DISCUSSION PAPER SERIES

Labor Supply Responses to Learning the Tax and Benefit Schedule

Andreas R. Kostøl
Andreas S. Myhre

DISCUSSION PAPER SERIES

Labor Supply Responses to Learning the Tax and Benefit Schedule

Andreas R. Kostøl
Arizona State University, Statistics Norway and IZA

Andreas S. Myhre
Statistics Norway

NOVEMBER 2020

ABSTRACT

Labor Supply Responses to Learning the Tax and Benefit Schedule[1]

While optimization frictions have been shown to attenuate earnings responses to financial incentives, less is understood about the individual factors shaping the response. The main contribution of this paper is to separately quantify the role of learning the tax and benefit schedule versus other kinds of frictions. A unique combination of notches in the tax and benefit schedule and an information policy in a Norwegian welfare reform facilitate our study. The presence of notches allows us to measure overall frictions. Quasi-random assignment of a letter targeting misperceptions about the slope and locations of benefit phase-out regions allows us to pin down the role of information. Our analysis delivers two main findings. First, about 50% do not behave as predicted by standard labor supply models, and optimization frictions are particularly prevalent when financial incentives change. Without adjusting for these overall frictions, estimated elasticities would be attenuated by at least 70%. Second, the observed elasticity among those who receive the information letter is at least twice as large as among the non-informed, suggesting governments can partly offset the attenuation with information policy. Our calculations suggest misperceptions of the tax and benefit schedule account for two-thirds of the attenuation in earnings responses to financial work incentives. The findings have important implications for the effectiveness of tax and transfer policy.

Corresponding author:
Andreas Ravndal Kostøl
Statistics Norway (SSB)
PB 8191 Dep.
0033 Oslo
Norway

E-mail: kos@ssb.no

1 Introduction

A well-established fact from labor economics is that optimization frictions attenuate the earnings response to changes in financial incentives (e.g., Chetty, 2012 and Kleven & Waseem, 2013). Much less is known about whether the factors originate from the demand side or from supply-side constraints in the labor market.[1] In their review of the empirical evidence, for example, Saez *et al.* (2012) argue that "taxpayers may not be aware of the minute details of the tax code, and hence might not respond to very localized changes in their marginal tax rate situation". Distinguishing between these factors matters for whether governments can shape behavioral responses with policy (see, e.g., Slemrod & Kopczuk, 2002) and for the design of optimal tax and transfer policies (e.g., Farhi & Gabaix, 2020). Yet, unpacking the "black box" of optimization frictions has proven difficult due to measurement and identification challenges. To make progress, researchers need large-scale data on labor supply under different tax regimes including measures of how incentives are perceived and other adjustment costs. On top of these measurement hurdles, separating a person's ability to learn complex tax incentives or negotiate with employers from the person's underlying labor market productivity is hard. Without addressing this selection a bias of unknown sign and size will hamper any conclusions drawn from the data.

The contribution of this paper is to quantify the relative importance of information about financial incentives versus other types of frictions in shaping earnings responses. Our study overcomes the measurement and identification challenges by drawing on key advantages from the Norwegian context. The first is notches in the disability insurance (DI) system, which allows us to measure the prevalence of overall optimization frictions from dominated regions where part-time employed DI recipients are better off by working fewer or more hours. The second is an information policy targeting recipients' perceptions about a new kink in the tax and benefit schedule. The policy was implemented in June 2015 and informed recipients about the location and the slope of the kink. However, the social security administration (SSA) decided that only individuals likely to locate above the kink would receive the letter. To implement the targeted intervention, the SSA used monthly earnings records from January to May 2015 to forecast annual earnings. Our research design uses forecast errors due to fluctuations in monthly payments and electronic reporting by employers generating quasi-random variation in information letters. We use this variation to see whether the earnings elasticity is shaped with information policy by comparing bunching behavior around the kink with additional information (i.e., the treated) to a baseline information case (i.e., the non-treated).

The informational treatment was contained in a letter detailing the location and the slope of a new kink in the annual tax and benefit schedule.[2] We view the treatment as changing perceptions of marginal incentives around the DI recipient's current earnings level. Survey evidence indicated that most recipients were aware of a change in their tax and benefit schedule but did not fully understand how the benefits would be phased

---

[1] A long literature discusses the implications of hours constraints (see e.g., Pencavel, 1986; Altonji & Paxson, 1988; Dickens & Lundberg, 1993; and Blundell & Macurdy, 1999), and more recently the role of imperfect information (see e.g., DellaVigna, 2009 and Saez, 2010). Existing empirical evidence is limited to the effects of information on take-up of the EITC (see e.g., Chetty & Saez, 2013, Chetty *et al.*, 2013 and Bhargava & Manoli, 2015) and whether an information brochure aiming to correct misperceptions about the Social Security earnings test could affect the labor supply of old-age retirees (Liebman & Luttmer, 2012). None of these studies are able to pin down the relative importance of information to the overall attenuation of the response to incentives.

[2] It also encouraged DI recipients to update annual earnings expectations on a web portal with access to an application that allowed a person to simulate disposable income for different gross earnings levels.

out with their labor earnings. If the information treatment updates perceptions toward the actual schedule and informed recipients are primarily responsive along the intensive margin, we would expect increased bunching around the new annual kink. The unique combination of the information treatment and dominated regions allows us to identify the role of information about financial incentives and overall frictions in shaping earnings responses. To pin down the relative role of information vs. other kinds of frictions, we assume the structural elasticity is policy-invariant; that is, an agent's preferences over leisure and consumption do not depend on the strength of incentives. The role of information is then pinned down by comparing the elasticity change due to the information treatment in 2015 with the structural elasticity identified from the notch in 2014.

Our main empirical findings can be summarized with three broad conclusions. First, we find that about 50 percent do not behave as predicted by standard labor supply models, and that optimization frictions are particularly prevalent when financial incentives change. Without adjusting for these overall frictions, estimated elasticities would be attenuated by at least 70 percent. Second, we show that governments can offset part of this attenuation in behavioral response with information policy. Among the non-treated, we find the observed elasticity falls from 0.2 to 0.06 after the tax and benefit schedule change, whereas the earnings elasticity equals 0.15 among those who received the information letter. These four elasticities imply about two-thirds of the increase in attenuation from 2014 to 2015 is due to misperceptions of the tax and benefit schedule, and the remainder is due to other adjustment frictions. Third, we provide several pieces of evidence suggesting our findings reflect real labor supply responses to information about financial incentives. We find that the employment rate from July to December falls by 17 percent for the treated relative to the control group, i.e., those not informed. Using detailed information on contracted hours, and fixed and variable pay, we provide further evidence suggesting that workers adjust by either renegotiating work contracts with their current employer or working fewer hours.

Recognizing that the information letters, in practice, do not fully correct for imperfect information, we view our approach as identifying a lower bound on the role of information in shaping earnings responses. We take several additional steps to assess our research design's validity. One concern is that our conclusion may be specific to our setting, where hours constraints, for example, are less likely to constrain adjustments for part-time workers than full-time workers. We address this concern by assessing whether the response varies across industries with varying flexibility in hours worked, but do not detect significant differences in treatment effects. A natural question is whether the treatment effect persists or reflects a temporary change in behavior to a "nudge". We exploit the time-dimension in our data to assess this question and find the treatment effects in 2015 persisted in 2016. This persistence supports the view that the information treatment affects earnings primarily from learning the tax and benefit schedule and not by other short-lived behavioral biases (see, e.g., Levitt, 2020). Finally, we find that the main conclusions from our bunching analysis hold across several assumptions about the counterfactual earnings distributions, and show that the information letters' assignment is unrelated to earnings distribution and trend before the change in 2015 took place.

Our paper is closely related to a small number of studies that experimentally control the type of information tax filers receive (e.g., Liebman & Luttmer, 2012 and Chetty & Saez, 2013), and how mobility across areas with varying knowledge about the earned income tax credit affects tax refunds (Chetty et al., 2013).

We contribute to this line of research by showing that governments can shape earnings elasticities by information policy and by pinning down the relative importance of information for overall attenuation in earnings responses.[3] Our paper also relates to the literature on bunching at kinks and notches, beginning with Saez (2010), Chetty *et al.* (2011), and Kleven & Waseem (2013).[4] In terms of understanding the factors that shape bunching responses, we contribute by documenting a sharp increase in the number of nonoptimizers after the locations of kinks and notches change. This matters for the interpretation of evidence on earnings elasticities deriving from tax reforms (see, e.g., Saez *et al.*, 2012). The evidence also highlights a difference between temporal factors (i.e., adjustment costs and information friction) and more permanent factors (i.e., preferences or ability) underlying optimization frictions. Relatedly, Gelber *et al.* (2019) document attenuated responses to the elimination of the earnings test in the US. Our evidence echoes this evidence, underscoring the difference between short vs. long-run responses to financial incentives.

Our paper also relates to Kline & Tartari (2016), who study labor supply responses to welfare reform with adjustment frictions, and other empirical studies of information and complexity in labor markets. Abeler & Jäger (2015) show that agents systematically under-react to complex incentives in an experimental setting, and Rees-Jones & Taubinsky (2019) document that individuals tend to use the average tax to forecast annual incentives on hourly or weekly income. Morrison & Taubinsky (2019) test for costly attention to incentives, and find that people increase the accuracy of their assessment of incentives when the stakes increase.[5] We contribute to these studies in two ways. First, using cross-sectional variation in notches' size, we find that the fraction of nonoptimizers does not vary with incentives' strength. This evidence is consistent with adjustment costs that are zero or prohibitively high to respond, and with models where nonresponse is explained by a lack of information about the notch. Second, our evidence from the informational treatment is consistent with models where agents either underestimate the marginal tax rate and where agents are inattentive to kinks' existence.

Finally, our findings have broad and specific policy implications. Our evidence lends broad support to models in public finance where the elasticity of taxable income is subject to policy control (e.g., Slemrod, 1994, Slemrod & Kopczuk, 2002 and Farhi & Gabaix, 2020). In stark contrast to classical work on optimal tax and transfer policy, where behavioral elasticities characterize the tradeoff between redistribution gains and the incentive costs of high taxes and benefits, these models suggest the efficiency losses from redistribution can be limited while strengthening the insurance from transfer programs. Our specific focus on the DI

---

[3]Chetty & Saez (2013) study whether tax preparers in private firms affect the bunching around the EITC kink. On average, they find no evidence of the information provided by tax preparers on earnings. Liebman & Luttmer (2012) run a field experiment among retired workers, and find that an information brochure increased labor force participation by five percent among the elderly. The remaining evidence on salience effects is limited to alcohol and consumer goods (Chetty *et al.*, 2009), commuting tolls (Finkelstein, 2009) and cigarette consumption (Goldin & Homonoff, 2013). While our evidence highlights large attenuation in the intensive margin of labor supply, our findings are also consistent with information frictions to explain the absence of extensive margin responses to expansions of the EITC (Kleven, 2019).

[4]The bunching approach has been subsequently used to study the earnings test in social insurance (Gelber *et al.*, 2019), impacts of minimum wages (Harasztosi & Lindner, 2019; Cengiz *et al.*, 2019), inter-temporal responses to mortgage contracts changes (Best *et al.*, 2019), transaction taxes in housing markets (Kopczuk & Munroe, 2015; Best & Kleven, 2017), and corporate taxation (Best *et al.*, 2015).

[5]A large empirical literature studies how information and complexity affects a broader range of economic decisions. These decisions include how attention affects savings decisions (Jones, 2010), and over-withholding of tax liabilities (Jones, 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.

system speaks to a debate among academics and policymakers on the effectiveness of improving financial work incentives to induce DI recipients to work part-time.[6] While some researchers find some policies to be effective, Schimmel *et al.* (2011) find minimal earnings responses to shifts in the location of a notch under the US social security DI program, suggesting optimization frictions limit the scope for success.[7] However, our findings suggest the "$1 for $2 offset" policy proposal – that would replace the notch by a kink – may be much more successful and induce larger labor supply responses if an informational treatment accompanies the reform.

The remainder of the paper is organized as follows. Section 2 discusses institutional setting and Section 3 describes the data we use. Section 4 motivates our empirical framework with a static model of labor supply and Section 5 performs an observational analysis of bunching and nonoptimization. Section 6 documents how the information treatment shapes earnings responses, Section 7 assesses the labor supply margins through which the information treatment's effect operates, and Section 8 concludes.

2   Policy Environment

This section describes Norwegian Disability Insurance (DI) program, its work incentives and the informational setting.

2.1   The Norwegian DI System

The Norwegian DI program is designed to provide partial earnings replacement to all workers below retirement age who cannot 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 calculates a worker's average indexed annual earnings (**AIE**).[8] Like other European DI programs, the Norwegian system distinguishes between total disability awards and partial awards that permit beneficiaries to use their residual work capacity. Since the inception of the Norwegian DI program in 1967, beneficiaries can earn up to a substantial gainful activity (**SGA**) threshold without losing any benefits.[9]

---

[6]Over the past 50 years, DI rolls steadily increased from below 1% to over 5% of the US adult population, 1% to 7% in the UK, and 2% to almost 10% in Norway (for a review, see Autor & Duggan, 2006). This rise has led to several attempts to induce DI recipients to work part-time by improving financial work incentives; for example, the US "$1 for $2 offset" policy proposal is meant to reduce caseloads by increasing the outflow. In our setting, part-time employed DI recipients keep approximately $1 for every $3 in earnings that they accumulate above the substantial gainful activity (SGA) threshold.

[7]Weathers & Hemmeter (2011) study the effects of a $1 for $2 earnings test among DI recipients who self-select into a pilot project, but are randomly assigned to the return-to-work program and the baseline system, including a notch at the SGA level. They find a 25 percent increase in employment among a group likely to be well informed given the self-selection into the program. Kostol & Mogstad (2014) study the impact of a similar return-to-work program in Norway that was provided randomly among existing recipients around an exogenous cutoff and find that employment impacts rise from 3 to 9 percentage points over the first three years after the change. Ruh & Staubli (2019) study the Austrian DI system and estimates a structural elasticity of 0.25 using bunching around notches. Similarly, Zaresani (2020) finds evidence of substantial adjustment costs in the Canadian DI system.

[8]Past wages are indexed to present wages using a deflator equal to the average wage growth in the economy. The years with the lowest earnings are excluded, and the proportion of income replaced falls with the level of previous earnings.

[9]Kostol & Mogstad (2014) summarize differences relating to demographics and replacement rates between Norway and the US. In terms of work incentives, SGA thresholds were similar in both countries (approximately $12,000 per annum in Norway and $13,000 per annum in the United States). There are two key differences. First, the SGA threshold is at the annual level in Norway, but at the monthly level in the US Social Security Disability Insurance (SSDI) system. Second, in contrast to the partial DI system in Norway, a person earning above the US's SGA amount is no longer eligible for benefits. A recent US policy proposal – known as

The SGA threshold plays a key role in determining the financial work incentives.[10] While the SGA amount has been adjusted every year to account for average wage growth, the first (real) change to the SGA threshold in Norway happened in May 1997, where the SGA level increased from $6,000 to $10,000. The SGA amount was further increased by an incremental $2,000 to $12,000 in 1998. These changes are summarized in the first row of Table 1 and illustrated by the first two long-dashed lines in Figure 1. The solid black lines illustrate the tax and benefit schedules in 1996, and the dashed line represents the schedules in 1997 and 1998. The figure also illustrates the discontinuous increase in tax liability at the SGA threshold – the notch – which creates a strong incentive to keep earnings below the SGA or above the upper limit of the dominated region, represented by the two vertical short-dashed lines to the right.[11]

Figure 1: Changes in the SGA Thresholds
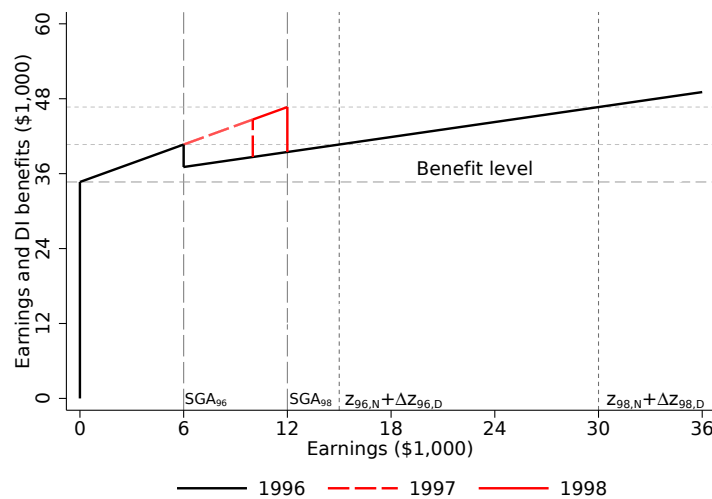
Notes: The solid black lines represent the budget sets for recipients under 1996 rules, and the red dashed lines represent the budget sets that applied to recipients in 1997 and 1998. $z_{t,N} + \Delta z_{t,D}$ is the upper bound of the average dominated region in 1996 and 1997. The calculations are based on the sample of DI recipients with full benefits in the period 1997 to 2003. The changes are summarized and described in Table 1.

2.2 Benefit Phase-Out

A unique feature in the Norwegian DI system has been the co-existence of two sets of rules governing how benefits are phased out. At the end of 2004, the Social Security Administration (SSA) decided that recipients who had been awarded DI before January 1st of 2004 were eligible for a kinked phase-out of DI benefits (see Kostol & Mogstad (2014) for details). Ten years after the change, in December 2014, about half of all

---

the $1 for $2 benefit offset – would eliminate the notch in recipients' budget sets and replace the notch encouraging workers with residual work capacity to engage in the labor force (i.e., the Benefit Offset National Demonstration project).

[10]Earnings up to this point are subject to income taxation only and are exempt from benefit offset rules. Before 2015, the income tax rate on earnings is 3 percent higher than for DI benefits. After 2015, the income tax rates on earnings and benefits are the same. We disregard dependent benefits for the sake of simplicity and with minimal loss of generality about the expected impacts of the return-to-work program.

