Discrete earnings and optimization errors: Evidence from student's responses to local tax incentives*

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Abstract

We study how different optimization frictions prevent taxpayers from responding to tax incentives. We utilize an income notch created by the study subsidy system for university students in Finland, and analyze a reform that shifted out the location of the notch. In addition to distinctive local bunching responses, we find that the whole earnings distribution shifts out with the notch. This implies that labor market frictions stemming from discrete earnings possibilities prevent a smooth response to tax incentives. This indicates larger welfare effects than observed bunching estimates suggest. Moreover, by utilizing data on secondary school math grades, we find evidence that optimization errors attenuate local responses.

Keywords: tax incentives, optimization frictions, bunching
JEL Classification Codes: H21, H24, J22

1 Introduction

Working-age individuals face numerous taxes and other regulation. In the jungle of various taxes and complex rules, it is likely that some taxpayers do not respond to incentives – not because they would not like to, but because they cannot. This observed non-responsiveness can stem from various sources: inflexible labor markets, failure to understand complex rules or the lack of knowledge to respond optimally. In all of these cases, not being able to respond is likely to reduce the welfare of those not responding.

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Therefore, it is of key importance to gain knowledge on the factors that explain *why* we do not observe individuals responding to tax incentives.

An increasingly active literature discusses non-responsiveness to income taxes. A good example of this is the bunching literature. In the bunching framework, observed excess mass relative to the surrounding distribution defines the behavioral response to a local discontinuity in the budget set caused by taxes or other regulation (see Kleven 2016 for a survey). Reasons explaining small observed bunching even to substantial changes in incentives are generally labeled as optimization frictions attenuating observed responses. These frictions collectively include all factors outside of a standard labor-leisure framework, such as adjustment costs, job search costs or inattention (Chetty *et al.* 2011, Chetty 2012, Chetty *et al.* 2013, Chetty and Saez 2013, Kleven and Waseem 2013 and Gelber *et al.* 2016).

However, the effect of various frictions might not be limited to the extent of observed local responses. For example, discrete earnings responses, analyzed for example by Dickens and Lundberg (1993), might produce a more scattered and wide-ranging impact in the earnings distribution which cannot be captured by a local estimator. Neglecting these kinds of discrete responses can have significant implications related to welfare estimates of various tax and benefit regulations derived using the standard estimation framework that do not necessarily account for these types of responses.

In this paper we study how various optimization frictions prevent taxpayers from responding to tax incentives. In particular, we focus on detecting discrete earnings responses. We attempt to fill the gap in the literature on understanding the role of different frictions by utilizing a novel design: a combination of an income notch and a reform that shifted out the location of the notch. The notch in the budget set is caused by an income threshold in a study subsidy program for higher education students in Finland. We believe that university students are an excellent population to study the presence of optimization frictions, particularly those stemming from the labor market. University students are, on average, in the higher part of the ability distribution, and in the Finnish context, very typically participate in the flexible part-time labor market while studying. If any frictions such as discrete earnings responses can be detected from these labor markets, they are likely to be present in more permanent, non-temporary labor markets as well.

The monthly study subsidy is approximately 500 euros. A student loses one month of the subsidy if she exceeds an annual income threshold. The threshold thus creates an income notch, which induces a strong incentive to remain below it by, for example, cutting back on working hours. In 2008, a reform shifted out the income thresholds by approximately 30%, allowing students to earn more without losing any benefits.

The notch combined with its relocation allows us to study the importance of different optimization frictions. First, exceeding the threshold results in losing disposable income, creating an area of dominated choice just above the threshold. Utilizing this dominated region, we are able to separate the presence of optimization frictions from low underlying responsiveness, since without some type of optimization frictions students would not locate themselves in the dominated range (see Kleven and Waseem (2013)). Second, the reform allows us to estimate in what income range students react to the threshold. If they respond in a wide income range far below the threshold, it points to the direction that optimization frictions do not just attenuate local behavior around the notch but induce significant responses not included in local estimators. Third, the reform allows us to see how quickly the local excess mass disappears from the old notch and appears at the new threshold, indicating to what extent students are generally aware of the change in local incentives.

We use register-based panel data on all Finnish taxpayers from 1999–2013. The data include detailed tax and transfer variables from tax and social benefit administrations. The excellent quality of Nordic administrative data combined with a large number of observations allow us to accurately analyze behavioral responses associated with various tax and social benefit programs in Finland, and reliably separate bunching behavior from other irregularities in the income distribution.

Our results show that students respond to the income threshold in the study subsidy program. We find evident bunching behavior below the notch. At the same time, we find that frictions play an important role in explaining responses, as many students are located in the dominated region just above the notch.

As our main result, we find clear evidence that the whole earnings distribution shifted out when the income threshold was increased. In particular, we find that students far below the old threshold significantly increased their earnings. First, this implies that discrete earnings responses prevent students from marginally adjusting their labor supply to match the notch point. Second, this indicates that discrete earnings responses create significantly larger behavioral responses to the notch than what can be recovered utilizing only local responses around it. Taking into account these responses within a wider income range, we estimate that the local approach understates the extent of income responses by a factor of 3.6. In order to further support this conclusion, we show that the earnings distributions of other young part-time workers who are not subject to study subsidy rules remained constant within the same period, highlighting that the drastic changes in the earnings of students are in fact caused by changes in study subsidy rules and not the general development of the part-time labor market.

The above result establishes that optimization frictions can entail a larger behavioral effect than what was previously thought. Utilizing the bunching estimator or other local approaches might lead to an underestimation of the underlying elasticity, even when accounting for factors attenuating local responses which reduce excess mass or induce taxpayers to locate themselves in the dominated region. In fact, since the shape of the income distribution changed drastically when the threshold was increased, the surrounding density around the notch does not deliver a reliable estimate for the counterfactual density at the notch needed to derive a robust estimate for local excess bunching.

Nevertheless, despite the apparent limitations of the bunching approach in this context, the local response can still give us information on the significance of other optimization frictions. For example, larger excess mass in one subgroup relative to another is potentially informative about the influence of optimization errors. In fact, we find that university students with higher secondary school math scores bunch more actively and are more unlikely to locate themselves in the dominated region compared to those with lower scores. This alludes that higher optimization ability is positively correlated with the extent of observed responsiveness. In addition, we find that the excess mass below the old notch disappears and reappears below the new threshold right after the reform, showing that students are in general aware of the threshold rule.

In addition to optimization frictions and the bunching estimator, this study contributes to the literature on observed responses to kinks and notches (Saez 2010, Bastani and Selin 2014, Slemrod 2010, Chetty *et al.* 2011 and Kleven 2016). Kleven and Waseem (2013) show that wage earners bunch actively at income tax notches in Pakistan. We add to this study by estimating responses to income notches in a developed country where the tax system is strongly enforced, and thus the responses are more related to labor supply decisions as opposed to reporting behavior. Other existing evidence on responses to notches comes from a range of different institutions, for example, the medicaid notch in the US (Yelowitz 1995), eligibility for in-work benefits in the UK (Blundell and Hoynes 2004 and Blundell and Shepard 2012), social security and financial incentives in retirement rules (Gruber and Wise 1999 and Manoli and Weber 2011), and car taxes affecting the fuel economy of cars (Sallee and Slemrod 2012).

This paper proceeds by presenting the relevant institutions in Section 2. In Section 3 we discuss the role of different behavioral frictions in explaining taxpayers' behavior, and present the empirical methodology. Data and descriptive statistics are presented in Section 4. Section 5 presents the results, and Section 6 concludes the study.

2 Institutions

We focus on studying the behavioral effects of discontinuous labor supply incentives created by the Finnish study subsidy program. In Finland, all students that are enrolled in a university or polytechnic can apply for a monthly-based study subsidy, administered by the Finnish Social Insurance Institution (SII). The subsidy is intended to enhance equal opportunities to acquire higher education, and to provide income support for students who often have low disposable income. In Finland, university education is publicly provided and there are no tuition fees. A large proportion of individuals receive higher education in Finland (ca. 40% of individuals aged 25-34 have a degree), and the study subsidy program is widely used among students. Despite the wide coverage of the subsidy, working part-time during studies and study breaks is very typical among university and polytechnic students. Therefore, the means-tested study subsidy system creates relevant discontinuous changes in labor supply incentives, which we describe in detail below. We describe the part-time labor market of students and other part-time workers in Finland in more detail in Section 4.

The maximum amount of the study subsidy is 461 euros per month in the academic year 2006/2007. Students can apply for the subsidy for a limited number of months per degree (max. 55 months). Typically, students first apply for the subsidy when they are accepted to a higher education program. The default number of study subsidy months per academic year is 9 (fall + spring semester), which students also typically receive. The eligibility for the study subsidy depends on personal annual gross income (earned income + capital income), and academic progress (completing a certain predefined number of credit points per academic year). Parental income or wealth does not affect eligibility nor the amount of the benefit for university or polytechnic students.[1]

The discontinuity in labor supply incentives is created by the income thresholds: if annual gross income (earned income + capital income) is higher than the threshold, the study subsidy of one month is reclaimed by the SII. An additional month of the subsidy is reclaimed for an additional 1,010 euros of gross income above the threshold. With the typical 9 months of the subsidy per calendar year, the annual gross income limit is 9,260 euros (in 2006/2007). Students can alter the number of subsidy months by application, or by returning already granted subsidies by the end of March in the next calendar year. Having more study subsidy months reduces the income limit, and vice versa.[2]

Students face large local incentives not to exceed the income threshold. Earning income over the threshold leads to losing one study subsidy month. This results in an implied marginal tax rate of over 100% in a region just above the threshold, creating a *notch* in the budget set of students. Therefore, the study subsidy notch induces a strictly dominated region just above the threshold, where students can earn more disposable income by reducing their gross income level.

The left-hand side of Figure 1 illustrates the effect of the study subsidy notch on disposable income close to the notch point with the standard case of 9 study subsidy months in 2007. In the figure, the vertical axis denotes disposable income including the subsidy, and the horizontal axis denotes gross income relative to the notch point (9,260

[1] The full study subsidy includes a study grant and housing benefit. The standard study grant is 259€/month and the maximum housing benefit is 202€/month (in 2006/2007). Housing benefits are granted only for rental apartments, and the housing allowance is reduced if spousal gross income exceeds 15,200 per year (in 2007). In addition to the study subsidy, students can apply for repayable student loans which are secured by the central government.

[2] The formula for the annual gross income limit is the following: 505 euros per study subsidy month plus a fixed amount of 170 euros, and 1,515 euros per month without the study subsidy (in 2006/2007).

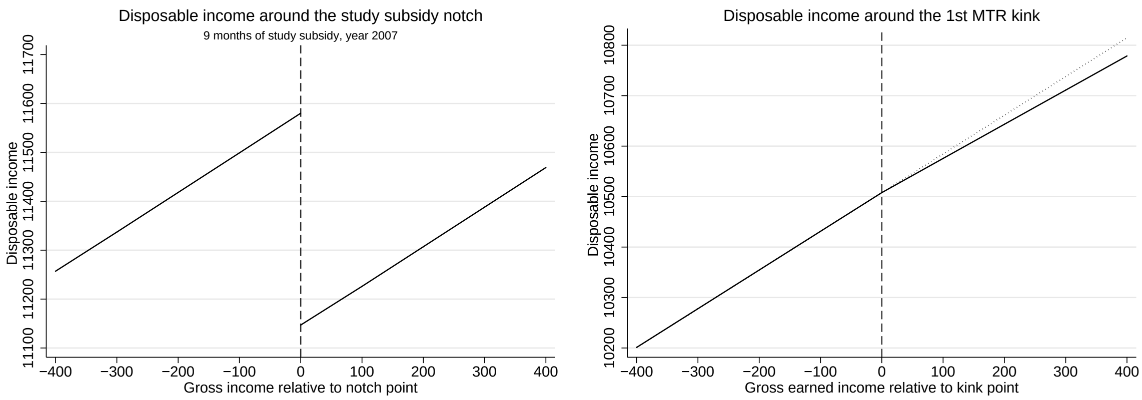

Figure 1: Disposable income around the study subsidy notch (left-hand side) and the first MTR kink point (right-hand side), year 2007

euros). The figure shows that once the gross income threshold is exceeded, losing one month of study subsidy causes a significant dip in disposable income.

