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# **A Data-Driven Procedure to Determine the Bunching Window**

*An Application to the  
Netherlands*

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## - An Application to the Netherlands -

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### Abstract

This paper presents empirical evidence on taxpayers' responsiveness to taxation by estimating the compensated elasticity of taxable income with respect to the net-of-tax rate in the Netherlands. Applying the bunching approach introduced by Saez (2010), we find clear evidence of bunching behaviour at the thresholds of the Dutch tax schedule with a precise estimated elasticity of 0.023 at the upper threshold. In line with the literature, we find much larger estimates for women and self-employed individuals. We also identify significant bunching behaviour for individuals in paid employment which we attribute to tax deductions for couples. This paper adds to the literature on bunching by proposing the use of information criteria to determine the counterfactual model, and by the development of an intuitive, data-driven procedure to determine the bunching window.

*JEL Classification:* H21, H24

*Key words:*

Bunching, Elasticity of Taxable Income, Optimal Bunching Window

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# 1 Introduction

A central topic in public economics is the assessment of welfare losses caused by behavioural responses to income taxation. Following the seminal paper by Feldstein (1995), a large literature emerged where welfare losses are inferred from the elasticity of taxable income (ETI).<sup>1</sup> Notwithstanding the large variation in identification strategies and data used in these studies, a common finding is that the elasticities are modest. Recent studies hint at different explanations for these modest estimates, such as optimisation frictions (Bastani and Selin, 2014; Chetty et al., 2011), shifting of income over time (Le Maire and Schjerning, 2013) or shifting across tax bases (Harju and Matikka, 2016). More fundamentally, other papers claim that the structural parameter cannot be retrieved from these estimates, because the ETI depends on the institutional framework, such as the exact definition of taxable income (Slemrod, 1998; Saez et al., 2012; Doerrenberg et al., 2015).

A recent strand of the literature utilises the bunching method to obtain an estimate of the ETI (Saez, 2010; Chetty et al., 2011). This method exploits the clustering behaviour of individuals at kinks in a non-linear tax system<sup>2</sup> to identify the ETI by the number of individuals that adjust their income to stay below the threshold. Using the bunching method is attractive as it is an intuitive and non-parametric method that builds on a sound theoretical foundation and is not susceptible to endogeneity biases, a problem suffered by previous ETI literature (Saez, 2010; Gruber and Saez, 2002; Weber, 2014).

However, the large number of robustness checks in previous studies hints at the uncertainty regarding the optimal choice of the bunching window and the appropriate counterfactual model. The aim of our study is twofold: First, we use the information criteria to determine the appropriate counterfactual model and solve the issue of finding an optimal bunching window by proposing an intuitive, data-driven procedure. Finding the correct, potentially asymmetric bunching window is crucial for the unbiasedness of the ETI as it directly affects the estimation of the counterfactual density in the spirit of Chetty et al. (2011). Second, we estimate the compensated elasticity of taxable income with respect to the net-of-tax rate in the Netherlands using the refined bunching approach. We employ a unique longitudinal data set containing exact declared taxable income and tax deductions for a representative sample of the Dutch population (IPO 2003 to 2013). Information on taxable income and deductions is provided by the Dutch tax authority and, therefore, free of measurement errors – something that is vital to obtain reliable estimates with the bunching method. Since we observe the exact taxable income, we do not need to rely on imputation techniques. The data also contains covari-

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<sup>1</sup>See Saez et al. (2012) for a comprehensive overview.

<sup>2</sup>Kinks appear at thresholds in a tax schedule, where marginal tax rates jump up.

ates, such as age, gender and marital status as well as information on self-employment, which enable us to analyse various sub-samples.

Our main findings are as follows. First, we estimate an ETI with respect to the net-of-tax rate of 0.023 at the highest tax threshold, significant at the one-per-cent level. This result is in line with some of the bunching literature, such as in Chetty et al. (2011) who find an elasticity below 0.02 for their full sample of Denmark, but differs from, for example, Bastani and Selin (2014) who report an elasticity of only 0.004 for Swedish tax payers. Second, a Monte Carlo simulation shows our refinement of the method to be robust under different binwidths, sample sizes, tax rate changes and degrees of optimisation frictions. In our preferred specification the bunching window is left-side asymmetric going from -550 to +350 euros from the threshold and the counterfactual is estimated with a linear model. Third, we find significantly higher compensated ETIs for women and self-employed individuals. However, contrary to most other studies, we are able to identify a non-zero elasticity for individuals in paid employment. Fourth, by analysing the anatomy of response, we find that most employees reduce their taxable income by utilising mortgage interest deductions. Further exploration reveals that this effect is driven by married couples that have the possibility to shift these deductions between them.

This study's contribution to the literature is threefold. First, we improve on the bunching method by using information criteria to select the best counterfactual model. Our case-by-case selection of the order of polynomials for the counterfactual distribution improves the efficiency of the bunching estimator relative to the common practice. Second and more importantly, we propose a simple, data-driven procedure to determine the bunching window, instead of the visual inspection used in the literature. As a consequence, our method allows the bunching window to be asymmetric around the threshold and to be more flexible. Third, we are the first to estimate the ETI for the Netherlands by employing the bunching method. We carefully analyse the anatomy of responses, which show that bunching for wage earners is concentrated among couples with mortgage interest deduction. This finding supports the claim that the ETI is not a structural parameter.

The paper proceeds with Section 2, which introduces the bunching methodology as well as our improvements. Subsequently, the institutional setting and the data are presented in Sections 3 and 4, respectively. Section 5 presents our estimation results. Section 6 provides the conclusions.

## 2 Methodology

There are three potential ways in which people respond to taxation. The first is a real response. As suggested by standard microeconomic theory, the distortion of prices and wages in the economy due to taxation induces individuals to adjust their working hours and effort as well as their educational or training decisions. The second response is that of legal tax avoidance, such as using deductions or moving income to other time periods to reduce the taxable income in the current period. The third type of response is that of tax evasion. This is relevant for income earned from self-employment or from businesses that lack third-party reporting. As will become apparent in our empirical analysis, Dutch workers predominantly use a legal opportunity to shift income between partners.

### 2.1 Bunching

To test the prediction from microeconomic theory and to quantify the responses, we follow the literature and identify the compensated ETI in the spirit of Feldstein (1995). This central parameter is defined as the percentage change in taxable income  $z$  due to an increase in the net-of-tax rate  $(1 - \tau)$  of one percent:

$$e(z) = \frac{dz}{z} \bigg/ \frac{d(1 - \tau)}{(1 - \tau)}. \quad (1)$$

Theoretically, the introduction of a kink in the budget set of individuals induces bunching behaviour within a certain income range provided that preferences are convex and smoothly distributed among the population. This will lead to a spike in the density exactly at the kink, but due to adjustment costs and optimisation frictions, a bunching window around the kink is observed more often in reality (Chetty et al., 2011). Comparing the income density with a counterfactual scenario without a kink, the excess mass of taxpayers can be used to determine the elasticity  $e(z)$ . A detailed derivation of the bunching estimator can be found in Saez (2010) and Chetty et al. (2011). The compensated ETI, identified locally at the threshold  $k$ , is then given by

$$e(k) = \frac{b}{k \cdot \log\left(\frac{1-\tau_1}{1-\tau_2}\right)}, \quad (2)$$

where the net-of-tax rate changes by  $\log\left(\frac{1-\tau_1}{1-\tau_2}\right)$  per-cent.<sup>3</sup> The relative excess mass of taxpayers at the threshold  $k$  is given by  $b$ , which is the only parameter that needs to be estimated. To estimate  $b$ , Chetty et al. (2011) propose to determine the counterfactual

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<sup>3</sup>It is identified if and only if the derivative of the counterfactual density function  $h_0(z)$  with respect to  $z$  is continuous in  $z \forall z$ .

density by running a local polynomial regression on binned data, while excluding data bins within the bunching window.