[11]Before the outward shift of the notch in 1997, the dominated region included earnings from the SGA threshold to $15,000, denoted by the dashed line. After the shift, the dominated earnings region increased from a $9,000 range to an $18,000 range, up to an upper limit of $30,000, denoted by the rightmost dashed line. By comparison, the average earnings of DI recipients before disability onset was about $50,000.
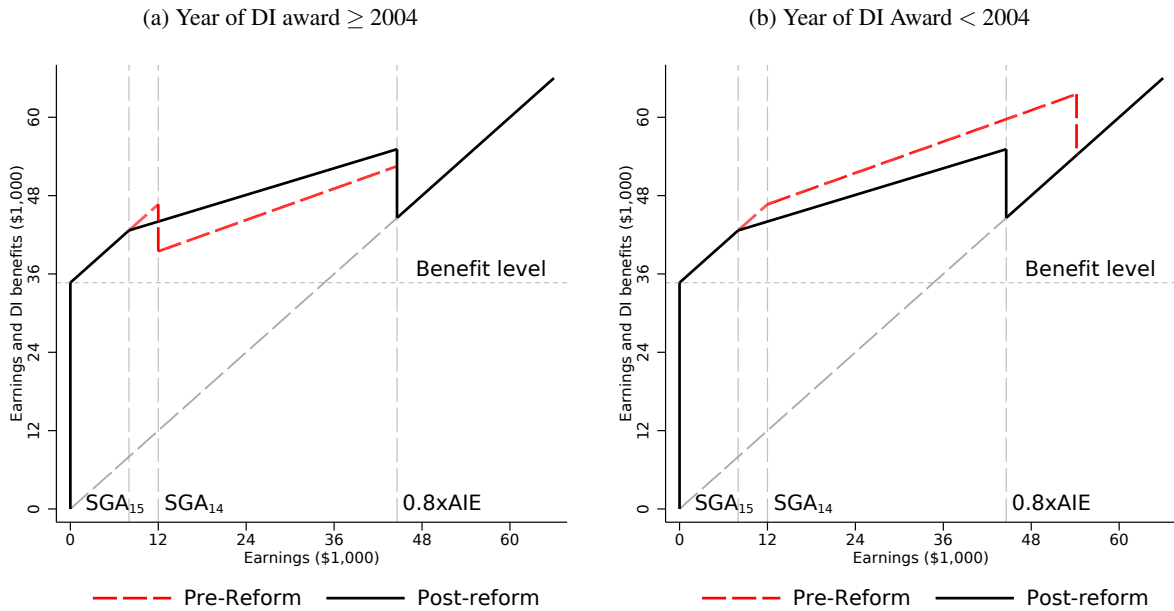
DI recipients faced a kink, while the other half faced a notch when their earnings reached the SGA level.

Under the notch regime, the benefit phase-out is described by b_N in the equation below. The rules create a discontinuous reduction of size T in benefits and very high marginal tax rates from working one extra hour at the notch. After the notch, there is a τ_b reduction in benefits for every dollar in earnings which equals about 60 percent for the average recipient. When earnings exceed the maximum permitted amount, equal to 80 percent of a person's previous indexed earnings capacity, $N_E = 0.8 \cdot AIE$, the person is automatically disenrolled from the program. We illustrate the notched budget constraint for the average DI recipient by the dashed line in Figure 2a. Under the kink regime, the discontinuous fall in benefits at the SGA notch is eliminated, and the maximum permitted earnings amount is increased to N_e. The dashed line in Figure 2b illustrates the kinked budget constraint and the exact benefit phase-out is described by b_K in the equation below.

$$
b_N = \begin{cases} b^0 & \text{if } z \leq SGA \\ b^0 - \tau(z - SGA) - T & \text{if } SGA < z \leq N_E \\ & \text{where } T = \frac{SGA}{AIE}b^0, \tau_b = \frac{b^0}{AIE} \\ 0 & \text{if } z > N_E \\ & \text{where } N_E = 0.8 \times AIE \end{cases}
\qquad
b_K = \begin{cases} b^0 & \text{if } z \leq SGA \\ b^0 - \tau(z - SGA) & \text{if } SGA < z \leq e \\ & \text{where } \tau_b = \frac{B^0}{AIE} \\ 0 & \text{if } z > N_e \\ & \text{where } N_e = 0.8 \times (SGA + AIE) \end{cases}
$$

Figure 2: Changes in the Tax and Benefit Schedule

(a) Year of DI award ≥ 2004 (b) Year of DI Award < 2004

Notes: The solid black lines represent the budget sets for recipients under current rules and the red dashed lines represent the budget sets that applied before 2015 (see Kostol & Mogstad, 2014 for a detailed description of these two programs). To compute DI benefits and AIE, we use the average levels of all fully disabled DI recipients in January 2015. With minimal loss of generality, we disregard income taxation and dependent benefits. The changes are summarized and described in Table 1.

The last noteworthy change replaced the notch with a kink for everyone and reduced the SGA threshold from \$12,000 to \$8,000.[12] The change in the kink's slope and location in 2015 is illustrated by the solid lines

---

[12]The new SGA level of \$8,000 applied until 2018 for recipients awarded DI before January 1st, 2015. After 2018, and for recipients awarded DI after January 1st, 2015, the new SGA level was set to approximately \$4,800.

in Figure 2a and 2b , where the marginal tax rate on earnings between SGA_{14} and SGA_{15} increased from zero to about 66 percent.[13] The new rules can be characterized by the phase-out equation b_K with two minor adjustments. The benefits level increased to compensate for the higher income tax rate. This change leads to a slightly higher phase-out rate for earnings above the new SGA level. The second was that the maximum permitted amount was reduced to N_E. Table 1 summarizes the relevant changes in the financial incentives.

Administration of the Benefit Phase-out.   There are two ways in which DI benefits are phased out. In-dividuals can report earnings expectations directly to the SSA, which leads to immediate adjustments to benefits. The other is by ex-post adjustments. Before 2015, these ex-post adjustments were made after the DI program received information from the tax authorities. The DI program typically received this informa-tion around August in the following calendar year. After 2015, employers reported income monthly, which meant that the DI system would start phasing out benefits once the cumulative monthly earnings exceeded the annual SGA amount. With monthly reporting, this information would reach the DI system earlier and at a higher frequency.

Table 1: Timeline of Reforms

Dates:	Jan 1967	May 1997	Jan 1998	Dec 2004	Jan 2015
SGA level:	$6,000	$10,000	$12,000	$12,000	$8,000
Incentive:	Notch	Notch	Notch	Kink replaces notch (awards < 1.1.2004)	Kink

Notes: This table summarizes the welfare-to-work reforms in the Norwegian disability insurance (DI) system from 1967 to 2015. The changes in the SGA levels are represented by Figure 1, and the notch versus kink tax and benefit schedules are presented in figures 2a and 2b. SGA amounts represented at 2015 levels are adjusted using the average wage growth in the economy. All variables are measured in 2015 dollars (NOK/\$ = 7.5).

2.3   Informational Setting

To characterize the knowledge about the new benefit phase-out in 2015, the SSA administered a survey among existing DI recipients at the end of 2014. The main finding was that most recipients knew about the changes to their tax and benefit schedule in 2015. The majority of respondents were aware that benefits would be taxed as earnings in 2015 and agreed to the statement that it will always pay to work more (i.e., kinked phase-out in 2015; see Section 2.2). However, the survey also revealed that many did not fully understand the extent to which the benefits would be phased out with their labor earnings. Only 34 (27) percent of respondents with (no) positive earnings were aware of how the changes in 2015 would affect their economic circumstances. The survey's main findings are summarized in Appendix Table A.1.

To target misperceptions about the new tax and benefit schedule, the SSA decided to issue information letters in May 2015. The information letter was sent by regular mail to a recipient's residential address and included SSA's emblem, as imprinted on standard SSA payment checks. The letter informed individuals

---

[13]The marginal tax rate above notch increased by approximately six percentage points because gross benefits were increased to compensate for being taxed at the same rate as labor earnings. Hence, for every \$1 above the SGA, benefits were offset according to the replacement ratio. Since the replacement ratio was slightly higher after 2015, the marginal tax rate for earnings above the SGA was higher.

about i) the exact location of the kink (e.g. $K = SGA_{15}$ in Figure 2a), ii) that it would always pay to work more (i.e., the elimination of the notch), and iii) encouraged individuals to report any expected change in annual earnings to the SSA. Recipients were also encouraged to use a web portal administered by the SSA. The portal included a micro-simulation tool allowing recipients to simulate the after-tax income for any level of earnings. An example of the information letter is displayed in Appendix Exhibit A.10.

However, the social security administration (SSA) decided that only individuals likely to locate above the kink by December 2015 would receive the letter.[14] To implement the information policy, the SSA used monthly earnings data reported directly from employers to project whether annual earnings would exceed the annual kink.[15] To forecast annual earnings, the SSA collected information about recipients' earnings for the first five months of the year using actual wage payments in January and February and earnings from March to May to project earnings for the remainder of the calendar year. Overweighing earnings from March to May meant recipients with high earnings these months were more likely to receive the letter than individuals whose earnings were below their annual average in these months.

3 Data

This section describes the administrative data sources, our main analytical samples and key variables.

3.1 Data Sources

Our empirical analysis combines several administrative data sources linked by unique and anonymized identifiers for every resident individual and employer. The administrative nature of our data reduces the extent of measurement errors in wages and employment relationships. 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). Since administrative data are a matter of public record, there is no attrition due to nonresponse or non-consent by individuals or firms. Individuals can only exit these data sets due to natural attrition (i.e., death or out-migration).

3.2 Variables

Our primary outcome variable is labor earnings, which we observe at monthly frequency from January 2015 and onward but only at the annual level before 2015. The main advantage of the monthly data is that sources of income are reported regularly by every employer and the SSA, and are continuously updated as new

---

[14]Individuals who had informed SSA about expected annual earnings above SGA would not receive the letter. Individuals with cumulative earnings above the SGA in May 2015 were not eligible for the information letter. See the description of the administration of the benefit phase-out in Section 2.

[15]The projected annual earnings (PAE) is defined as $\hat{z}_i^{15} = \sum_{m=1}^{2} z_{im} + 3 \cdot \sum_{m=3}^{5} z_{im}$ where z_{im} is earnings for individual i in month m. Earnings in March, April, and May were used to forecast the annual earnings. Moreover, since the SSA used eleven months, they targeted individuals who would reach the annual kink by the end of November. This policy design accommodated an adjustment in the "last" month of the year, provided the information letter contained relevant information. To the extent that individuals' annual earnings were predictable, they could start re-adjusting annual earnings (by negotiating fixed hours contract, etc.) in July.

files from employers are received. The data files include information about contracted hours, hourly wages, bonuses, and other taxable benefits, and allows us to distinguish between bunching at kinks due to strategic reporting of income from self-employment and other types of behavioral responses. The monthly files from the SSA include cash payments from different types of transfer programs. The SSA data also includes records of whether a person received a letter in June 2015 that informed DI recipients about changes in the financial work incentives.

Finally, we link several characteristics of DI recipients to our estimation file, including the date of award, whether the award was for partial or full DI benefits; the age, gender, prior and current occupation, educational attainment, and household information of recipients.

3.3 Samples

We consider two samples for our empirical analysis. The first sample includes individuals deemed fully disabled by the SSA during the period from 1993 to 2003 to study shifts in the notch location in 1997 and 1998. The second sample considers individuals engaged in the labor market during the period from January to May 2015. We exclude DI recipients aged above 66 due to eligibility for old-age retirement benefits beginning at age 67. We further restrict the sample to individuals who were deemed fully disabled by the SSA due to a lack of information on the kink's exact location among the partially disabled.[16]

---

[16]We also restrict to awards from before January 1, 2015 because recipients awarded benefits in 2015 or later faced a different set of work incentives.

Table 2: Summary Statistics in 2015

Sample	Full sample of		Main Analytical Sample, After Introduction of Kink in 2015					
	DI recipients		Any income		Notch in 2014		Kink in 2014	
Column:	(1)		(2)		(3)		(4)	
Earnings:	mean	sd	mean	sd	mean	sd	mean	sd
Monthly earnings Jan-May in 2015 ($)	89	472	524	1,039	516	1,173	533	883
Annual earnings in 2014 ($)	1,469	5,432	6,539	8,888	6,375	9,470	6,704	8,256
DI information:								
Age at DI award	40.29	13.78	35.79	14.68	43.19	13.94	28.33	11.21
Years on DI	12.26	11.14	13.85	11.17	4.36	2.78	23.42	7.77
Uncapped annual DI benefits ($), b^0	34,569	5,954	35,302	5,223	35,224	5,853	35,380	4,498
Annual indexed earnings ($)	55,791	18,241	56,333	17,596	59,311	20,149	53,331	13,949
Characteristics:								
Females	.56		.53		.52		.55	
Married/cohabitants	.49		.43		.48		.39	
Years of Schooling	10.35	2.81	10.21	2.75	10.46	2.79	9.95	2.69
Number of Children	1.62	1.4	1.43	1.4	1.56	1.4	1.29	1.39
Observations	229,648		39,073		19,616		19,457	

Notes: The sample consists of all DI recipients with full (100 percent) benefit at the beginning of the calendar year. The sample is further restricted to awards made before the 1st of January 2015, for individuals aged 18 to 66. The first column shows earnings and characteristics of the full sample of DI recipients, and the second column reports earnings and characteristics of individuals who had positive labor earnings in at least one month during January-May 2015. The third column shows the earnings and characteristics of recipients with positive earnings and faced a notch in 2014 (see the tax and benefit schedule in Figure 2a). The fourth column shows earnings and characteristics of recipients with positive earnings and faced a kink in 2014 (see the tax and benefit schedule in Figure 2b). Annual indexed earnings (AIE) summarize earnings history before the disability onset. All variables are measured in 2015 dollars (NOK/$ = 7.5).

Table 2 reports summary statistics for the latter sample. The first column shows the average recipient has spent nearly 12 years on the DI program and receives benefits replacing about 62 percent of his previous earnings. The second column reports summary statistics for individuals with some earnings. The average recipient earned about half of the SGA amount in 2014 and $524 per month during the first five months of 2015. The third and fourth columns further split the working DI recipients into two groups based on their tax and benefit schedule in 2014. These two columns illustrate that due to the award cutoff date, the notch sample is younger than the kink sample and has received DI benefits for a considerably shorter time. The notch sample has spent four years on the program on average, while the kink sample has spent more than 23 years on the program in 2015. This age difference is due to the award cutoff explained in Section 2.2.

A key feature of the monthly income data is that employers can update their reported monthly wages at any point until the tax return is filed in April the following year. This feature generates variation in the letter's receipt even among those eligible for the information treatment (i.e., those with annual earnings forecasts above the threshold).[17] Using the data on earnings from January to May 2015, we reconstructed the assignment rule used by SSA in targeting the information letter. Appendix Table A.2 reports pre-determined

---

[17]Note that we could implement a regression discontinuity (RD) design where we identify the effect of the information treatment for individuals at the threshold. However, since our focus is on how information shapes bunching behavior, we do not consider this empirical design, but instead implement a difference-in-difference (DD) estimator. Compared to the RD design, the DD approach's main advantage is that it allows us to consider mean impacts for the same population we use in our bunching analysis.

earnings and characteristics among treated individuals and those who were eligible but did not receive the information letter.

4 Empirical Framework

This section presents a conceptual framework that motivates our empirical strategy.

4.1 A Stylized Model of Labor Supply

We follow Saez (2010) and Chetty (2012) and assume that agents maximize utility by choosing consumption (c) and pre-tax earnings (z) subject to the constraint $b + z - T(z) = c$. Higher consumption increases utility, and higher earnings generates dis-utility from effort. The tax system is linear, $T(z) = \tau_t z$, where τ_t is a proportional tax on earnings. Unearned cash income, or benefits, is represented by b. We follow the convention in public economics in assuming quasi-linear and iso-elastic flow utility $v_i(c,z) = c - \frac{a_i}{(1+1/e)} \left(\frac{z}{a_i}\right)^{1+1/e} - \psi_i$, where the parameter e is the structural elasticity of labor supply with respect to net after-tax earnings, a_i is ability and ψ_i is cost of adjusting earnings for individual i. In absence of adjustment costs, individual labor supply is given by $z_i^* = a_i(1 - \tau_t)^e$.[18]

In standard labor supply models, adding a convex kink τ_b to the linear tax schedule will induce individuals with earnings initially above the (new) kink to reduce their earnings. We assume that agents optimize perfectly before the change in work incentives to focus our analysis on mistakes arising only from changes in incentives. The new tax system is perceived as $T(z) = \tau_t z_i + \theta_i \tau_b (z_i - K) \cdot 1_{z>K}$, where the parameter θ_i measures the degree to which agent i under- or overreacts to the tax τ_b at the bracket cutoff K. Labor supply can now be written as

$$z_{F,i} = \begin{cases} a_i(1 - \tau_t - \theta_i \tau_b \cdot 1_{z>K})^e & \text{if } v_i(c, z_F) - v_i(c, z^*) \geq \psi_i \\ a_i(1 - \tau_t)^e & \text{if } v_i(c, z_F) - v_i(c, z^*) < \psi_i. \end{cases} \tag{1}$$

This equation illustrates that both adjustment costs and information frictions attenuate the structural earnings response to the change in work incentives. Only agents with costs below the gain from adjusting, and only individuals aware of the kink respond. The attenuation in the overall earnings response is given by $\frac{\Delta z_F}{\Delta \tau_b} = (1 - \alpha)\Delta z^*$, where Δz^* is the structural earnings response, and α is the fraction of agents that do not respond due to adjustment costs being greater than utility gains $\psi_i > v_i(c, z_F) - v_i(c, z^*)$, or due to incorrect perception of the tax $\theta \neq 1$. The equation also highlights the interdependence of the two classes of frictions. Increasing the fraction of individuals with the correct perception of the tax also changes the perceived gains from re-optimizing.