In order to compare the incentives created by the study subsidy notch to those created by the graduated income tax rate schedule, the right-hand side of Figure 1 illustrates the effect of the first kink point in the marginal income tax rate (MTR) on disposable income. Earning income above the kink results in less disposable income than before the kink. For example, 100 euros of gross income above the kink results in 9 euros less disposable income than below the kink. Importantly, Figure 1 underlines that the difference between the study subsidy notch and the MTR kink points is remarkable, as the study subsidy notch creates very significant local incentives to adjust earnings close to the discontinuity point. In addition to study subsidy, we briefly study bunching at MTR kink points in Section 5. The step-wise MTR schedule in Finland is illustrated in detail in Figure A1 and Table A4 in the Appendix.

The study subsidy program was reformed in 2008. The main outcome of the reform was that the income thresholds were increased by approximately 30%. For a typical student with 9 study subsidy months, the income threshold increased from 9,260 to 12,070 euros. In addition, the monthly study subsidy was increased from 461 to 500 euros per month. As with the old regime, an additional month of the subsidy is reclaimed after an additional 1,310 euros of gross income above the threshold. Other details of the system were not changed, including the academic criteria.[3]

Figure 2 illustrates the study subsidy schedule both before and after 2008 for a student who collects the default 9 subsidy months. The figure underlines the distinctive change in incentives caused by the increase in the income thresholds in 2008, and the step-wise nature of the threshold rule where additional subsidy months are reclaimed for income

[3]After 2008, the formula for the annual gross income limit is the following: 660 euros per study subsidy month plus a fixed amount of 220 euros, and 1,970 euros per month when no study subsidies are collected.

above the threshold. In particular, the figure highlights that the reform significantly increased disposable income if the student earned income above the old threshold (9,260e), thus increasing incentives to earn more. Finally, Table A1 in the Appendix shows the income thresholds in numbers before and after 2008, and presents the relative loss in disposable income that incurs when the income threshold is exceeded.

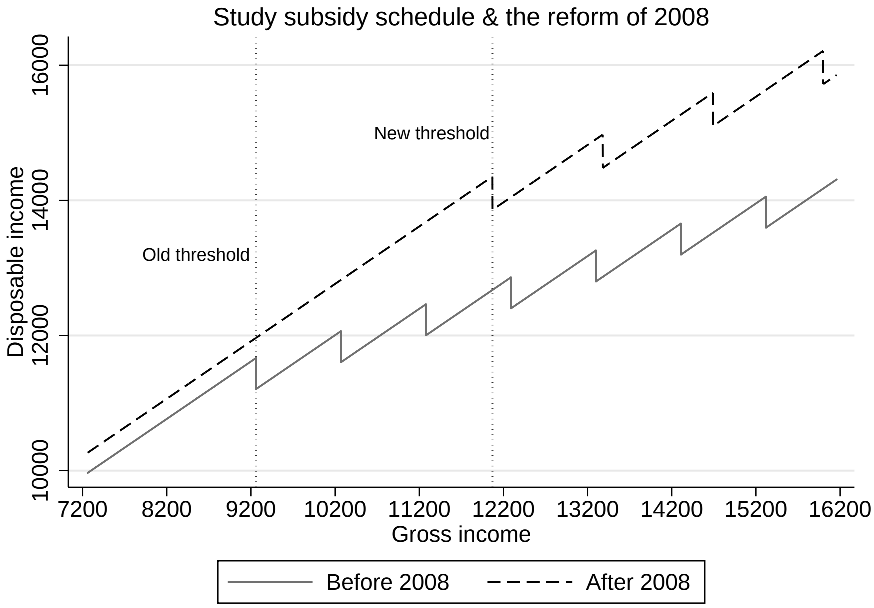

Figure 2: Disposable income at different gross income levels, students with 9 subsidy months in 2007 and 2008

3 Conceptual framework and empirical analysis

3.1 Responses to notches and optimization frictions

We follow the bunching literature in utilizing discontinuous incentives in tax schedules to analyze the effect of tax incentives on taxpayers' behavior. We study responses to notches, jumps in average tax rates, following the bunching analysis of Saez (2010) and Kleven and Waseem (2013). The bunching methodology is recently surveyed by Kleven (2016). We focus on understanding the role and implications of different types of optimization frictions. Notches are particularly useful to this end. They typically create a striking incentive to locate below the income threshold. In addition, notches create a dominated region just above the notch where it is clearly not optimal to locate, as individuals can gain disposable income by reducing their gross income.

In the absence of frictions, when individuals follow standard labor-leisure preferences we should find an excess mass in the income distribution just below the notch point (Kleven and Waseem 2013). Relating the size of the excess mass in the income distribution to the relative change in incentives caused by the notch gives an elasticity estimate, describing the extent of the welfare loss caused by tax incentives (Saez 2010). However, optimization frictions might prevent individuals from responding to incentives despite their underlying labor-leisure preferences. In this case, the local elasticity estimate can capture short-term behavioral responses, but not the underlying structural longer-term welfare effect.

We focus on the role and significance of various optimization frictions in affecting observed responses and welfare implications. In general, if all behavioral responses are not observed because of frictions, the elasticity estimate and the estimated welfare effects are typically biased towards zero. In this paper, we are especially interested in frictions that prevent smooth, marginal labor supply responses, therefore creating a discrete choice set of potential earnings and working hours for the individual. These types of optimization frictions are related frictions stemming from the labor market, such as the sparse menu of working hours contracts discussed in Saez (1999), and search costs analyzed by e.g. Chetty *et al.* (2011). In addition, previous literature has discussed and analyzed the significance of optimization errors and inattention in attenuating observed behavioral responses (Chetty *et al.* 2009, Chetty 2012, Chetty *et al.* 2013, Chetty and Saez 2013).

Frictions stemming from the labor market can prevent accurate responses to tax incentives. In more detail, the discreteness of individual earnings choices stemming from, for example, working-hours constraints discussed in Saez (1999), prevents individuals from marginally adjusting their working hours and earnings, and thus prevent them from locating themselves just below the notch. First, this would lead to attenuated the observed local response. Second, limited earnings choices can lead to individuals sub-optimally locating themselves in the dominated region just above the notch.

However, the notch can also affect earnings such that it causes individuals to choose either earnings far below the notch, or far above it. Thus, when individual earnings are discrete, the observed response can spread in wider income range than just the neighborhood of the notch point. Therefore, in the baseline model of marginal responses to incentives, frictions that lead to discrete responses can prevent us from measuring all potential responses that occur further away in the earnings distribution.

In a simple cross sectional notch framework, it is not possible to distinguish discrete earnings responses from other optimization frictions that attenuate local responses. However, when utilizing a design incorporating an income notch and a change in the location of the notch, it is possible to separate discrete earnings responses from other frictions. Empirically, if discrete earnings responses occur, we would observe some individuals shifting their location in the income distribution far away from the notch, leading to large changes in the shape of the overall earnings distribution when the location of the notch is changed. In contrast, if optimization friction are only attenuating marginal responses to the notch, the change in the overall shape of the distribution would no be detected.

We also study how optimization errors affect the local response. Due to optimization errors, some taxpayers fail to adjust their income such that they locate themselves in the dominated region, or locate themselves unintentionally way below the notch point. Separating optimization errors from other frictions causing a similar type of attenuation in bunching responses is relevant. For example, if we want to reduce the share of taxpayers in the dominated region, we need to know whether they are there because they do not know about tax incentives (inattention), or because they do not understand the regulations or fail to optimize. In the case of significant optimization errors, reducing complexity and increasing the salience of regulations can reduce the welfare costs for individuals failing to optimize (Chetty *et al.* 2009, Reck 2016).

In order to analyze optimization errors, we use register-based data on secondary school final scores at the age of 14–15 to proxy for optimization ability. In particular, we utilize the math scores to characterize the ability to optimize earnings such that the notch point is not exceeded. In addition, math scores are also likely to be correlated with the ability to understand the numerical rules related to the study subsidy. We would expect that better understanding and optimization ability leads to larger excess mass below the notch, and to smaller share of students in the dominated region.

3.2 Empirical estimation

Local bunching responses

First, we estimate local responses to the notch following the standard bunching approach in Kleven and Waseem (2013). The local counterfactual density is estimated by fitting a flexible polynomial function to the observed distribution, excluding an area around the study subsidy income threshold z^* from the observed gross income distribution. We re-center gross income in terms of z^*, and group students into income bins of 100 euros. We then estimate a counterfactual density by excluding the region around the threshold $[z_L, z_H]$ from the regression

$$c_j = \sum_{i=0}^{p} \beta_i (z_j)^i + \sum_{i=z_L}^{z_H} \eta_i \cdot \mathbf{1}(z_j = i) + \varepsilon_j \tag{1}$$

where c_j is the count of firms in bin j, and z_j denotes the income level in bin j. The order of the polynomial is denoted by p. Thus the fitted values for the counterfactual density are given by $\hat{c}_j = \sum_{i=0}^{p} \beta_i (z_j)^i$. The local excess bunching is then estimated by relating the actual number of firms close to the threshold within (z_L, z^*) to the estimated counterfactual density in the same region:

$$\hat{b}(z^*) = \frac{\sum_{i=z_L}^{z^*} (c_j - \hat{c}_j)}{\sum_{i=z_L}^{z^*} \hat{c}_j / N_j} \tag{2}$$

where N_j is the number of bins within $[z_L, z^*]$.

Following Kleven and Waseem (2013), we set the lower limit of the excluded region (z_L) based on visual observations of the income distribution to represent the point in the income distribution where the bunching behavior begins, that is, when the density begins to increase. We determine z_H such that the estimated excess mass $\hat{b}_E(z^*) = (\sum_{i=z_L}^{z^*} c_j - \hat{c}_j)$ equals the estimated missing mass above the threshold, $\hat{b}_M(z^*) = (\sum_{i=z>z^*}^{z_H} \hat{c}_j - c_j)$. We apply this convergence condition by starting from a small value of z_H, and increasing it gradually until $\hat{b}_E(z^*) \approx \hat{b}_M(z^*)$. This convergence condition also defines the marginal buncher student with income $z^* + \triangle z$. The marginal buncher represents the last student to reduce his/her earnings in order to locate below the income threshold.[4]

In addition, we relate the income response of the marginal buncher to the relative change in disposable income caused by exceeding the threshold by $\triangle z$. Following Kleven and Waseem (2013), we calculate the elasticity at the notch using the following quadratic formula: $e \approx (\triangle z/z^*)^2/\triangle t$, where $\triangle z/z^*$ is the relative income response of the marginal buncher, and $\triangle t$ denotes the change in the implicit marginal tax rate, including the lost study subsidy, caused by exceeding the income threshold by $\triangle z$.[5]

Changes in the shape of the distribution

In addition to local responses, we evaluate the effects of the income threshold on the overall shape of the earnings distribution further away from the notch point. Estimation of the local excess bunching and the local counterfactual density could produce incorrect estimates of the extent of behavioral responses to the income threshold if the notch affects the whole distribution. As discussed above, one potential cause for responses within larger income intervals around the notch are discrete earnings responses, which can affect the shape of the distribution far below the income threshold.

To distinguish the effect of discrete earnings responses from other optimization frictions, we utilize the change in the location of the income threshold in 2008. In the analysis, we use the pre-reform density as the counterfactual when numerically illustrating changes in the distribution caused by the increase in the income threshold. The method follows the lines of the local approach presented above, except that we denote the distributions

[4]Following Kleven and Waseem (2013), we calculate standard errors for all the estimates using a residual-based bootstrap procedure. We generate a large number of income distributions by randomly resampling the residuals from equation (1) with replacement, and generate a large number of new estimates of the counterfactual density based on the resampled distributions. Based on the bootstrapped counterfactual densities, we evaluate variation in the estimates of interest. The standard errors for each estimate are defined as the standard deviation in the distribution of the estimate.

