Price elasticity of giving in the Netherlands

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Abstract

In this paper we estimate price elasticities of giving in the Netherlands. We make use of price variation present in tax data available from 2001-2007. To address the problems of omitted variable bias and endogeneity we apply a regression discontinuity approach to compute local price and quasi elasticities. Using a number of extensions to previous studies we find significant but mixed results. Significant positive price elasticities indicate that people are not well aware of their current marginal tariffs. Only for people with stable income we estimate significant and consistent price effects. We conclude that RD is not a robust method to estimate elasticity, because of its sensitivity to irregularities in the tax system and the low amount of variation in the data on giving.

Contents

1 Introduction

Each year Dutch citizens collect roughly 330 million euro of tax reductions due to donations to charity (TD (2008)). The deductability therefore has a considerable impact on the annual state budget. In the Netherlands deductability of donations was introduced in 1952 to ease the financial burden on charitable, religious, philosophical, cultural, scientific and other non profit organizations. In 2011 the facility was part of the political debate once again, because the government introduced the somewhat controversial multiplier. This multiplier increases the amount deductable: for every euro donated 1.25 euro is now deductable from gross taxable income. The purpose of this is to encourage donating behavior. However, literature has not uniformly confirmed such an effect. Studies on the price sensitivity of giving have produced mixed results.

Tax deductability changes the cost of giving. For instance, at a tax rate of 40%, the after tax cost of giving is not 1 euro, but just $1 - 0.40 = 0.60$ euro. Both philanthropy and politics have been interested in the effects of this on behavior. If giving is purely altruistic then it is probably not very sensitive to price changes. If it is not completely altruistic and a small price change has a disproportional upward effect on giving, than it can actually be an efficient way to support charitable organizations. In other words, it could be an efficient subsidy instrument.

The goal of this paper is to estimate price elasticities for Dutch households by using the variation in tax data. The price sensitivity of giving has been studied in the US intensively, but only recently the number of studies on other countries increased as well. An example of such is the evaluation study of the Ministry of Finance (TD (2008)), which used tax data and the regression discontinuity method (RD) to estimate elasticities. The approach assumes that people are well aware of their applicable tax tariffs. However, if they are not well informed the estimates might be biased. In this paper we work along a similar approach. We test the awareness assumption by using lagged income and tax information, because people file tax for the year that has passed instead of the current year. Next to that we focus on people with stable incomes for whom it may be easier to anticipate price effects.

Also we experiment with the specification of the RD model. RD looks at people who are just below or just above a tax bracket threshold[1]. In standard applications as well as in TD (2008) this neighborhood around a threshold is relatively small: ± 1,500 euro. However, a donation deduction can push someone back into a lower tax bracket. If the neighborhood is too small

[1] in Dutch: Belastingschijfgrens

the people experience a much smaller price effect than the model assumes, which leads to biased estimates. The small proportion of people who deduct donations ($\pm 5\%$) is another reason why the neighborhood may need to be larger, because otherwise the data may not contain enough variation. In this paper we investigate the sensitivity of the analysis to this by using different neighborhoods as well as leaving out the people who are pushed back into a lower bracket.

Finally we estimate elasticities at a latent tariff threshold, implied by so called tax discounts[2]. For people below the threshold, the tax due is completely covered by their personal tax discount. People above the threshold still have to pay tax after their tax discount is subtracted. It is in essence the threshold from the fictive bracket 0 (no tax) to the first tax bracket.

The remainder of this paper is organised as follows: We present a highlight of the literature on motives for giving, previous estimates of price elasticities and some of the techniques applied for estimation in section 2. Section 3 covers some of the main features of the Dutch tax system that impact the estimation process. In section 4 we elaborate on the empirical strategy used to estimate price elasticities. Section 5 describes the tax data and summarizes the sample selections applied throughout this study. After that section 6 provides estimation results and discusses the outcomes. And finally section 7 sums up the main findings and gives recommendations for further research.

2 Previous literature

For decades economics has shown great interest in the behavior of giving. Economics is all about maximizing utility and at first glance giving seems to be opposite to that. Not surprisingly the literature contains many studies that try to answer why people donate and attempt to put giving into an economic framework. Andreoni (2006) gives some economic explanations on what motivates people to make donations: 1) People may give for reasons that are not entirely unselfish. For instance, a person might donate to a natural park nearby which he visits regularly to enjoy the surroundings. This means he benefits of the donation himself as well. 2) Another explanation would be the 'just-in-case' donation. Think of one who gives to poverty relief in order to sustain the institution, not knowing he might need it himself in the future. 3) Another explanation is of course altruism towards others. For example giving to the poor in a distant land or making a donation after one dies. In that case one does not experience the benefits himself, but maximizes other peoples utility functions. 4) In many cases the personal contribution

[2] in Dutch: Heffingskortingen

has only very small impact. Andreoni argues that in such situations the gift may cause a warm glow feeling that accompanies the act of giving. 5) Andreoni closes with stating that ultimately economic theory may not be suitable for explaining giving behavior, because it cannot be captured by rational preferences and quasi-concave utility functions.

Price elasticity is a key item in the literature, because it holds some answer to the motives for giving. If giving is influenced by price effects, then one might argue that it is - at least - not entirely altruistic in nature. For example, think off a charitable organization that offers a 50 euro discount on a tablet pc on becoming a new member. In that case the cost of giving is lowered for the selfish goal of buying oneself a tablet pc.

Policy makers have also shown great interest in the price elasticity of giving. In almost all OECD countries there is a donation deduction facility. This reduces tax revenues, making it an budget expenditure. However, if the incentive to spend more on charity outweighs the loss in tax revenues, than the measure is still efficient: i.e. treasury efficient. It turns out this can be measured in terms of elasticity. Price elasticity measures the %-change in demand as a result of a 1% increase in price. Treasury efficiency corresponds to a price elasticity of -1.0 or larger (Price elasticities are usually negative, so we refer to a price elasticity of -1.6 as being *larger* than -0.5. and vice versa.).

Andreoni (2006) gives a brief overview of the history of studies on the topic of price elasticity of giving. The first study (Taussig (1967)) used 47,000 tax returns from the 1962 Treasury tax file. He introduced the constant price elasticity or log-log specification, which has become of major importance in all of economics. Later Feldstein and Clotfelter (1976) applied this specification to survey data and obtained a price elasticity estimate of -1.15. Another study by Feldstein and Taylor (1976) on tax data found elasticities between -1.1 and -1.5. Many of the other studies up to 1990 produced similar findings. Only after 1990 this consensus view was challenged. Papers using the log-log specification started reporting elasticities much lower and higher than -1. Even more, a number of studies appeared using other specifications and consistently reported smaller elasticities.

Two of these studies stand out: Randolph (1995) uses the log-log specification in combination with a model that differentiates between short term and long term elasticities. The other paper (Auten et al. (2002)) applied a dynamic fixed effects model. Both make use of the same data set, which had ideal characteristics (Andreoni (2006)): tax panel data spanning a couple of tax reforms (Reforms are especially useful, because they serve as a natural experiment). Both methods lead to remarkably different results even though the data was the same. Randolph (1995) indicated price elasticities of -0.51, whereas Auten et al. (2002) reported -1.26. In this case treasury efficiency is dependent on the method that is used.

The reason for the difference is twofold (Andreoni (2006)): 1) The estimation method. Randolph (1995) uses instrumental variables to distinguish between temporary and permanent changes. Auten et al. (2002) on the other hand apply restrictions to the covariance matrix of price and income. 2) The log-log specification in Randolph (1995) estimates constant price elasticities, whereas Auten et al. (2002) specification allows price elasticities to vary across prices and income. As it is impossible to say which approach is the better, Andreoni (2006) invites further study on how to measure elasticities of charitable giving. There have been many reviews of analyses, but most of these are not empirical in nature, underlining the need for new econometric analyses (Peloza and Steel (2005)).

Recently an analysis was done in Germany (Bönke et al. (2011)). They worked with a data set of nine million income tax returns for the year 1998, 2001 and 2004. Because of all sorts of thresholds tax data is usually a censored version of actual giving behavior. Censoring makes ordinary OLS estimates inconsistent. Bönke et al. (2011) address this problem using censored quantile regression analysis. Furthermore they take into account the aspect of crowding out. This is the process where increased government spending on public goods may cause a decrease of private contributions to charitable organizations that provide similar services. They find that - ignoring crowding out - tax units with very generous donations are highly responsive to tax incentives, but overall the policy is not treasury efficient. However, if they take crowding out into account, then the results indicate treasury efficiency.

TD (2008) estimated price elasticities for the Netherlands using a regression discontinuity approach on two types of discontinuities in tax data: The first type looks at individuals just below and above a tax bracket threshold. Because these groups face different tariffs, it is possible to estimate price effects. The second type uses the tax reform of 2001 as a natural experiment. The reform resulted in substantial tariff changes. Comparing individuals in a couple of years just before the change and a couple of years after allows for estimation of price effects as well.

The estimated price elasticities were between -0.22 and -0.67, indicating that the policy is not treasury efficient. However, none of the estimates was statistically significant. Also, a number of reported elasticities was positive, indicating that a decrease in the cost of giving reduces the number and the amount of donations. This is counter intuitive and not supported by economic theory.

3 Background

Dutch Tax system in a nutshell Income tax is regulated by the Income Tax Law of 2001. It is collected in 2 steps. The first is an indirect step in which the Tax Department collects tax from the employer instead of the employee, a so called Pre Tax. In the second step the employee is asked to file tax himself. This step looks deeper into the personal situation of the tax subject, which allows for modifications to the Pre Tax. For example: deductions, discounts, etc. In the Netherlands roughly 10 million of the 11.5 million tax subjects file tax. For only a small portion the Pre Tax is also the final tax.

Boxes, brackets and tariffs Income tax is divided in 3 categories:

- Box 1: Income as a result of labor (both employee and self-employed)
- Box 2: Income as a result of a large share in a Legal Entity
- Box 3: Income as a result of capital (property such as housing, savings or derivatives).