Suppose we would randomize information about the location and slope of the kink just after the reform and eliminate misperceptions about the kink. Assuming that a fraction of the noninformed (i.e., the control group) perceives the tax to be lower or are unaware of its introduction, i.e., $\theta < 1$, the experiment would

---

[18]We disregard heterogeneity in the elasticity for expositional clarity. In our empirical application, our goal is to estimate the average structural elasticity.

induce a stronger response to the introduction of the kink. The labor supply of an agent with ability a_i is now given by

$$
z_{I,i} = \begin{cases} a_i(1 - \tau_t - \tau_b \cdot 1_{z>K})^e & \text{if } v_i(c, z_I) - v_i(c, z^*) \geq \psi_i \\ a_i(1 - \tau_t)^e & \text{if } v_i(c, z_I) - v_i(c, z^*) < \psi_i. \end{cases} \tag{2}
$$

In such a hypothetical information experiment, the ratio of earnings elasticities equals the ratio $(1 - \alpha')/(1 - \alpha) < 1$. If the adjustment cost was sufficiently small, so that $\alpha' \approx 0$, the information experiment would identify the structural elasticity e.

4.2 Empirical Strategy

Consider the density of earnings $h_0(z)$ and the behavioral response to introducing a kink (K). Theory predicts individuals with initial labor earnings in the range $[K, K + \Delta z]$ will bunch exactly (or near) the kink in response to the introduction of the tax τ_b.[19] Our empirical strategy employs a bunching approach to estimate excess mass and to identify attenuation in earnings responses from information (e.g., θ) versus other types of frictions (e.g., ψ). In the special case without frictions, the amount of bunching $B(e)$ at the kink depends on the structural elasticity and the size of the tax and equals the integral over the bunching segment $\int_K^{K+\Delta z} h_0(z)dz$. In a more realistic setting, Kleven (2016) shows that the amount of bunching in the presence of optimization frictions depends on both the elasticity, the perception of the tax, and the adjustment costs $B_F(e, \theta, \psi)$. Under the assumption that the baseline (counterfactual) density is constant on the bunching segment, Saez (2010) showed that bunching is proportional to the marginal response Δz^*. This assumption implies the earnings response can be inferred by dividing the total amount of bunching by the height of the density at the kink.

Strategy 1: Identifying the fraction of nonoptimizers. Our first strategy exploits regions of dominated choice that arise from notches in the tax and benefit schedule. Denoting this region $[z_N, z_N + \Delta z_D]$, where z_N is the notch's location in the tax and benefit schedule, we follow Kleven & Waseem (2013) to estimate the population's share inert to the change in disposable income from a notch. The basic idea is that any form of preference for leisure and consumption dictates that earnings below the notch are preferred to earnings above it: Reducing labor supply from just above a notch increases utility through higher leisure and consumption. Individuals who locate in the dominated region do so either because adjustment costs are higher than the gain from reoptimizing or lack of information about the notch's presence. With an estimate of the counterfactual density, $h_0(z)$, the population share inert to the notch can be calculated as the ratio $\alpha \equiv \int_{z^*}^{z^*+\Delta z_D} h(z)dz / \int_{z^*}^{z^*+\Delta z_D} h_0(z)dz$. In combination with estimates of the observed earnings response, the quantity helps recover the structural earnings response $\Delta z^* = \Delta z/(1 - \alpha)$.

---

[19]This behavioral response can be illustrated graphically by drawing indifference curves in a budget set without a kink. The introduction of a kink only affects the utility (and indifference curves) of agents who initially (i.e., before the reform) supply labor earnings above the kink location. This argument relies on an assumption of no income effects. Bastani & Selin (2014) shows that this assumption does not materially affect the estimate of the compensated elasticity.

Strategy 2: Information Experiment. Our second strategy exploits the quasi-experimental variation in information letters targeting perceptions about the tax and benefit schedule. Assuming the treatment affects Δz_I relative to Δz_F only through the effect of changing θ, the effect of the information policy on behavioral elasticities can be inferred from the difference between bunching among the treated $B_I(e,\psi)/h_0(K)$ and bunching among non-treated $B_F(e,\theta,\psi)/h_0(K)$. Under the assumption that adjustment costs are sufficiently large, the average perception of the tax can be recovered from the ratio $B_F(e,\theta,\psi)/B_I(e,\psi) = \theta$.[20]

5 Observational Bunching Analysis

This section estimates the fraction of nonoptimizers under a notch and the earnings elasticity under a kink using bunching techniques.

5.1 Empirical Implementation

The key challenge confronting research on bunching behavior is obtaining a valid estimate of the counterfactual density, $h_0(z)$. We address this challenge in two ways. Our first approach exploits policy-induced changes in notch thresholds in 1997 and 1998 to obtain a non-parametric estimate of the density in 1996. The change in the dominated region allows us to reconstruct a counterfactual distribution of earnings in the interval ranging from \$6,000 to \$12,000 under the assumption of no other distortions to this region of the earnings distribution in 1997/1998.

Figure 3 illustrates this non-parametric approach. We use a histogram to estimate the empirical and counterfactual densities and group DI recipients into earnings bins of \$267 (2,000 NOK) based on their annual earnings. The left panel displays a (nominally adjusted) histogram of the earnings distributions in 1996 and 1997 and shows that the two densities are virtually indistinguishable for earnings below \$5,000. The right panel shows that the bin counts below \$5,000 in 1996 and 1998 are also similar. Noticeable differences in the earnings distribution slope occur around \$8,000 in 1997 and around \$10,000 in 1998, indicating that optimization frictions create bunching regions about \$2,000 below the new SGA levels. The solid vertical line and the dashed line farthest to the right illustrate that we can identify nonoptimizers from about 20 percent of the full dominated region using the 1997 data and about 44 percent of the full range if we use the 1998 data. We calculate the population share of nonoptimizers from the cumulated observed bin counts in the dominated range and divide it by number by the cumulated counterfactual bin counts in the dominated range.

---

[20]Assuming average earnings are pre-determined and $\bar{z}_N = \bar{z}_I$. If adjustment costs are small, then the fraction of agents responding to the change in work incentives may also be affected by the information experiment. This means that earnings adjust because $\Pr[v_i(c,z_F) - v_i(c,z^*) < \psi_i] < \Pr[v_i(c,z_I) - v_i(c,z^*) < \psi_i]$ and because $a_i(1 - \tau_t - \tau_b \cdot 1_{z>K})^e \neq a_i(1 - \tau_t - \theta\tau_b \cdot 1_{z>K})^e$.

Figure 3: Illustration of Non-Parametric Approach

(a) 1997 as Counterfactual	(b) 1998 as Counterfactual
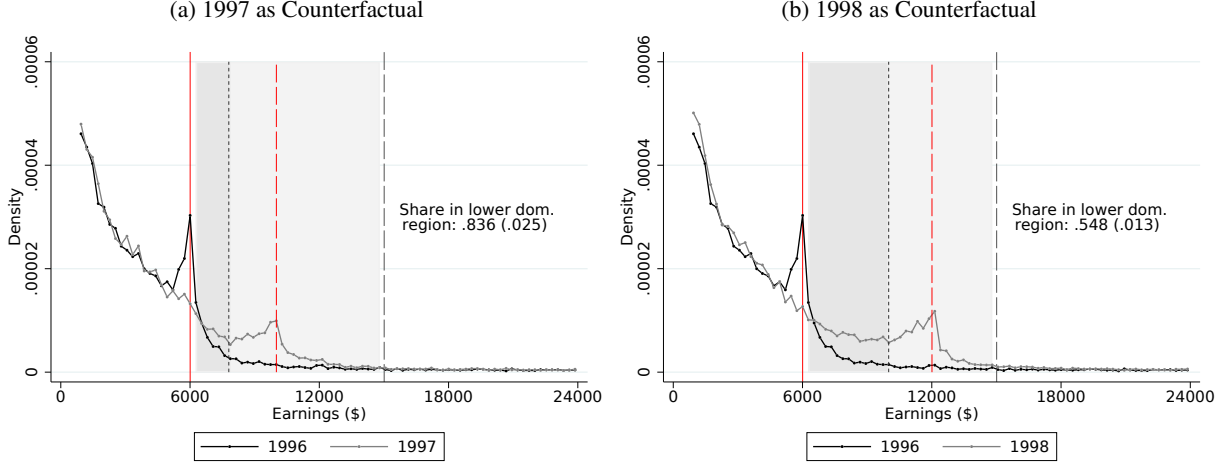
Notes: Figure a illustrates the earnings distributions in 1996 and 1997, and Figure b illustrates the earnings distributions in 1996 and 1998. The light-gray shaded region and long-dashed line denote the dominated region in 1996. The dark shaded region and short dashed lines denote the lower part of the dominated region in which we can identify the fraction of nonoptimizers for in 1996. Using 1997 as a counterfactual for 1996, it covers 20 percent of the dominated region (left panel). Using 1998 as a counterfactual for 1996, it covers 44 percent of the dominated region (right panel). The lower dominated region share is calculated by comparing the total range frequency in 1996 over the counterfactual frequency (i.e., 1997/1998). The standard deviation in parenthesis is calculated with 500 bootstrap repetitions. The solid red (dashed) line denotes the old (new) SGA threshold. The sample consists of DI recipients with full (100 percent) benefit at the beginning of the calendar year from 1996 to 1998. Earnings are adjusted using the average wage growth and are reported in 2015 dollars (NOK/$ = 7.5).

Our second approach fits a flexible polynomial to the histogram of earnings to obtain an estimate of the counterfactual distribution (see, e.g., Chetty *et al.*, 2011). We follow standard practice and estimate

$$c_j = \sum_{i=0}^{p} \beta_i (z_j)^i + \sum_{k=z^L}^{z^U} \gamma_k \mathbf{1} (z_j = k) + \varepsilon_j, \tag{3}$$

where c_j is the number of recipients in income bin j, z_j is the earnings level of bin j, and z^L is determined by visual inspection. The indicator variables for each bin in the excluded range ensure that the polynomial is estimated without considering the range of earnings $[z_L, z_U]$ below and above the SGA. The procedure for deciding z^U differs for kinks and notches. For kinks, z^U is determined by visual inspection. The counterfactual density function is then adjusted so that the estimated missing mass above the kink is equal to the estimated bunching mass at the kink.[21] We cannot determine z^U by visual inspection for notches due to the thin right tail of the DI recipients' earnings distribution. Instead, we assume no extensive margin response. This assumption implies the missing mass above the SGA threshold must equal the bunching mass below the SGA threshold. We identify the upper bound by increasing it in small increments, and the equation above is re-estimated until the estimated missing mass is equal to the estimated bunching mass. Another choice is the order of the polynomials p. We leverage identification from the non-parametric approach and choose a polynomial order that minimizes the distance between the estimate from the non-parametric approach and the

---

[21]This is done by first calculating the fraction of number of individuals in the bunching region over the estimated counterfactual, $\hat{c} = \sum_{k=z^L}^{z^U} \sum_{i=0}^{p} \beta_i (z_k)^i$. Then, we calculate the ratio of the actual frequency and estimated counterfactual above the bunching region. These two ratios should equal to ensure that the sum of the bins in the histogram equals one. This is achieved by upward shifts in the counterfactual distribution to the right of the kink, which is done in increments until the counterfactual satisfies the integration constraint.

polynomial approach. As the non-parametric approach is limited to the lower part of the dominated range, the polynomial approach allows us to estimate the fraction of nonoptimizers in the full dominated range.

Structural Elasticity. Kleven & Waseem (2013) show that the structural elasticity e can be inferred from the observed earnings response and the fraction of nonoptimizers. This result is derived from the fact that the marginal bunching individual is indifferent between locating at the SGA threshold and some interior point. They show that it is possible to identify the elasticity e as an implicit function of the tax parameters, the SGA threshold, and the average earnings response. This function can be written as

$$\frac{1}{1+\Delta z/z_N} - \frac{1}{1+1/e}\left[\frac{1}{1+\Delta z/z_N}\right]^{1+1/e} - \frac{1}{1+e}\left[1-\frac{\Delta t}{1-t}\right]^{1+e} = 0 \tag{4}$$

where the structural response Δz^* identifies the structural elasticity e. Using the observed earnings response $\Delta z = (1-\alpha)\Delta z^*$ identifies an "observed" elasticity e_F, which is attenuated by information and adjustment frictions.

Inference. We calculate standard errors using bootstrap methods. First, we generate many earnings distributions by random resampling with replacement. We then re-estimate the parameters of interest within each sample, and define the standard error as the standard deviation of the distribution of interest. In the non-parametric approach, we may observe the same individual more than once. To account for potential serial correlation in the error terms, we perform block-bootstrap with replacement over individuals, keeping all observations of each individual that we resample. In all estimations, we use 500 repetitions.

5.2 Overall Frictions

From the histograms in Figure 3, we calculate the share of nonoptimizers in the lower dominated region in 1996 to be equal to 0.55 when we use 1998 as a counterfactual, and 0.85 where we use 1997 as the counterfactual distribution. These non-parametric estimates are highly statistically significant and are comparable to findings in Kleven & Waseem (2013), who consider income tax filers in Pakistan, and Ruh & Staubli (2019), who consider DI recipients in Austria.

   One concern with the non-parametric approach is that the earnings distribution in 1997 may be prone to inertia. Some individuals who previously bunched at the $6,000 threshold may remain at this earnings level in 1997. Such inertia would invalidate the assumption of no behavioral distortions to the lower part of the earnings distribution and inflate the density used to calculate the counterfactual, leading to an upward bias in the estimated fraction of nonoptimizers. To address this concern, we re-estimate the lower part of the exact same dominated range but using the earnings distribution in 1998, where we expect less inertia if individuals adjust to changes in the notch with a lag. Reassuringly, our estimate of 0.81 is similar, and we cannot reject the null hypothesis that the estimate is equal to 0.85 using 1997 as the counterfactual density. This comparison is illustrated in Appendix Figure A.1.

   We expand our assessment to the full dominated range using the polynomial approach. Figure 4a shows the fitted counterfactual and the actual earnings histogram, and Figure 4b shows that the estimate stable

across different polynomial specifications (choices of p in equation 3). The circles represent point estimates, and the solid vertical lines represent two-sided 95 percent confidence intervals illustrating that the estimates are all within the confidence interval of the highest order polynomial.[22] Our baseline estimate equals 0.51. This smaller fraction of nonoptimizers for the full range than the lower dominated ranges is somewhat surprising. In theory, the share of nonoptimizers depends on the utility gain from moving to the notch point and the underlying optimization frictions. Since the utility gain of reoptimizing falls the closer a person is to the point of indifference between an interior solution and locating at the notch, we expect the fraction of nonoptimizers to increase with higher earnings. Hence, a smooth distribution of adjustment costs implies the fraction of nonoptimizers is underestimated when focussing on the lower part of the dominated range. However, under a discrete distribution of adjustment costs, this relationship is weakened, and the relationship reverses if adjustment costs (i.e., unobserved heterogeneity) are negatively correlated with earnings potential.

Figure 4: Fraction of Nonoptimizers

(a) Nonoptimizers Over Full Dominated Range   (b) Nonoptimizers By Polynomial Order
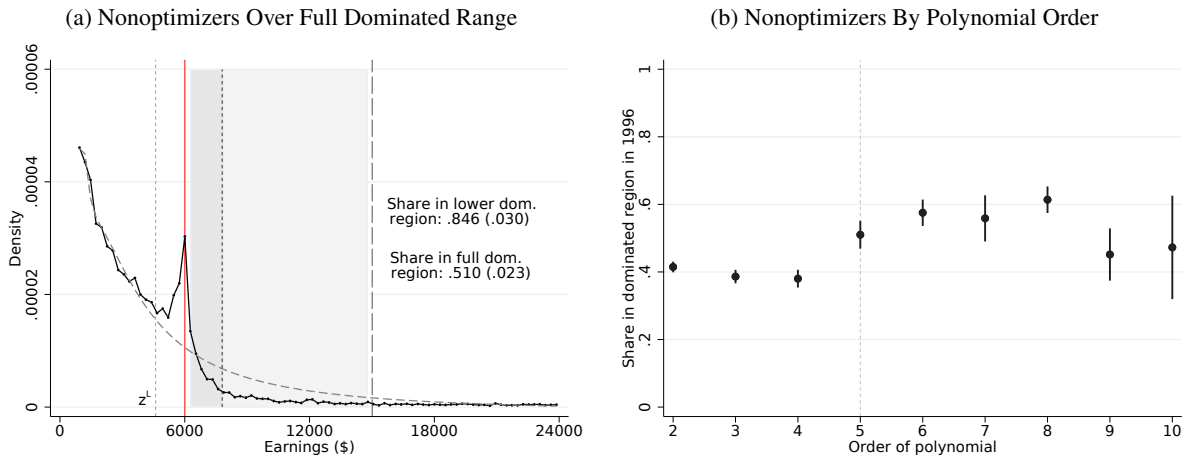
Notes: Figure a illustrates the earnings distributions of DI recipients in 1996 and the fitted counterfactual density using the polynomial approach. The polynomial order is chosen to minimize the distance between the estimate of nonoptimizers from the non-parametric approach and the parametric approach for the lowest range of the dominated region (see Figure 3a). The dark shaded region and short dashed lines denote the lower part of the dominated region in which we can identify nonoptimizers using 1997 as a non-parametric estimate of the counterfactual distribution in 1996. The light-gray shaded region and long-dashed line denote the full dominated region in 1996. The red (dashed) line denotes the old (new) SGA threshold. Figure b shows the sensitivity of the estimated fraction of nonoptimizers over the full dominated range. The dashed vertical line denotes our baseline specification. The sample consists of DI recipients with full (100 percent) benefit at the beginning of 1996. Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/\$ = 7.5).