[5]Implicit marginal tax rates remain relatively high (>50%) even further away above the notch, as an extra month of the subsidy is reclaimed after additional 1,010€ above the income limit (1,310€ after 2008). Thus, the effective tax schedule for students inherently includes multiple notches. However, we only observe significant bunching at the first notch, which justifies the analysis of the first notch only, also rationalized by the fact that students can alter the number of study subsidy months until the march of next tax year.

in relative terms in order to take into account the fact that the number of students at certain income levels might differ between the years.

As an example, the change in the shape of the overall distribution below the old threshold can be measured as

$$\hat{b}(z) = \frac{\sum_{i=z_1}^{z^*} \left[(c_j^A/N_A) - (c_j^B/N_B) \right]}{\sum_{i=z_1}^{z^*} (c_j^B/N_B)/N_j} \tag{3}$$

where $\sum_{i=z_1}^{z^*}(c_j^A/N_A)$ is the relative share of students after 2008 within an income range of $z_1 - z^*$, where z^* denotes the threshold before the reform of 2008, and z_1 the first income bin starting from zero earnings. In our baseline case, N_A denotes the overall number of students earning less than 18,000 euros per year after the reform. Similarly, $\sum_{i=z_1}^{z^*}(c_j^B/N_B)$ is the relative share of students in the income range $[0, z^*]$ before the reform. N_j is the number of bins within $[z_1, z^*]$. In our analysis, we focus on the years right before and after 2008 in order to focus on the effects of the reform.

However, it could be that other factors than the change in the income threshold cause changes in the shape of students' income distribution, such as overall changes in the economic environment, particularly the downturn starting from 2009, which could significantly affect the Finnish part-time labor market. In order to take these into account, we utilize changes in the distribution of young, part-time non-student workers who roughly match students' job and age characteristics. These individuals are thus not subject to the income threshold but work in similar types of jobs as students. We discuss the composition and the characteristics of this group in Section 4.

Intuitively, even though current students might differ from current non-student part-time workers in some non-observed characteristics, the income development of other part-time workers still captures the underlying general economic trend that affects the earnings potential of the part-time labor force. Therefore, in order to take the general economic development into account, we utilize a difference-in-differences type of a setup where we subtract the change in the non-student distribution from the change in the student distribution before and after the reform, utilizing a similar estimation approach as depicted above.

Measuring the extent of behavioral responses: local bunching vs. discrete earnings responses

[TO BE ADDED HERE]

4 Data

We use panel data on all working-aged individuals (15–70 years) living in Finland in 1999–2013. Data include a variety of register-based variables, such as detailed tax register and social benefit data, including data on the study subsidy program. In addition, we utilize register data on secondary school final grades, and data on the field of study collected from the universities. Furthermore, we characterize the nature of the jobs students work in by utilizing firm-level data on the field of industry linked to individual registers. With these data, we can analyze responses to incentives created by the study subsidy program, and learn how various individual characteristics affect behavioral responses.[6]

			Individual characteristics			
	Age	Female	Labor income	Gross income	Working months	
Mean	23.7	.56	9,130	8,718	7.7	
Median	23	1	6,325	5,825	8	
sd	5.128	.496	9,524	11,347	3.85	
N	5,126,594	5,126,594	4,351,213	5,114,,098	3,557,732	
	Income threshold	Study subsidy months	Years studied	Math score	Finnish score	Average score
Mean	12,997	6.7	2.1	7.7	8.0	7.3
Median	12,070	8	2	8	8	7.82
sd	3,868	3.05	1.91	1.41	1.12	2.36
N	5,118,447	5,126,594	3,933,607	3,347,095	3,343,930	3,790,333
			Field of study			
	Arts & humanities	Business & soc. science	Tech. & science	Health & soc. serv.	Other/unknown	
Mean	.10	.15	.24	.12	.40	
sd	.30	.36	.39	.32	.45	
N	5,126,594	5,126,594	5,126,594	5,126,594	5,126,594	
			Field of industry			
	Industry	Services	Administration	Health & soc. serv.	Other/unknown	
Mean	.12	.12	.20	.04	.52	
sd	.33	.32	.40	.19	.50	
N	5,126,594	5,126,594	5,126,594	5,126,594	5,126,594	

Table 1: Descriptive statistics, all students, 1999–2013

Table 1 shows the descriptive statistics for all students who collected some amount of study subsidy in 1999–2013. The average labor income is 9,130 euros and average gross income excluding the study subsidy is 8,718 euros per year. This indicates that many students have part-time or full-time jobs during their studies and breaks between semesters. The average number of working months for students is 7.7. However, working months variable contains calendar months in which a student has had an employment contract, which does not necessarily indicate that students have actually been working in all of the months the contract has been in place.

[6]The data set is based on the Finnish Longitudinal Employer-Employee Data (FLEED), to which we have linked various essential variables from other register data sources. The data are provided by Statistics Finland.

The average income threshold for students is around 13,000 euros, and average number of study subsidy months collected per year is 6.7. An average student in the data has been studying for approximately 2 years. The table also includes descriptive statistics on math, Finnish and average secondary school scores, which we utilize to characterize optimization ability in our analysis. In addition, nearly 25% of students have a technology or science major. 15%, 12% and 10% of students study business and social sciences, health and social services, and arts and humanities, respectively. However, information on the major is missing from the data for a significant share of university students. Finally, 20% of students work in administrative and support services, 12% in the service industry (mainly restaurants and hotels), 12% in industry (including repair and maintenance), and 4% in health and social services. Nevertheless, the industry classification is missing or unknown for many students in the data.

Table 2 shows the descriptive statistics for students who received the default 9 subsidy months. Overall, these student represent approximately one third of all students who receive a positive study subsidy among university/polytechnic students. On average, these students earn less and have fewer working months than the overall student population who, on average, receive less subsidy months and thus have higher income thresholds. Otherwise students receiving the default number of subsidy months are rather similar to the overall student population.

	Individual characteristics					
	Age	Female	Labor income	Gross income	Working months	
Mean	22.4	.57	5,634	5,177	6.8	
Median	22	1	4,751	4,162	6	
sd	4.23	.49	5,224	5,930	3.78	
N	1,593,322	1,593,322	1,360,728	1,592,445	1,086,127	
	Income threshold	Study subsidy months	Years studied	Math score	Finnish score	Average score
Mean	10,393	9	2.0	7.8	8.1	7.4
Median	9,260	9	2	8	8	8
sd	1,378	-	1.41	1.38	1.10	2.28
N	1,592,695	1,592,445	1,536,115	1,090,476	1,089,406	1,204,429
	Field of study					
	Arts & humanities	Business & soc. science	Tech. & science	Health & soc. serv.	Other/unknown	
Mean	.12	.18	.29	.14	.27	
sd	.32	.38	.43	.35	.34	
N	1,593,322	1,593,322	1,593,322	1,593,322	1,593,322	
	Field of industry					
	Industry	Services	Administration	Health & soc. serv.	Other/unknown	
Mean	.10	.11	.16	.03	.61	
sd	.30	.31	.36	.16	.49	
N	1,593,322	1,593,322	1,593,322	1,593,322	1,593,322	

Table 2: Descriptive statistics, students with 9 subsidy months, 1999–2013

Finally, Tables A2 and A3 in the Appendix present the descriptive statistics for the non-student population aged 19–50 years and for young, non-student part-time workers, respectively. In our analysis, we utilize young part-time workers as a comparison group to students, who are also typically young and work part-time during their studies. The group of non-student part-time workers is selected to roughly match students' job and age characteristics. Students typically work in part-time jobs or in full-time jobs for a part of the year, that is, they work less than 12 months a year. In addition, students tend to be young as shown above. Thus, the control group comprise of individuals who we observe to have less than 12 working months per year, and who are 19–24 years old. The age interval is chosen to match between the 25–75 percentile points of the students age distribution. In addition, the sample is restricted to those who we observe to have a working contract for less than 12 months in a year. For this group, the observed working months are similar to those receiving 9 months of the study subsidy, and their annual earnings are also within the same ballpark as for students', albeit slightly larger. In addition, these young part-time workers are employed in similar types of jobs (industries) as the student population.

5 Results

5.1 Local responses to notches

First, we present the results on bunching at the study subsidy notch.We then characterize the role and significance of various frictions in the subsequent sections, focusing on frictions stemming from the labor market and optimization errors.

We find clear local responses to the income threshold of the study subsidy program. Figure 3 shows the gross income distribution and the counterfactual distribution relative to the notch in bins of 100 euros in the range of +/- 6000 euros from the notch in 1999–2013. The dashed vertical line denotes the notch point above which a student loses one month of the subsidy. The solid vertical lines denote the excluded range used in the estimation of the counterfactual, which is estimated using a 7th-order polynomial function. The dash-point vertical line above the notch shows the upper limit for the dominated region. The figure also includes estimates and standard errors for the local excess mass at the notch, the share of individuals in the dominated region, and the upper limit of the counterfactual which defines the marginal buncher, following the local estimation approach used in Kleven and Waseem (2013).

The upper graph in Figure 3 indicates a visually clear and statistically significant excess mass below the notch for all students (excess mass estimate 2.2). This indicates that students are both aware of the notch and respond to the strong incentives created by it. The lower graph shows the results for students receiving the default number of 9 subsidy months in a year. Responses to the notch are clearly significant also for this group, and the local excess mass estimate is of a similar magnitude (2.0) as for all students

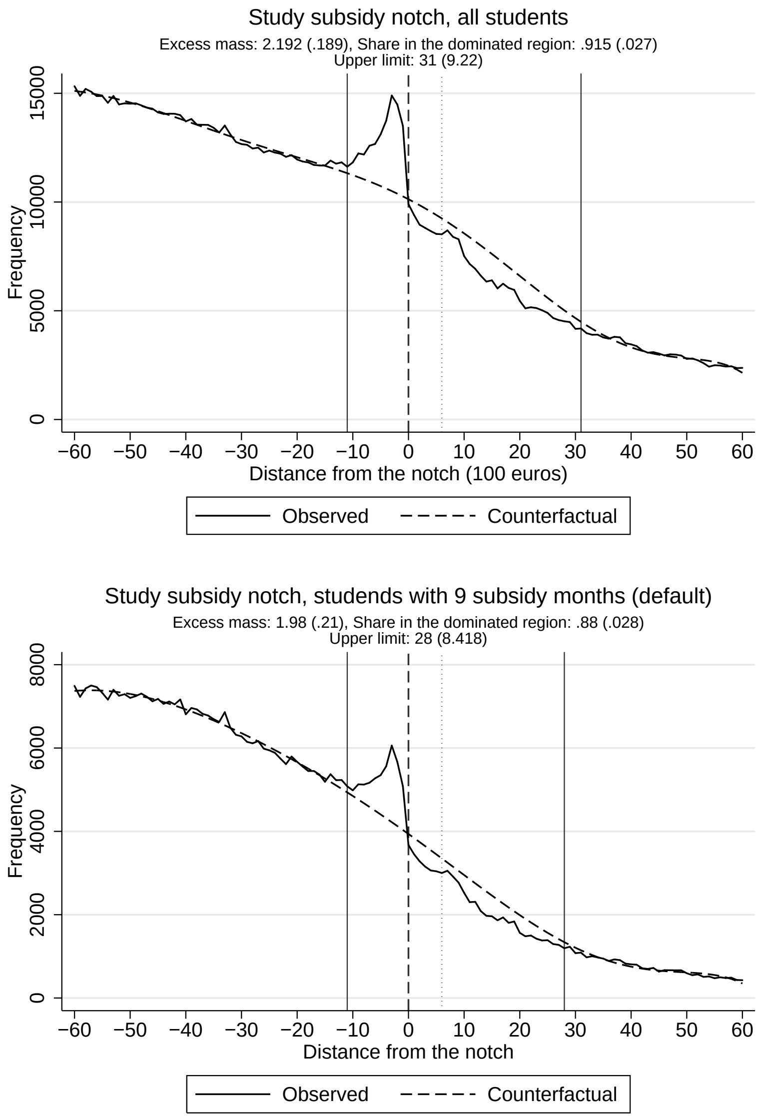

Figure 3: Bunching at the study subsidy notch, 1999–2013

with a varying number of subsidy months.