A major drawback of the bunching method is that it is sensitive to the choice of bunching window (Adam et al., 2015). A commonly used approach is that of selecting the window by visual inspection, which makes it vulnerable as it is selected at the researcher’s discretion. Furthermore, recently published papers select the counterfactual by trial-and-error and the model seems to be chosen ad libitum. Neither visual inspection, nor this selection of the counterfactual model are optimal for efficiency and reliability.

## 2.2 Extension

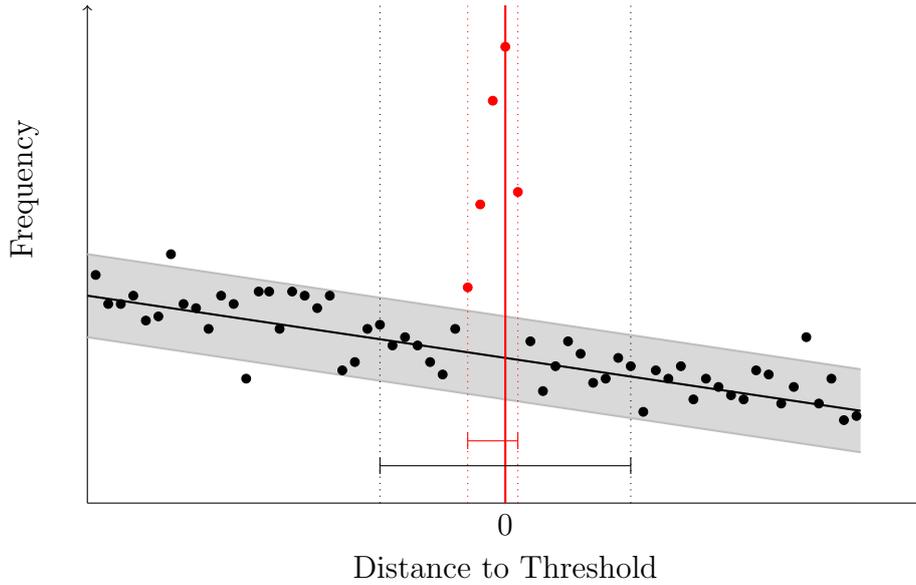
Motivated by the drawbacks of the usual implementation of the bunching approach, we extend the estimation procedure in two ways. First, we exploit information criteria to select which model would be best suited as counterfactual in each specification, thus making the choice of the counterfactual endogenous. Because of the large sample size, we prefer Schwarz’s Bayesian Information Criterion (BIC), which has a better punishing mechanism for high  $N$ .

Second, to determine the bunching window, we rely on the data at hand rather than on visual inspection. Removing the researcher’s discretion in this matter is preferable in its own right, but we also argue that our method produces more efficient estimates of the elasticity. The optimal situation would be for the bunching window to comprise all the individuals who would adjust their taxable income as a response to the tax change at the threshold. The bunching window should not be too small, for fear of omitting some taxpayers that attempt to bunch at the kink, nor should it be too large, which would bias the results by also including non-bunchers. The existing literature implements symmetric bunching windows around the kink with varying sizes that are determined by graphical inspection. We propose the use of a possibly asymmetric bunching window with an endogenously determined size.<sup>4</sup> The argument in favour of an asymmetric bunching window is that risk-averse individuals are expected to be more likely to over-adjust their income to make sure they realise an income which is below the threshold. This psychological component will lead to an asymmetric bunching window, with more mass to the left of the threshold. See Figure 1 for a graphical intuition. The binpoints around the threshold that have a higher actual number of taxpayers than predicted (coloured in red in Figure 1) are then used to determine the bunching window. In order to determine the optimal bunching window, we propose the following step-wise procedure:

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<sup>4</sup>Using an optimal window renders robustness checks with different bunching windows obsolete. To show the gain in efficiency, Table A.2 of the Appendix shows a comparison with two different model specifications.

Figure 1: Data-driven procedure to determine the bunching window



Notes: This figure shows the bin midpoints as well as the fitted values of a linear regression. The grey confidence band is calculated with the standard errors of the point prediction. Here, five subsequent bin midpoints around the threshold lie outside and therefore determine the relevant (asymmetric) bunching window.

1. Set an excluded region around the threshold.
2. Run a local regression through all data bins outside the excluded region and predict the frequencies.
3. Compute a confidence interval around the prediction.
4. Subsequent bin midpoints outside the confidence interval comprise the bunching window.

In general, the excluded region can be set arbitrarily; however, we propose to iterate through different combinations of upper and lower bounds of the excluded region. This hedges against concerns that the chosen excluded region could affect the determination of the bunching window.<sup>5</sup> The choice of the appropriate confidence interval is also at the researcher's discretion, with higher confidence levels tending to lead to a smaller bunching window. In other words, the probability that we erroneously include non-bunchers decreases. Depending on the setting and the data, this will lead to more conservative estimates of the elasticity.

The bunching window is formally derived as follows: Let  $x_- \in \{-X, (-X + 1), \dots, 0\}$  and  $x_+ \in \{0, 1, \dots, X\}$  be the respective lower and upper bound of the excluded region.

<sup>5</sup>Our results indicate virtually no sensitivity of the bunching window to the size of the excluded region.

Furthermore, define  $l(x_-, x_+)$  as the lower bound of the bunching window and  $u(x_-, x_+)$  as the upper bound, given the excluded region from  $[x_-, x_+]$ . For every tuple  $(x_-, x_+)$ , run a local regression of polynomial order  $q$ :

$$\tilde{N}_j^{BW} = \sum_{i=0}^q \beta_i Z_j^i + \varepsilon_j \quad \forall j \notin [x_-, x_+]. \quad (3)$$

Then predict the counterfactual values  $\hat{N}_j^{BW}$  and the standard error of the point prediction:

$$\hat{N}_j^{BW} = \hat{\beta} Z_j \quad \forall j \quad (4)$$

$$\hat{S}E_{fcst} = \sqrt{\left(\frac{1}{n-1} \sum_{j=1}^n \hat{\varepsilon}_j^2\right) \left(1 + \frac{1}{n}\right)}. \quad (5)$$

To allow for noise in the data, calculate the upper value of the confidence interval  $CI_j^+$  for a given  $t$ -value using standard procedures. To determine the excess mass, subtract the  $CI_j^+$  from the observed number of taxpayers in income bin  $j$ :

$$E_j = N_j - CI_j^+. \quad (6)$$

If all  $E_j$  are negative, no bunching is present in the sample. Otherwise, the lower bound of the bunching window is given by:

$$l(x_-, x_+) = j_l^* + 1, \quad \text{where } j_l^* = \max\{j \in \mathbb{Z}_- : E_j < 0\} \quad (7)$$

which is the smallest subsequent income bin  $j$  that still satisfies the condition  $E_j > 0$ . Similarly, the upper bound is given by:

$$u(x_-, x_+) = j_u^* - 1, \quad \text{where } j_u^* = \min\{j \in \mathbb{Z}_+ : E_j < 0\} \quad (8)$$

which is the largest subsequent income bin  $j$  that still satisfies the condition  $E_j > 0$ .

By following this procedure, several values are obtained for the lower and upper bounds of the bunching window that come from the various excluded regions. Several possibilities arise for which values of  $l(x_-, x_+)$  and  $u(x_-, x_+)$  to use as the limits of the bunching window, but we advocate using the mode of all estimated values. This ensures that, in most cases, the exact bounds of the bunching window will be obtained.<sup>6</sup> To estimate the ETI from Equation (2), the excess mass  $b$  is the only parameter that needs to be estimated, as the other parameters are known policy parameters.  $b$  is estimated in the

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<sup>6</sup>Other possibilities would be to use the minimum, maximum or mean, although we do not find large variations among these choices.

following way:

$$\hat{b} = \frac{\hat{B}}{\frac{\sum_i^u \hat{N}_j}{(u-l+1)}}, \quad (9)$$

where the estimate of  $\hat{B}$ , which is the number of individuals that bunch, satisfies the integration constraint and  $\hat{N}_j$  represents the counterfactual number of individuals within an income bin  $j$  that are determined by local polynomial regression of the form:

$$\hat{N}_j = \sum_{i=0}^q \beta_i \cdot Z^i + \sum_{i=l}^u \gamma_i \cdot I[Z_j = i] + \varepsilon_j. \quad (10)$$

## 2.3 Evaluation

We assess the validity of our endogenously determined bunching window by Monte Carlo simulations, and evaluate the performance for two predictions: how well the approach can recover the true elasticities and how well it can identify the bunching individuals. Moreover, we test the robustness of our approach by varying the key parameters of the model. We especially examine the variations in binwidth, amount of frictions, sample size and size of the tax rate change at the threshold.