We exploit variation in the size of the notch across individuals to assess whether the smaller share of nonoptimizers in the upper part of the dominated region may be driven by unobserved heterogeneity. In the Norwegian DI program, lower average indexed earnings lead to higher replacement rates, and higher replacement rates create larger notches. We examine whether the size of the notch varies with the response to it by dividing our sample by the strength of the notch incentive, and re-estimate the fraction of nonoptimizers for groups of individuals with different replacement rates. We find no significant relationship between this

---

[22]The SGA-amount has not changed in real terms since 1998 but has only undergone minor nominal adjustments to account for average wage growth. We repeat the exercise for the most recent notch-year and find the share of nonoptimizers in the full range in 2014 is about 0.4, and is similar but slightly lower than the estimate from 1996. Appendix Figure A.2 illustrates these results and shows that the fraction is very stable across specifications.

fraction and the strength of the incentive to re-optimize. These findings are reported in Appendix Figure A.3.

Figure 5: Fraction of Nonoptimizers Over Time

(a) Relative to 1997 Reform

(b) Relative to Award Year

Notes: Figure a illustrates repeated estimates of the fraction of nonoptimizers in the full dominated region from 1993 to 2004. The substantial gainful activity (SGA) threshold changed from $6,000 to $10,000 in 1997 (dashed vertical line) and to $12,000 in 1998 (solid vertical line). Figure b illustrates repeated estimates of nonoptimizers in the full dominated region from the year of DI award to eight years after. The polynomial order ($p = 5$) is chosen to minimize the distance between the estimate of nonoptimizers from the non-parametric and the parametric approach for the lowest range of the dominated region (see Figure 4). The sample consists of DI recipients with full (100 percent) benefit at the beginning of the calendar year over the period 1993 to 2007 who face a notch in their budget set. Earnings are adjusted using the average wage growth.

To further examine the nature of optimization frictions, we take three steps. First, we study how the fraction nonoptimizers vary with the notch location changes in 1997 and 1998. We expect to observe increases in the number of nonoptimizers during 1997 and 1998, followed by a decline if people learn about the financial work incentives or overcome other adjustment costs with a time lag. We estimate the counterfactual and fraction nonoptimizers using the polynomial approach for each year from 1993 and 2003, and plot the time pattern in Figure 5a. It shows that the number of nonoptimizers increases sharply during the reform and then falls back to the 1996 level three to four years later. In the second step, we assess how the number of nonoptimizers evolves since first entering the DI program. Figure 5b shows that five years after the entry year, the fraction falls from 0.55 to below 0.4. This evidence suggests that optimization frictions can be divided into two broad classes of factors. One class appears to have a temporal nature, and is consistent with learning the tax and benefit schedule and with the idea that people overcome hours constraints (or other adjustment frictions) with a time lag. The second class is consistent with permanent traits, such as preferences or ability, giving rise to persistence in dominated behavior.[23]

In the last step, we assess the role of career concerns. If there is a continuous relationship between current and future wages, career concerns would reduce, but not eliminate, the dominated range. We follow Ruh & Staubli (2019) and group recipients in each year into four segments of earnings z. The first segment is the bunching region ($z_L \leq z \leq SGA$) and the second segment is the dominated region ($SGA < z \leq z_D$). The third and fourth segments include earnings below the bunching region and above the dominated region.

---

[23]While beyond the scope of this paper, this latter explanation speaks to the potential undesirable distributional impacts of increasing the complexity of transfer programs to control the behavioral elasticity (see Taubinsky & Rees-Jones, 2017).

Subsequent moves above the dominated earnings would represent career concerns, where agents rationally locate in the dominated region today to increase their career prospects tomorrow. By tracking individuals relative to the first year a person is observed in the dominated region, we find that nearly all nonoptimizers either return to the bunching segment or reduce their earnings to below the bunching region. Only 10 percent of the nonoptimizers remain in the dominated region after the first year, and only five percent are earning above the dominated region five years later. This evidence is presented in Appendix Figure A.4.

5.3 Bunching Elasticity

Under the assumption of no anticipation effects, we can use the non-parametric approach to identify the counterfactual density of earnings around the new kink in 2015, $\hat{h}_0(K)$.[24] We plot histograms of earnings distributions in 2014 and 2015 for the notch-sample (i.e., awards prior to January 1, 2004) in Figure 6a and for the kink-sample (i.e., awards after January 1, 2004) in Figure 6b. Earnings bins are by $267 (2,000 NOK) increments, the solid line is the new SGA threshold at $8,000, and the dashed line is the threshold from 2014, at $12,000. We see that the two densities are very similar for earnings bins below $6,000 in both samples. After this point, it is somewhat unclear where the bunching segment starts. We set the lower-bound, z_L, represented by the lower short-dashed line to approximately $7,000. We set the upper-bound z_U to the point where the two earnings distributions intersect at just below $9,000, represented by the upper short-dashed line. Next, we calculate the excess mass by integrating the area above the earnings distribution in 2014 and divide by the average height of the density in the bunching region. This ratio gives us a normalized bunching mass of 3.2 for the notch-sample and a slightly higher bunching estimate for the kink-sample. We can not reject the hypothesis that the two bunching estimates are the same.

We multiply the bunching estimate with the bin-width to get the non-parametric estimate of the observed earnings response. Our estimate is about $850 for individuals awarded benefits after January 1st, 2004, and $960 for individuals awarded benefits before January 1st, 2004. We then divide by the SGA threshold and multiply by a normalized tax change at the kink. The normalization divides the tax change by the average net after benefit offset earnings and provides non-parametric estimates of the kink-elasticity of around 0.1.[25] We proceed by applying the polynomial approach to the kinks in 2015 and estimate slightly smaller bunching elasticities but still quantitatively similar to the non-parametric approach. Appendix Figure 4a illustrates the fitted counterfactual earnings distribution for the notch- and kink-samples, and Appendix Figure A.6 shows that the elasticities are remarkably stable across specifications.

---

[24]The earnings response is subsequently inferred from the total amount of bunching, which is approximately equal to $\hat{h}_0(K)\Delta z$. Since earnings are grouped into bins, the earnings response is equal to the normalized excess mass, or total bunching, multiplied by the bin width $266 \cdot \left(B/\hat{h}_0(K)\right)$.

[25]By comparison, Zaresani (2020) estimates the elasticity of earnings with respect to net-of-tax income to be 0.1 in the Canadian DI system. Bunching elasticities from notches and kinks among wage earners tend to be much smaller. Estimates reported by Chetty et al. (2011), Le Maire & Schjerning (2013), and Bastani & Selin (2014) range from 0-0.05.

Figure 6: Non-Parametric Evidence of Bunching Elasticity in 2015
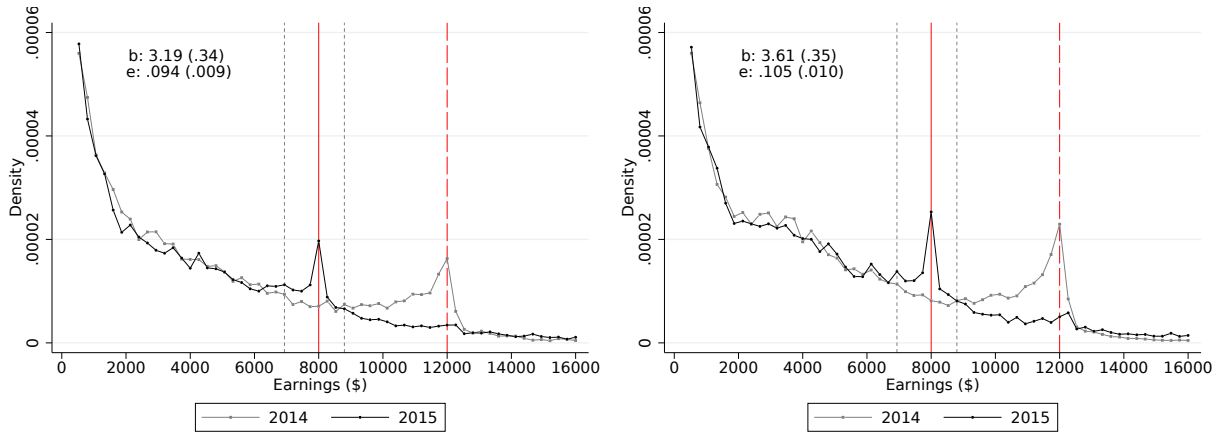
(a) Notch sample: 2014 vs 2015   (b) Kink sample: 2014 vs 2015

Notes: Figure a illustrates the earnings distributions in 2014 and 2015 for DI recipients with awards from before January 1st, 2004 (i.e.,. notch sample), and Figure b illustrates the earnings distributions in 2014 and 2015 for DI recipients with awards from after January 1st, 2004 (i.e.,. kink sample). The solid line is the new SGA threshold, and the dashed line is the SGA threshold from 2014. The sample consists of DI recipients with full (100 percent) benefits during 2014 and 2015. Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/$ = 7.5).

Table 3 summarizes our bunching analysis. Columns 3 and 4 of Panel B reports the estimates of bunching and earnings elasticities in 2015 using the polynomial approach. The point estimates of the observed elasticities are 0.065 and 0.07 are precisely estimated with bootstrapped standard errors of 0.007. By comparison, Panel A reports estimates of bunching behavior in 2014. The first row reports the fraction of nonoptimizers, and the second row reports our estimate of bunching at the notch. The estimate of 11.75 translates into a somewhat imprecise estimate of 0.087 for the observed notch-elasticity. Using the share of nonoptimizers to adjust the earnings response, we estimate a structural elasticity of 0.286 by applying equation 4. The estimate is precisely estimated with bootstrapped standard errors of 0.027. Assuming the structural elasticity (*e*) is a deep parameter, i.e., it is policy-invariant and does not change with the change in incentives from 2014 to 2015 – we can compare the amount of attenuation in observed elasticities before and after the reform. The last row reports the implied attenuation by comparing the observed elasticities with the structural elasticity. We calculate large attenuation in the observed elasticity in 2014 and conclude that an observational bunching analysis would miss 70 percent of the underlying response. The third and fourth column shows a slightly larger but comparable attenuation rate of observed elasticities after the reform.

Table 3: Bunching Elasticity in 2014 and 2015

Year of DI award:	A. Pre-reform		B. Post-reform	
	≥ 2004	< 2004	≥ 2004	< 2004
Incentive:	Notch at $12,000	Kink at $12,000	Kink at $8,000	Kink at $8,000
	(1)	(2)	(3)	(4)
Fraction of Nonoptimizers (α):	.387***			
Standard error	(.027)			
Normalized Bunching ($B/\hat{h}_0$):	11.75***	8.96***	2.12***	2.26***
Standard error	(.71)	(.51)	(.21)	(.23)
Observed Bunching Elasticity:	.087	.217***	.065***	.070***
Standard error	(.059)	(.012)	(.007)	(.007)
Structural Elasticity (e):	.286***			
Standard error	(.077)			
Attenuation rate (%):	69.6	24.1	77.3	75.5
Parametric approach	Yes	Yes	Yes	Yes
Observations	21,463	21,581	25,484	22,209

Notes: This table provides estimates of the fraction of nonoptimizers, normalized bunching, the implied observed elasticity and structural elasticity using equation 4 and adjusting for nonoptimizers. The estimates are obtained using the fitted values from the polynomial approach. The polynomial order ($p = 5$ for notch and $p = 7$ for kink) is chosen to minimize the distance between the estimate from the non-parametric and the parametric approach in 2015 (see Figure A.9). The sample consists of DI recipients with full (100 percent) benefit at the beginning of the calendar year in 2014 and 2015 (see Table 2 for details). Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/$ = 7.5).

One concern with our approach is that the notch and kink elasticities may be different because notched incentives are much stronger and, therefore, more likely to overcome any form of friction. To assess this concern, we report estimates of bunching and the earnings elasticity in 2014 for the kink sample in Panel A of Table 3. The kink-elasticity in column 2 is about three times larger than the elasticity for the notch sample in column 1. At first glance, this may seem surprising. Yet, the similarity of the estimated elasticities in 2015 from Panel B of Table 3 suggests the discrepancy is not explained by differences in ability or underlying heterogeneity in the elasticity. Instead, Table 2 documents that DI recipients in the kink-sample have been in the program more than five times as long as the notch-sample. This observation suggests that with more time since entry, overall optimization frictions matter less in attenuating the kink-elasticity.

5.4 Threats to Identification.

We have identified the bunching elasticity under the assumptions of no distortions to the lower part of the earnings distribution in 2014 (below the SGA) for the non-parametric approach, and that a polynomial specification identifies the counterfactual distribution for the parametric approach. To further challenge the validity of the histogram and polynomial approach, we implement two alternative non-parametric methods that impose different assumptions.

The first approach addresses concerns about the shape of the unobserved ability distribution. Consider the bunching segment defined by the vertical lines in Figure 6. If the true slope of the counterfactual density

is flatter (steeper) than implied by the line between the upper and lower part of the bunching segment, the estimated elasticity from a linear approximation will be biased upward (downward). Bertanha *et al.* (2019) show that the elasticity can be set identified by making an assumption about the absolute value of the slope of the counterfactual density in the bunching segment.[26] We implement this approach on a logarithmic transformation of earnings in 2015 and vary the maximum slope parameter to identify the bunching elasticity bounds. We plot these bounds and describe our implementation in Appendix Figure A.8. The estimated bounds are relatively sharp for a wide range of slope parameters. Importantly, our estimates from both the histogram and polynomial approach lie inside the non-parametric bounds.

The second approach assumes that the ability ranking is preserved when DI recipients move from a notch or kink at $12,000 to a kink at $8,000. Blomquist *et al.* (2019) show that under this assumption, the earnings response can be identified non-parametrically by inverting the cumulative distribution function (CDF). Similar to the histogram approach, it uses the earnings distribution from 2014 to estimate the counterfactual for 2015. The CDF approach differs from the histogram approach in that it identifies the observed earnings response by inverting the two CDFs to the point where the cumulative probabilities equaled the cumulative probability at the kink in 2015. We then follow the standard formula for calculating the kink-elasticity. Reassuringly, this approach delivers estimates of the elasticity ranging from 0.07 to 0.12. Throughout the rest of the paper, we are confident that we can rely on the polynomial approach to estimate both the share nonoptimizers and the bunching elasticity. We illustrate the CDFs and describe the implementation in Appendix Figure A.7.

6 How Information Frictions Shape Earnings Responses

This section examines whether earnings responses can be shaped by information policy, and pins down the relative importance of information frictions versus other kinds of frictions.

6.1 Quasi-Experimental Design

To assess the assignment of the information letters, we compare the earnings distributions of the informed and non-informed in 2014. Figure 7 illustrates that both groups display strong bunching behavior around the SGA threshold in 2014. The density of non-informed is somewhat less stable due to the smaller sample size, but otherwise tracks the earnings histogram of the informed sample reasonably well. While a Kolmogorov-Smirnov test of equality rejects the null hypothesis that raw earnings distributions are equal, we apply a

---

[26]The intuition is that the elasticity is determined by the bunching segment's length and the excess bunching. By imposing structure on the counterfactual shape within the bunching segment, it is possible to derive a lower bound and an upper bound of the elasticity without taking a stance on whether a polynomial function approximates the slope well. The challenge is that the counterfactual distribution could, in principle, take any form within the segment. Bertanha *et al.* (2019) allow the counterfactual to be both steeper and flatter than the linear approximation, and shows that when the maximum slope parameter in absolute terms equals a line between the lower and upper part of the bunching segment, their bounding approach collapses to the trapezoid estimator of Saez (2010). Suppose the maximum slope is steeper than the trapezoid. In that case, the density within the bunching segment becomes thinner and necessitates a larger elasticity to rationalize the observed bunching (i.e., an upper bound). If the slope is flatter, the counterfactual density inside the bunching segment becomes thicker, and a smaller elasticity rationalizes the observed bunching (i.e., a lower bound). This bound can be assessed for different values of the slope parameter. When the maximum slope parameter is such that there is a zero mass point within the bunching segment, the bunching elasticity's upper bound equals infinity.

weighting approach proposed by Kline (2011) that accounts for the pre-determined differences between the two groups. This approach adjusts each unit's importance to account for the fact that the two groups differ in some dimensions of our data.[27] Appendix Figure A.12 shows that the re-weighted earnings distribution tracks the pre-determined earnings distribution of the treatment group significantly better. Importantly, we are no longer able to reject the null-hypothesis that the two distributions are equal. The p-value of the Kolmogorov-Smirnov test is 0.4, and supports the assumption that conditional on the observed differences in characteristics, the assignment of the information letter was random.