In addition, Figure 3 shows clear evidence of the existence of optimization frictions. There is an economically and statistically significant mass of students – 88-92% of the mass compared to the counterfactual – at the strictly dominated region above the notch where students can increase their net income by lowering their gross income.

Furthermore, the distributions in the figure are drawn for gross income, including both earned income and capital income. However, as significant amounts of capital income are uncommon among the student population, the local distributions in Figure 3 largely resemble those for labor earnings only. The distributions for labor income are presented in the next subchapter.

In order to have some understanding on the extent of the local response to the notch, we calculate local elasticity estimates following the methods of Kleven and Waseem

(2013). Reduced-form earnings elasticities when not taking frictions into account are 0.083 (standard error 0.019) for all students and 0.065 (0.007) for students with 9 subsidy months.[7] These estimates imply that even though excess bunching is evident and notable earnings responses occur ($\triangle z$ is around 15% of disposable income at the notch), the estimated local elasticities are moderate at most. This is partly because the change in incentives at the income threshold is also very distinctive, which produces small elasticity estimates even with large behavioral responses. In the next subsection, we study how discrete earnings responses in a wider income range affect responses to the income threshold, and evaluate how this type of a friction affects the scope of behavioral estimates.

Finally, we also compare the responses of students at the study subsidy notch to those at the MTR kink points. There is a striking difference between bunching at notches and tax rate kinks. Figure A3 in the Appendix shows the income distributions and counterfactuals around MTR kink points for current students (first MTR kink), university graduates (last MTR kink) and students who previously bunched at the study subsidy notch (first MTR kink). For all of these groups, we find no bunching at any MTR kink point in any year. In addition, Figure A2 in the Appendix indicates that taxpayers in general do not bunch at the MTR kink points in Finland, not even those with higher secondary school math scores which we use to proxy for optimization ability below in Section 5.4.

5.2 Changes in the shape of the distribution

To recover evidence of discrete earnings responses, we utilize the reform in 2008 that shifted out the income thresholds by approximately 30%. We analyze how this relocation of the notch point affected the income distribution not just locally around the notch but also within larger income intervals. In the analysis, we focus on students that have 9 months of subsidy before and after 2008. For this group, the income threshold increased from 9,260 to 12,020 euros in 2008. By fixing the number of subsidy months, we can isolate the effect of the change in the location of the notch on the earnings distribution for a large part of the student population. In addition, we plot the earnings distributions of young, part-time workers who are not students. The idea of the non-student group is to serve as a suggestive control group for the income development of students, capturing the general trend in the income development of low-income part-time workers, such as the economic downturn starting from 2009 in Finland.

Figure 4 displays the relative real labor income distributions of students and young part-time workers in bins of 100 euros in 2006–2007 and 2008–2009 (pre and post-reform years, respectively). The vertical axis denotes the percentage share of individuals in each 100 euro bin within an income interval of 0-18,000 euros of annual labor income. The

[7] Elasticity estimate for all students is calculated using the average number of 7 study subsidy months.

solid vertical lines in the figure denote the old and new income thresholds of the study subsidy system.

The figure illustrates that the earnings distribution of students has a drastically different shape when comparing the periods before and after the reform of 2008. After the increase in the income threshold, students' income distribution shifted to the right, and a significant mass of the student population has moved up from far below the old notch point. In comparison, the earnings distribution of non-student part-time workers remained practically constant, implying no significant changes in real earnings of other young part-time workers who are not subject to the income threshold.

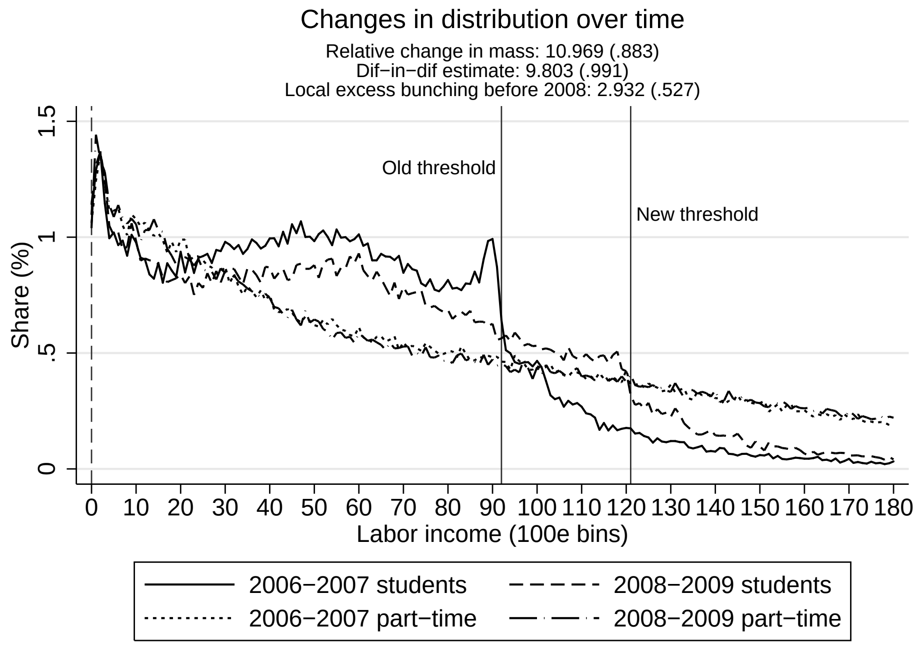

Figure 4: Labor income distributions of students (9 months of subsidy) and non-student part-time workers before and after the reform of 2008

In order to numerically illustrate the significance of the change in the shape of the distribution, Figure 4 includes an estimate of the relative change in the mass of students below the old income threshold. The estimate is calculated by relating the relative mass in 2006–2007 to that in 2008–2009 within the income range of 0–9,200 euros. The results indicate that the overall change in the distribution when comparing pre and post-reform periods is over three times larger when compared to the local change in the distribution near the notch point before 2008.

In addition, we calculate a difference-in-differences type of an estimate where we subtract the change in the mass of non-student part-time workers within the same income range, accounting for general changes among young part-time workers who were not subject to the income threshold. However, as the changes in the earnings distribution for non-students are small, this estimate does not significantly differ from a simple comparison of pre and post reform distributions of students.

In Figure 5, we plot student's labor income distributions from a longer period before and after 2008. The figure shows that the change in student's earnings occurred exactly at the time of the relocation of the income threshold. This indicates that any gradual shifting of the distribution of earnings does not explain the observed pattern, and further underlines the overall change in the earnings distribution is due to the income threshold reform in 2008.

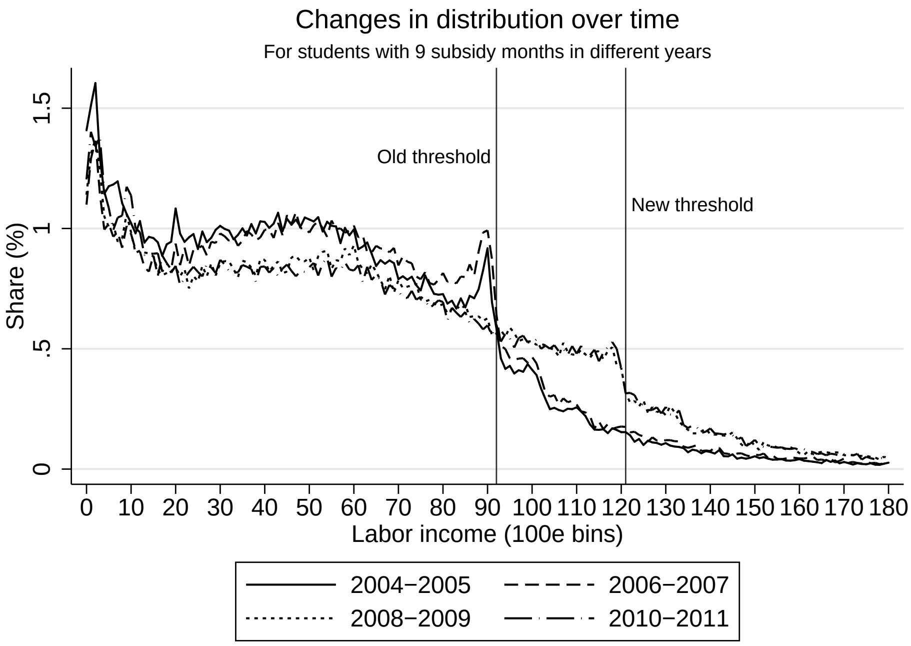

Figure 5: Labor income distribution in different years before and after the reform, students with 9 subsidy months

Overall, our results highlight that the income threshold significantly affects the shape of the whole labor income distribution, not just the region close to the notch point. In particular, the results suggest that some students responded to the old threshold by locating significantly below it. This is consistent with discrete earnings choices and lumpy labor markets where there are a limited number of potential jobs available close to the threshold. Consequently, when the threshold was increased, it also affected the earnings of students well below the old threshold who were now able to increase their earnings and labor supply without exceeding the new threshold, as more extensive set of working contracts became available as an optimal choice for the student.

In addition, Figures 4 and 5 also suggest that students are aware of the location of the income thresholds. Local bunching response fully disappeared below the old threshold after the reform, and a new excess mass appeared below the new threshold immediately after 2008. Since these changes occurred instantly, we find no evidence of some students still believing that there is a notch at the old location, nor that there would be a slug-

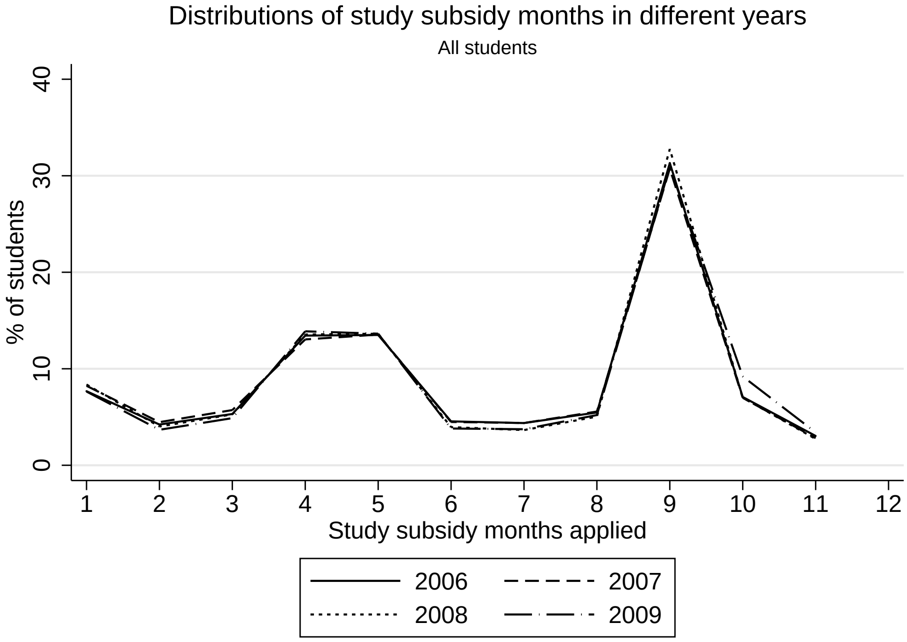

Figure 6: Study subsidy months during years 2006 to 2009

gish response to the relocation of the threshold. However, as shown in Figure A4 in the Appendix, local excess bunching is slightly larger before the reform in 1999–2007, compared to that in 2008–2013. One explanation for this is that local incentives not to exceed the notch are somewhat smaller after 2008, since the relative significance of losing one month's subsidy in terms of disposable income is smaller than before 2008 when the threshold was at a lower income level.