Box 1 is the most relevant category for the majority of the Dutch population. It also has the most favorable characteristics for Regression Discontinuity analysis, because it is the only box with substantial tariff jumps. Box 2 has an (almost) flat tariff of 25%. Box 3 has a flat effective tariff of 1.2%.

In this research we focus on the Box 1 income, but it is important to note that people can have a low income in box 1 whilst having a substantial income in box 2 or 3. In case a person has income in different categories, he is obliged to deduct a donation first in box 1, then box 3 and finally box 2 (Stevens (2010)).

In Box 1 the tariff system is as follows:

1. Bracket 1 from 0 to 17,000 euro at 34% (or 15% for 65 plus)
2. Bracket 2 from 17,000 to 31,000 euro 41.95% (or 22% for 65 plus)
3. Bracket 3 from 31,000 to 52,000 euro 42%
4. Bracket 4 from 52,000 euro and more 50%

People at the age of 65 and above have different tariffs for the first two brackets, as they do not pay premium for the elderly state pension (AOW). As a result they face the largest jump: from 22% to 42%. Over the years the tariffs have remained practically unchanged (less than $\pm 1\%$). The brackets however have increased with respectively 2,000, 3,275 and 5,319 euro. Changes are partly because of indexing, but also because of policy changes. A summary of the most important tariffs and levels for the years 2001 to 2011 is included in Appendix A.

Besides donations, an individual can have other deductions too, such as certain travel expenses, study costs and others. In our analysis we always assume that the donation deduction is the last one subtracted from the income. This is necessary to establish the marginal tariff. The same approach is used in TD (2008).

As noted in the introduction individuals can be pushed back into a lower tariff because of a donation deduction. If the distance between the tax bracket and annual income is less than deduction, than the deduction is split. The part above the threshold is priced against the upper tariff, the part below is priced against the lower tariff. This reduces price effects.

Tax discounts and latent threshold A Dutch tax principle states that one should only tax individuals that have a certain minimum amount of financial capability (Stevens (2010)). The practical implication of this is the existence of so called Tax Discounts. They work as follows: First the due tax over all boxes is determined, for example $0.34 * 15,000 = 5,100$ euro in Box 1 and zero elsewhere. From this the individual specific tax discount is subtracted. There are a number of discounts: General, Elderly, Single-Parent, etc. After applying these discounts, the final tax due would be $5,100 - 1,990 = 3,110$ euro. Because most of these discounts are fixed amounts, they create in fact latent thresholds. For instance, the individual above would not pay any tax if his annual income remained below $1,990/0.34 = 5,852.94$ euro. Based on past tariffs and levels for each of these discounts, we can construct the thresholds for each individual with reasonable accuracy.[3] Proportional discounts were ignored, as these do not influence the location of the threshold.

Distortions The so called labor discount creates a potential distortion in the marginal costs of giving. It is a proportionate discount that lowers the effective tax in Bracket 1 with roughly 10% if individuals receive income from labor. This is meant to stimulate/reward this type of activity. This

[3]The tax discount variable in the IPO data was censored and therefore unusable. However, most of the decisive characteristics upon which the discounts are distributed were available in the IPO dataset. When absent, we determined its value using a pragmatic approach.

creates a distortion when analyzing price elasticities. However it is unclear if people actually take this into account when determining their marginal cost of giving and also it is difficult to 'rebuild' this into the data. We choose to ignore it. Nevertheless it illustrates the presence of distorting factors in the tax system that may harm the estimation of price elasticity.

4 Empirical strategy

The most straightforward approach to estimate price elasticity is by estimating equation 6.1 in Andreoni (2006):

$$\ln G_{it} = \alpha + \beta_1 \ln P_{it} + \beta_2 \ln Y_{it} + BX_{it} + \varepsilon_{it} \tag{1}$$

Where:
- G_{it} is the outcome variable (donation);
- P_{it} is the cost of giving $(1 - t)$;
- Y_{it} is the income level;
- β_1 is the price elasticity;
- β_2 is the income elasticity;
- X_{it} is a set of covariates;
- ε_{it} is the usual error term.

However, from treatment evaluation we know that normal OLS is biased. A simple comparison of people who did donate and who did not, ignores all kinds of differences between people that influence their choice of donating, also known as selection bias. A basic approach to remove selection bias would be to include control variables to make up for differences between people. Although it corrects for basics like age, education, household size, and others, it has proven to be insufficient in many cases (Pischke and Angrist (2010)). Even more, the tax data does not contain some important variables like education, religion and personality.

To address this problem of endogeneity and omitted variables we use the regression discontinuity design. A tariff jump can in fact be seen as an experiment in which the price of giving is randomly assigned conditional on the annual box 1 income. Individuals below the tax bracket threshold do not get treated and therefore pay marginal price A. Individuals with an income that exceeds the threshold get treated and pay marginal price B.

For individuals it is difficult to precisely control their income and assignment. As a result, we expect that people just below the threshold are very similar to those just above the threshold. Treatment is the only difference. So if we compare these two groups with different marginal tariffs but similar characteristics, than the problem of omitted variable bias is eliminated. This means there is also no need for control variables. In contrast to the specification 6.1 in Andreoni (2006) our estimates will be *local* price elasticities, applicable to the point of the threshold. This is inherent to the RD approach.

Not only do we expect that people give more if the marginal cost of giving drops, but we may also see an increase in the number of people who donate or the probability of giving. These effects will be analyzed separately and throughout this paper we will refer to these as the extensive margin (probability of giving) and intensive margin (amount given).

Price effects The standard representation of the RD design model is given by:

$$G_{it} = \alpha + \tau D + \beta Y_{it} + \varepsilon_{it} \tag{2}$$

Where:
- D is the treatment dummy for which $D \in \{0, 1\} : D = 1$ if $Y_{it} \geq c$ and $D = 0$ if $Y_{it} < c$ where c is the threshold level;
- τ is the treatment effect (not elasticity);
- β is an income effect (not elasticity).

The specification we apply in this study differs in two respects. First the effect of the assignment variable does not need to be similar on both sides of the threshold. The model is therefore extended with slope parameters β_l and β_r instead of just β (Lee and Lemieux (2009)). It is convenient to subtract the cutoff value from the assignment variable, i.e $Y^*_{it} = (Y_{it} - c)$. The intercept α then yields the value of the regression at the cutoff point (Lee and Lemieux (2009)).

Secondly, because we want to estimate elasticity, we replace the standard treatment dummy (0/1) by the percentage change in marginal cost of giving:

$$\Delta p_{it} = \left(\frac{p_a - p_{it}}{p_a} \right) \tag{3}$$

where:
- p_a is the cost of giving for the control group;
- p_{it} the cost of giving for a specific individual i in year t.

For example, for the treated the marginal cost changes from 0.67 to 0.58 and Δp_{it} will be $(0.58 - 0.67)/0.58 = -0.155$. For the control group the marginal cost does not change and the treatment variable will be $(0.58 - 0.58)/0.58 = 0$. Note this variable still serves as a dummy, but now the estimate of τ will be interpretable as elasticity. For the intensive margin the model than becomes:

$$\ln G_{it} = \alpha + \tau \Delta p_{it} + \beta_l Y^*_{it} D_l + \beta_r Y^*_{it} D_r + BX_{it} + \varepsilon_{it} \tag{4}$$

where:
- τ is the local price elasticity;
- β_l is the income effect for the control group (not elasticity);
- β_r is the income effect for the treated (not elasticity);
- $D_l = 1$ if $Y^*_{it} < 0$ and zero elsewhere;
- $D_r = 1$ if $Y^*_{it} \geq 0$ and zero elsewhere;
- X a set of covariates, in our case consisting of year dummies only.

Pooling over the available sample years ensures a large sample size and estimates an average effect over all years and not just 1 year. The pooling is done in such a way that per year incomes are standardized to the corresponding tax bracket level applicable in that specific year.

The above approach works for binary outcome variables as well. The model is equivalent to a linear probability model, for which it holds that we can interpret the coefficients as probabilities or proportions (Pischke and Angrist (2009)). In this case the estimated elasticity is in fact a quasi local elasticity, because it is the elasticity of probability, rather than donated money. For the extensive margin this gives:

$$Q_{it} = \alpha + \xi \Delta p_{it} + \beta_l Y^*_{it} D_l + \beta_r Y^*_{it} D_r + BX_{it} + \varepsilon_{it} \tag{5}$$

where:
- Q_{it} is a 0/1 variable indicating if a person donated;
- ξ is the quasi local elasticity.

First analyses with (4) and (5) indicate that the results are very sensitive to the volatility of both donations and proportions of giving conditional on standardized box 1 income. For example, a bandwidth of 1,500 will yield positive elasticity and a 3,000 bandwidth will yield negative elasticity. As it is unlikely that the true relation between giving and income is that volatile, it seems reasonable to estimate the income relation on a wider interval than the interval used to estimate treatment effects. To allow for this longer estimation interval for income we make one more adjustment to the standard RD model and add an extra dummy variable. Let b_1 be the bandwidth for price elasticity and b_2 be the bandwidth for income effects, where $b2 \geq b1$. Then:

$$\ln G_{it} = \alpha + \tau \Delta p_{it} D_{r1} + \beta_l Y^*_{it} D_l + \beta_r Y^*_{it} D_r + \tilde{\tau} \Delta p_{it} D_{r2} + BX_{it} + \varepsilon_{it} \quad (6)$$

where:
-$D_{r1} = 1$ if $0 \leq Y^*_{it} \leq b_1$ and zero elsewhere;
-$D_{r2} = 1$ if $b_1 < Y^*_{it} < b_2$ and zero elsewhere.

The extra term $\tilde{\tau}\Delta p_{it} D_{r2}$ makes sure that τ still only captures the elasticity related to the original bandwidth b_1 whilst allowing income to be estimated based on bandwidth b_2. A similar approach holds for the extensive margin.

Without placing to much restriction on the estimation of the income effects we set the bandwidth b_2 at ± 6,000 for all analyses. This is equal to the largest bandwidth we consider for b_1 and it seems reasonable to capture income effects from an economic perspective as well.