Figure 7: Earnings Distributions Around the SGA Threshold in 2014: By Information Status
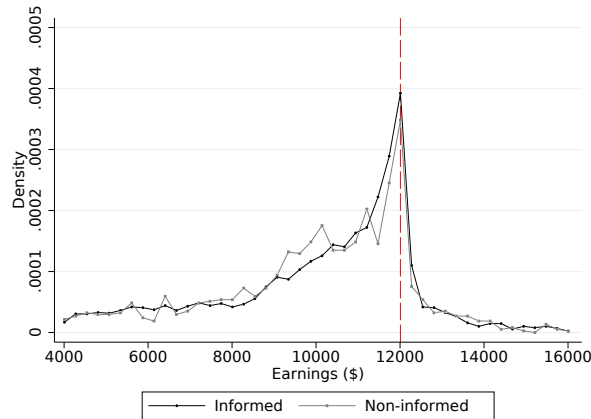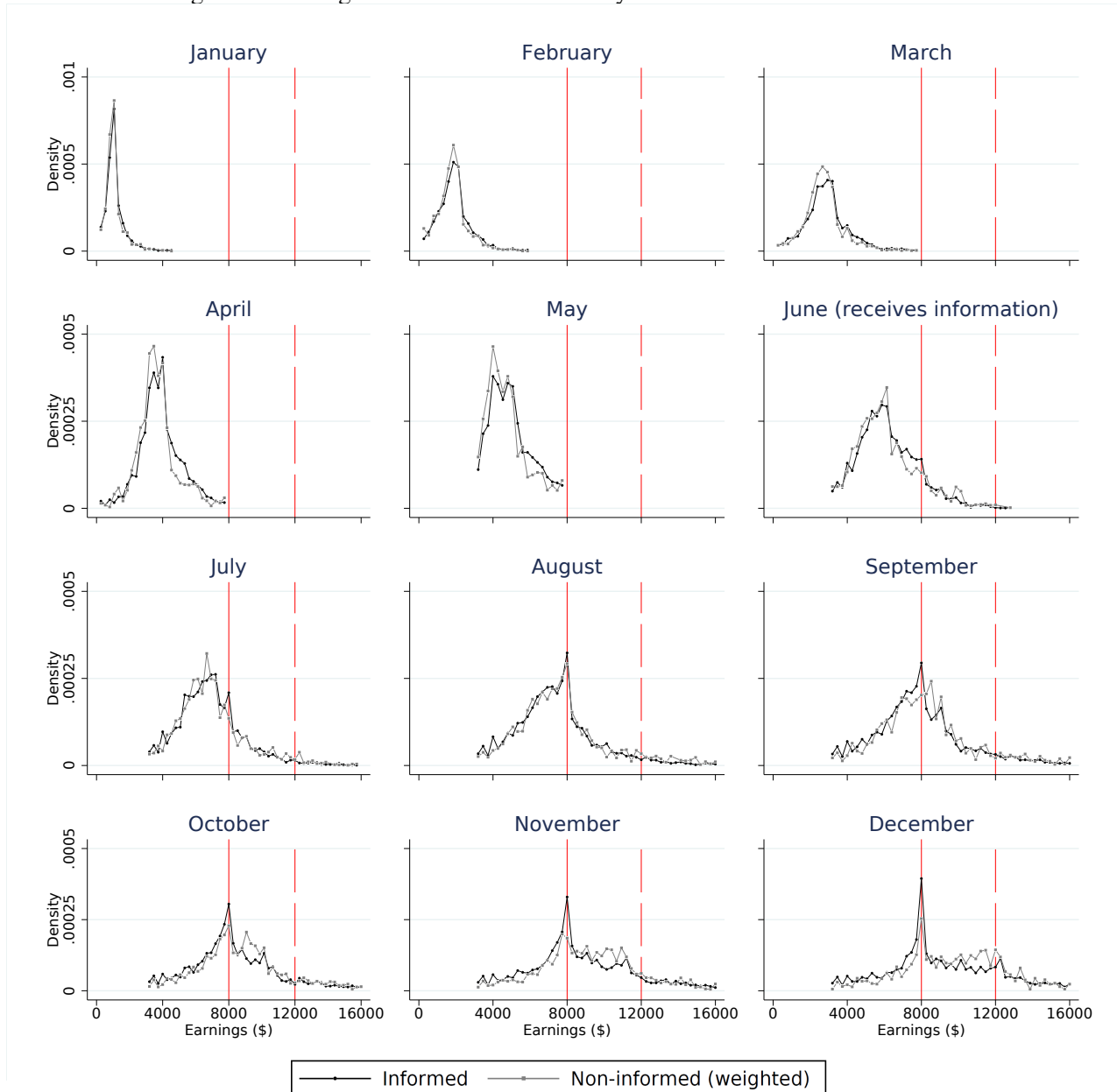

Notes: This figure shows the distribution of annual earnings in 2014 around the SGA threshold (marked by the red dashed line) in $267 (2,000 NOK) bins by information status. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 who were eligible to receive the information letter (i.e., PAE above the cutoff). Earnings are measured in 2015 dollars (NOK/$ = 7.5).

We take two additional steps to examine the validity of our empirical design. First, we assess the trends in average earnings of the two groups before the information event. Reassuringly, we are unable to detect any significant differences in the trend in earnings in the months leading up to the information letter. Appendix Figure A.14 illustrates the estimates. Second, we examine the distribution of cumulative earnings by each month in 2015 in Figure 8. The solid line represents the informed sample's earnings distributions, and the dashed line represents the non-informed sample. The two earnings distributions track each other well over the first five months of the year; in May, the month before the information letter was sent, none of the two groups show signs of bunching at the new kink.

---

[27]We implement this adjustment by estimating the probability a person is exposed to the letter with logistic regression using the characteristics listed in Appendix Table A.2. We then re-weight non-treated individuals 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 information treatment. To perform an adjusted test of equal earnings distributions, we have left out the earnings in 2014 and earnings from January to May of 2015 from estimating the propensity score.

## Figure 8: Earnings Distributions in 2015: By Month and Information Status

Notes: These figures show the distribution of earnings ($) for each month of 2015 in $267 (2,000 NOK) bins by information treatment status. Non-informed individuals are weighted by 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 information treatment. $P(I=1|x)$ is estimated with a logit model using DI benefits, AIE, age, years on DI, gender, cohabitation status, number of children and years of schooling as control variables. The red solid line indicates the SGA threshold at $8,000, and the red dashed line indicates the SGA threshold in 2014 at approximately $12,000. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 who were eligible to receive the information treatment (PAE above the cutoff). Earnings are measured in 2015 dollars (NOK/$ = 7.5).

6.2 The Effects of the Information Letter on Bunching Behavior

Figure 8 examines the within calendar-year variation in the earnings distributions of the informed and non-informed. In August, two months after the letter was received, both earnings distributions display clear

bunching at the kink but otherwise remain similar. After this point, we see that bunching among the informed grows slightly, whereas the earnings distribution among the non-informed is gradually shifting to the right. By the end of the year, the two distributions differ primarily in the region between the new kink and old SGA threshold. Next, we apply the bunching approach from Section 5 to estimate the information letter's impacts on bunching behavior.[28] By comparing bunching at the end of the year, we can infer the extent to which the information letter led to sharper bunching. Figure 9 displays the distribution of cumulative earnings in December 2015 of the informed and non-informed, where the counterfactual distribution is obtained from fitted values from the polynomial approach, and is visualized by the gray dashed lines for the informed in the left panel and the non-informed sample in the right panel. The actual earnings distribution is illustrated by the solid lines, and shows that bunching at the new kink (i.e., vertical solid line) is significantly sharper among the treated than the non-treated whose earnings are more likely to remain around the old SGA threshold (i.e., the long-dashed line to the right).

Figure 9: Earnings Distributions Around the SGA Threshold in 2015

(a) Informed

b: 4.49 (.41)
e: .139 (.013)

(b) Non-Informed (weighted)

b: 2.52 (.75)
e: .078 (.023)
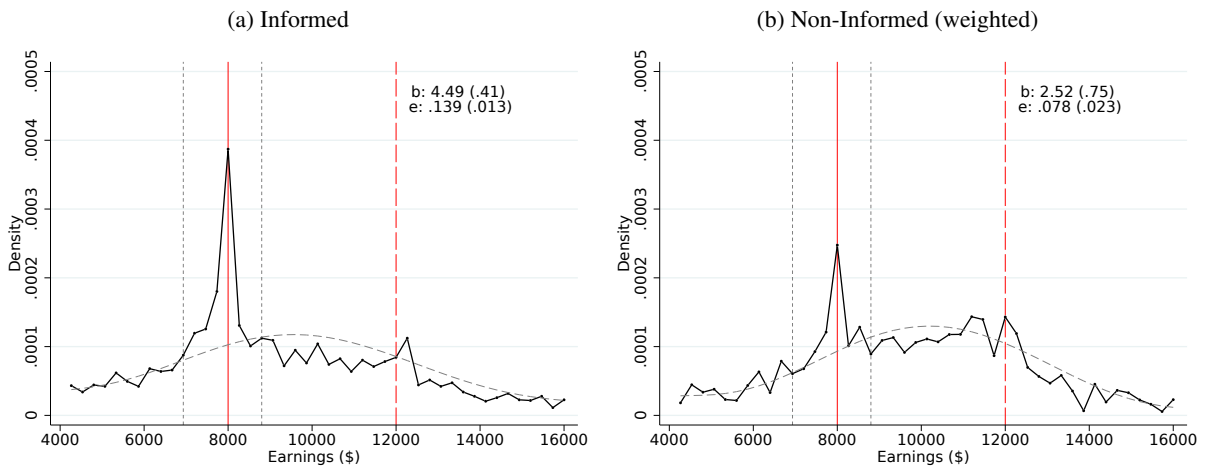
Notes: Figure a shows the distribution of annual earnings in 2015 around the SGA threshold (marked by the red solid line, the red dashed line indicates the SGA threshold in 2014) in $267 (2,000 NOK) bins for the sample of recipients (PAE above the cutoff) who received the information letter from SSA in June 2015. Figure b shows the earnings distribution in 2015 for eligible individuals who did not receive the information letter in June 2015, with the sample being weighed by 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 treatment. $P(I=1|x)$ is estimated with a logit model using DI benefits, AIE, age, years on DI, gender, cohabitation status, number of children and years of schooling as control variables. In all figures, the gray dashed line illustrates a 7th degree polynomial fitted to the empirical distribution. The excluded bunching region is indicated by the vertical gray lines. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 who were eligible to receive the information letter (PAE above the cutoff). Earnings are measured in 2015 dollars (NOK/$ = 7.5).

We summarize our evidence on bunching and elasticities for the two groups in Table 4. The first column shows that (normalized) bunching is highly statistically significant and relatively strong, equal to about 4.5 times the height of the density and an observed elasticity equal to 0.14.[29] The third column displays the

---

[28]Note that we cannot use the non-parametric approach because of the sample of eligible recipients conditions on having earnings over a certain threshold in May 2015. If we used annual earnings in 2014 as a counterfactual, we would underestimate the height of the earnings density in 2015. Moreover, we are unable to reconstruct a comparable sample of eligible in 2014 due to missing data (i.e., the monthly earnings data was introduced in 2015).

[29]We get the elasticity by multiplying the normalized bunching estimate with the bin width and the normalized change in the net after-tax earnings and then divide by the kink location.

estimated bunching and observed elasticity for the non-informed sample. While the bunching estimate is statistically significant, it is only half of the size of the estimate of the informed sample. The stark difference shows that the information letter led to stronger responsiveness to changes in financial incentives. Assuming the information letter did not affect the share of individuals with utility gains larger than the adjustment cost, the average misperception, $\bar{\theta}$, equals about 0.56 with a bootstrapped standard error of 0.18. This interpretation is consistent with the average part-time working DI recipient underestimating the tax rate by one-half or that nearly half of the recipients were inert to the new location of the kink (e.g. Jones, 2012 and Gelber *et al.*, 2019).

Table 4: Bunching Behavior With and Without Information Treatment

	A. Informed		B. Non-informed	
	(1)	(2)	(3)	(4)
Normalized Bunching ($B/\hat{h}_0$):	4.49 ***	4.85***	2.52***	1.88**
Standard error	(.42)	(.43)	(.75)	(.64)
Observed Bunching Elasticity:	.139***	.150***	.078***	.058***
Standard error	(.013)	(.013)	(.023)	(.020)
Counterfactual	Informed	Both	Non-informed	Both
Parametric Approach	Yes	Yes	Yes	Yes
Reweighed	No	No	Yes	Yes
Observations:	3,642	5,163	1,521	5,163

*** significant at 1% level, ** significant at 5% level, * significant at 10% level
Standard errors (in parentheses) are calculated by bootstrap using 500 replications.
Notes: This table presents estimates of excess mass for the sample of recipients who were eligible to receive the information treatment (PAE above the cutoff), separately for treated individuals (received information letter in June 2015) in columns 1 and 2, and untreated recipients (did not receive information letter) in columns 3 ad 4. Bunching behavior is estimated using bins of $267 (2,000 NOK) and a 7th degree polynomial for the counterfactual density (see Table 3). Columns 3-4 report estimates after non-treated recipients are re-weighted 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 (see text for details). Columns 2 and 4 use the sample of eligible for the information letter to estimate the counterfactual density.

One concern with our approach is that any bias from estimating the two different counterfactual densities would bias our conclusion. However, under the assumption of conditional random assignment of the information letter, the two groups' counterfactual density should be the same. In the second and fourth columns, we estimate bunching behavior where we use both groups to estimate the counterfactual density. This specification ensures that any bias in the first step would be identical for the two groups and cancel out. Our estimates of bunching and the observed elasticity for the informed sample, reported in columns 1 and 2, are not significantly different. Similarly, the estimates reported in columns 3 and 4 are also not significantly different from each other. While the attenuation parameter is somewhat smaller, now at 0.39, we cannot reject the null hypothesis that it is equal to our baseline estimate of 0.56.[30] Taken together, the policy-induced

---

[30]We perform additional specification checks on the estimated elasticities by changing the polynomial order. These specification checks are reported in Appendix Figure A.11 and confirm that the observed elasticity is stable.

difference in bunching lends support to models in public finance where behavioral elasticities are subject to policy control (see, e.g., Slemrod & Kopczuk, 2002 and Farhi & Gabaix, 2020).

6.3 Unpacking Optimization Frictions

What is the relative importance of misperceptions of tax and benefit schedules in shaping earnings responses? We assess this question by unpacking overall optimization frictions using a decomposition approach. In the first step of our approach, we estimate the fraction of nonoptimizers and the structural elasticity among our sample of eligible recipients who faced a notched budget set in 2014 (see details in Appendix Figure A.13). The first column of Table 5 shows that the eligible sample appears to be somewhat more likely to optimize than the overall sample – reflected by the lower share of nonoptimizers and the higher observed elasticity. While the estimate of the average structural elasticity is somewhat higher for this sample, we lack the precision to reject that it is equal to the estimate from Section 5. In the second and third columns, we copy the observed elasticities for the non-informed from Table 4.

In the second step, we maintain the assumption that the structural elasticity is a deep parameter and is unaffected by the reform. The first column of Panel C reports the total attenuation as the difference between the observed elasticity in 2014 and the structural elasticity. Moving to columns 2 and 3, we see that the attenuation doubles from 0.15 to about 0.3 in 2015. The next row copies in the estimated effect of the information treatment on the observed elasticity, and the third column suggests that at least 30 percent of the total attenuation in earnings elasticities can be attributed to learning the *new* tax and benefit schedule. The remaining difference between the structural and the observed elasticity is attributed to other types of frictions. In our alternative specification, where we use the separate distributions to estimate the counterfactual density the conclusion remains unchanged. Still, it is worth noting that our evidence likely represents lower bounds of the true importance of information because, in practice, the information letters do not fully correct for misperceptions of the tax and benefit schedule.

We can similarly infer the contribution of misperceptions of the tax and benefit schedule to the increase in attenuation. To perform this calculation, we compare the change in the observed elasticity from 2014 to 2015, 0.30-0.154. We then relate our estimate from the previous section, 0.092 to this difference. We find that at least two-thirds of the increase in attenuation is due to informational frictions: $.092/(.300-.154) \approx$ 2/3. If we use the separate distributions to compute the counterfactual instead, we conclude that half of the increase in attenuation is due to misperceptions of the tax and benefit schedule. These calculations suggest that a reform that improves the financial work incentives by 10 percent would induce a 0.6 percent increase in labor supply. However, if the reform were accompanied by an information intervention and absent induced entry effects, the response would increase by 150 percent and substantially increase government revenue.

27

Table 5: The Relative Importance of Information versus Other Types of Frictions

	A. Pre-reform	B. Post-reform	
	(1)	(2)	(3)
Share nonoptimizers:	.288***		
Standard error	(.032)		
Observed elasticity:	.204***	.078***	.058***
Standard error	(.070)	(.023)	(.020)
Structural elasticity:	.358***		
Standard error	(.093)		
	C. Decomposition of Attenuation		
Total Attenuation	.153	.280	.300
Attenuation: Information friction		.061	.092
Attenuation: Other types of frictions		.219	.208
Attenuation rate (%)	42.8	78.2	83.8
Information, % of total attenuation		21.8	30.7
Counterfactual	Eligible Notch	Non-informed	Both
Parametric Approach	Yes	Yes	Yes
Observations:	2,381	5,163	5,163

*** significant at 1% level, ** significant at 5% level, * significant at 10% level
Standard errors (in parentheses) are calculated by bootstrap using 500 replications.
Notes: Panel A presents estimates of the fraction of nonoptimizers, observed and structural elasticity in 2014 using the sample of recipients eligible to receive the information treatment (PAE above the cutoff). Bunching behavior is estimated using bins of $267 (2,000 NOK) and a 7th degree polynomial for the counterfactual density (see Table 3). Panel B copies in estimates from Table 4. Panel C reports the decomposition of total attenuation. Column 1 reports the difference between the observed elasticity in 2014 and the structural elasticity, and the attenuation rate, which is equal to the difference divided by the structural elasticity. Columns 2 and 3 report changes in the attenuation and decompose it into the part due to the information letter and other kinds of frictions as the residual.

7   Assessing Margins of Response

This section presents regression evidence on the effects of the information letter and decomposes the effect into intensive and extensive margins of labor supply response.

7.1   Regression Model

To assess the margins of labor supply response, we estimate a standard event study specification

$$y_{it} = d_0 + d_1 I_i + \sum_{t=2}^{T=12} \gamma_t + \sum_{t=2}^{T=12} \delta_t I_{it} + \varepsilon_{it}, \tag{5}$$

where month effects are captured by γ_t, omitting January to allow for pre-existing differences between the two groups, and y_{it} is the outcome for a person at a given month in 2015. The indicator I_{it} is equal to one

in month t if the person received the information letter and zero otherwise. The parameters of interests, the treatment-on-the-treated (TOT) effects are represented by δ_t for the period after the letter was received $t \in [6, 12]$. The validity of our quasi-experimental design hinges on the parallel trend assumption. This assumption would be violated if, for example, worker outcomes or labor productivity grow at different rates by treatment status. Another concern is that treated DI recipients are employed by more technologically advanced firms that provide more information about their workers' tax and benefit system. This behavior would lead to different trends in earnings, even without the information treatment.[31] Fortunately, our data allows us to assess the parallel trend assumption by inspecting the estimates of δ_t for $t \in [2, 5]$.