Finally, we look at other potential changes in the behavior of students in connection with the reform that might affect the observed change in the shape of the distribution. First, we study whether the amount of study subsidy months applied by the students changed after the reform. Figure 6 presents the share different subsidy months used by students in 2006–2009. First, the figure shows clearly that 9 months is the most typical choice in all of the years. Second, the figure indicates that there were no significant change in the distribution of subsidy months associated with the reform. This indicates that students responded to the reform by changing their earnings, but not, on average, by claiming more or less subsidies per year.

Second, we look at whether the reform is accompanied by extensive margin responses. Figure 7 presents the share of students having earnings less than 500 euros, which would typically correspond to not working more than 2–3 full weeks even in a low-income job in Finland. Overall, this share hovers below 20% for all students in 2004–2013, highlighting the fact that most students in Finland tend to work at least a bit during their studies.

The share of students not working does not respond to the reform of 2008. However, there is an increase in the share one year later in 2009. The timing is not consistent with

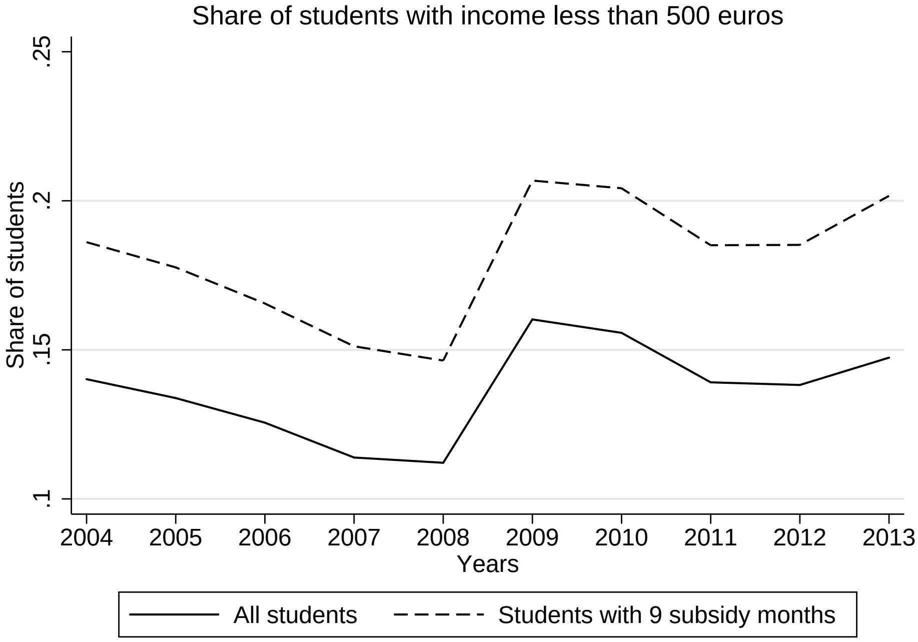

Figure 7: Extensive margin responses

a response to the reform as we observe an immediate change in the earnings distribution, but more consistent with the financial crisis affecting the Finnish labor markets from 2009 onward. Furthermore, the increase in the income threshold would have suggested an increase in the share of students working, as they can earn more without exceeding the threshold if they would participate in the labor market after 2008.

5.3 Mechanisms and implications of the change in the earnings distribution

Figures 4 and 5 above show that the change in the location of income threshold affected the overall shape of earnings distribution. Next, we present more detailed evidence of discrete earnings responses to the reform. Also, in order to provide some guidance on the underlying mechanisms behind observed behavior, we study how different types of students working in different types of firms responded to the reform. In addition, we characterize how the discrete earnings response affects the interpretation of the overall behavioral response, and elasticity and welfare estimations based on the traditional local bunching approach which ignores these types of responses.

Detecting discrete earnings and labor supply responses

In order to describe the change in the earnings distribution in more detail, Figure 8 presents the average annual individual changes in labor income in base-year income bins of 3000 euros for students with 9 subsidy months in 2005–2006, 2006–2007 and 2007–2008.

First, the figure shows that annual changes in individual income are very similar before the reform, and that there is a visible pattern of mean reversion (smaller income is followed by larger income in the previous year, and vice versa). Consistent with the hypothesis of discrete earnings responses, the figure shows that labor income increased significantly within 2007–2008 relative to the years before the reform particularly for those students below the new income threshold (12,100 euros) in base-year bins of 6000–9000 and 9000–12, 000 euros, and even in the 3000–6000 euro bin that is well below the old threshold (9,200 euros). However, we find no significant difference between the years for income bins above the new threshold.

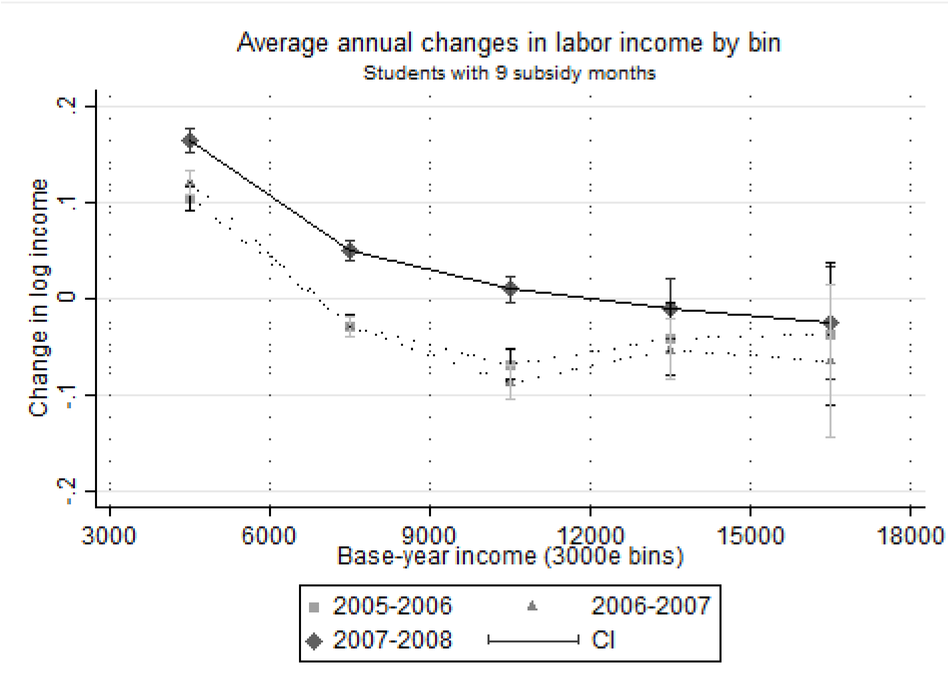

Figure 8: Average annual changes in labor income in base-year bins of 3000 euros, students with 9 subsidy months in 2005–2006, 2006–2007 and 2007–2008

Next, we divide average individual changes in income in each 3000 euro bin by size into four equally large groups. Figure 9 presents average individual labor income changes within these groups. Intuitively, if income responses above in Figure 8 occur through discrete changes in earnings, we should particularly observe more large individual increases in income after the reform that drive the change in the overall earnings distribution. This would imply that we observe larger income changes within higher quantiles below the new income threshold in 2007–2008, in comparison to the pre-reform period (2005–2006 and 2006–2007).

In line with the intuition above, Figure 9 shows that there are no significant differences between the years in average changes in earnings in the first quantile. In contrast, we find that increases in labor earnings are more focused on 3rd and 4th quantiles, which support the hypothesis of discrete, larger income responses explaining the shift in the earnings distribution.

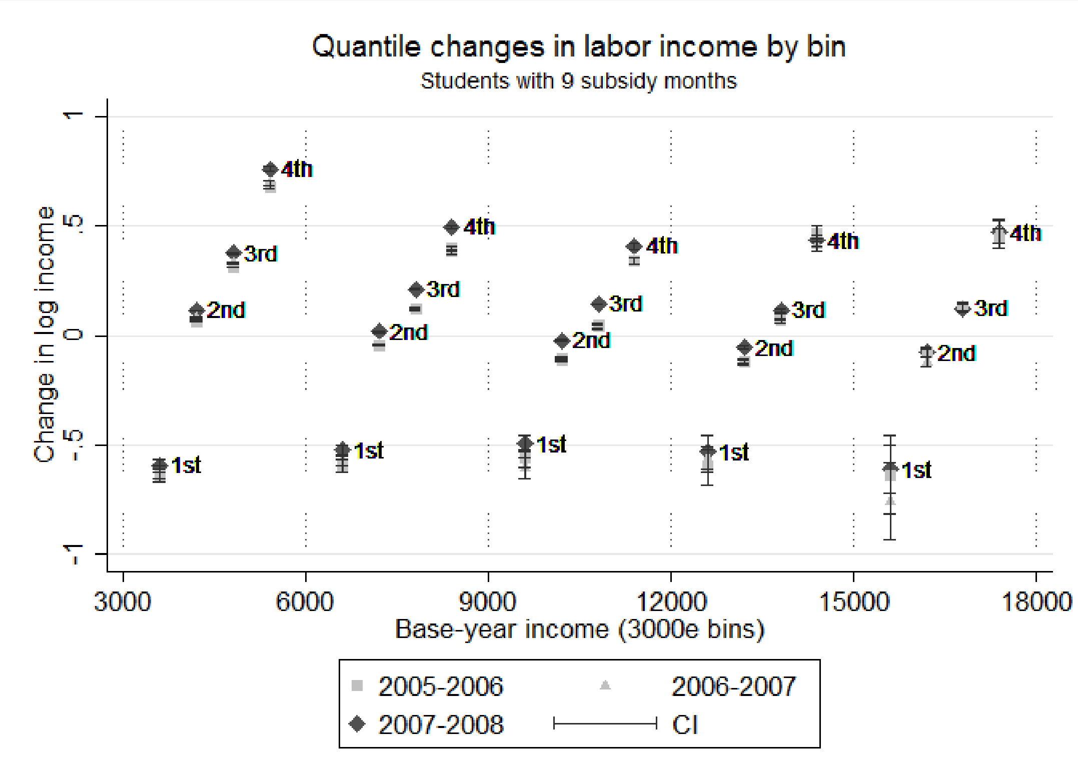

Figure 9: Quantile changes in labor income within bins of 3000 euros, students with 9 subsidy months in 2005–2006, 2006–2007 and 2007–2008

[MORE TO BE ADDED HERE]

Heterogeneity and firm characteristics

[TO BE ADDED HERE]

Implications for welfare estimation

Our results imply that the elasticity estimates based on local behavioral responses inaccurately define the scope of the welfare effects of the income notch. Since the study subsidy threshold affects the shape of the distribution within a large income interval below it, the estimated local counterfactual and thus the excess mass is bound to be incorrectly estimated.

In order to numerically characterize the magnitude of the bias, we calculate how many euros are being earned less because of the income threshold using both the local bunching approach and wider changes in the earnings distribution. For the local approach, we find that the notch reduced earnings by approximately 140 euros. This number is calculated as the difference between the bin-level average earnings for the observed distribution and the counterfactual distribution within the income interval between the notch and the upper limit of the counterfactual density, which also defines the income response of the marginal buncher – the last individual who responds by relocating below the threshold because of the notch in the budget set (see Figure 3 above). Following the intuition of the local estimation approach, this number thus describes how many euros students are earning less on average because they choose to reduce their earnings from above the threshold to just below the notch point.

As a comparison, we find that the average reduction in earnings is approximately 510 euros when utilizing wider changes in the income distribution before and after 2008. This number is calculated as the difference between real average bin-level earnings of students in 2006–2007 and in 2008–2009 within an income range of 9,200–18,000 euros, thus outlining the average income loss caused by the old threshold. When comparing these measures, we approximate that limiting the analysis to local responses underestimates the potential income effects by a factor of 3.6. Although this measure is an income loss measure, and not a welfare loss measure, the measure is informative about the order of magnitude that welfare effect could be underestimated when ignoring the optimization frictions.