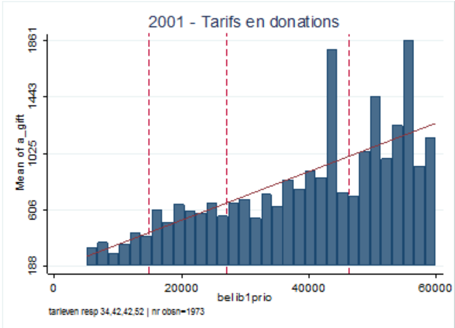
Setting the bandwidth The research in TD (2008) is similar but has some limitations. The bandwidth was set at $\pm 1,500$ euro around a threshold. There are three reasons why we suspect the bandwidths need to be larger:

The first is the fact that an individual is sometimes pushed back into a lower tariff. For an individual with an income just above the threshold the initial marginal tariff is the higher tariff. But as soon as the deducted income drops below the tariff bracket, the remaining part is taxed against the lower tax tariff. As a result, only people with a large enough distance to the tariff bracket experience a change in the cost of giving. If one is too close to the threshold, a major part of the donation is taxed against the lower tariff instead of the higher. If we take into account that the average donation is about 700 euro with a standard deviation of about 1,100 euro, than a bandwidth of $\pm 1,500$ around the cutoff is likely to give biased estimates.

Secondly, a persons marginal tariff is determined by annual taxable income. This is often a variable amount, which means individuals must anticipate what next years annual income will be. If estimated income is too close to the threshold, people cannot be certain about their marginal tariff and probably are not likely to react to it. We expect that as income is further away from the threshold, people have more certainty on their marginal tariff and hence are more likely to react to a price change. This would opt for larger bandwidths as well.

Finally, estimating ones marginal tariff is even more difficult, because the tariff brackets are not constant over time. Every year they increase with a non fixed amount ranging between 300-1,500 euro due to inflation and/or

Figure 1: Example of an RD graph with averages per bin



policy changes. This introduces an extra uncertainty regarding the location of the tariff jump and ones marginal tariff.

Based on these three effects we hypothesize that people only expect to benefit of the tariff jump if their income is at least 2,000 euro above the tariff threshold. In this paper we look at three bandwidths: $\pm 1,500$, $\pm 3,000$ and $\pm 6,000$. For RD it is important that individuals are comparable within the sample. With a bandwidth of $\pm 6,000$ individuals can differ as much as 12,000 euro in annual income or 1,000 euro per month. This may seem large, but after tax the difference is only somewhere between 500 and 650 euro.

Graphic approach There is an intuitive way to visualize RD designs using a special type of histogram. Instead of counts per bin, this type of histogram returns the average value of the outcome variable per bin (in our case the amount of the donation) (e.g. Figure 1). In these Conditional Mean (CM) graphs one can quickly identify possible jumps in the outcome variable in the neighbourhood of thresholds. In case of binary outcome variables the CM graph reports proportions per bin, which is most useful for the extensive margin (giving 0/1).

Diagnoses The main assumption of RD is that individuals are not able to precisely control the assignment variable. Only then there is no significant difference between individuals on the left and on the right side of the threshold, in which case it is justified to compare these two groups.

Although the assumption seems justified it is nevertheless important to check. The assumption implies an even spread of observations both on the left as well as on the right of the cutoff. A gap or a sudden jump would suggest sorting of some kind, which would immediately imply the main assumption - individuals not being able to precisely control the outcome variable - is violated.

Testing the assumption can be done both visually and numerically. The first option involves inspecting histograms of the assignment variable around the cutoff. The second is based on McCrary (2008) which involves computing the means of the assignment variable for several bins - similar to an CM graph - and then running local linear regressions on these values.

In line with the key assumption of RD we expect to have almost no difference in the covariates on either side of the cutoff. Lee and Lemieux (2009) suggest testing this assumption with Seemingly Unrelated Regressions. A more pragmatic approach would be to inspect CM graphs of the covariates. We will do the latter.

5 Data

This study uses data from the national Income Panel Survey (IPO) conducted by Statistics Netherlands and made available by DANS. The IPO is a panel survey of roughly 70,000 individuals with annual increments which contains information on social economical characteristics, income and tax files. Together they give an accurate representation of the Dutch population. We have access to anonymized data of the years 2001, 2002, 2005, 2006 and 2007. Unfortunately the anonymized data only allows for the creation of two subpanels: 2001-2002 and 2005-2006. 2007 could not be linked to the other data sets.

Sample selections Statistics Netherlands provides an extensive description of the IPO data, year by year. It includes a number of recommended sample selections for income related studies that were applied in this analysis as well, unless stated otherwise:

- Only include individuals for which income is known and not extreme;
- Select only people living at private addresses, not institutions;
- Select only core persons of each home;
- Select only people with a full year of income;
- Leave out students, because their income cannot be registered correctly;
- Only select individuals with personal income.

The following additional selections were made, unless stated otherwise:

- Select only people of age 20 and older, because tax is not very relevant below;

- Leave out observations with donations larger than 15,000 euro;
- Leave out observations with negative income and negative donations.

Fiscal policy allows for non-married couples to register for tax as if married. In this paper we therefore refer to these groups simply as married.

Table 1 gives an overview of the proportions of people who donate and the means of the donations.[4]

Table 1: Means, st.dev and counts of extensive margin (probability of giving) and intensive margin (amount donated).

		Extensive				Intensive			
		Age 20-64		65plus		Age 20-64		65plus	
Year		Single	Married	Single	Married	Single	Married	Single	Married
2001	Mean	0.072	0.136	0.158	0.080	672	788	736	869
	St.dev.	0.259	0.343	0.365	0.272	1,071	1,116	924	1,274
	n.	18,392	4,260	3,039	34,960	411	1,333	581	480
2002	Mean	0.077	0.147	0.165	0.085	679	872	739	893
	St.dev.	0.266	0.354	0.371	0.279	781	1,130	924	1,136
	n.	18,610	4,344	3,057	35,506	438	1,430	640	503
2005	Mean	0.080	0.174	0.187	0.094	709	988	792	966
	St.dev.	0.271	0.379	0.390	0.292	868	1,251	1,157	1,330
	n.	17,823	4,381	3,297	34,964	481	1,420	764	615
2006	Mean	0.080	0.177	0.182	0.094	723	1,038	795	981
	St.dev.	0.272	0.382	0.386	0.292	881	1,315	1,144	1,369
	n.	17,934	4,425	3,497	35,505	487	1,439	785	636
2007	Mean	0.080	0.184	0.185	0.096	772	1,058	797	967
	St.dev.	0.271	0.387	0.389	0.294	1,060	1,411	1,192	1,303
	n.	18,092	4,580	3,601	36,184	509	1,448	841	667
Total	Mean	0.078	0.164	0.176	0.090	714	951	775	941
	St.dev.	0.268	0.370	0.381	0.286	939	1,256	1,089	1,292
	n.	90,851	21,990	16,491	177,119	2,326	7,070	3,611	2,901

6 Results

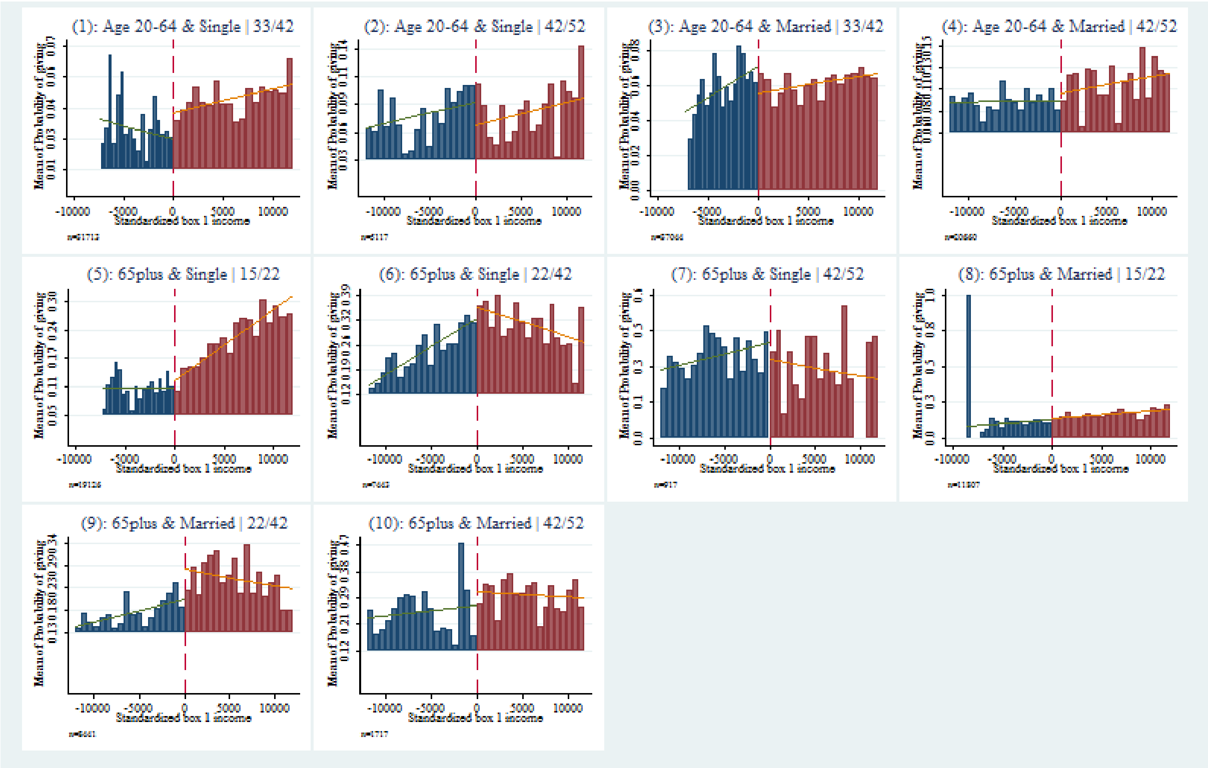
6.1 TD approach with extra bandwidths

Our first approach is very similar to TD (2008), which allows comparison of the results. The main difference is that, instead of estimating each year separately, we pool across the five available years.