The baseline specification has  $N = 1,000,000$  observations, a threshold  $k$  at  $z = 50,000$ , a binwidth of 100, and a tax change of 10 percentage points<sup>7</sup>. We run estimations for three true elasticities:  $e = 0.02$ ,  $e = 0.1$  and  $e = 0.5$ . As the bunching literature tends to find small elasticities, the paper only reports the detailed results for  $e = 0.02$ .

A comparison of the income distribution in case of a kink with a counterfactual scenario without a kink can be used to determine the elasticity (see Section 2.1). To abstract from any uncertainty regarding the counterfactual model, potential incomes  $z_0$  are drawn randomly from a triangular distribution.<sup>8</sup> They are used to calculate pre- and post-reform taxable incomes  $z_1$  and  $z_2$  respectively, where  $z_1 = z_2$  for all individuals who would be at or below the kink, as they would not be affected by the new tax system.<sup>9</sup> We identify all individuals as bunchers that have their highest post-reform utility at income level  $k$ , provided they had  $z_1 > k$ . To model optimisation frictions, we introduce a random component in the income of the bunching individuals, described by  $\varepsilon \sim N(0, 142.3)$  in our baseline specification.<sup>10</sup>

<sup>7</sup>More specifically, the change is from 42% to 52%, resembling the change at the top tax threshold in the Netherlands.

<sup>8</sup>Because we draw from a triangular distribution, we know that the counterfactual model is best approximated by a linear model

<sup>9</sup>The choices of  $z_1$  and  $z_2$  come from maximising a quasi-linear utility function. The approach is similar to the approach taken in the working paper version of Bastani and Selin (2014).

<sup>10</sup>The variance component comes from the working paper version of Bastani and Selin (2014) and is adjusted for Euro values. It is altered in a later specification.

Table 1: Monte-Carlo simulations of elasticity

	Bias ( $e = 0.02$ )		Ratio	
	Mean	Std. Dev.	Mean	Std. Dev.
Baseline	-0.0001	0.0003	0.9892	0.0038
<i>Binwidth</i>				
200	0	0.0004	0.9905	0.1085
400	0.0003	0.0004	0.99998	0.00003
<i>Variance (<math>t=1.96</math>)</i>				
100	0.0014	0.0006	0.9876	0.0017
300	-0.0067	0.0005	0.5956	0.0069
<i>Variance (<math>t=1</math>)</i>				
100	0	0.0007	0.9917	0.0043
300	-0.0005	0.0011	0.9622	0.0189
<i>Observations</i>				
550,000	-0.0006	0.0011	0.9606	0.0233
2,050,000	-0.0002	0.0005	0.9867	0.0066
<i>Tax Change</i>				
42% – 48%	-0.0008	0.0013	0.9466	0.0231
42% – 60%	-0.0002	0.0004	0.9887	0.0039

Notes: This table shows the results from the Monte Carlo simulations running 600 repetitions. The baseline consists of binwidth 100, variance 142.3, observations 1,000,000 and tax change 42%-52%. All specifications use a t-value of 1.96, except the third, which uses t-value of 1. Note that a bias of zero indicates that the bias is less than 1/10000.

Table 1 shows the results of our Monte Carlo simulations. The columns present the difference between the true and simulated elasticity as well as the ratio of identified bunchers to actual bunchers, which resembles an estimation error. Each row represents a different specification. In the baseline setting, the estimated elasticities have a mean very close to the true elasticity of  $e = 0.02$ . At the same time, we are able to identify 98.92% of the bunchers using our data-driven procedure. To assess the robustness of our approach we change the size of key parameters.

Throughout the bunching literature, various binwidths are implemented. Many studies alter the binwidth in robustness checks and show limited sensitivity to changes in the binwidth (Chetty et al., 2011; Bastani and Selin, 2014). The results in Table 1 show no significant changes regarding the estimated elasticities. A greater binwidth naturally would improve the identification of the number of bunchers by up to almost 100 %, but the number of individuals wrongly assumed as bunching would also rise with an increased binwidth (bias-efficiency trade off).

Next to the binwidth, the variance that represents optimisation frictions could affect the performance of our data-driven procedure. Indeed, increasing the variance term in the randomised component has a severely negative effect on the performance of the bunching estimator. We estimate an elasticity of  $e = 0.013$  which is far off the true elasticity and are only able to identify 59.65% of the bunching taxpayers. A potential driver behind this could be the choice of confidence interval. A high confidence interval should provide a narrow bunching window. But because the optimisation frictions are so high, we would expect a much wider range of the bunching window as well as a flatter area of excess mass around the kink point. Therefore, for the third specification, we use a t-value of 1 instead of 1.96. The results improve significantly, and our procedure is able to identify 96.22% of all bunching individuals when the variance term is 300. In light of this, researchers should take the anticipated amount of optimisation frictions into account when setting the t-value for the confidence interval. For example, a more complex or dynamic tax system should lead to more optimisation frictions.

Because of its non-parametric nature, the bunching estimator relies on a large sample size. We test the impact of different sample sizes on the efficiency of our estimation procedure. Unsurprisingly, we find that an increased sample size increases efficiency, although the gains asymptotically decrease to zero.

The size of the tax change matters for overcoming optimisation frictions which cause the observed elasticity to differ from the structural elasticity (Chetty, 2012). As larger tax rate changes have more severe consequences for individuals, we should observe more precise bunching with greater tax rate differences, as the costs of adjusting taxable income are increasingly outweighed by the benefits (Chetty et al., 2011). The true elasticity can be identified more precisely by increasing the size of the difference between the two

marginal tax rates, which confirms the results by Bastani and Selin (2014) and Chetty (2012) that larger jumps in the marginal tax rate are more informative of the true ETI.

### 3 Institutional Background

The Dutch tax system is almost fully individualised and tax liabilities mainly depend on individual worldwide income. There are a few exceptions, two of which are relevant for our analysis. The first exception is that of means-tested subsidies, such as on health tax, child care and rent, which are all based on taxable household income. The second is that personal tax-favoured expenditures are transferable between partners, thus reducing taxable income. This last possibility is attractive under a progressive tax schedule such as that of the Dutch tax on labour income.<sup>11</sup>