In our baseline specification, we impose a common effect over months within a calendar year but allow the effect to differ by year to test for persistence in the effect of the information treatment. Our estimating equation is given by

$$y_{it} = d_0 + d_1 I_i + \gamma_0 Post_{i,15} + \gamma_1 Post_{i,16} + \delta_0 I_i \cdot Post_{i,15} + \delta_1 I_i \cdot Post_{i,16} + \varepsilon_{it}. \tag{6}$$

where $Post_{i,15}$ is an indicator variable equal to one if the observation is in June to December in 2015, and $Post_{i,16}$ equals one if the observation in from 2016. The effect of the information treatment in 2015 is given by δ_0, and the effect of the treatment in 2016 is given by δ_1. Throughout this section, all standard errors are clustered at the individual level and are robust to heteroskedasticity.

7.2 Evidence

A virtue of the event study design is that it provides a transparent way of showing how we identify the labor supply responses. To this end, we plot the estimated coefficients from the distributed lag model in equation 5 in Appendix Figure A.14. Reassuringly, we are unable to detect statistically significant differences in monthly earnings prior to the letter. There is a sharp fall in monthly earnings after the letter is sent, consistent with the evidence from the bunching analysis in the previous section.

We next turn to estimates from our baseline specification. Panel A of Table 6 reports the estimated effect of treatment in 2015. The second column presents the baseline estimate of how the information letter impacts monthly earnings. The average treatment effect on the treated equals about $200. This effect is highly statistically significant. It corresponds to a 25 percent decrease in monthly earnings and suggests that individuals can adjust their labor supply over the remaining six months of the year. Panel B shows the effect of the treatment persisted in 2016. The estimate is somewhat smaller than the estimated effect in 2015 but still corresponds to 18 percent of the average monthly earnings in January-May of 2015. This finding suggests that our findings do not reflect the effects of a nudge that temporarily induced treated individuals to move away from the status quo (see, e.g., Levitt, 2020). To assess whether the effects are coming from existing employment relationships or from new employers who permit fine-tuning their labor supply, the first column reports the estimated impact on the probability of switching employers. While the estimate is less

---

[31] Note that such effects would arguably be present before the reform and assessed by inspecting the earnings distribution in 2014. More information transmitted from employers to workers should lead to stronger bunching. The data do not support this concern, and we are unable to reject the null hypothesis of equal distributions with a p-value of 0.4 from Kolmogorov-Smirnov tests (see Appendix Figure A.12).

precisely estimated, it suggests that adjustments in existing employment relationships primarily explain the response.

Table 6: Effect of Information Treatment on Labor Market Outcomes

	Effects on Labor Supply						
	Probability to Switch Firm	Monthly earnings ($)	Any earnings	Fixed pay ($)	Variable pay ($)	Contract hours	Observations <individuals>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Post-Treatment, 2015	-.009*	-195***	-.086***	-28***	-113***	-1.2***	61,956
	(.005)	(21)	(.010)	(11)	(16)	(.2)	<5,163>
p-value	.079	<.001	<.001	.009	<.001	<.001	
B. Post-Treatment, 2016	-.019**	-142***	-.071***	-25*	-68***	-.79**	123,912
	(.008	(22)	(.012)	(14)	(16)	(.34)	<5,163>
p-value	.020	<.001	<.001	.063	<.001	.018	
Dep. mean (Pre-Treatment)	.04	789	.690	235	430	8.76	

*** 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 estimates of the impacts of the information letter on labor market outcomes during 2015. The event study is implemented using a difference in difference design, where we include a dummy for the treatment group, a dummy for the post-treament time period for 2015, a dummy for the post-treatment time period for 2016, and an interaction between the treatment indicator and the post-treatment period for each year respectively. Non-treated units 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 treatment, and $P(I=1|x)$ is estimated by logit regression using the characteristics from Table 2. Fixed pay is defined by the work contract. Variable pay is defined as wages paid on an hourly basis, bonuses, overtime pay, or other payments as defined by employers. Switching employer is an indicator variable equal to one if the current employer is different than the main employer at the beginning of the calendar year. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 who were eligible to receive the information treatment. Earnings are measured in 2015 dollars (NOK/$ = 7.5). The sample is restricted to individuals that are observed in the monthly earnings data. Dependent mean (control group) is measured before treatment.

Using the detailed data on earnings and hours reported by the employer, we decompose total earnings into fixed and variable pay and contracted hours. As only one percent of our sample has any income from self-employment, the scope for reporting behavior to be an important driver of our results is very limited. Relevant margins of response are changing number of hours worked – either at the intensive margin of hours or by stopping work entirely. We begin by estimating the effect of the information letter on the probability of being observed in a given month with zero earnings. The third column of Table 6 reports the estimated impacts of the information letter on having any earnings in a given month. The point estimate shows a statistically significant decrease of 8.6 percent in 2015 and 7.1 percent in 2016. This finding suggests that the information experiment led to a 10-12 percent reduction in the extensive margin of labor supply, indicating that the extensive margin may explain half of the total effect on earnings.[32] We further decompose total earnings into fixed pay (e.g. according to the work contract) and variable pay that includes wages on an hourly basis, bonus and overtime payments.[33] The estimates reported in columns 4 and 5 show that variable pay reductions are

---

[32]The average earnings among those who work is $789/.690. The extensive margin effect can thus account for 0.086*$1143=$98 of the total effect on monthly earnings.

[33]Total earnings also include other variable and irregular income sources such as severance pay, summer salary, and other taxable

the primary reason why earnings fall. By contrast, we find a small, but still statistically significant reduction in fixed pay. As expected, the sixth column shows the information letter lead to a reduction in the average number of hours worked. The point estimate shows a statistically significant decrease in contracted hours by 1.2 hours, equal to a 16 percent relative to the dependent mean. Taken together, our evidence supports the view that informational frictions attenuate earnings and that the effects of the information letter reflect real labor supply responses.

Finally, we address the concern that our conclusions may be specific to our setting. Hours constraints, for example, could be less binding among part-time than among full-time workers. We assess whether the response varies across industries with varying flexibility levels. Appendix Table A.3 illustrates that we are unable to detect significant differences in treatment effects, lending some support to our analysis's external validity.

8 Conclusion

A growing line of empirical research has stressed the importance of optimization frictions in attenuating earnings responses to financial incentives. While these frictions may arise from real constraints such as hours of work restrictions or the tax and benefit schedule not being fully understood, to date, evidence on the role of factors shaping the response is scant. This lack of evidence is unfortunate and limits the practical implications of optimization frictions for optimal tax and transfer policies. The main reason so little is known is that labor supply elasticities are attenuated by a variety of frictions that are unobserved to the econometrician.

This paper aimed to help fill this literature gap by assessing how information about the tax and benefit schedule shapes earnings elasticities. Two features from the Norwegian setting allowed us to make progress. The first was policy-induced changes in the existence of notches in the tax and benefit schedule. A key feature under a notch regime is that an incremental change in earnings causes discrete changes in the level of net tax liability. Exploiting the regions of dominated choice in combination with individual earnings, we found that about half of DI recipients did not behave as predicted by standard labor supply models, which led to substantial attenuation in the observed elasticity of labor supply. Our setting's second key feature was an informational quasi-experiment that targeted recipients' perceptions about the location and slope of a new kink. We found the information letter lead to a doubling in the bunching probability compared to the non-treated, indicating that policymakers have some control over behavioral elasticities. We unpacked overall optimization frictions by combining the excess bunching with and without the informational treatment and dominated behavior under the notch. We found that a substantial fraction of attenuation in the response to financial incentives can be attributed to informational frictions.

Our paper made progress in understanding the factors that shaped the earnings response and has several policy implications. The first is to show that governments can shape earnings responses with targeted information letters, and the second to decompose overall optimization frictions into information vs. other behavioral frictions. This decomposition approach may be applied and prove useful in other settings. Ac-

---

employment benefits such as employer-paid phone.

cess to experimental variation in information (or other measurable barriers to optimal choice) and dominated choice (like a notched budget set) allows for evaluating the costs and benefits of information intervention. When policymakers exert some control over behavioral responses, as we document they do, the additional policy-levers may help reduce the efficiency losses from redistribution and even strengthen the insurance from programs such as the DI system.

References

ABELER, JOHANNES, & JÄGER, SIMON. 2015. Complex tax incentives. *American Economic Journal: Economic Policy*, **7**(3), 1–28.

ALTONJI, JOSEPH G, & PAXSON, CHRISTINA H. 1988. Labor supply preferences, hours constraints, and hours-wage trade-offs. *Journal of labor economics*, **6**(2), 254–276.

ATKINSON, A., RAINWATER, L., & SMEEDING, T.M. 1995. Income Distributions in OECD countries: Evidence from the Luxembourg Income Study. *OECD Publications and Information Center*.

AUTOR, D. H., & DUGGAN, M. G. 2006. The growth in the social security disability rolls: A fiscal crisis unfolding. *Journal of Economic Perspectives*, **20**(3), 71–96.

BASTANI, SPENCER, & SELIN, HÅKAN. 2014. Bunching and non-bunching at kink points of the Swedish tax schedule. *Journal of Public Economics*, **109**, 36–49.

BERTANHA, MARINHO, MCCALLUM, ANDREW H, & SEEGERT, NATHAN. 2019. Better bunching, nicer notching. *Nicer Notching (December 23, 2019)*.

BEST, MICHAEL, CLOYNE, JAMES, ILZETZKI, ETHAN, & KLEVEN, HENRIK JACOBSEN. 2019. Interest rates, debt and intertemporal allocation: evidence from notched mortgage contracts in the United Kingdom. *Review of Economic Studies*.

BEST, MICHAEL CARLOS, & KLEVEN, HENRIK JACOBSEN. 2017. Housing market responses to transaction taxes: Evidence from notches and stimulus in the UK. *The Review of Economic Studies*, **85**(1), 157–193.

BEST, MICHAEL CARLOS, BROCKMEYER, ANNE, KLEVEN, HENRIK JACOBSEN, SPINNEWIJN, JOHANNES, & WASEEM, MAZHAR. 2015. Production versus revenue efficiency with limited tax capacity: theory and evidence from Pakistan. *Journal of political Economy*, **123**(6), 1311–1355.

BHARGAVA, SAURABH, & MANOLI, DAYANAND. 2015. Psychological frictions and the incomplete take-up of social benefits: Evidence from an IRS field experiment. *The American Economic Review*, **105**(11), 3489–3529.

BLOMQUIST, SÃ¶REN, NEWEY, WHITNEY, KUMAR, ANIL, & LIANG, CHE-YUAN. 2019. On Bunching and Identification of the Taxable Income Elasticity.

BLUNDELL, RICHARD, & MACURDY, THOMAS. 1999. Labor Supply: A Review of Alternative Approaches. Handbook of Labor Economics, Elsevier.

CENGIZ, DORUK, DUBE, ARINDRAJIT, LINDNER, ATTILA, & ZIPPERER, BEN. 2019. *The effect of minimum wages on low-wage jobs: Evidence from the United States using a bunching estimator*. Tech. rept. National Bureau of Economic Research.

CHETTY, RAJ. 2012. Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply. *Econometrica*, **80**(3), 969–1018.

CHETTY, RAJ, & SAEZ, EMMANUEL. 2013. Teaching the tax code: Earnings responses to an experiment with EITC recipients. *American Economic Journal: Applied Economics*, **5**(1), 1–31.

CHETTY, RAJ, LOONEY, ADAM, & KROFT, KORY. 2009. Salience and taxation: Theory and evidence. *American economic review*, **99**(4), 1145–77.

CHETTY, RAJ, FRIEDMAN, JOHN, OLSEN, TORE, & PISTAFERRI, LUIGI. 2011. Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records. *Quarterly Journal of Economics*, **126**, 749–804.

CHETTY, RAJ, FRIEDMAN, JOHN N, & SAEZ, EMMANUEL. 2013. Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings. *The American Economic Review*, **103**(7), 2683–2721.

DELLAVIGNA, STEFANO. 2009. Psychology and economics: Evidence from the field. *Journal of Economic literature*, **47**(2), 315–72.

DICKENS, WILLIAM T, & LUNDBERG, SHELLY. 1993. Hours Restrictions and Labor Supply. *International Economic Review*, **34**(1), 169–92.

FARHI, EMMANUEL, & GABAIX, XAVIER. 2020. Optimal taxation with behavioral agents. *American Economic Review*, **110**(1), 298–336.

FINKELSTEIN, AMY. 2009. E-ztax: Tax salience and tax rates. *The Quarterly Journal of Economics*, **124**(3), 969–1010.

GELBER, ALEXANDER M, JONES, DAMON, & SACKS, DANIEL W. 2019. Estimating Earnings Adjustment Frictions: Method and Evidence from the Earnings Test. *American Economic Journal: Applied Economics*.

GOLDIN, JACOB, & HOMONOFF, TATIANA. 2013. Smoke gets in your eyes: cigarette tax salience and regressivity. *American Economic Journal: Economic Policy*, **5**(1), 302–36.

HARASZTOSI, PÉTER, & LINDNER, ATTILA. 2019. Who Pays for the minimum Wage? *American Economic Review*, **109**(8), 2693–2727.

HASTINGS, JUSTINE S, & WEINSTEIN, JEFFREY M. 2008. Information, school choice, and academic achievement: Evidence from two experiments. *The Quarterly journal of economics*, **123**(4), 1373–1414.

JENSEN, ROBERT. 2010. The (perceived) returns to education and the demand for schooling. *The Quarterly Journal of Economics*, **125**(2), 515–548.

JONES, DAMON. 2010. Information, Preferences, and Public Benefit Participation: Experimental Evidence from the Advance EITC and 401 (k) Savings. *American Economic Journal: Applied Economics*, **2**(2), 147–163.

JONES, DAMON. 2012. Inertia and overwithholding: explaining the prevalence of income tax refunds. *American Economic Journal: Economic Policy*, **4**(1), 158–185.

KLEVEN, HENRIK. 2019. *The EITC and the Extensive Margin: A Reappraisal*.

KLEVEN, HENRIK J., & WASEEM, MAZHAR. 2013. Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan. *Quarterly Journal of Economics*, **128**, 669–723.

KLEVEN, HENRIK JACOBSEN. 2016. Bunching. *Annual Review of Economics*, **8**, 435–464.

KLINE, PATRICK. 2011. Blinder-Oaxaca as a reweighting estimator. *American Economic Review: Papers and Proceedings*, **101**(3), 532–537.

KLINE, PATRICK, & TARTARI, MELISSA. 2016. Bounding the labor supply responses to a randomized welfare experiment: A revealed preference approach. *American Economic Review*, **106**(4), 972–1014.

KOPCZUK, WOJCIECH, & MUNROE, DAVID. 2015. Mansion tax: the effect of transfer taxes on the residential real estate market. *American economic Journal: economic policy*, **7**(2), 214–57.

KOSTOL, ANDREAS RAVNDAL, & MOGSTAD, MAGNE. 2014. How Financial Incentives Induce Disability Insurance Recipients to Return to Work. *American Economic Review*, **104**(2), 624–55.

LE MAIRE, DANIEL, & SCHJERNING, BERTEL. 2013. Tax bunching, income shifting and self-employment. *Journal of Public Economics*, **107**, 1–18.

LEVITT, STEVEN D. 2020. Heads or Tails: The Impact of a Coin Toss on Major Life Decisions and Subsequent Happiness. *The Review of Economic Studies*, 05. rdaa016.

LIEBMAN, JEFFREY B., & LUTTMER, ERZO F.P. 2012. Would People Behave Differently If They Better Understood Social Security? Evidence From a Field Experiment. *American Economic Journal: Economic Policy*, **7(1)**(17287), 275–99.

MORRISON, WILLIAM, & TAUBINSKY, DMITRY. 2019. *Rules of Thumb and Attention Elasticities: Evidence from Under-and Overreaction to Taxes*. Tech. rept. National Bureau of Economic Research.

PENCAVEL, JOHN. 1986. Labor supply of men: a survey. *Handbook of labor economics*, **1**, 3–102.

REES-JONES, ALEX, & TAUBINSKY, DMITRY. 2019. Measuring Schmeduling. *The Review of Economic Studies*.

RUH, PHILIPPE, & STAUBLI, STEFAN. 2019. Financial incentives and earnings of disability insurance recipients: Evidence from a notch design. *American Economic Journal: Economic Policy*, **11**(2), 269–300.

SAEZ, EMMANUEL. 2010. Do taxpayers bunch at kink points? *American economic Journal: economic policy*, **2**(3), 180–212.

SAEZ, EMMANUEL, SLEMROD, JOEL, & GIERTZ, SETH H. 2012. The elasticity of taxable income with respect to marginal tax rates: A critical review. *Journal of economic literature*, **50**(1), 3–50.

SCHIMMEL, JODY, STAPLETON, DAVID C, & SONG, JAE G. 2011. How Common is Parking among Social Security Disability Insurance Beneficiaries-Evidence from the 1999 Change in the Earnings Level of Substantial Gainful Activity. *Soc. Sec. Bull.*, **71**, 77.

SLEMROD, JOEL. 1994. Fixing the leak in Okun's bucket optimal tax progressivity when avoidance can be controlled. *Journal of Public Economics*, **55**(1), 41–51.

SLEMROD, JOEL, & KOPCZUK, WOJCIECH. 2002. The optimal elasticity of taxable income. *Journal of Public Economics*, **84**(1), 91 – 112.

TAUBINSKY, DMITRY, & REES-JONES, ALEX. 2017. Attention variation and welfare: theory and evidence from a tax salience experiment. *The Review of Economic Studies*, **85**(4), 2462–2496.

WEATHERS, ROBERT R, & HEMMETER, JEFFREY. 2011. The impact of changing financial work incentives on the earnings of Social Security Disability Insurance (SSDI) beneficiaries. *Journal of Policy Analysis and Management*, **30**(4), 708–728.

ZARESANI, AREZOU. 2020. Adjustment Costs and Incentives to Work: Evidence from a Disability Insurance Program. *Journal of Public Economics*, **188**(104223).