5.4 Local optimization frictions

The results above show that discrete earnings responses can have a significant effect on how individuals respond to discontinuous changes in incentives. This also affects the accuracy of the local bunching estimate for the purpose of welfare analysis. Despite this shortcoming, the local response can still be used to analyze other types of frictions, such as optimization errors and inattention. Next, we utilize divided sample analyses to illustrate the significance of optimization errors in explaining observed local responses.

First, we examine the role of optimization ability by looking at bunching responses for students with different elementary school math scores. Figure 10 shows the earnings distributions around the study subsidy notch in 1999–2013 for students with different secondary school math scores. The scale for the elementary school grades in Finland is 4–10. The figure excludes the grade 4 (fail) due to very small number of observations.

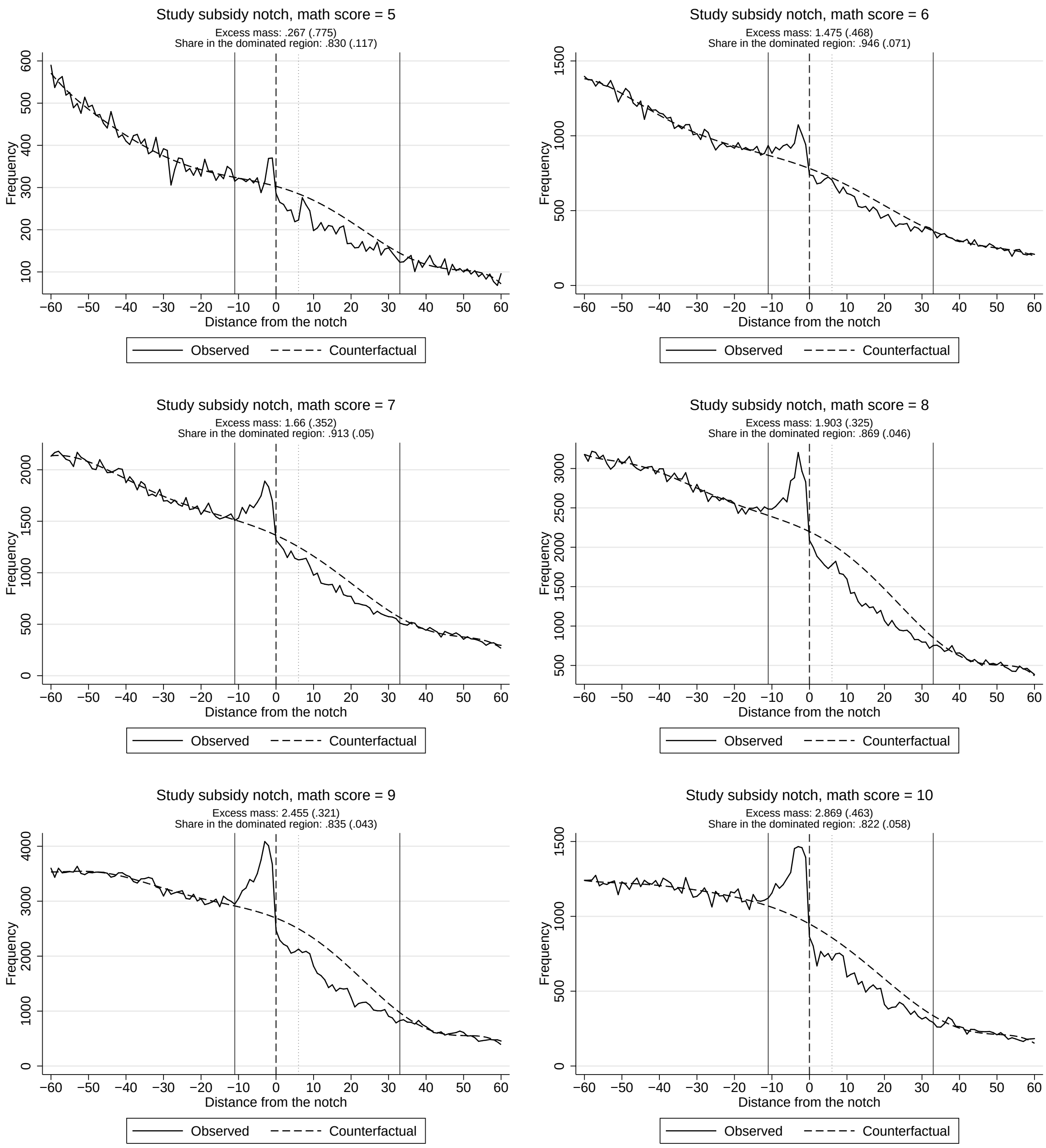

Figure 10: Local bunching at the study subsidy notch: students with different math scores, 1999–2013

The figure clearly shows that bunching is more prominent for students with higher math scores. In addition, the figure shows that the share of students in the dominated region tends to be smaller the higher is the math score. These findings suggest that the ability to optimize and to understand the somewhat complicated rules of the program is correlated with the probability of making optimization errors, and thus the extent of observed optimization fictions.

Scores of different school subjects are typically highly correlated with each other. Therefore, similar types of results as in Figure 10 can be found using different subjects and the average score. As an example, Figure A5 in the Appendix presents the bunch-

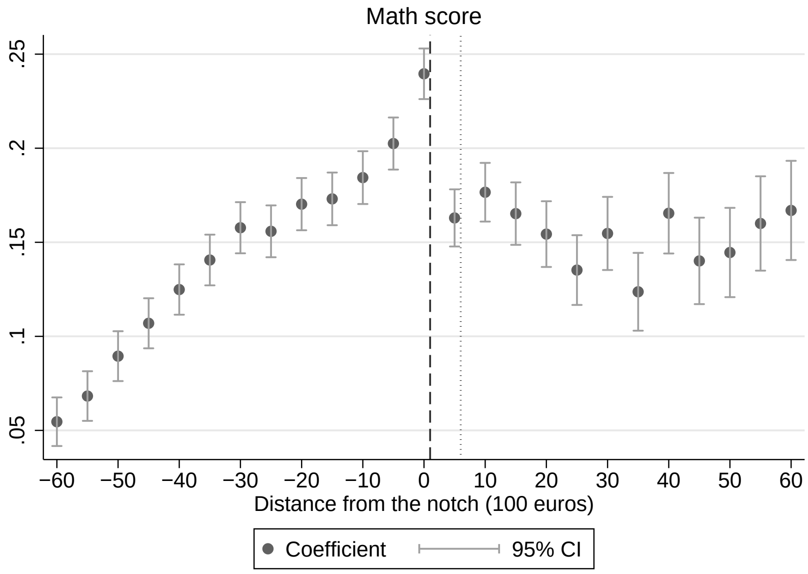

Figure 11: Differences in average math scores in different bins around the study subsidy notch, 1999–2013

ing results for low scores (4–6), medium scores (7–8) and high scores (9–10) in Finnish language, again showing that bunching responses are larger for students with higher scores. However, it could be that the math score in particular is an important indicator of optimization ability. Nevertheless, Figure A6 in the Appendix shows that the bunching responses are rather similar for students with higher math scores and lower Finnish scores, and vice versa. Still, we find that locating in the dominated region is slightly less common for those with higher math scores, suggesting that numerical ability is important in avoiding optimization errors that lead to exceeding the threshold.

Next, we provide further descriptive evidence of the determinants of local bunching behavior. First, Figure 11 revisits the effect of secondary school math score on local responses to the threshold. The figure plots the coefficients with 95% confidence intervals from a regression where math score is regressed with income bin dummies on both side of the threshold. In addition, the regression includes a wide variety of covariates, such as age, university fixed effects, study subsidy months, number of years studied, major subject, and the field of industry of the workplace. Thus the figure illustrates the significance of math score in explaining local responses conditional on various characteristics that are presumably correlated with it, such as major and industry.

Similarly as above, the figure shows that students located just below the notch tend to have higher math scores. Furthermore, those located in the dominated range just above the notch have lower math scores, which again supports the notion that optimization ability can explain local optimization errors.

Figure 12 shows the results for other selected characteristics. First, there are no significant differences in local responsiveness regarding sex or younger or older students (conditional on other covariates). The results for the average score and Finnish language score in secondary school provide similar results as the math score above. Furthermore, having arts and humanities majors is positively correlated with locating in the dominated range, suggesting that students in these fields make more optimization errors (on average). In contrast, students with business, law or medical majors respond to the threshold more actively, and are also less likely to locate themselves in the dominated region. The results on different majors thus provides additional suggestive evidence on the impact of optimization ability on local responses. Finally, we find no clear-cut differences between different industries. This indicates that the response is not driven by students working in industries where it is presumably easier to marginally adjust working hours, such as services.

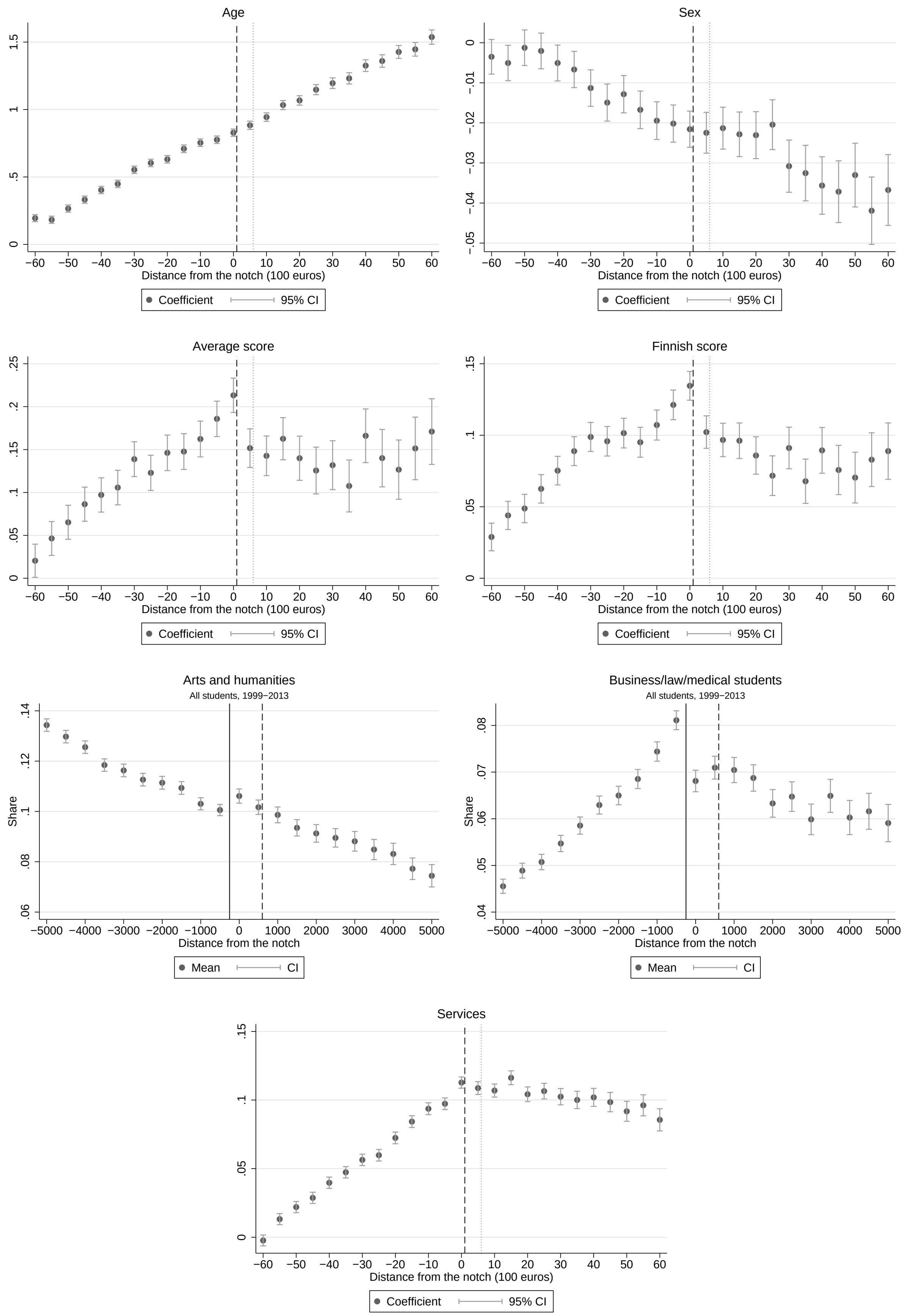

Figure 12: Differences in various characteristics in different income bins around the study subsidy notch, 1999–2013

6 Concluding remarks

We find that students bunch actively at the income notch induced by the study subsidy program in Finland. At the same time, we find that a significant share of students are located in the region of dominated choice just above the threshold where they could gain disposable income by reducing their earnings. This is a strong indication of significant optimization frictions.