Because CM graphs help to understand what is actually happening close to a threshold, we have provided graphs per subgroup (Figure 2). The red

[4]These statistics cover the sample after making the selections as described in this section.

Figure 2: TD approach: Conditional mean graphs on the extensive margin (probability of giving). The bars indicate average probability per bin.



lines represent the location of a tariff jump. Each graph starts at 12,000 euros to the left of a tariff jump and ends at 12,000 euros to the right of a tariff jump to help identify local and global effects. Graphs for the jump of bracket 2 to 3 were excluded for the Single and Married groups with age 20-64, because the tariff change is near to zero for these groups at these thresholds. The size of the jumps is given in the title of each graph. For instance, 33/42 stands for a jump from 33% to 42% tax. A first glance at panels (1)-(12) of Figure 2 reveals that the tax data is not very smooth. The averages of the proportion of givers are rather jumpy. This makes it difficult to distinguish between price effects and other effects from looking at the graphs alone. Nevertheless, in panels 1,4,6,9, and 10 the depicted regression lines clearly jump upwards at the threshold. In panels 2,3,7 we can actually see a downward movement at the threshold. Note that regression slopes of income vary from downward, flat to upward on both sides of cutoffs. This is not in line with the intuitive idea that more income leads to a higher probability of giving.

Regression estimates give a better understanding of the size of effects. Table 2 gives the results for 3 bandwidths: 1,500, 3,000 and 6,000 above and below each threshold. The 1,500 bandwidth is also used in TD (2008). Q.e. is the quasi elasticity as described in Section 4. For most subgroups and bandwidths the number of observations is reasonably large, except for (7) and (8). Table 2 confirms the hunch from the CM graphs about panels 1,4,6,9, and 10. These indeed have negative elasticity. Note that only for (1) and (8) we estimate significant effects at the 10% level. In terms of elasticity the effects are quite small though.

Table 2: TD approach - Extensive margin (probability of giving)

	Age 20-64				65plus					
	Single		Married		Single			Married		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tariff change (%)	$33 \rightarrow 42$	$42 \rightarrow 52$	$33 \rightarrow 42$	$42 \rightarrow 52$	$15 \rightarrow 22$	$22 \rightarrow 42$	$42 \rightarrow 52$	$15 \rightarrow 22$	$22 \rightarrow 42$	$42 \rightarrow 52$
Bandwidth +/-1500										
Q.e.	-0.076*	0.160	0.055	-0.058	0.069	-0.158	-0.071	-0.286	-0.081	-0.256
S.e.	(0.042)	(0.152)	(0.063)	(0.072)	(0.145)	(0.144)	(0.599)	(0.183)	(0.105)	(0.362)
n	21,395	2,123	18,064	9,471	15,507	3,043	367	8,743	3,860	853
Bandwidth +/-3000										
Q.e.	-0.078*	0.141	0.097	-0.081	-0.068	-0.160	0.049	-0.290	-0.081	-0.232
S.e.	(0.044)	(0.160)	(0.063)	(0.077)	(0.151)	(0.149)	(0.622)	(0.184)	(0.110)	(0.386)
n	21,395	2,123	18,064	9,471	15,507	3,043	367	8,743	3,860	853
Bandwidth +/-6000										
Q.e.	-0.089**	0.197	0.081	-0.040	0.030	-0.171	0.103	-0.329*	-0.093	-0.253
S.e.	(0.042)	(0.147)	(0.061)	(0.070)	(0.144)	(0.140)	(0.587)	(0.178)	(0.103)	(0.358)
n	21,395	2,123	18,064	9,471	15,507	3,043	367	8,743	3,860	853

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$

Figure 3 shows CM graphs for the intensive margin. Again, the averages are not smooth. None of the regression lines suggests large price effects. However, these lines are based on a bandwidth of 12,000. It is possible that for smaller bandwidths the effects are stronger.

Table 3 confirms that most effects are not significant. Note however that estimated elasticities for (1), (2) and (7) are much larger (≥ -1) than elasticities estimated on the extensive margin and quite consistent across bandwidths. The significant positive estimates in (8) and (10) are puzzling in terms of elasticity. Looking at the corresponding CM graphs, the results are no surprise though.

The appendix contains a number of graphs to check for both continuity in the assignment variable as well as in a number of available covariates. These seem to indicate that the continuity conditions are met. Summarizing, there seem to be significant effects of marginal cost on giving for the extensive margin, but only for certain groups of people: Age 20-64 Singles and 65 Plus Married. The intensive margin produces mixed results.

Figure 3: TD approach: Conditional mean graphs on the intensive margin (amount donated). The bars indicate average donations per bin.

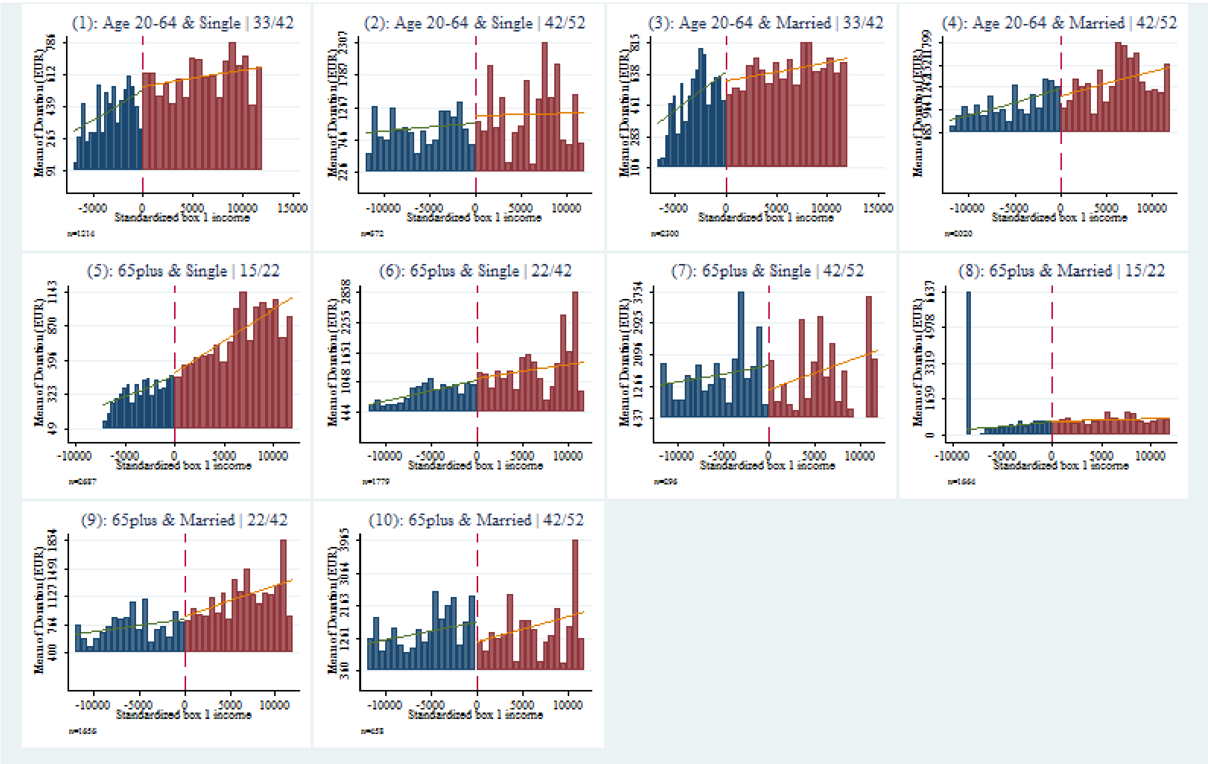


Table 3: TD approach - Intensive margin (amount donated)

	Age 20-64				65plus					
	Single		Married		Single			Married		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tariff change (%)	33 → 42	42 → 52	33 → 42	42 → 52	15 → 22	22 → 42	42 → 52	15 → 22	22 → 42	42 → 52
Bandwidth +/-1500										
P.e.	-1.855	-1.882	0.807	0.703	0.392	-0.296	-1.955	0.875	-0.126	3.603**
S.e.	(1.547)	(1.829)	(1.368)	(0.970)	(1.419)	(0.685)	(2.472)	(1.717)	(0.569)	(1.640)
n	739	168	1,091	942	1,923	898	123	1,161	848	238
Bandwidth +/-3000										
P.e.	-1.699	-2.235	0.489	0.499	0.528	-0.068	-1.540	3.702**	-0.173	3.048*
S.e.	(1.586)	(1.974)	(1.394)	(1.026)	(1.420)	(0.706)	(2.711)	(1.779)	(0.594)	(1.766)
n	739	168	1,091	942	1,923	898	123	1,161	848	238
Bandwidth +/-6000										
P.e.	-0.975	-2.286	0.417	0.477	0.252	-0.301	-1.979	2.373	-0.074	3.109*
S.e.	(1.530)	(1.839)	(1.339)	(0.963)	(1.383)	(0.660)	(2.471)	(1.687)	(0.560)	(1.590)
n	739	168	1,091	942	1,923	898	123	1,161	848	238

6.2 Extension 1: Lagged variables

As mentioned earlier an important assumption is wether tax subjects are at any time aware of their marginal cost of giving. Annual tax filing creates an opportunity to adjust behavior. However, this process takes place after a tax year has ended, which gives information that is delayed by 1 year and does not give the new location of the moving brackets. Hence, it is interesting to see whether delayed thresholds, brackets and income have more explanatory power than the actual tariffs and thresholds. The panel structure of years 2001/2002 and 2005/2006 allows for this type of analysis.

Figure 4 shows the results for the extensive margin. The regression lines indicate moderate price effects at most. However, a closer look at graphs 1, 4, 8 and 10 reveals that for smaller bandwidths we may expect stronger effects. Note again the broad range of slopes for income: upward, downward and flat.

Table 4 shows the effect of the lagged thresholds on the extensive margin.