**For Online Publication:**

Appendix

A Additional Tables and Figures

## Figure A.1: Nonoptimizers in Lower Range of Dominated Region
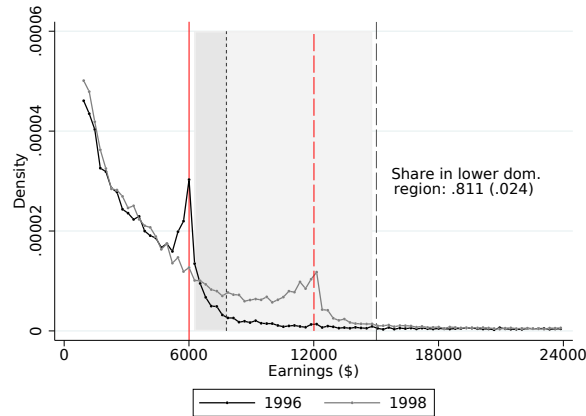
Notes: The figure illustrates the earnings distributions of DI recipients in 1996 and 1998. The dark shaded region and short dashed lines denote the lower part of the dominated region in which we can identify the fraction of nonoptimizers for in 1996. Our non-parametric approach covers 20 percent of the dominated region using 1998 as a counterfactual. The light-gray shaded region and long-dashed line denote the full dominated region in 1996. The sample consists of DI recipients with full (100 percent) benefit at the beginning of the calendar year during the period 1996 to 1998. Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/$ = 7.5).

Figure A.2: Fraction of Nonoptimizers in 2014

(a) Nonoptimizers Over Full Dominated Range　　　　(b) Nonoptimizers By Polynomial Order
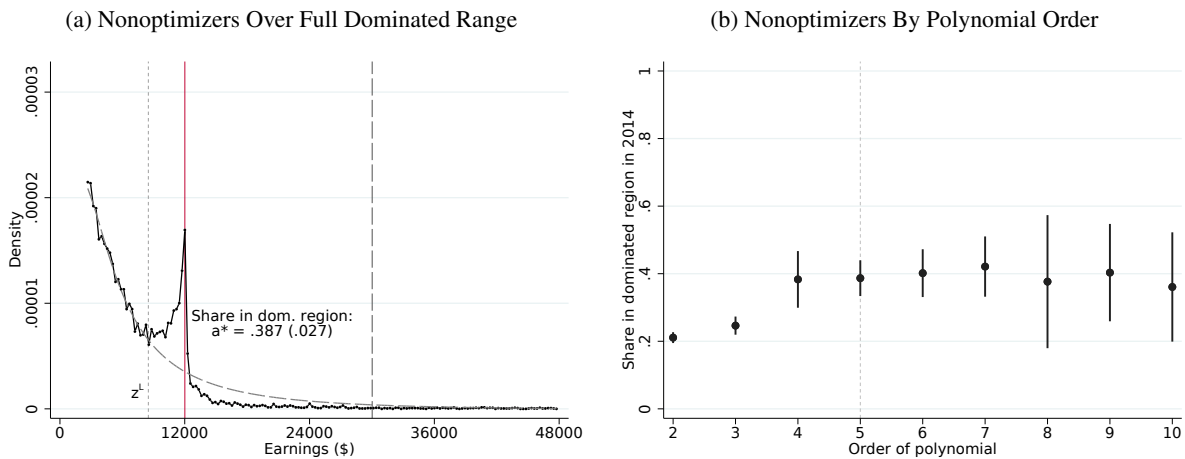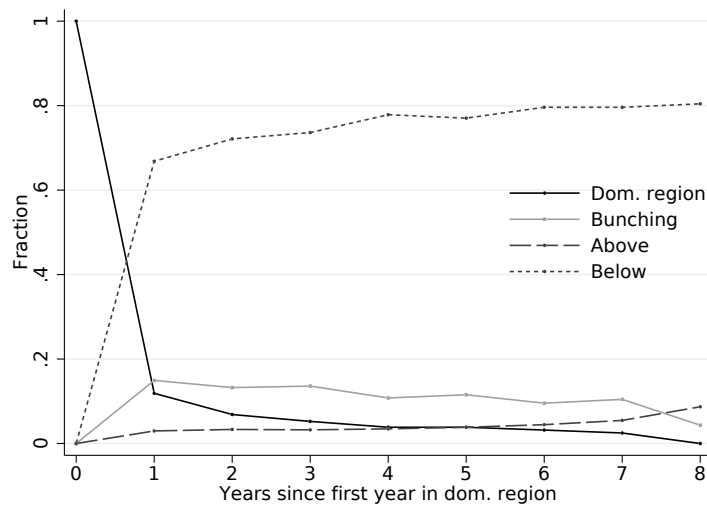

Notes: Figure a illustrates the earnings distributions of DI recipients in 2014 and the fitted counterfactual density using the polynomial approach. The polynomial order is chosen to minimize the distance between the estimate of nonoptimizers from the non-parametric approach and the parametric approach for the lowest range of the dominated region (see Figure 3a). The long-dashed line denote the full dominated region, the red line denotes the SGA threshold in 2014. The short dashed line represent the lower part of the excluded range. Figure b shows the sensitivity of the estimated fraction of nonoptimizers. The sample consists of DI recipients with full (100 percent) benefit at the beginning of 2014 and an award date from after January 1st, 2004. Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/$ = 7.5).

Figure A.3: Dominated Behavior and Strength of Notch Incentives
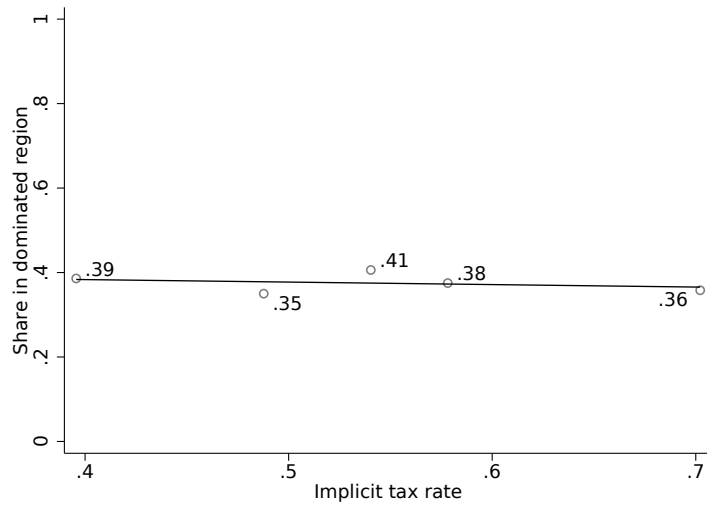
Notes: This figure plots subsample estimates of the fraction of nonoptimizers among DI recipients in 2014 using the polynomial approach (see Figure 4). The implicit tax rate is calculated using the benefit level over average indexed earnings. The sample consists of DI recipients with full (100 percent) benefit at the beginning of 2014, where the award date is after January 1st, 2004.

Figure A.4: Dynamics of Dominated Behavior Over Time

Notes: The figure illustrates the dominated behavior of individuals relative to the first year a person is observed with earnings in the dominated region. The sample consists of DI recipients with full (100 percent) benefit at the beginning of the calendar year and an award date from after January 1st, 2004.

Figure A.5: Polynomial Approach: Bunching Elasticity in 2015
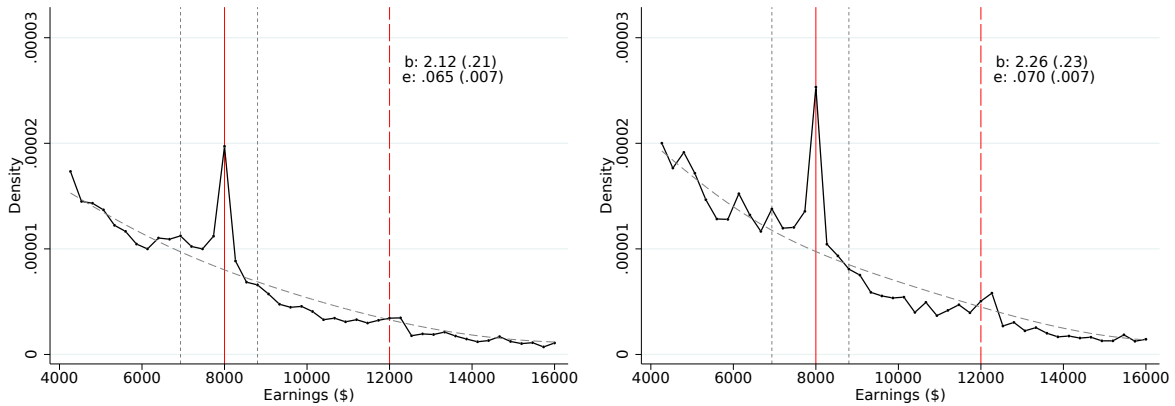
b: 2.12 (.21)
e: .065 (.007)

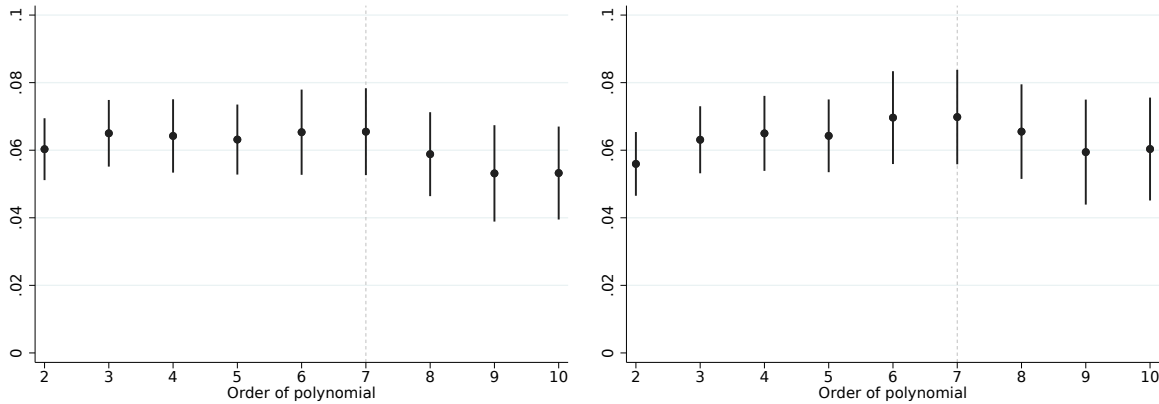b: 2.26 (.23)
e: .070 (.007)

(a) Notch sample: Bunching Elasticity in 2015   (b) Kink sample: Bunching Elasticity in 2015

Notes: Figure a illustrates the earnings distributions in 2015 of DI recipients awarded benefits prior to January 1, 2004 and the fitted counterfactual density using the polynomial approach. Figure b illustrates the earnings distributions in 2015 of DI recipients awarded benefits after January 1, 2004 and the fitted counterfactual density using the polynomial approach. The red (dashed) line denotes the old (new) SGA threshold. The polynomial order is chosen to minimize the distance between the estimate from the non-parametric approach and the parametric approach (see Figure A.5). The sample consists of DI recipients with full (100 percent) benefit at the beginning of 2015. Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/$ = 7.5).

Figure A.6: Specification Checks for Polynomial Approach: Bunching Elasticity in 2015
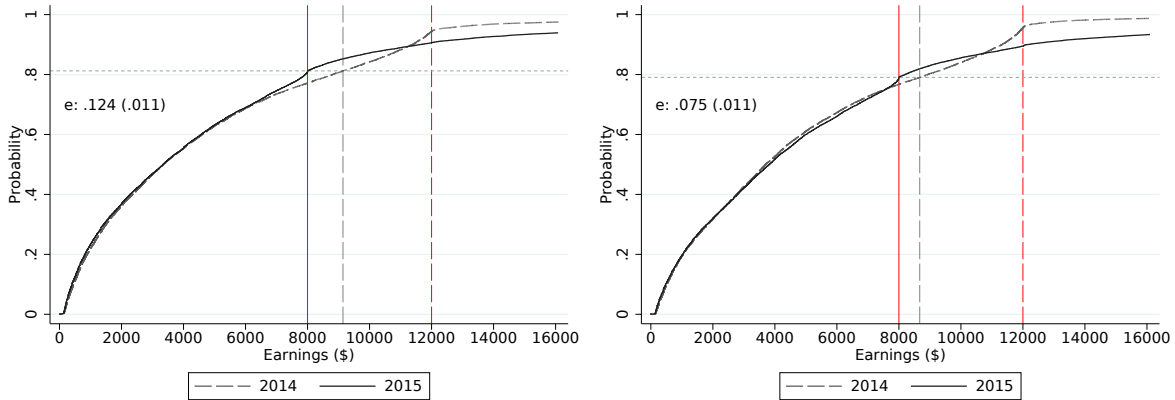

(a) Notch sample: Sensitivity of Bunching Elasticity in 2015   (b) Kink sample: Sensitivity of Bunching Elasticity in 2015

Notes: Figure a illustrates the estimated bunching elasticity in 2015 for DI recipients awarded benefits prior to January 1, 2004. Figure b illustrates the earnings distributions in 2015 of DI recipients awarded benefits after January 1, 2004 and the fitted counterfactual density using the polynomial approach. The dots represent point estimates, and the vertical lines represent 95 percent confidence intervals. The x-axis represent different specifications for the polynomial order in equation 3. The two samples consist of DI recipients with full (100 percent) benefit at the beginning of 2015. Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/$ = 7.5).
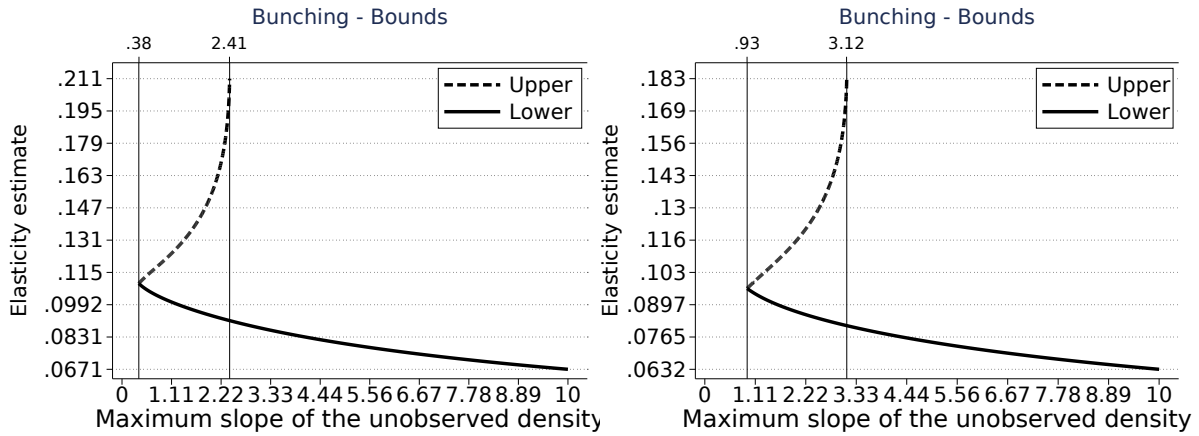
Figure A.7: CDF Approach: Bunching Elasticity in 2015

(a) Notch sample: Bunching Elasticity in 2015 (b) Kink sample: Bunching Elasticity in 2015

Notes: Figure a illustrates the cumulative earnings distributions in 2014 and 2015 for DI recipients with awards from before January 1, 2004 (i.e.,. notch sample), and Figure b illustrates the cumulative earnings distributions in 2014 and 2015 for DI recipients with awards from after January 1, 2004 (i.e.,. kink sample). The red (dashed) line denotes the old (new) SGA threshold. The gray dashed line represent the earnings response, and is inferred from the earnings level in 2014 that has the same CDF as the CDF at the SGA threshold in 2015, and subtracting off the SGA amount. The response is calculated as the difference $F_{14}^{-1}(F_{15}(\$8,000)) - \$8,000$ (see Blomquist *et al.* (2019) for a detailed description of the approach). The sample consists of DI recipients with a full (100 percent) benefit during 2014 and 2015. Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/\$ = 7.5).

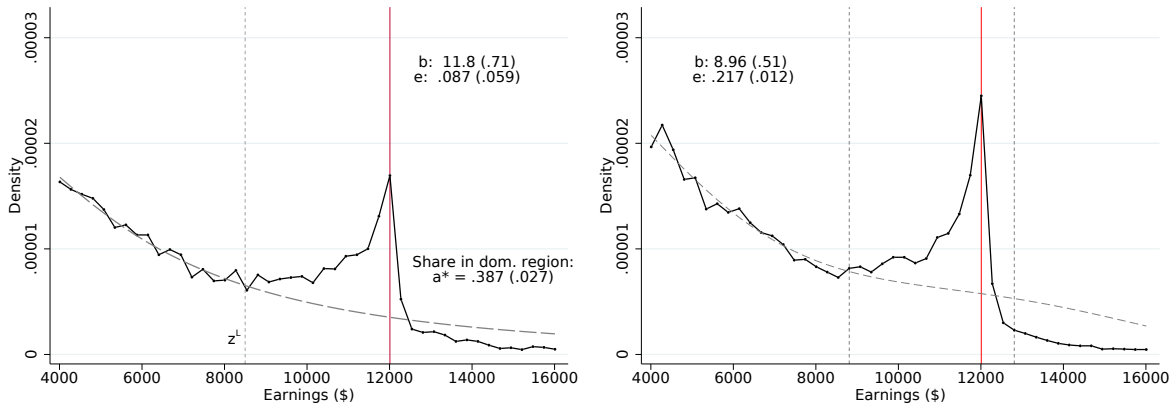Figure A.8: Bounds on the Bunching Elasticity in 2015

(a) Notch sample: Bunching Bounds in 2015 (b) Kink sample: Bunching Bounds in 2015

Notes: Figure a illustrates upper- and lower bounds for the bunching elasticity for DI recipients with awards from before January 1, 2004 (i.e.,. notch sample), and Figure b illustrates upper- and lower bounds for the bunching elasticity for DI recipients with awards from after January 1, 2004 (i.e.,. kink sample). Earnings is transformed by the natural logarithm, and the earnings distribution is filtered in the bunching segment (from ln(8,000) - 0.12 to ln(8,000)+0.12). We then vary the maximum slope parameter from 0 to 10 to identify the bounds (see Theorem 2 in Bertanha *et al.* (2019) for a detailed description). The vertical lines denote the minimum and maximum slope of the unobserved heterogeneity. The line to the left is the smallest slope that allows a continuous probability density function (PDF) to be consistent with both the bunching mass and observed income distribution. The right line is the maximum slope before the set of possible distributions allows for a PDF that equals zero in the bunching interval (see Figure 1 in Bertanha *et al.* (2019)). The sample consists of DI recipients with a full (100 percent) benefit during 2015.