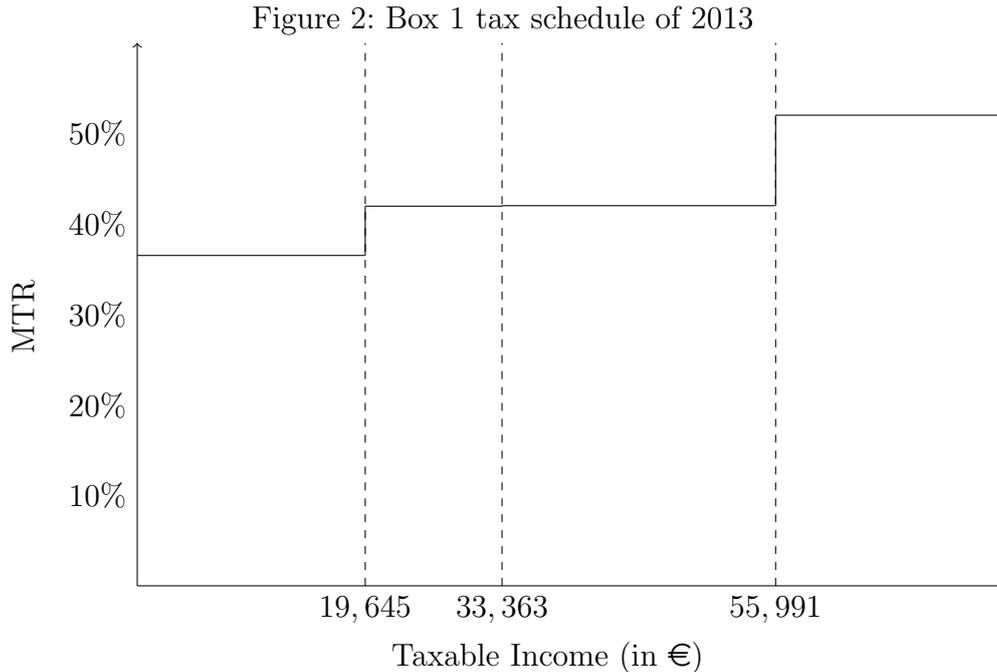
Since 2001, income from different sources is treated in three different “boxes”, each with their own taxable income concept and tax schedule. In Box 1, income from profits, employment and home ownership is taxed. This includes wages, pensions and social transfers. Box 2 consists of income from substantial shareholding such as dividends and capital gains. Any other income from savings and investments is taxed in Box 3. Income in Box 1 is taxed at progressive rates that jump up at certain thresholds and thus create kinks in the tax schedule, whereas income in Box 2 and Box 3 is subject to a flat tax, that, in 2013, was 25% and 30% respectively.<sup>12</sup> For our analysis, we use the kinks in the Box 1 tax schedule for identification. It is furthermore worth noting that income losses in one box cannot be used to counterbalance taxable income in one of the others.

Income in Box 1, minus personal deductions, is taxed at progressive tax rates. Figure 2 provides an overview of the Dutch tax schedule of 2013. The marginal tax rate is represented by the solid line. It jumps up at each threshold, thus creating a kink in the budget set. The tax schedule of Box 1 consists of four tax brackets with increasing marginal tax rates. Figure A.2 in the Appendix shows the development in marginal tax rates over time. The two lower tax rates also include a general social security contribution of around 31% for old-age pensions and exceptional medical expenses. There is an increase in the marginal tax rate of 8 percentage-points at the first threshold. The social security contribution in the third tax bracket is compensated by a similar rise in

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<sup>11</sup>From a labour supply perspective, a third exception is also relevant. A non-working spouse can transfer the lump-sum tax credit to his or her partner. The moment this spouse starts working, their income will be taxed starting at the marginal tax rate. This, however, is not the the focus of our study.

<sup>12</sup>We are aware of the possibility of moving income between the boxes, which could be especially pronounced for self-employed individuals. For information on the importance of shifting between tax bases see Harju and Matikka (2016). Because of data limitations, we are unable to extend our analysis in that way.



Notes: The figure shows marginal tax rates for the year 2013. At each threshold, denoted by the dashed lines, the marginal tax rate jumps up.

tax rate, implying that marginal tax rates in the second and third brackets are similar. However, there is a large jump in the marginal tax rate, from 42% to 52%, in the last bracket. For the considered time period, the income thresholds were adjusted upwards to account for inflation and to avoid the phenomenon of “cold progression”.

One important channel of changing taxable income is legal tax avoidance by using deductions, such as pension contributions (Chetty et al., 2011). Other deduction possibilities are alimonies paid, charitable givings, health expenditures or mortgage interest deductions.<sup>13</sup> In the Netherlands, the mortgage interest deduction is quite high and common among house-owners. More importantly, all of these deductions can be shifted between partners. An overview of the computation of taxable income is given in Table 2.

Important for any analysis looking on bunching is the exact tax payment procedure. It should be emphasised that for people in paid employment, their employer withholds income tax from the income taxed under Box 1, which can be seen as a prepayment credited against the final tax amount payable at the end of the year. This “third-party reporting” is important for the interpretation of the results as it makes systematic tax evasion – one way of adjusting taxable income – more difficult (Kleven et al., 2011).

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<sup>13</sup>These are (at least in parts) common in other countries like Great Britain or Germany.

Table 2: Box 1 taxable income

<b>Gross wage</b>
– Pension fund and unemployment insurance contributions employee + Health insurance contribution employer
<b>= Taxable Labour Income</b>
+ Income from housing + Freelance earnings – Alimony/maintenance paid – Charity donations – Mortgage interest deductions – Health expenses deduction – Other personal deductables
<b>= Taxable Income Box 1</b>

Notes: This table shows the computation of Box 1 taxable income. Gross wage includes pension benefits and received social transfers.

Final income taxes are determined after the end of the fiscal year, when tax deductions and income from other sources are all taken into account.<sup>14</sup> An important distinction is single filing or joint filing of tax returns. Even though the Dutch tax system is rather individualised, married couples file their returns jointly. In addition, cohabiting couples are also allowed to jointly file their tax return. Taxes can be filed digitally (computer-assisted) or on paper. The share of digital filers has increased dramatically from about 30 percent in 2003 to almost 95 percent in 2015. Digital filing of tax returns is not only helpful when deducting certain personal expenditures, but also facilitates the optimal shifting of income. The exact threshold becomes more salient and enables people to locate at the threshold.

In sum, the Dutch tax system can induce bunching behaviour because of a combination of three things: 1) partners can move deductions between them and this is most attractive in the highest income tax bracket; 2) mortgage interest deductions are quite large; 3) the filing of tax returns digitally clearly reveals tax thresholds as well as the related benefits of shifting certain deductions. As is shown below, these specific features of the Dutch tax system result in sharp bunching at the third threshold.

<sup>14</sup>The tax thresholds in the Netherlands are known before the start of each fiscal year, as these are published together with the governmental budget which is presented each year, on the third Tuesday of September (Prinsjesdag).

## 4 Data

The data used in this study is the Income Panel Data (IPO) provided by Statistics Netherlands. This longitudinal data set covers the period from 2001 to 2013. It contains administrative data on all possible sources of income, on an individual level, as well as a very detailed account of possible deductions from the tax base. The panel is updated with new information on marital status and include other, randomly selected individuals, in every period to account for people who are no longer observable. Most importantly for this study, Statistics Netherlands provides the information on relevant taxable income for Box 1 (see Table 2). The taxable income variable is obtained from the tax department, representing the exact taxable income per individual. This circumvents the problem of measurement error, which is vital for analyses that use the bunching method. As our income measure includes all tax deductions, we do not have to rely on tax simulators that are used in other studies (Gruber and Saez, 2002; Chetty et al., 2011) to determine the tax liabilities, thus mitigating bias that could stem from this exercise.

In addition to the information on taxable income and deductions, the dataset also includes demographic characteristics, which we exploit to study heterogeneity in the bunching behaviour of different socio-economic groups. The information we use include self-employed individuals, who theoretically would be more prone to bunching because of the lower costs and greater possibilities of adjusting their taxable income. Furthermore, we distinguish people according to gender and marital status. Our estimation sample is restricted as follows. We exclude students as well as all people receiving governmental benefit payments, as most of them receive similar amounts, thus creating an artificial mass point. Because the tax is different for individuals aged 65 and over, we also exclude them from our estimation, as well as those below the age of 18. We omit the years 2001 and 2002 to avoid the inclusion of any after effects of the 2001 major Dutch tax reform.<sup>15</sup> Furthermore, we only retain individuals with a positive reported taxable income. The pooled sample consists of  $N = 1,219,572$  individuals, which is roughly 1% of the Dutch population per year. The sample is evenly balanced with respect to gender (55% male) and married individuals (65%). Furthermore, the sample include 14% self-employed individuals. This includes CEO's, who would be in a position to decide on their own salary and are be able to adjust it.