In addition to local responses, we find that a reform that increased the income threshold shifted out the whole income distribution of students. This result has several important implications. First, it implies that significant discrete earnings responses occur, and these effects cannot be recovered by utilizing the local bunching approach, not even when utilizing observations in the dominated region. Second, the result suggests that optimization frictions are even more prevalent in explaining taxpayers' behavior than previously thought. Third, the findings imply that the local bunching estimate is biased if earnings responses are discrete, caused by the fact the estimates of the counterfactual density do not represent the true counterfactual state if the observed density further away from the notch is affected by optimization frictions.

Finally, we find that university students with higher secondary school math scores bunch more actively and are more unlikely to locate themselves in the dominated region compared to those with lower scores. This indicates that higher optimization ability is correlated with the extent of local responsiveness, implying that optimization errors significantly explain local behavioral frictions.

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Appendix

Descriptive statistics

	Before 2008 (academic year 2006/2007)		After 2008 (academic year 2008/2009)	
Study subsidy months	Income limit	Relative income loss at the margin if income limit is exceeded	Income limit	Relative income loss at the margin if income limit is exceeded
1	17,340	3.1%	22,550	2.5%
2	16,330	3.2%	21,190	2.7%
3	15,320	3.5%	19,930	2.9%
4	14,310	3.7%	18,620	3.1%
5	13,300	4.0%	17,310	3.3%
6	12,290	4.3%	16,000	3.6%
7	11,280	4.7%	14,690	3.9%
8	10,270	5.2%	13,380	4.3%
9	9,260	5.7%	12,070	4.8%

Note: The relative loss from marginally exceeding the income limit is calculated using the full study subsidy (461 euros and 500 euros before and after 2008, respectively) plus 15% interest collected by the Social Insurance Institution.

Table A1: Income limits in the study subsidy system and the relative marginal loss if the income limit is exceeded (in proportion to gross income at the limit)

	Individual characteristics				
	Age	Female	Labor Income	Gross Income	Working months
Mean	36.4	.48	25,912	27,080	10.8
Median	37	0	24,152	23,786	12
sd	8.91	.50	29,241	70,785	2.88
N	29,261,269	29,261,269	24,634,474	28,634,030	31,383,598
	Math score	Finnish score	Average score		
Mean	7.0	7.4	6.4		
Median	7	7	7		
sd	1.39	1.17	2.52		
N	5,694,016	5,687,883	7,432,227		
	Field of industry				
	Industry	Services	Administration	Health & Social Services	Other/unknown
Mean	.20	.10	.23	.04	.43
sd	.40	.30	.42	.19	.50
N	39,206,521	39,206,521	39,206,521	39,206,521	39,206,521

Table A2: Descriptive statistics, non-students aged 19–50, 1999–2013

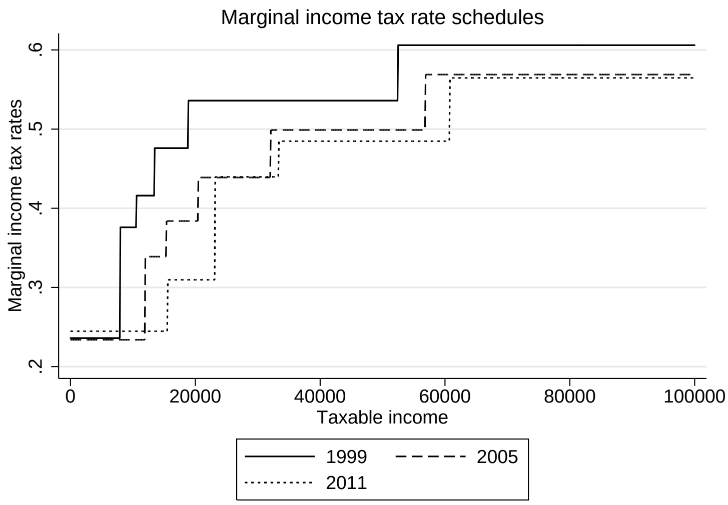
	Individual characteristics				
	Age	Female	Labor Income	Gross income	Working months
Mean	21.0	.38	8,317	10,075	6.1
Median	21	0	6,741	8,736	6
sd	1.71	.48	7,229	19,464	3.16
N	940,786	940,786	932,527	939,370	940,786
	Math score	Finnish score	Average score		
Mean	7.0	7.3	7.0		
Median	7	7	7		
sd	1.36	1.17	1.46		
N	707,438	707,150	738,327		
	Field of industry				
	Industry	Services	Administration	Health & Social Services	Other/unknown
Mean	.20	.14	.20	.03	.43
sd	.40	.35	.40	.17	.50
N	940,786	940,786	940,786	940,786	940,786

Table A3: Descriptive statistics, non-student part-time workers aged 19–24, 1999–2013

Income taxation and marginal tax rate kink points

This Appendix presents the institutions related to the discontinuities in the nationwide central government marginal income tax rate schedule.[8] Different kink points are associated with MTR increases between 4-11 percentage points. At the first income threshold, there is a clear increase in the MTR varying between 6-14 in percentage points in different years, which relates to a 22-53% decrease in the overall net-of-tax rate ($1-MTR$). The last kink involves the most salient and distinctive increase in the MTR, associated with a 6-9 percentage points increase in the MTR, and 9-16% decrease in the overall net-of-tax rate. Figure A1 presents the marginal income tax rate schedule for the years 1999, 2005 and 2011. The Figure illustrates the discontinuous changes in the income tax rate at different levels of taxable income. Table A4 gives similar information in a more precise table form.

[8]The Finnish income tax system comprises of three components: progressive central government income taxes, proportional municipal taxes and mandatory social security contributions. The average municipal income tax rate is 18.3, and the average social security contribution rate is 5.1 (in 1999-2013). In general, municipal income taxation and social security contributions do not induce kink points since they are proportional.



Note: Marginal tax rate includes central government income taxes, average municipal income taxes and average social security contributions.

Figure A1: Nominal marginal tax rates (MTR) on earned income, years 1999, 2005 and 2011

Year	Taxable income (in euros)	Marginal tax rate
1999	7,905-10,596	5,5
	10,596-13,455	15,5
	13,455-18,837	19,5
	18,837-29,601	25,5
	29,601-52,466	31,5
	52,461-	38
2000	8,006-10,697	5
	10,697-13,623	15
	13,623-19,005	19
	19,005-29,937	25
	29,937-52,979	31
	52,979-	37,5
2001	11,100-14,296	14
	14,296-19,678	18
	19,678-30,947	24
	30,947-54,661	30
	54,661-	37
2002	11,500-14,300	13
	14,300-19,700	17
	19,700-30,900	23
	30,900-54,700	29
	54,700-	36
2003	11,600-14,400	12
	14,400-20,000	16
	20,000-31,200	22
	31,200-55,200	28
	55,200-	35
2004	11,700-14,500	11
	14,500-20,200	15
	20,200-31,500	21
	31,500-55,800	27
	55,800-	34
2005	12,000-15,400	10,5
	15,400-20,500	15
	20,500-32,100	20,5
	32,100-56,900	26,5
	56,900-	33,5
2006	12,200-17,000	9
	17,000-20,000	14
	20,000-32,800	19,5
	32,800-58,200	25
	58,200-	32,5
2007	12,400-20,400	9
	20,400-33,400	19,5
	33,400-60,800	24
	60,800 -	32
2008	12,600-20,800	8,5
	20,800-34,000	19,0
	34,000-62,000	23,5
	62,000 -	31,5
2009	13,100-21,700	7
	21,700-35,300	18
	35,300-64,500	24
	64,500 -	30,5
2010	15,200-22,600	6,5
	22,600-36,800	17,5
	36,800-66,400	22,5
	66,400 -	30
2011	15,600-23,200	6,5
	23,200-37,800	17,5
	37,800-68,200	22,5
	68,200 -	30
2012	16,100-23,900	8
	23,2900-39,100	17,5
	39,100-70,300	21,5
	73,300 -	29,5
2013	16,100-23,900	6,5
	23,900-39,100	17,5
	39,100-70,300	21,5
	70,300 -100,000	29,75
	100,000 -	31,75

Note: Finnish marks are converted to euros before 2002.

Table A4: Central government marginal income tax rates, 1999–2013

Responses to marginal tax rate kink points

First, we present taxable income distributions around different MTR kink points for all taxpayers in 1999–2013. The figures plot the observed income distributions and counterfactual distributions relative to each MTR kink point in bins of 100€ in the range of +/- 5000€ from the kink. The figures denote the local excess mass estimates (with standard errors), and the implied elasticity estimates based on observed excess bunching. As shown in Table A4 in the Appendix, the number of kink points have decreased from 6 to 4 in the period we study. Throughout the study, the first MTR kink point always includes the threshold where the national income tax rate first applies. The other kink points in Figure A2 correspond to the kink points still existing after 2007.

In each graph, the kink point is marked with a dashed vertical line. The excluded counterfactual region (the bunching window) is marked with solid vertical lines. In each graph, the bunching window is +/- 7 bins from the kink. The counterfactual density is estimated using a 7th-order polynomial function. Our results are not sensitive to the choice of the bunching window and the order of the polynomial.

The Figure shows that there is no bunching at the marginal tax rate kink points in Finland. The only conceivable exception might be the second kink. However, the second kink is likely to produce upward-biased excess bunching because of the locally hollow shape of the income distribution around the kink. Consequently, the elasticity estimates are zero or very close to zero at all MTR kink points. This result of no bunching at MTR kink points in figure A2 indicates that marginal tax rates do not induce local behavioral responses. This could be explained by both the low underlying (local) tax elasticity and various optimization frictions.