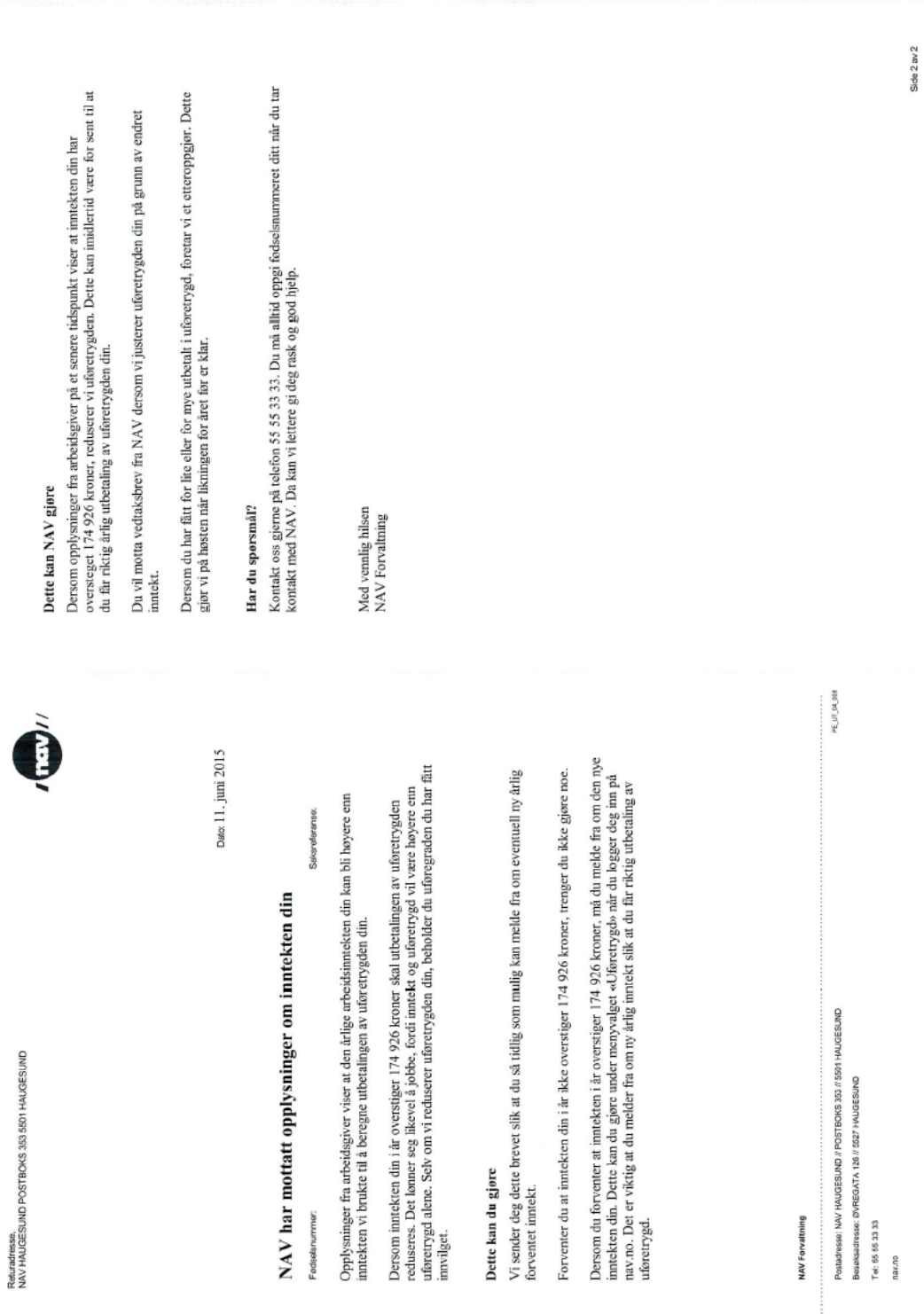Figure A.9: Polynomial Approach: Bunching Elasticity in 2014

b: 11.8 (.71)
e: .087 (.059)

Share in dom. region:
a* = .387 (.027)

z^L

(a) Notch sample: Bunching Elasticity in 2014

b: 8.96 (.51)
e: .217 (.012)

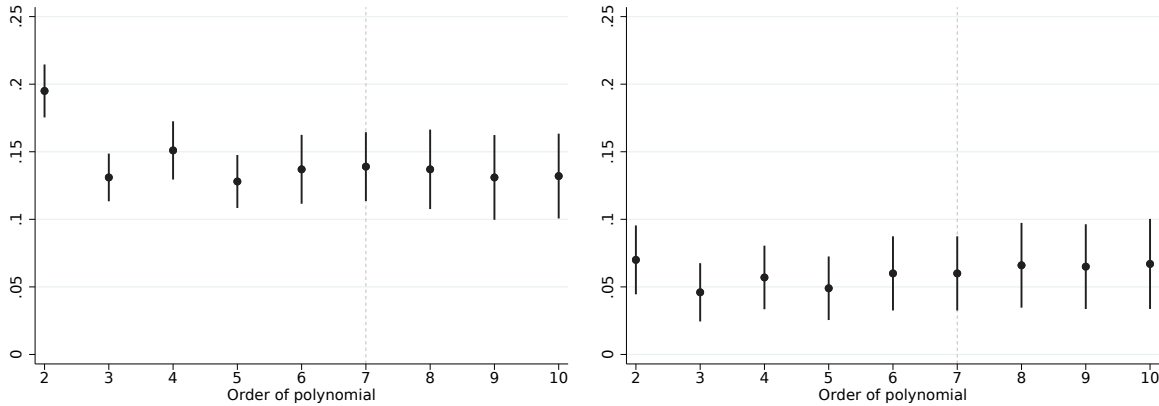(b) Kink sample: Bunching Elasticity in 2014

Notes: Figure a illustrates the earnings distributions in 2014 of DI recipients awarded benefits prior to January 1, 2004 and the fitted counterfactual density using the polynomial approach. Figure b illustrates the earnings distributions in 2014 of DI recipients awarded benefits after January 1, 2004 and the fitted counterfactual density using the polynomial approach. The red line denotes the SGA threshold in 2014. The polynomial order is chosen to minimize the distance between the estimate from the non-parametric approach and the parametric approach in 2015 (see Figure A.9). The sample consists of DI recipients with full (100 percent) benefit at the beginning of 2015. Earnings are adjusted using the average wage growth, and are reported in 2015 $.

Figure A.10: 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: DYREGATA 126 // 5527 HAUGESUND
Tel: 55 55 33 33
nav.no

PL_UT_04_088

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 for 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 degree of disability 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 expect you annual earnings to not exceed X, you do not need to do anything. Fifth paragraph: If you report your expected annual 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: Du 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 many or too few benefits, we will make an after settlement. **"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.11: Specification Checks for Polynomial Approach: Bunching Elasticity in 2015

(a) Informed: Sensitivity of Bunching Elasticity in 2015   (b) Non-informed: Sensitivity of Bunching Elasticity in 2015
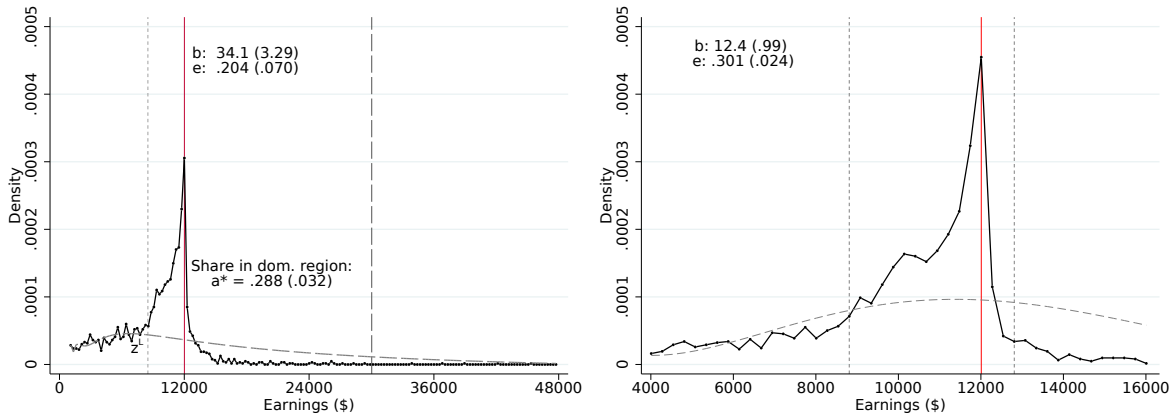
Notes: Figure a illustrates the estimated bunching elasticity in 2015 for treated DI recipients . Figure b illustrates the earnings distributions in 2015 for non-treated DI recipients and the fitted counterfactual density using the polynomial approach. The dots represent point estimates, and the vertical lines represent 95 percent confidence intervals. The x-axis represent different specifications for the polynomial order in equation 3. The two samples consist of DI recipients with full (100 percent) benefit at the beginning of 2015 who were eligible for the information treatment. Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/$ = 7.5).

Figure A.12: Weighted Earnings Distributions Around the SGA Threshold in 2014: By Information Status
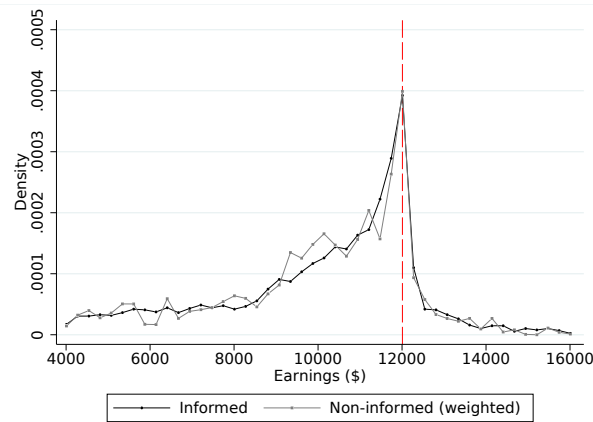
Notes: This figure shows the distribution of annual earnings in 2014 around the SGA threshold (marked by the red dashed line) in \$267 (2,000 NOK) bins by information status, where the non-treated units is weighted by propensity score weights $w(x) = \frac{P(I=1|x)}{P(I=1)} \frac{1-P(I=1)}{1-P(I=1|x)}$ where $P(I=1)$ denotes the probability of receiving information treatment. $P(I=1|x)$ is estimated with a logit using DI benefits, AIE, age, years on DI, female, cohabitant, number of children and years of schooling (same as in table 2, not including earnings in 2014 and 2015) as control variables. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 who were eligible to receive the information letter (PAE above the cutoff). Earnings are measured in 2015 dollars (NOK/$ = 7.5).

Figure A.13: Polynomial Approach: Bunching Among Eligible in 2014

(a) Eligible Notch Sample: Bunching Elasticity in 2014   (b) Eligible Kink Sample: Bunching Elasticity in 2014

Notes: Figure (a) illustrates the earnings distributions in 2014 of DI recipients awarded benefits prior to January 1, 2004 and the fitted counterfactual density using the polynomial approach. Figure (b) illustrates the earnings distributions in 2014 of DI recipients awarded benefits after January 1, 2004 and the fitted counterfactual density using the polynomial approach. The red line denotes the SGA threshold in 2014. The polynomial order is chosen to minimize the distance between the estimate from the non-parametric approach and the parametric approach ($p = 5$ for notch and $p = 7$ for kink).. The sample consists of DI recipients with full (100 percent) benefit at the beginning of 2015, and who were eligible for the information treatment. Earnings are adjusted using the average wage growth, and are reported in 2015 dollars (NOK/\$ = 7.5).

Figure A.14: Average Earnings By Information Status

Notes: This figure shows the regression coefficients from the distributed lag lag model that tests for significant differences between the two groups prior to the information treatment (see Section 7). The non-treated units is weighted by propensity 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 information treatment. $P(I = 1|x)$ is estimated with a logit using DI benefits, AIE, age, years on DI, female, cohabitant, number of children and years of schooling (same as in table 2, not including earnings in 2014 and 2015) as control variables. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 who were eligible to receive the information letter (with PAE above the cutoff). Earnings are measured in 2015 dollars (NOK/\$ = 7.5).

Table A.1: Survey evidence on knowledge about the change in work incentives

| | Agree (Strongly agree), % | |
| | Positive earnings | No earnings |
Column:	(1)	(2)
Panel A:		
Agrees to statement "Cash benefit is higher in 2015 than 2014"	73 (54)	68 (48)
Panel B:		
Agrees to statement "Cash benefit is taxed as labor income"	92 (78)	86 (70)
Panel C:		
Agrees to statement "From 2015, it will always pay to work more"	79 (58)	71 (51)
Panel D:		
Understands how the change affects **myself**	34 (13)	27 (14)
Number of respondents	784	884

Notes: This table displays results from the SSA's (NAV) survey of recipients after the information package in the fall of 2014 had been sent. The letter informed recipients about the overall goal of the reform and details of the changes in work incentives. 39 percent of the sample (78 percent with assistance) recollected receiving the information package about individual thresholds and benefit levels. Survey is made available from NAV.

Table A.2: Descriptive Statistics: By information status

Sample:	Eligible ($\hat{z} > K$)				Ineligible ($\hat{z} < K$)	
	Informed		Non-informed		Comparison group	
Column:	(1)	(2)	(3)	(4)	(5)	(6)
Earnings:	mean	sd	mean	sd	mean	sd
Earnings Jan-May in 2015 ($)	4,861	(1,219)	4,713	(1,203)	1,297	(1,038)
Annual earnings in 2014 ($)	9,679	(6,344)	9,246	(5,724)	4,442	(6,340)
DI information:						
Age at DI award	41.57	(12.46)	36.85	(12.16)	34.72	(15.18)
Years on DI	13.38	(10.01)	11.36	(9.78)	14.07	(11.53)
Uncapped annual DI benefits ($)	35,807	(6,255)	34,859	(5,351)	35,229	(4,970)
Annual indexed earnings ($)	58,200	(22,162)	56,614	(14,618)	55,833	(16,569)
Characteristics:						
Females	.53		.47		.53	
Married/Cohabitants	.57		.56		.39	
Years of Schooling	10.60	(2.32)	10.49	(2.38)	10.04	(2.83)
Number of Children	1.87	(1.29)	2.02	(1.46)	1.27	(1.38)
Observations	3,642		1,521		30,179	

Notes: Columns 1, 3, and 5 reports the means and Columns 2, 4 and 6 report standard deviations of key outcome variables and characteristics of three groups. The first group, "Informed" includes recipients whose projected earnings were above the cutoff and who received the information letter from SSA in June 2015. The second group, "Non-informed" includes recipients whose projected earnings were above the cutoff, but did not receive the information letter in June 2015 e.g. due to lags in reporting.and the group of individuals who were ineligible to receive the letter. The third group, "Comparison group" were ineligible to receive the information letter. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 and had positive earnings at some point during January-May 2015. Uncapped 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/$ = 7.5). The difference between the sample size in the second column of Table 2 and the total sample size of eligible and ineligible in this table is due to some individuals with high levels or earnings but who were ineligible for the letter. This group included individuals who reported a change in earnings before June 2015, and individuals who had already exceeded the limit and therefore received a letter from SSA informing them about a reduction in benefit payments.

Table A.3: Heterogeneous Effects of Information Treatment on Labor Market Outcomes

| | Probability to Switch Firm (1) | Effects on Labor Supply | | | | | Observations \<individuals\> (7) |
		Monthly earnings ($) (2)	Any earnings (3)	Fixed pay ($) (4)	Variable pay ($) (5)	Contract hours (6)	
A. Rigid hours	-.013	-206***	-.083***	-32**	-113***	-1.18***	28,788
	.009	30	.016	15	23	.31	\<2,399\>
p-value	.136	<.001	<.001	.037	<.001	<.001	
Dep. mean (Pre-Treatment)	.050	873	.807	243	485	9.03	
B. Flexible hours	-.009	-174***	-.079***	-20	-112***	-.97***	28,944
	.008	34	.015	18	26	.37	\<2,412\>
p-value	.270	<.001	<.001	.253	<.001	.009	
Dep. mean (Pre-Treatment)	.039	883	.727	282	473	10.51	

*** 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 estimates of the impacts of the information letter on labor market outcomes during 2015. The event study is implemented using a difference in difference design, where we include a dummy for the treatment group, a dummy for each month of the year, and an interaction between the post-treatment period and the treatment indicator. Non-treated units 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 treatment, and $P(I=1|x)$ is estimated by logit regression using the characteristics from Table 2. Fixed pay is defined by the work contract. Variable pay is defined as wages paid on an hourly basis, bonuses, overtime pay, or other payments as defined by employers. Switching employer is an indicator variable equal to one if the current employer is different than the main employer at the beginning of the calendar year. The sample consists of fully disabled recipients awarded DI before the 1st of January 2015 who were eligible to receive the information treatment. Earnings are measured in 2015 dollars (NOK/$ = 7.5). The sample is restricted to individuals that are observed in the monthly earnings data. Dependent mean (control group) is measured before treatment. Rigid vs Flexible hours is determined by whether the industry (five-digit) has more or less than the median fraction of contracts within the five most common hours categories. The estimates does not change if we instead use the three most common hours categories.