follows by observing that for any distribution supported on $[0, \bar{v}]$ with mean μ that is sufficiently close (in the total-variation distance) to the binary distribution with support $\{0, \bar{v}\}$ and mean μ, the value $F\left(K + \bar{\varepsilon} - z\right) - F\left(K - \bar{\varepsilon} - z\right)$ must be negligible for all $z \in [0, K - \bar{\varepsilon})$. □