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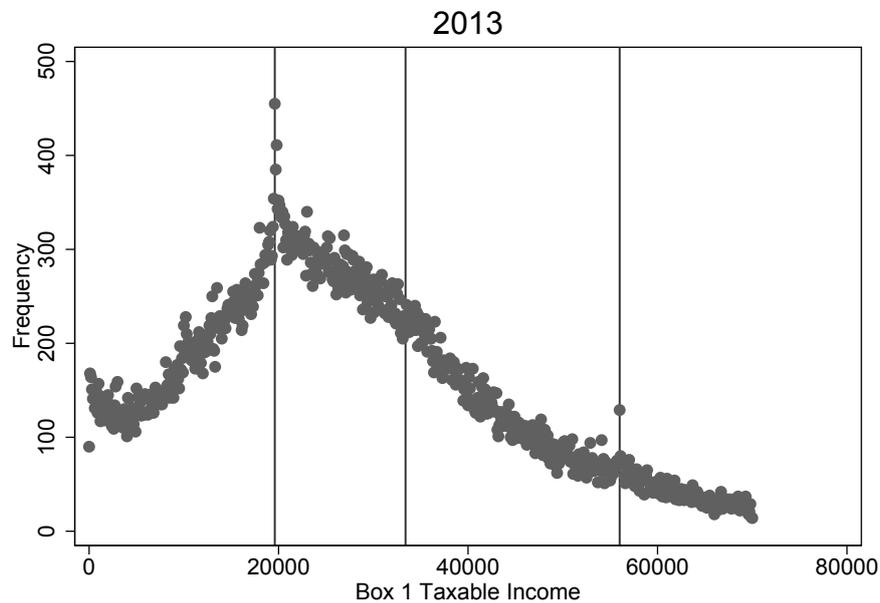
<sup>15</sup>The tax reform substantially changed the thresholds and marginal tax rates and introduced the system of income boxes.

## 5 Results

### 5.1 Bunching Evidence

Figure 3 gives a first hint of bunching behaviour. It displays the income distribution for the most recent year of our sample. The income thresholds of 2013 are indicated by vertical lines. Clear bunching behaviour can be seen at the first and third threshold. Note that the change in the marginal tax rate at the second threshold is merely 1.08% and so the incentive for adjusting taxable income is small. For this figure and the rest of the analysis the data is collapsed into income bins of 100 euros.<sup>16</sup>

Figure 3: Income distribution in 2013



Notes: This figure shows the sample distribution of income below 70,000 € in the Netherlands for 2013. The data is collapsed into 100-euro bins. The vertical lines represent the first, second and third threshold of the Dutch tax system respectively.

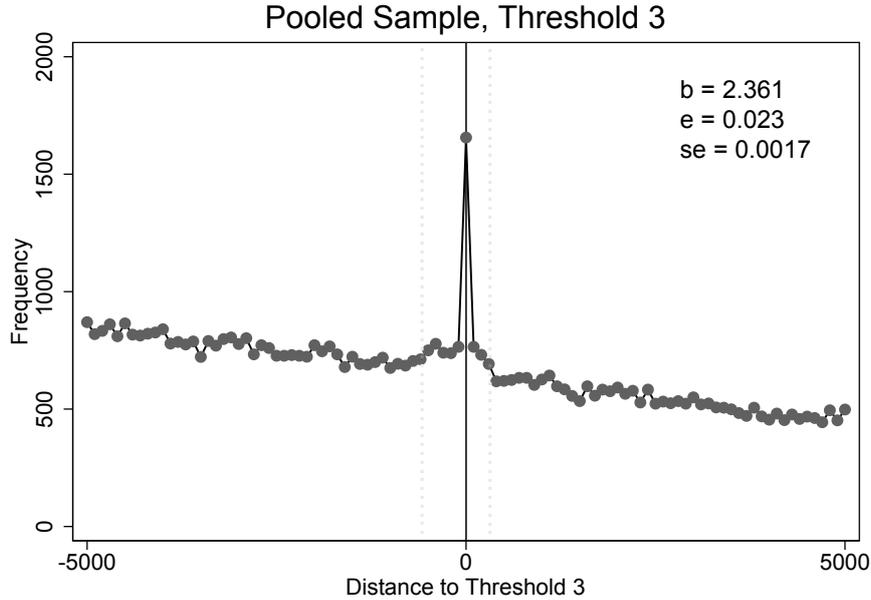
#### *Upper Threshold*

The change in the tax rate is largest at the upper threshold with 10 percentage-points (23.81%), which implies that bunching behaviour should be more pronounced here. Figure 4 reports the results for our pooled sample from 2003 to 2013 showing the number of observations per bin, relative to the threshold value. For pooled years, our method to

<sup>16</sup>Our results are not driven by the selection of this binwidth. At higher binwidths (200 and 400), the bunching window would be smaller and similar estimates of the elasticity are obtained, although the value of  $b$  slightly varies with binwidth.

endogenously determine the bunching window provides an asymmetric bunching window ranging from -550 to +350 euros. We implement a 95% confidence interval for determining the bunching window throughout this study.<sup>17</sup> The BIC criterion suggests a linear counterfactual model, which follows from the location of the kink point at the right tail of the income distribution. In order to calculate an elasticity, a weighted average threshold value is used. The weights are constructed by the number of taxpayers exactly at the threshold in each year, i.e. in income bin 0. Standard errors are calculated with a parametric residual bootstrap procedure.

Figure 4: Bunching at the third threshold - pooled sample



Notes: In this figure, bin counts are plotted relative to the threshold for the pooled sample from 2003 to 2013. Data is collapsed into 100-euro bins. The bunching window is between -550 and +350 euros and the counterfactual model is linear.

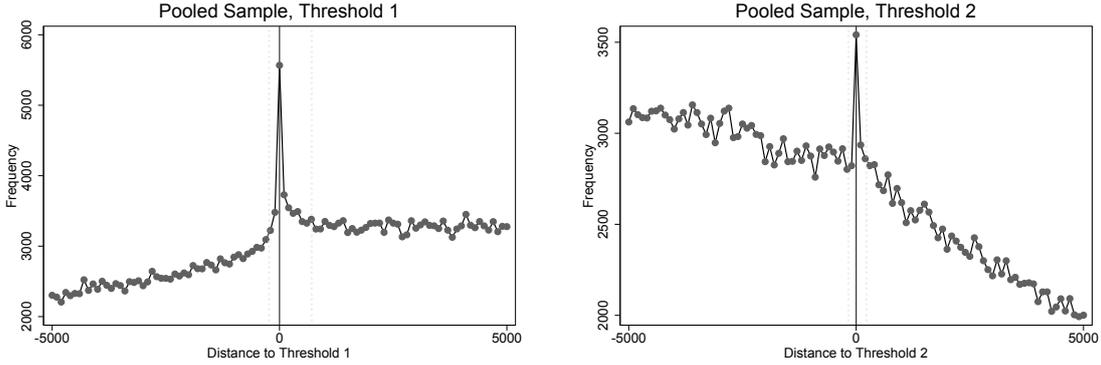
We observe sharp bunching at the threshold and estimate an excess mass of  $b = 2.36$ , which corresponds to 2.36 times more individuals being at the threshold than would have been the case in the absence of any tax change. This excess mass implies an ETI with respect to the net-of-tax rate of 0.023, which is statistically significant at all usual significance levels. Quantitatively, a 10% decrease in the net-of-tax rate would induce a 0.23% reduction in taxable income.

### *Other Thresholds*

<sup>17</sup>We also tested a smaller confidence level, i.e. a one-standard deviation increase, which corresponds to a 68% confidence interval. The results are slightly larger but less precisely estimated.