Table 4: Extension 1 - Lagged variables: extensive margin (probability of giving)

	Age 20-64				65plus					
	Single		Married		Single			Married		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tariff change (%)	33 → 42	42 → 52	33 → 42	42 → 52	15 → 22	22 → 42	42 → 52	15 → 22	22 → 42	42 → 52
Bandwidth +/-1500										
Q.e.	-0.079	0.015	0.067	-0.055	-0.093	-0.055	-0.313	0.438	-0.201	-0.090
S.e.	(0.075)	(0.270)	(0.113)	(0.123)	(0.237)	(0.222)	(0.853)	(0.270)	(0.155)	(0.552)
n	7,071	731	5,863	3,495	5,741	1,228	155	3,055	1,660	347
Bandwidth +/-3000										
Q.e.	-0.079	-0.029	0.085	-0.098	-0.180	-0.108	-0.521	0.405	-0.255*	-0.371
S.e.	(0.078)	(0.284)	(0.111)	(0.132)	(0.235)	(0.188)	(0.901)	(0.257)	(0.133)	(0.584)
n	7,071	731	5,863	3,495	5,741	1,228	155	3,055	1,660	347
Bandwidth +/-6000										
Q.e.	-0.097	0.027	0.063	-0.040	-0.090	-0.105	-0.370	0.321	-0.251**	-0.105
S.e.	(0.074)	(0.264)	(0.109)	(0.121)	(0.228)	(0.189)	(0.849)	(0.257)	(0.127)	(0.552)
n	7,071	731	5,863	3,495	5,741	1,228	155	3,055	1,660	347

Comparing the results with Table 2 we see that estimated elasticities for (7) and (9) have become stronger. Also (8) has completely changed sign. For the other subsets the changes are not that profound. Note that the p-value for (9) has decreased. Figure 5 suggest significant price effects for panels (1) and (2). The estimates in Table 3 are indeed strong, but not significant. For the 65 Plus Single 22 → 42 the results are significant at the 10% level and much larger than -1. In contrast to these stronger elasticities we find strong positive elasticities for (4), (8) and (10).

The intensive margin shows different results though. It contains less significant effects and quite different estimates for the price elasticities.

Figure 4: Extension 1 - Lagged variables: Conditional mean graphs on the extensive margin (probability of giving). The bars indicate average probability per bin.

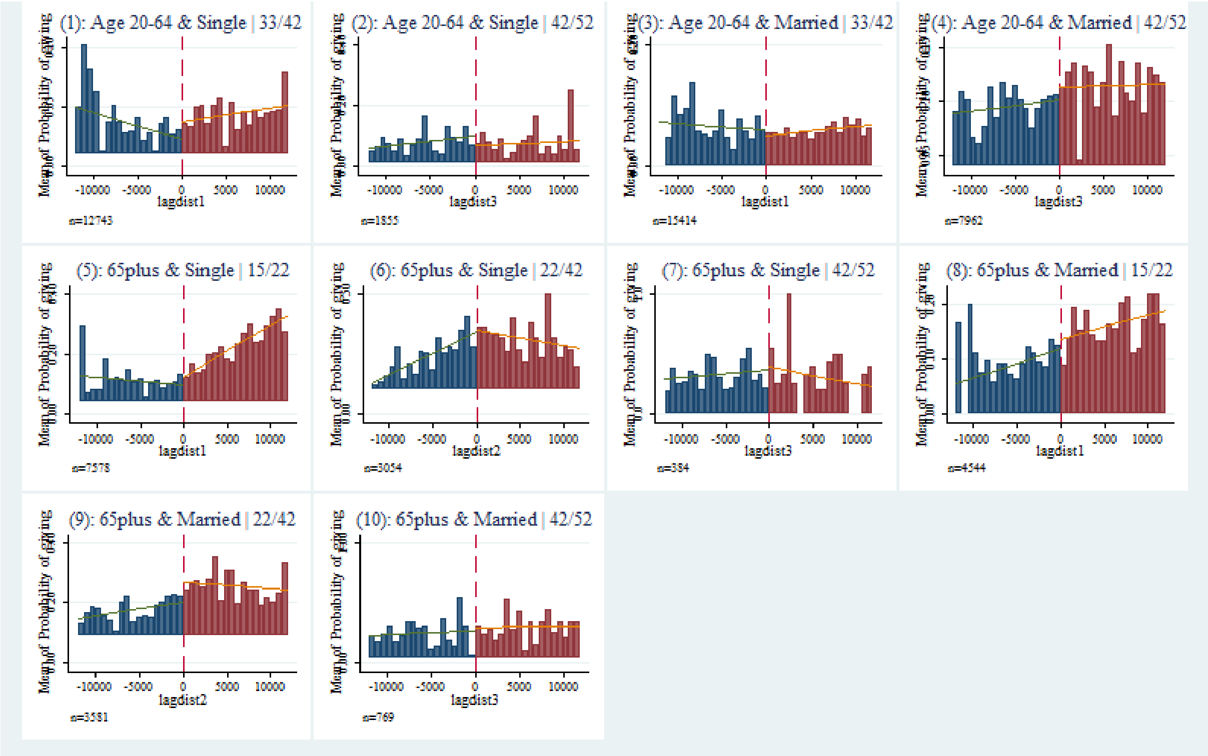
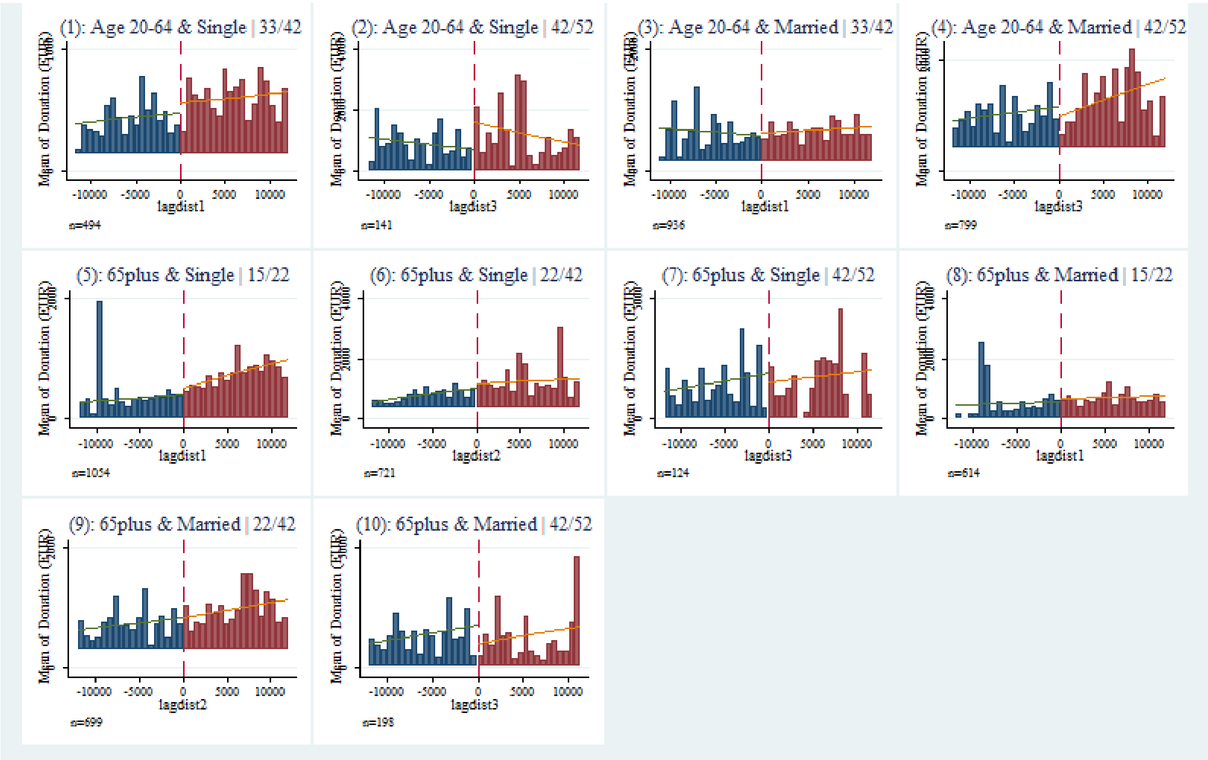


Table 5: Extension 1 - Lagged variables: Intensive margin (amount donated)

	Age 20-64				65plus					
	Single		Married		Single			Married		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tariff change (%)	33 → 42	42 → 52	33 → 42	42 → 52	15 → 22	22 → 42	42 → 52	15 → 22	22 → 42	42 → 52
Bandwidth +/-1500										
P.e.	-3.253	-3.269	-1.867	3.500**	1.915	-1.873**	-2.192	0.221	-0.183	3.476
S.e.	(2.738)	(3.800)	(2.443)	(1.388)	(2.205)	(0.812)	(4.504)	(2.973)	(0.900)	(2.562)
n	256	63	337	368	681	365	52	397	360	92
Bandwidth +/-3000										
P.e.	-2.787	-3.243	-2.414	2.796*	2.691	-1.357*	-1.981	4.730	-0.636	3.304
S.e.	(2.732)	(3.635)	(2.564)	(1.446)	(2.162)	(0.768)	(4.615)	(3.416)	(0.720)	(2.630)
n	256	63	337	368	681	365	52	397	360	92
Bandwidth +/-6000										
P.e.	-3.183	-3.072	-1.204	3.184**	2.054	-1.425*	-1.875	4.668	-0.839	3.265
S.e.	(2.627)	(3.383)	(2.423)	(1.362)	(2.126)	(0.765)	(4.430)	(3.238)	(0.676)	(2.552)
n	256	63	337	368	681	365	52	397	360	92

Figure 5: Extension 1 - Lagged variables: Conditional mean graphs on the intensive margin (amount donated). The bars indicate average donations per bin.



Although the estimates in this approach are not that significant, it is worth noting that the coefficients often have the expected negative sign. Also, the estimates are quite stable across all bandwidths. The lack of significance may be caused by the fact that we have very small panels. We loose 3 years of data in comparison with the other analyses in this paper. Even more, ideal data would span 10 years of more. This could make a considerable difference.