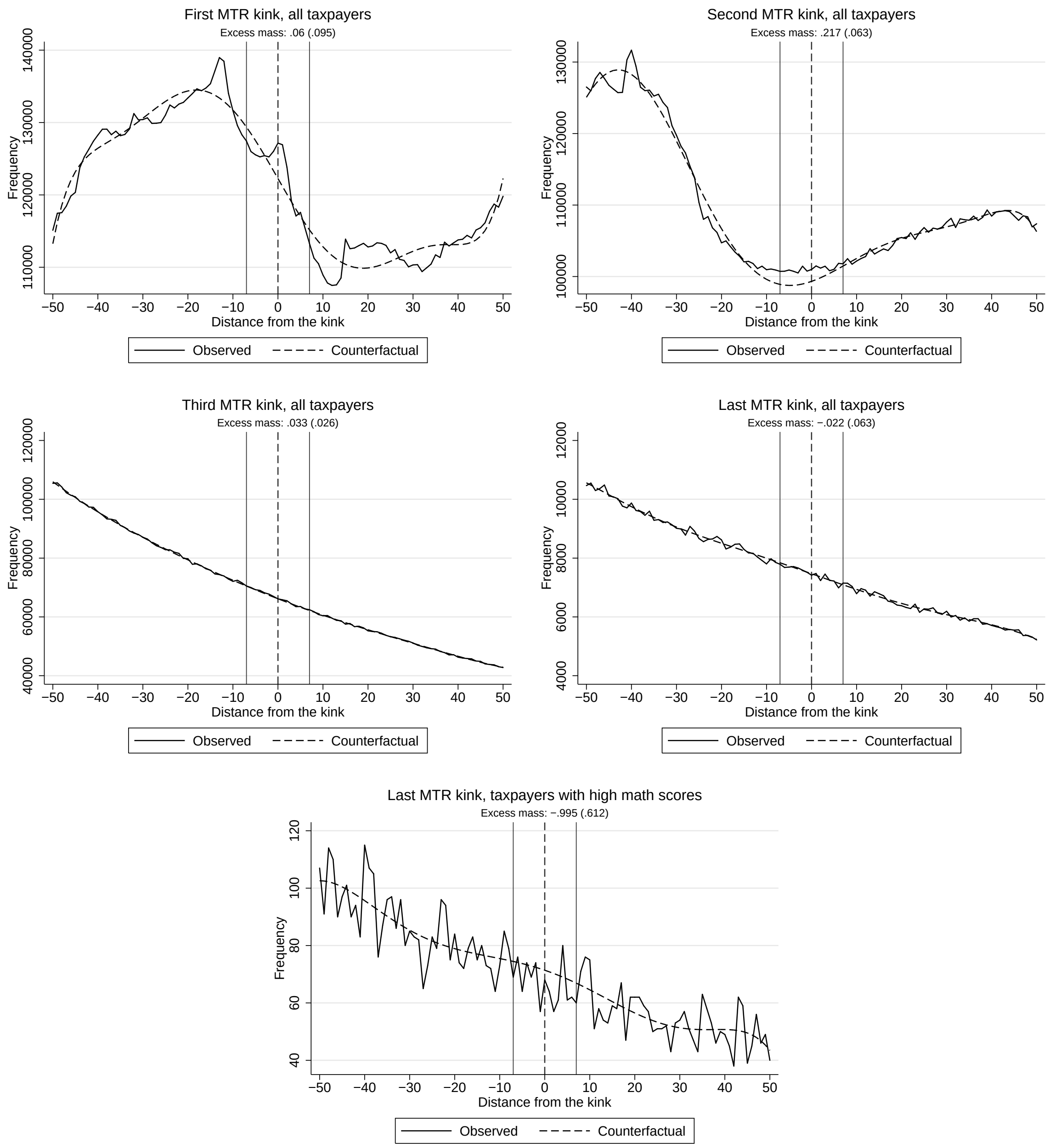


Figure A2: Income distributions around MTR kink points, 1999-2011

Figure A3 shows that university students do not bunch at kink points either. This holds for current students and for those that have already graduated from a university or polytechnic, and even for those who observed to bunch at the study subsidy notch. These observations show that the student population do not respond differently to the MTR schedule compared to other taxpayers.

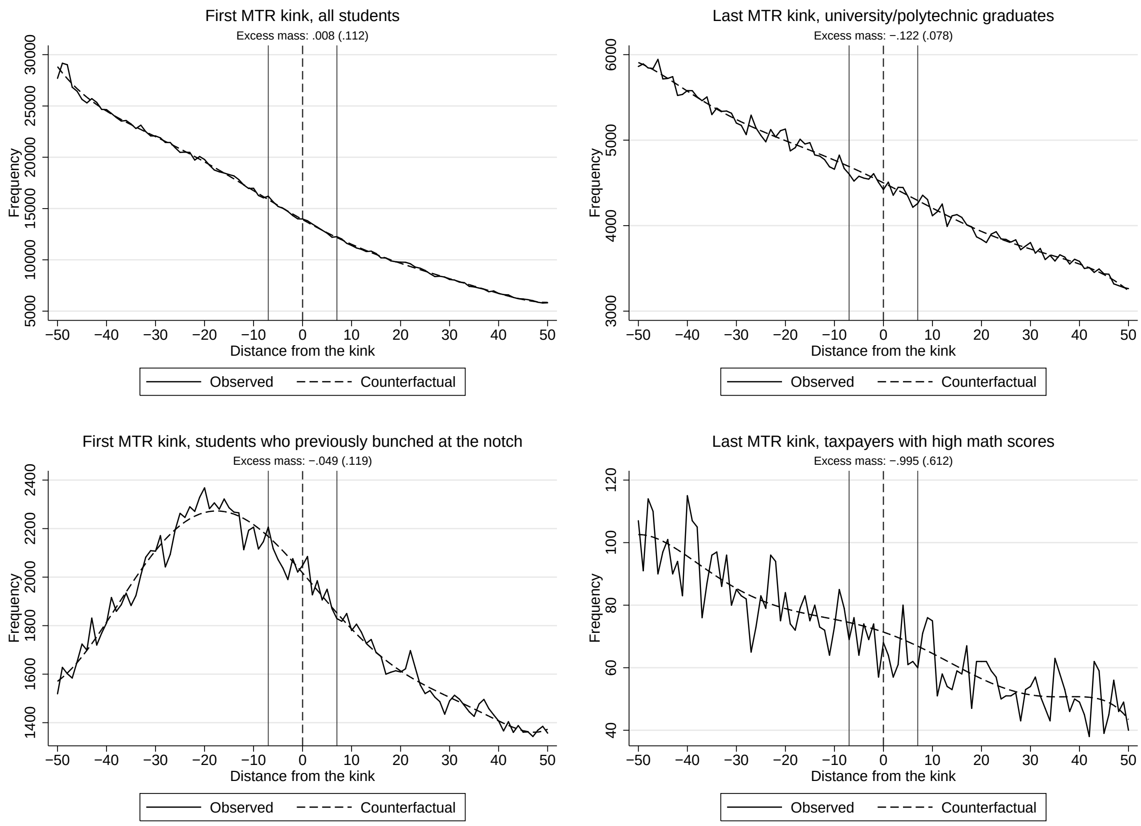


Figure A3: Bunching at MTR kink points: Current students, graduates, students who bunched at the study subsidy notch, and taxpayers with high (>8) math scores, 1999-2013

Additional results on study subsidy notches

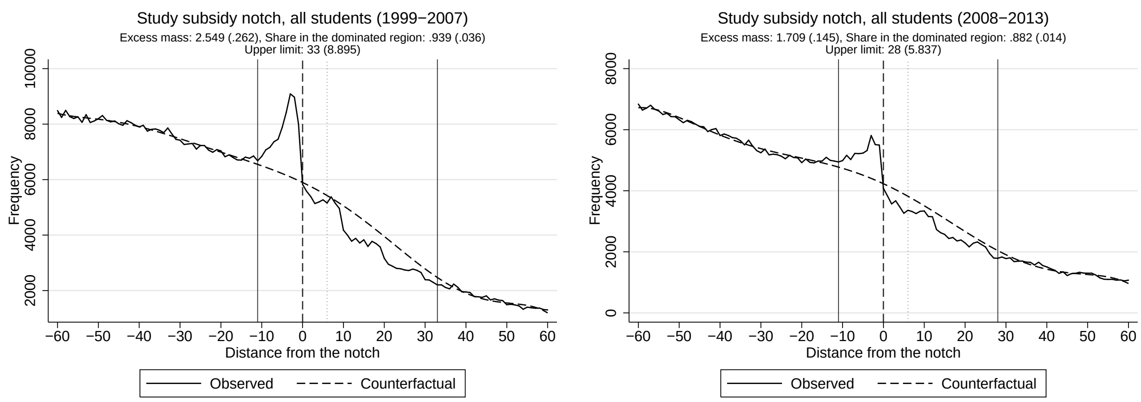


Figure A4: Bunching at the study subsidy notch: Before and after the reform of 2008

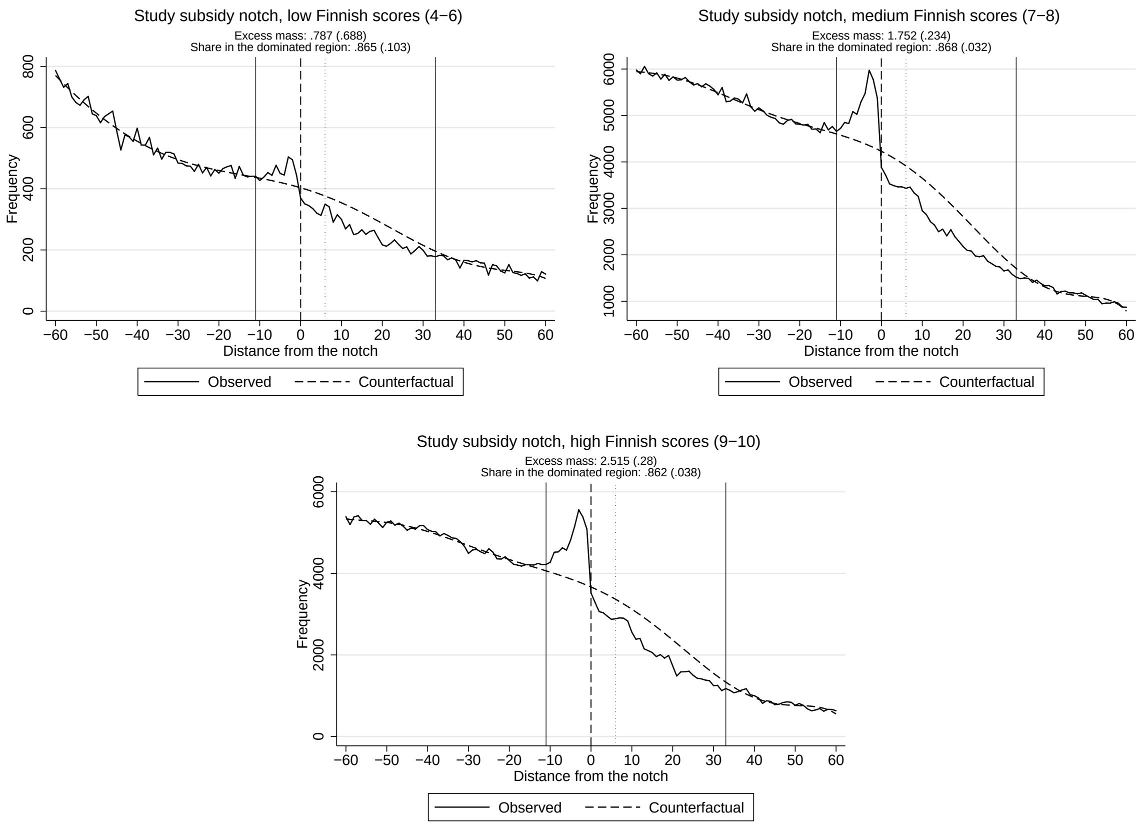


Figure A5: Bunching at the study subsidy notch: students with different secondary school Finnish scores

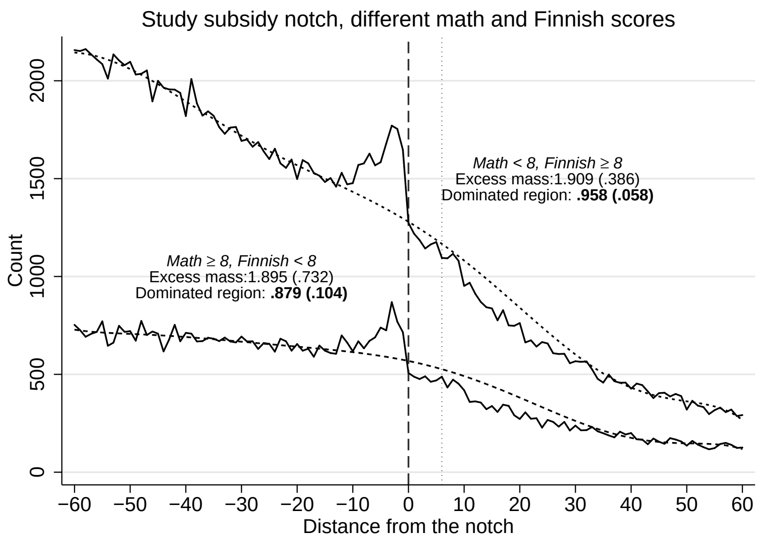


Figure A6: Bunching at the study subsidy notch by math and Finnish scores