A case could be made for bunching at the other thresholds of the Dutch tax system as well. At the second threshold, the change in the tax rate is very small, especially in the more recent years, as shown in Figure 2 and Figure A.2. At the first threshold, the income levels are quite low, which suggests that individuals are more dependent on their income and should therefore show little real responses to a change in the marginal tax rate.<sup>18</sup>

Figure 5: Bunching at the first and second threshold - pooled sample



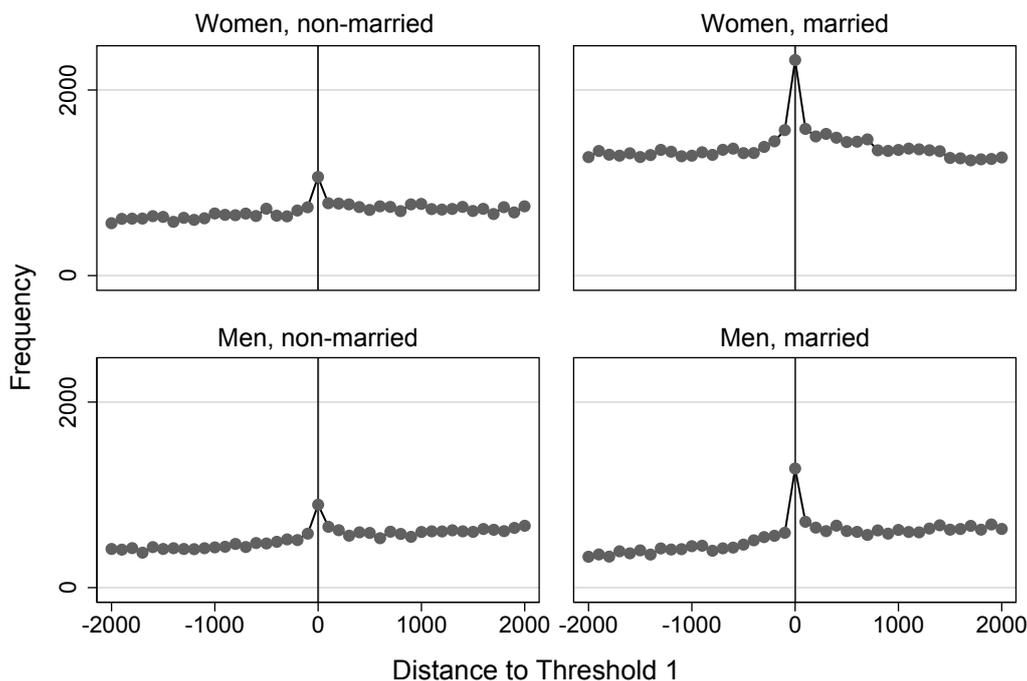
Notes: The figures show bunching at the first and second thresholds for the pooled sample from 2003 to 2013. Because of the varying tax changes at these thresholds, no excess mass is reported.

Figure 5 shows the graphs for the pooled sample. Surprisingly, we observe bunching behaviour of individuals at both thresholds. Exact estimates cannot be depicted for the excess mass or elasticities at these thresholds, because we have changing tax differences over time, in addition to the changing threshold values. Taking the average of the single-year estimates delivers an excess mass of 1.55 at the first threshold and 0.47 at the second threshold.<sup>19</sup> Especially at the first threshold, the estimated average excess mass is comparable to the single-year average excess mass at the third threshold, which translates into a significantly higher elasticity ( $e = 0.073$ ) given the smaller tax change at the first threshold. A possible explanation for this could be that the income of many second or part-time earners would be around this level. Given that these individuals would not be too dependent on this income, they would be less constrained than initially assumed. To confirm this, we estimate the ETI at the first threshold for married individuals. The elasticity is estimated at  $e = 0.075$  using a 7th order polynomial counterfactual and a bunching window from  $-250$  to  $+750$  euros, as well as average marginal tax rates. The

<sup>18</sup>Note that only the income share above the threshold is taxed at the higher tax rate and therefore, a higher pre-tax income will lead to a higher disposable income.

<sup>19</sup>The tax rate change at the second threshold is very small, therefore, as shown in the Monte Carlo simulations, the bunching estimator is not able to adequately retrieve the true compensated elasticity.

Figure 6: Bunching by gender and marital status



Notes: The figures show bunching at the first threshold by gender and marital status.

elasticity at the first threshold is more than three times that of married individuals at the third threshold ( $e = 0.021$ ). This is clear evidence in favour of the second-earner hypothesis. The effect is especially pronounced for married women, which is shown in Figure 6.

The graph further illustrates two other matters. First of all, there are less single than married individuals at the first threshold. The distribution between women and men (top- and bottom-left figures) is relatively equal for unmarried taxpayers (both singles and cohabiting couples). For the married individuals, however, a significantly greater share of women bunches at the first threshold. This indicates that, often, second earners are women. This is in line with earlier findings by Chetty et al. (2011), who also find significantly higher bunching for married women.

## 5.2 Sensitivity Analysis

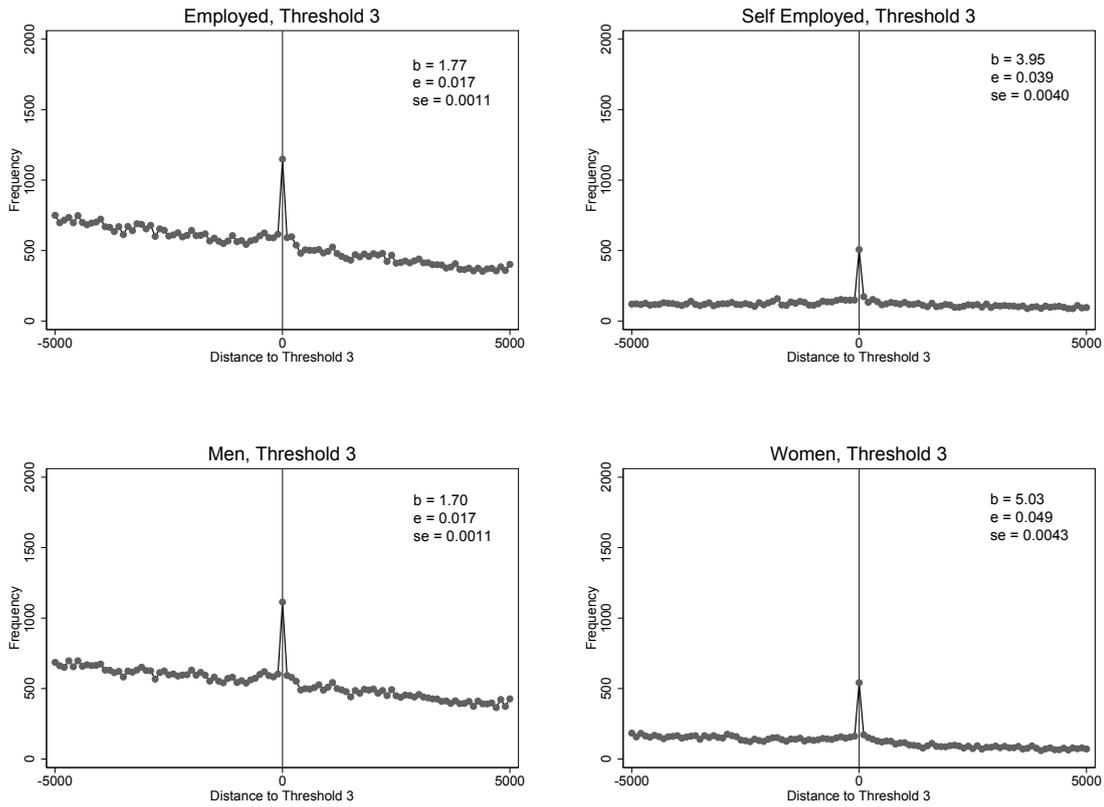
A possible concern that could arise is that, when pooling the data, we observe many individuals more than once. If, for example, a contract is signed for several years,

meaning that the salary would move along with the threshold, we would attribute bunching behaviour to this individual in every period, although the behavioural decision was made only once. This could lead to an overestimation of the excess mass. To hedge against this possibility, we randomly kept one observation per individual and reestimated the excess mass in the pooled sample. The excess mass then drops slightly to 2.02 ( $e = 0.020$ ), but this could also be driven by the smaller sample size.