6.3 Extension 2: Specific subgroups

TD (2008) looked at four subgroups (Single, Married, 65min and 65plus). However, the responsiveness to tax tariffs may differ based on other characteristics as well. For example, to anticipate on the price effect it helps if one has a stable income. This would greatly help the individual in identifying his marginal cost of giving and determining his benefit from a change in tax tariff. Because the analysis until now has produced some significant results for 65plus subgroups, we exclude this group in the following analysis (Table 6).

Table 6: Extension 2 - Specific subgroups: Extensive margin (probability of giving)

	Age 20-64					
	(1) Public Servant		(2) Income change $\leq$2.5%		(3) Income change $\leq$5%	
Tariff change (%)	33 $\rightarrow$ 42	42 $\rightarrow$ 52	33 $\rightarrow$ 42	42 $\rightarrow$ 52	33 $\rightarrow$ 42	42 $\rightarrow$ 52
Bandwidth +/-1500						
Q.e.	0.216	-0.093	-0.230	-0.146	-0.237**	-0.340*
S.e.	(0.260)	(0.183)	(0.176)	(0.262)	(0.105)	(0.193)
n	1,264	1,361	2,394	673	4,928	1,353
Bandwidth +/-3000						
Q.e.	0.166	-0.022	-0.275	-0.266	-0.239**	-0.329
S.e.	(0.254)	(0.199)	(0.174)	(0.273)	(0.106)	(0.206)
n	1,264	1,361	2,394	673	4,928	1,353
Bandwidth +/-6000						
Q.e.	0.221	-0.114	-0.270	-0.198	-0.244**	-0.360*
S.e.	(0.245)	(0.181)	(0.169)	(0.257)	(0.101)	(0.189)
n	1,264	1,361	2,394	673	4,928	1,353

Although we would expect that public servants have stable income and are well aware of their marginal cost, their responsiveness to changes in prices is not significant. People whose income has changed only a little in comparison to last years income are quite responsive though. Note that estimates are quite stable across different bandwidths. Table 6 gives the results for the intensive margin. The number of observations is very small in all cases, because of which it is likely we will not find significant results. An interesting feature however is the increasing price elasticity as income becomes more stable (from right to left in the table).

Table 7: Extension 2 - Specific subgroups: Intensive margin (amount donated)

	Age 20-64					
	(1) Public Servant		(2) Income change $\leq$2.5%		(3) Income change $\leq$5%	
Tariff change (%)	33 → 42	42 → 52	33 → 42	42 → 52	33 → 42	42 → 52
Bandwidth +/-1500						
P.e.	6.827	0.606	-6.087	-5.375	-3.345	-1.482
S.e.	(9.367)	(1.958)	(5.160)	(3.927)	(3.416)	(2.439)
n	69	134	125	73	219	154
Bandwidth +/-3000						
P.e.	4.781	2.360	-4.642	-3.576	-2.492	-0.783
S.e.	(9.110)	(2.147)	(5.260)	(4.186)	(3.472)	(2.527)
n	69	134	125	73	219	154
Bandwidth +/-6000						
P.e.	4.639	1.059	-5.952	-5.734	-3.466	-1.474
S.e.	(9.022)	(2.002)	(5.118)	(3.813)	(3.402)	(2.384)
n	69	134	125	73	219	154

6.4 Extension 3: Latent threshold

As described in the background section the Dutch Tax system contains another tariff jump that can be used: The Tax discount. From Figure 6 panel (1) we conclude that we have succeeded in effectively identifying every individuals latent threshold.

On the left side, people hardly pay any tax. On the right side of the threshold the amount of tax paid increases substantially and consistently. Panels (2) and (3) even indicate that the continuity assumption of RD holds to some extent, because there is no sudden jump at the threshold. Nevertheless, it will be difficult for our linear specification to estimate any significant effects, because the average tax paid appears to increase gradually rather than suddenly.

Indeed Figure 7 shows no signs of price effects. In Figure 8 the second panel shows some signs off price effects. The increase however is located at roughly 3,000 from the cutoff, making it difficult to say wether the effect is due to the latent threshold or wether there is another tax effect at work.

Table 8 gives the estimates for both extensive and intensive margin. Except for Age 20-64 Married all price effects have opposite signs.

Figure 6: Extension 3 - Latent threshold: Validity checks for graphically checking RD assumptions.

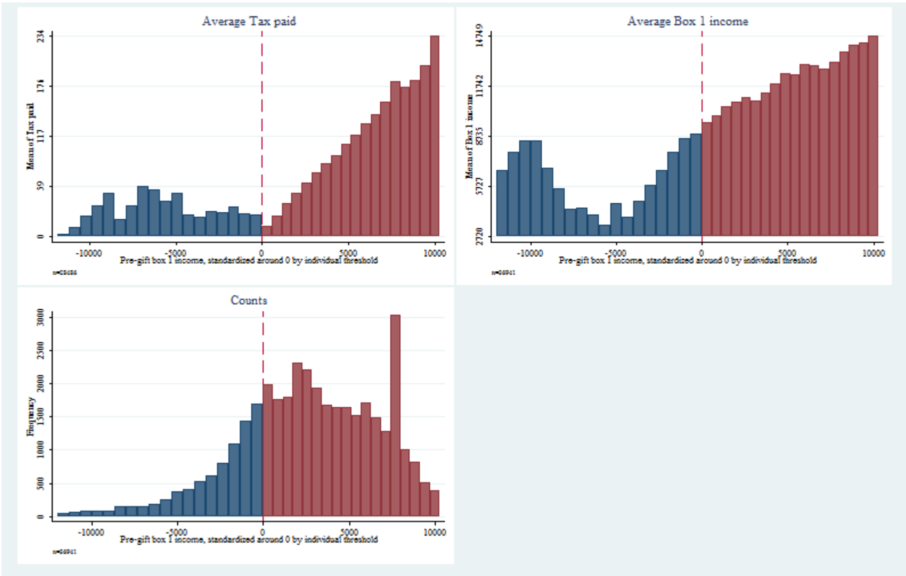


Figure 7: Extension 3 - Latent threshold: Conditional mean graphs on the extensive margin (probability of giving). The bars indicate average probability per bin.

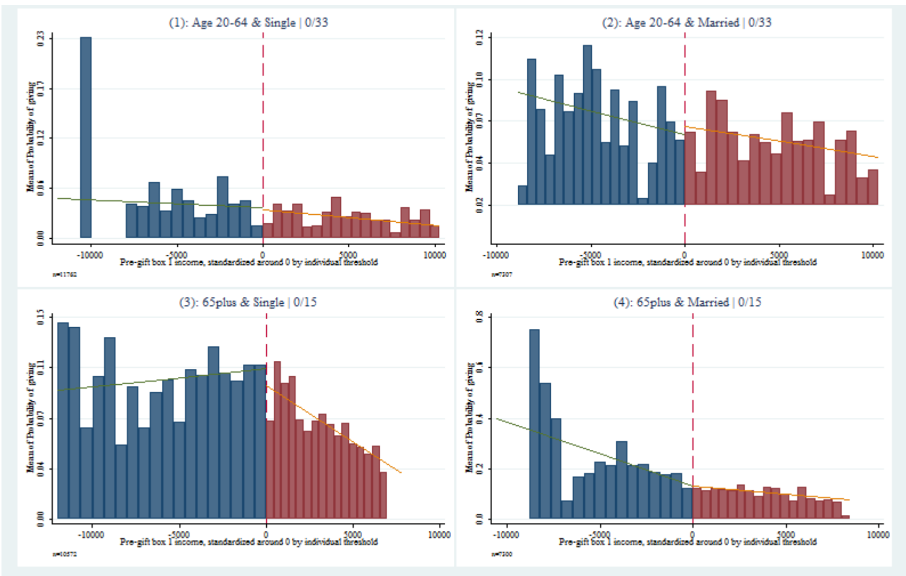


Figure 8: Extension 3 - Latent threshold: Conditional mean graphs on the intensive margin (amount donated). The bars indicate average donations per bin.

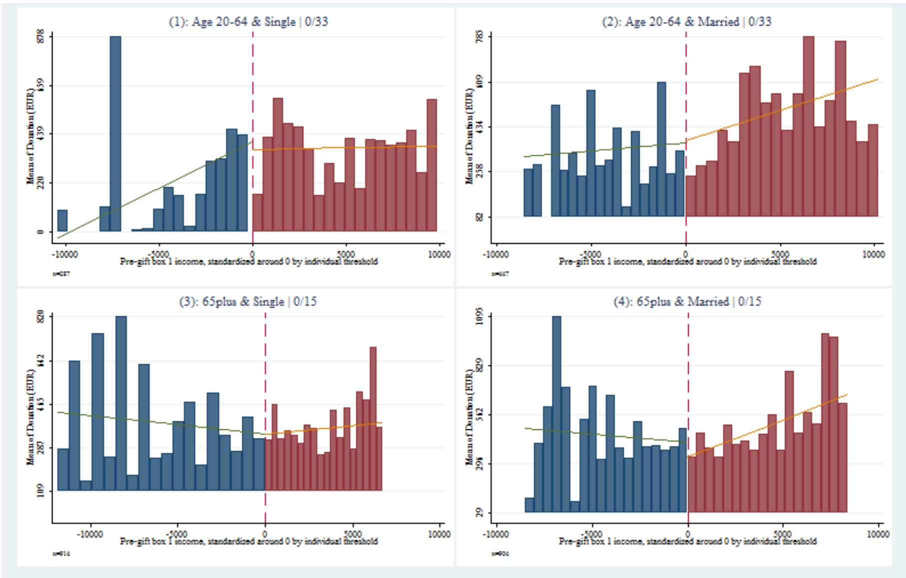


Table 8: Extension 3 - Using Tax Discount - Extensive and Intensive margin

	Extensive				Intensive			
	Age 20-64		65plus		Age 20-64		65plus	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Single	Married	Single	Married	Single	Married	Single	Married
Tariff change (%)	0 → 33	0 → 33	0 → 15	0 → 15	0 → 33	0 → 33	0 → 15	0 → 15
Bandwidth +/-1500								
Q.e./P.e.	0.005	-0.009	0.072	0.064	1.099	0.919	0.574	0.688
S.e.	(0.029)	(0.043)	(0.074)	(0.107)	(1.154)	(1.020)	(1.028)	(1.146)
n	5,501	4,968	9,853	6,300	169	316	853	814
Bandwidth +/-3000								
Q.e./P.e.	0.001	-0.003	0.083	0.073	1.505	0.572	0.987	1.268
S.e.	(0.029)	(0.043)	(0.075)	(0.108)	(1.155)	(1.035)	(1.074)	(1.203)
n	5,501	4,968	9,853	6,300	169	316	853	814
Bandwidth +/-6000								
Q.e./P.e.	0.005	-0.025	0.085	0.060	1.112	0.995	0.694	0.813
S.e.	(0.028)	(0.043)	(0.072)	(0.105)	(1.126)	(1.011)	(1.014)	(1.130)
n	5,501	4,968	9,853	6,300	169	316	853	814

6.5 Extension 4: Sensitivity to mixed tariffs

For this analysis we select bandwidths of +/- 3,500, 5,000 and 8,000 euro and exclude donations from the right side closer to the cutoff than 2,000 euro, because we expect that within those intervals people are not likely to react to price effects due to mixed tariffs.