To analyse if our results are driven by sub-groups, we split the sample according to employment status and gender. Self-employed individuals have better possibilities to adjust their taxable income and are therefore more prone to bunching. In addition, women, who are often second earners, are also more sensitive to changes in taxation. The results, shown in Figure 7, confirm the hypotheses, as the excess mass for the self-employed increases significantly to 3.95 ( $e = 0.039$ ), compared to the baseline analysis of the pooled sample. In contrast to findings in many other studies, we also find a significant excess mass for wage earners of 1.77 ( $e = 0.017$ ); therefore the baseline result is not purely driven by self-employed individuals. The observed bunching for wage earners might be an indication of collusion between employers and employees and of contracts being specifically designed to achieve a taxable income at the threshold. Another explanation could be that of trade unions jointly setting wage levels for groups of individuals. The argument here is that collective knowledge in the trade union would cause individual optimisation errors to be less pronounced and, therefore, lead to more (precise) bunching. An alternative explanation is that of wage earners utilising tax deductions. The bottom two graphs in Figure 7 are clear evidence in favour of the gender difference hypothesis, as the excess mass of women at the third threshold is 5.03 ( $e = 0.049$ ), while the excess mass for men is only 1.70 ( $e = 0.017$ ). For self-employed women, the excess mass rises to 7.17 (not depicted), which is still significant, but due to the very small sample size, this result should be viewed with caution.

Finally, we estimate the excess mass for taxpayers and the ETI at the third threshold for all years separately. This eases any concerns about using a weighted average threshold in the pooled sample to obtain the elasticity estimate. The results are provided in the Appendix (Figure A.1 and Table A.1). One striking observation is that of the bunching behaviour of individuals is increasing and becoming more precise over time. We ascribe this to learning effects, as taxpayers become more familiar with the tax system. For the year 2002 we still observe delayed effects from the major tax reform of 2001 and, therefore, the bunching behaviour is fuzzy and small. It then increases in the subsequent years until the excess mass reaches a level of around 2, corresponding to an elasticity of 0.02. Another explanation could be the emergence of digital filing tax returns, which made the threshold more salient to the general public.

Figure 7: Bunching at the Third Threshold - Subsamples



Notes: The figures show bunching at the third threshold from 2003 to 2013 for different sub-samples. The bunching window for the sample of wage earners is between -550 and +250 euros and the counterfactual model is linear. The bunching window for the sample of the self-employed is between -550 and +150 euros and the counterfactual is a second-order polynomial model. The bunching window for the male sample is between -550 and +250 euros and the counterfactual model is linear. The bunching window for the female sample is between -550 and +350 euros and the counterfactual model is linear.

### 5.3 Anatomy of Response

The channels through which individuals bunch at the thresholds in a tax system are manifold. In order to reduce taxable income, individuals could work fewer hours, which, from an efficiency point of view, would be an undesirable effect of the threshold. Furthermore, tax liabilities could be reduced by shifting income either over time or between marital partners (under a joint taxation component) or by (itemised) tax deductions. A recent study by Doerrenberg et al. (2015) shows the importance of tax deductions for welfare analyses with the ETI. As pointed out by Slemrod (1996), one way to reveal the channel that drives bunching is to look at the “anatomy of the behavioural response” (Saez et al., 2012). We analyse the anatomy of response of wage earners for 2011 for which year we have additional information on the shifting behaviour. Of all wage-earners in the vicinity of the third threshold, almost 88% claim mortgage interest deductions. A smaller part are partly self-employed and a few claim other expenditures such as for health expenditures or charity donations. We are unable to identify the source of bunching for about 5%. This could be driven by a real response, such as a reduction in working hours.<sup>20</sup>

It is interesting to examine the mortgage interest deduction, which can only be claimed for one, usually the main mortgage. Mortgage interest deductions are by far the biggest deduction claimed in the Netherlands with a total of 9.9 billion € in 2015, as reported by the Ministry of Finance.<sup>21</sup> Because of the progressive tax system, shifting the full deduction to the highest earning partner will reduce tax liabilities the most. However, the actual incentive depends on the distance of taxable income to the threshold. In cases where the highest earning partner claims the deduction to reduce his taxable income but, in doing so, will cross the threshold, he has two options once his income level reaches that threshold. He can then either deduct the rest of the amount at a lower marginal tax rate, or he can shift the remaining deduction to his partner. If his partner’s income is below the second threshold, he should not transfer part of the deduction to his partner. If his partner earns more than the second but less than the third threshold, then it makes no difference whether part of the deduction is shifted or not. If, however, his partner earns more than the third threshold, part of the tax deduction should be shifted. This last case will result in sharp bunching at the third threshold.<sup>22</sup>

The sharp shifting is clearly visible in Figure 8. The graphs show the share of mortgage interest deduction within couples. For high-earners, the average share is 75-80 % of total mortgage interest deduction of the couple. The higher the income, the higher the share of the mortgage interest deduction claimed by the high-earning partner. This is in line

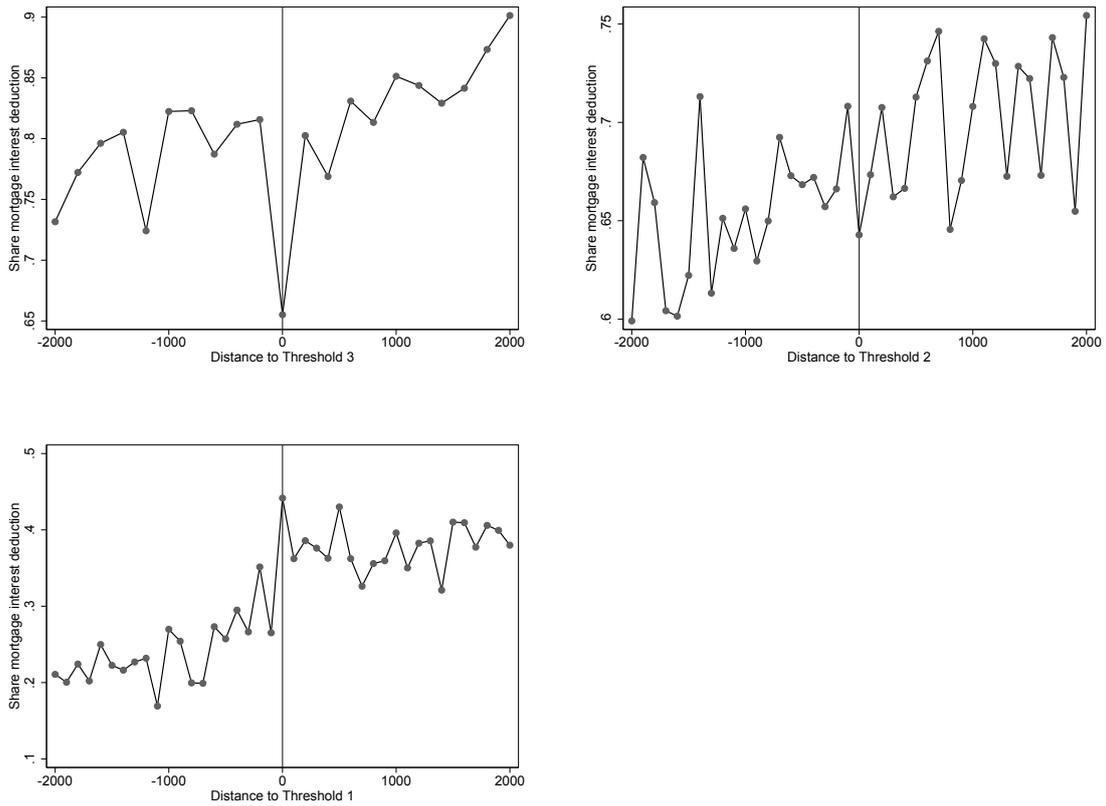
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<sup>20</sup>This also remains a possibility for the other 95%.