The results are given in Table 9 and 10. Comparing the extensive margin with 2 we see that for (1) the elasticity more than doubles. (2) and (3) already had wrong sign, and this problem increases even further in Table 9. Elasticity estimates for (5) and (6) also increase. (9) stands out as the effect become almost 5 times stronger than in the TD approach with extra bandwidths. Also we now have (1) and (9) with significant elasticity at the 1% level. The intensive margin produces some strong significant results for (6) and similar but not significant for (1). Very odd is the extremely positive price elasticity for (8).

Table 9: Extension 4: Sensitivity to mixed tariffs - Extensive margin (probability of giving)

	Age 20-64				65plus					
	Single		Married		Single			Married		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tariff change (%)	33 → 42	42 → 52	33 → 42	42 → 52	15 → 22	22 → 42	42 → 52	15 → 22	22 → 42	42 → 52
Bandwidth +/-3500 (-2000)										
Q.e.	-0.176***	0.403**	0.153**	0.027	-0.238	-0.244	0.154	-0.051	-0.410**	-0.198
S.e.	(0.059)	(0.194)	(0.071)	(0.104)	(0.255)	(0.207)	(0.889)	(0.247)	(0.163)	(0.561)
n	21,551	2,002	20,006	8,897	14,318	2,856	345	8,211	3,587	767
Bandwidth +/-5000 (-2000)										
Q.e.	-0.105	0.466*	0.094	0.131	-0.142	-0.190	0.437	-0.008	-0.537***	-0.617
S.e.	(0.076)	(0.256)	(0.087)	(0.131)	(0.292)	(0.258)	(1.195)	(0.284)	(0.203)	(0.723)
n	21,551	2,002	20,006	8,897	14,318	2,856	345	8,211	3,587	767
Bandwidth +/-8000 (-2000)										
Q.e.	-0.171***	0.382**	0.142**	0.043	-0.185	-0.235	0.398	-0.071	-0.419***	-0.252
S.e.	(0.058)	(0.186)	(0.071)	(0.099)	(0.251)	(0.202)	(0.848)	(0.246)	(0.161)	(0.529)
n	21,551	2,002	20,006	8,897	14,318	2,856	345	8,211	3,587	767

Table 10: Extension 4: Sensitivity to mixed tariffs - Intensive margin (amount donated)

	Age 20-64				65plus					
	Single		Married		Single			Married		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tariff change (%)	33 → 42	42 → 52	33 → 42	42 → 52	15 → 22	22 → 42	42 → 52	15 → 22	22 → 42	42 → 52
Bandwidth +/-3500 (-2000)										
P.e.	-1.076	1.815	-0.009	1.596	3.031	-1.583*	2.155	9.175***	0.140	0.657
S.e.	(1.908)	(2.939)	(1.549)	(1.368)	(1.955)	(0.902)	(4.661)	(2.331)	(0.840)	(2.598)
n	749	156	1,217	872	1,870	824	116	1,113	788	210
Bandwidth +/-5000 (-2000)										
P.e.	-2.211	0.774	1.092	1.683	2.429	-2.554**	-7.017	8.033***	-0.017	-1.748
S.e.	(2.385)	(4.143)	(1.808)	(1.893)	(2.297)	(1.127)	(5.039)	(2.577)	(1.041)	(2.743)
n	749	156	1,217	872	1,870	824	116	1,113	788	210
Bandwidth +/-8000 (-2000)										
P.e.	-0.862	0.151	-0.234	1.412	3.072	-1.756**	2.005	9.290***	0.201	0.112
S.e.	(1.930)	(2.885)	(1.545)	(1.363)	(1.954)	(0.855)	(4.259)	(2.328)	(0.810)	(2.340)
n	749	156	1,217	872	1,870	824	116	1,113	788	210

7 Conclusion

Price elasticity The evidence for price effects is mixed. The hypothesis that people react to lagged information about their marginal tariffs gives interesting results, with elasticities that have a correct sign in many cases. However the estimation suffers from a considerable drop in observations, because we only have access to 2 years of panel data. In the other analyses only two groups stand out. People with a stable income who can better anticipate their marginal tariff are significantly sensitive to price changes. The quasi elasticities lie between -0.24 and -0.36. This means that for a 1% decrease in price, the probability of giving increases by 0.24 to 0.36%. Their price elasticities are much larger, but estimation is hindered by small samples. Another group that stands out is the 65 plus and married group with significant quasi elasticities between -0.26 and -0.54.

For a small number of groups and thresholds we also find significant price elasticities ranging from -1.36 to -2.6, but it is difficult to interpret these numbers as we also find a number of significant and quite large *positive* price elasticities. These are not supported by economic theory. Overall the mixed results question the assumption that people are well aware of their marginal tariff.

Sensitivity analysis TD (2008) used separate data sets per year and found no significant results. We find that when estimating multiple years at once there are in fact statistically significant price effects. The statistical significance increases when allowing for larger bandwidths.

Our analysis shows there are a number of drawbacks to using RD on tax data to estimate price elasticities: A closer look at the tax system reveals that some people are pushed back into a lower tariff because of donations. From the pragmatic approach in extension 4 we can see that estimates are quite sensitive to inclusion and exclusion of these people. This is a shortcoming of a standard RD approach which cannot be fixed easily.

Furthermore a standard RD model assumes a linear relation between box 1 income and donations. The conditional mean graphs indicate that this may not be the case. We addressed this problem partially by estimating income on a large enough neighborhood. Lee and Lemieux (2009) gives more formal approaches regarding nonlinear RD models. But without an understanding of the origin of the non-linearity, it is perhaps better to keep the linear specification. The fact that the results are very sensitive to the functional specification is a drawback of the RD approach.

Because RD uses variation in the data in a small neighborhood around a tax bracket threshold, it becomes extra vulnerable to irregularities in the tax system. For example, the labor discount' is an extra facility in the system that complicates calculation of the marginal tariffs at the threshold from bracket 1 to bracket 2.

Recommendations Because only a small portion of the Dutch use the deduction facility, it is not straightforward to estimate price elasticity using tax data. Variation in the data will become too small very quickly. We recommend a further investigation of the lagged tariff approach with more robust panel data methods. The data should span a longer period (10 years) and contain a number of reforms (such as the 2001 reform and the introduction of the multiplier 2012). Preferably the data should allow distinction between occasional and periodic donations as these are treated differently in the system. Because of the complicated structure of the tax system it is important to have a thorough understanding of the system.

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A Appendix

A.1 Assumption checks for TD Approach with extra bandwidths

Figure 9: Diagnosis: histograms on assignment variable Pre-Tax box 1 income - Extensive margin (probability of giving)

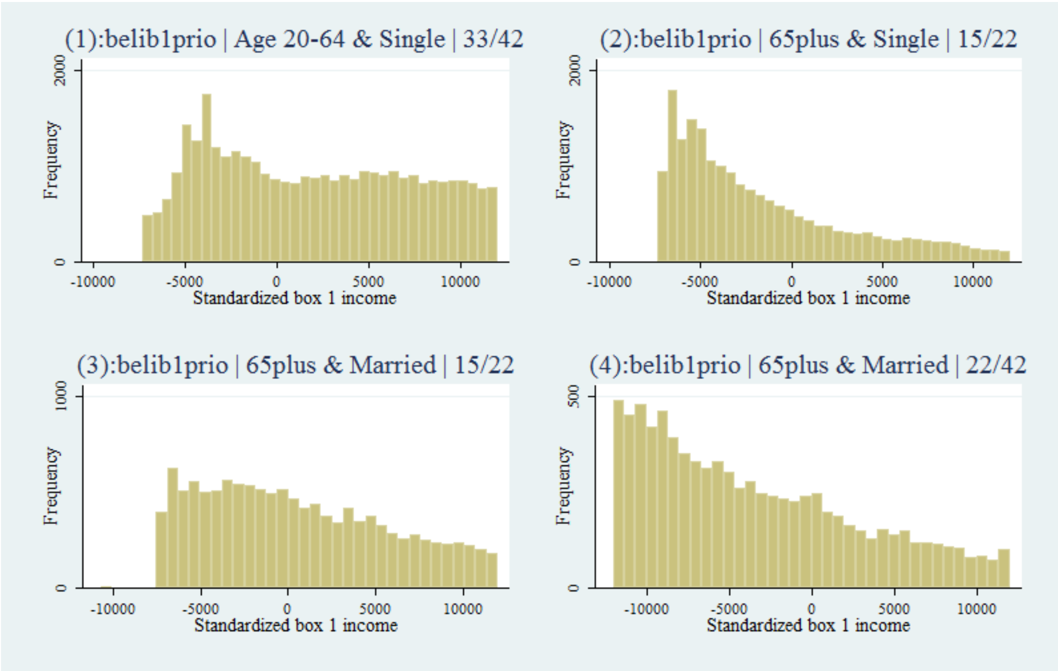


Figure 10: Diagnosis: Histograms on assignment variable Pre-Tax box 1 income - Intensive margin (amount donated)

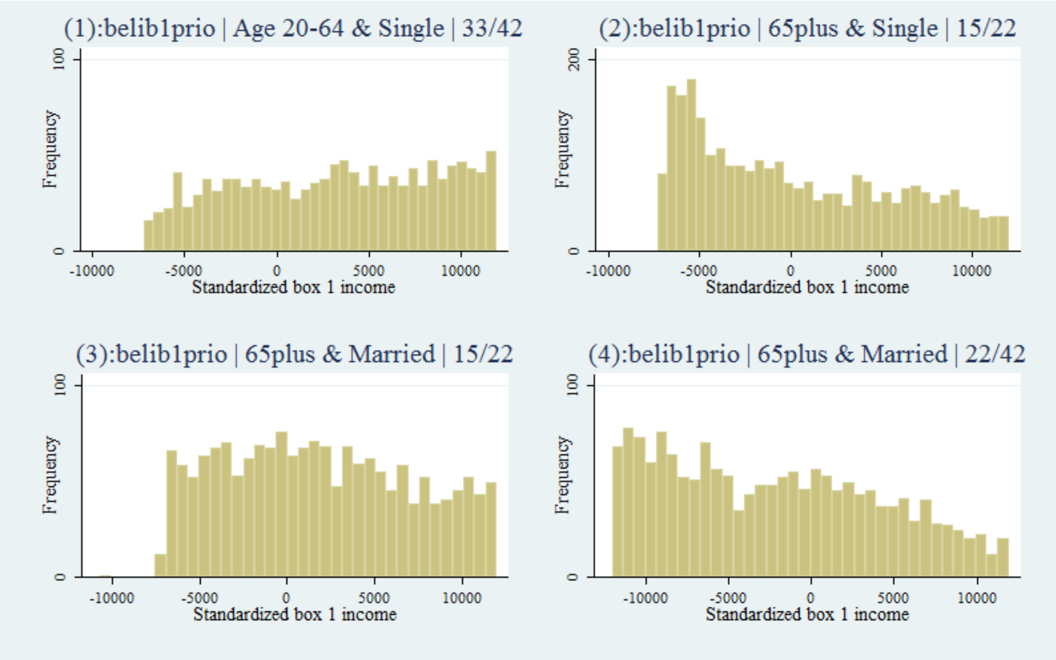


Figure 11: Diagnosis: Conditional Mean graphs for significant results on the extensive margin with TD approach.

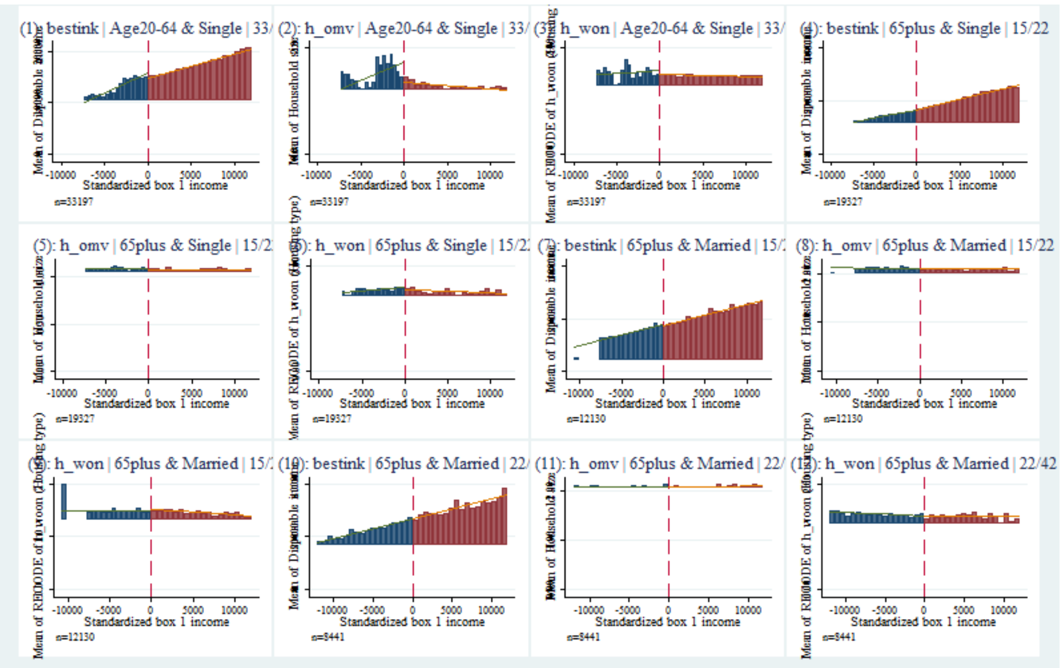
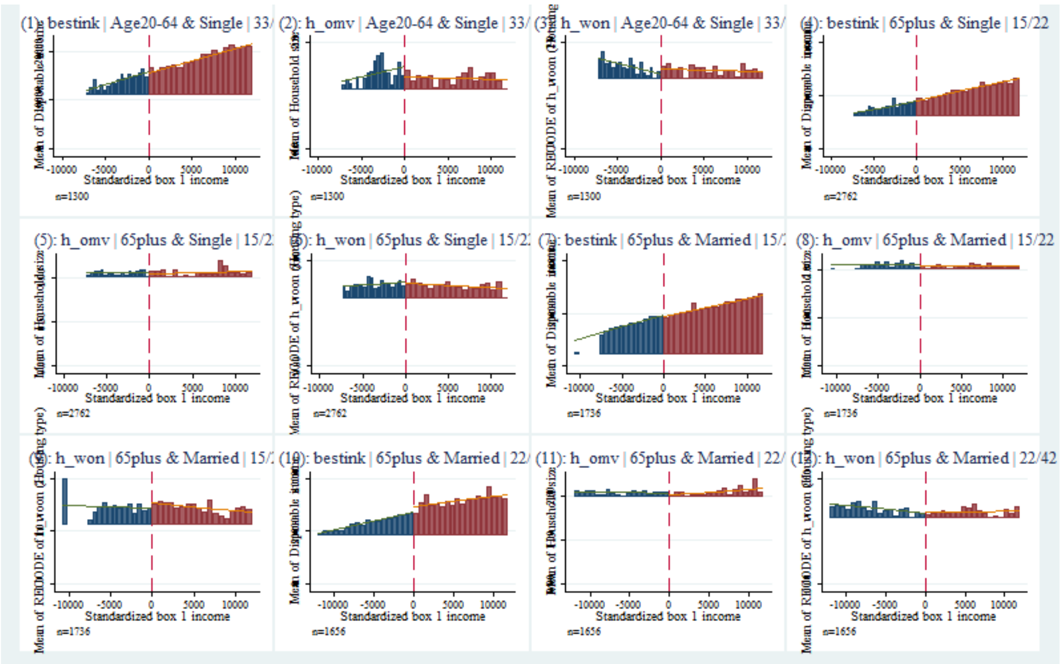


Figure 12: Diagnosis: Conditional Mean graphs for significant results on the intensive margin with TD approach.



A.2 Dutch Tax tariffs, brackets and other specifications

Table 11: Summary of Income Tax: Brackets, Tariffs and Discounts

	'01	'02	'03	'04	'05	'06	'07	'08	'09	'10	'11	'12
Kabinet	KokII	BalkI	BalkII	BalkII	BalkII	BalkIII	BalkIV	BalkIV	BalkIV	BalkIV	Rutte	Rutte
Grens eerste schijf	14,870	15,331	15,883	16,265	16,893	17,046	17,319	17,579	17,878	18,218	18,628	18,945
Grens tweede schijf	27,009	27,847	28,850	29,543	30,357	30,361	31,122	31,589	32,127	32,738	33,436	33,863
Grens derde schijf	46,309	47,745	49,464	50,652	51,762	52,228	53,064	53,860	54,776	54,367	55,694	54,491
Belastingtarief eerste schijf (gecombineerd)	33.50%	33.45%	33.00%	33.10%	34.40%	34.15%	33.65%	33.60%	33.50%	33.45%	33.00%	33.10%
Belastingtarief tweede schijf (gecombineerd)	42.00%	41.95%	41.95%	41.95%	41.95%	41.45%	41.40%	41.85%	42.00%	41.95%	41.95%	41.95%
Belastingtarief derde schijf	42.00%	42.00%	42.00%	42.00%	42.00%	42.00%	42.00%	42.00%	42.00%	42.00%	42.00%	42.00%
Belastingtarief vierde schijf	52.00%	52.00%	52.00%	52.00%	52.00%	52.00%	52.00%	52.00%	52.00%	52.00%	52.00%	52.00%
Belastingtarief eerste schijf 65+ (gecombineerd)	14.45%	14.45%	15.25%	15.50%	16.50%	16.25%	15.75%	15.70%	15.60%	15.55%	15.10%	15.20%
Belastingtarief tweede schijf 65+ (gecombineerd)	19.70%	19.95%	20.75%	22.45%	24.05%	23.55%	23.50%	23.95%	24.10%	24.05%	24.05%	24.05%
Algemene heffingskorting	1,576	1,647	1,766	1,825	1,894	1,990	2,043	2,074	2,007	1,987	1,987	2,033
Algemene heffingskorting voor 65plus	704	736	812	848	910	948	957	970	935	925	910	934
Alleenstaande ouderkorting	1,261	1,301	1,348	1,381	1,401	1,414	1,437	1,459	902	945	931	947
Aanvullende alleenstaande ouderkorting	1,261	1,301	1,348	1,381	1,401	1,414	1,437	1,459	1,484	1,513	1,523	1,319
Kinderkorting 2 kinderen of minder	nvt	468	575	657	802	924	939	nvt	nvt	nvt	nvt	nvt
Kinderkorting extra 3 kinderen of meer	nvt	30	63	64	65	-	-	nvt	nvt	nvt	nvt	nvt
Ouderenkorting	236	289	346	418	454	374	380	486	661	684	739	762
Aanvullende alleenstaande ouderenkorting	248	256	242	248	287	562	571	555	410	418	421	429