<sup>21</sup>This compromises the mortgage interest deduction and taxed fictional income from housing.

<sup>22</sup>This argument also holds for partners having similar incomes just above the other thresholds.

Figure 8: Share mortgage interest deductions



Notes: The top figures show the share of mortgage interest deduction within couples around the third threshold (left) and the second threshold (right). The bottom figure shows the share of mortgage interest deductions within couples around the first threshold. The binsize is 100 euro, except for the highest threshold, where 200 euro binsize is needed because otherwise the bin would contain fewer than 100 observations.

with the common expectation that the tax advantage is higher for the highest earner. Without the tax threshold one would expect a gradual increase in the share. However, at the tax threshold the incentive is different. For couples whose second earner also earns a high income, it is attractive to shift part of the mortgage interest deduction to this partner. This is the case, as the share suddenly drops around the upper tax threshold. At the first threshold, there appears to be shifting as well, although more mortgage interest deductions are claimed by the partner here to get below the threshold. This effect is hardly visible at the second threshold, where the tax incentive is absent. The graphs show that the mortgage interest deductions are an important channel for reducing taxable income to reach thresholds of the tax system.

A second possible channel is that of the response in hours worked. Due to the structure of our data, identification of these type of responses in hours could only be done indirectly: for example, via hourly wages. As bunchers come from above the threshold and hourly wage can be assumed to increase with taxable income, an individual that bunches should have a higher hourly wage than other individuals working the same number of hours. However, looking at data from 2006 to 2011, we cannot detect a significant difference between bunchers and non-bunchers left or right of the bunching window in terms of hourly wages, suggesting that real responses do not play a significant role in adjusting taxable income.

## 5.4 Relation to the literature

Our results relate to the literature in several ways, although cross-country comparisons of elasticities might be difficult due to different institutional features (Bastani and Selin, 2014). In line with other studies that implement the bunching approach, we find small but precise estimates of the compensated ETI with respect to the net-of-tax rate at the top tax threshold of 0.023. Chetty et al. (2011) find an elasticity at the upper threshold below 0.02 for their full sample on Denmark, while Bastani and Selin (2014) find close-to-zero elasticities on Sweden at the top tax threshold. Evidence on the United States, published by Saez (2010), indicates an elasticity of between 0.1 and 0.2, depending on the methodology, at the first threshold of the federal income tax schedule. They find a smaller response for married individuals than for singles. This is in stark contrast to our findings indicating significant bunching by married individuals in the Netherlands, even at the first threshold of the tax system.

One structural difference that may explain this deviation between the United States and the Netherlands is the social acceptance and federal legitimation of part-time work. Employees in the Netherlands are arguably more free to choose their working hours than workers in other countries because of the existence of the Dutch Working Hours

(Adjustment) Act. They can file a request for amendment (increase or reduction) of their working hours that the employer cannot refuse. In the United States, only 19% of the working population was working part-time in 2013, whereas in the Netherlands this figure was almost twice as high, with 36%. The significantly larger proportion of women bunching can also be explained by this. In the United States, 26% of the female workforce worked part-time, whereas in the Netherlands, this was 58% and these women would likely earn an income close to the first threshold.<sup>23</sup> This could be a reason for the differences in the results. Alternative explanations are differences in other institutional features, such as the possibility to shift tax deductions between partners and the presence of digital filing of tax returns.

Earlier studies for the Netherlands find larger elasticities. Jongen and Stoel (2013) find an elasticity of around 0.1 for the short run and 0.2 for the medium run. The aforementioned study employs a panel approach and uses instrumental variable techniques to correct for endogenous taxes in line with Gruber and Saez (2002). Consistent with their estimates, we also find higher elasticities for women. In contrast to our study, they had to rely on a tax simulator to obtain marginal tax rates and determine taxable income. This can potentially cause measurement error, which could explain some of the deviation between the results. Another explanation would be that the bunching approach identifies a local elasticity as opposed to an average elasticity derived from the IV approach (Chetty, 2012).

A recent study by Bettendorf et al. (2016) for managing directors that own at least 5% of a corporation<sup>24</sup> finds elasticities between 0.06 and 0.11 for the upper threshold of the Dutch tax schedule, using bunching techniques. This is slightly larger than the elasticity of 0.04 that we identify for self-employed individuals, and could suggest that our results are partly driven by the DGA sub-group. Unfortunately, the limited number of DGAs in our sample prevents us from running the estimation separately for this group.

In all bunching analyses, distinction is made between real response and income shifting. In a study on the self-employed in Denmark, Le Maire and Schjerning (2013) show that about 50% to 70% of the bunching in taxable income is due to income shifting over time. In a similar study for business owners in Finland, Harju and Matikka (2016) attribute two thirds of the ETI to income shifting between tax bases. However, we find that a large share (but not all) of bunching is driven by tax deductions in combination with shifting them between partners. The presence of deduction possibilities confounds welfare analyses using the ETI (Doerrenberg et al., 2015). Our results confirm the sig-

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<sup>23</sup>Shares are calculated from the OECD Statistics database, where the labour force is measured by national criteria.

<sup>24</sup>These so-called DGAs (*Directeur-Grotaandeelhouder*) face a special tax scheme. In our study, this sub-group belongs to that of the self-employed.

nificance of deduction possibilities for optimising taxable income. This finding mirrors earlier findings on itemised deductions (Saez, 2010).

Furthermore, our results shows little evidence of collusion between employers and employees. As final income taxes are based on taxable income and not on broad income on the payslip, it is harder for employers and employees to determine the exact taxable income. The same holds for the response in hours worked. Although, compared to employees in other countries, those in the Netherlands can more easily adjust the number of hours they work, adjusting the number of hours in such a way that the income stays below a certain taxation threshold is very difficult. This requires an extensive knowledge on those thresholds and the amount of all the deductions that turn labour income into taxable income in Box 1. Nevertheless, responses in hours worked could play a role when analysing self-employed, but due to a lack of data on the hours worked by self-employed, we are unable to test this hypothesis. Our results indicate that the shifting of deductions, particularly between partners, is the key cause of bunching behaviour in the Netherlands.

## 6 Concluding Remarks

In this paper we have estimated the elasticity of taxable income with respect to the net-of-tax rate in the Netherlands. Using a unique data set from Statistics Netherlands, containing exact taxable incomes, we exploited bunching behaviour at kink points in the Dutch tax schedule. We found an excess mass of 2.36, corresponding to an elasticity of 0.023. With an excess mass of 3.95 ( $e = 0.039$ ) for the self-employed and 5.03 ( $e = 0.049$ ) for women, the estimates are in line with the third-party reporting hypothesis and further suggest that women are more responsive to taxation. Our findings are quantitatively similar to recent studies exploiting bunching, with one exception. Where Chetty et al. (2011) and Bastani and Selin (2014) for Sweden find a nearly zero elasticity for wage earners in Denmark and Sweden, respectively, we find a small, yet statistically significant estimate of 0.02 for wage earners in the Netherlands. Further exploration of the anatomy of responses by wage earners revealed that bunching is caused by shifting tax deductions between partners. The shifting is facilitated by digital filing of tax returns, which makes the thresholds more salient. Our results corroborate earlier studies that claim that the ETI is not a structural parameter but depends on institutional settings.

Our study also contributed methodologically, in two ways. Elasticities derived with the bunching approach are found to heavily rely on both the estimated counterfactual density and the determination of the bunching window. To improve the reliability of the bunching estimation, we first proposed to choose the counterfactual model, based on information criteria. Second, we implemented an intuitive, purely data-driven procedure

to find an optimal, potentially asymmetric bunching window. Applying these extensions to our data, we found elasticities that are marginally smaller, yet statistically more significant. Our modifications thus form a valuable contribution to the literature, as they allow for a more precise calculation of the excess mass at the kink.

Overall, our empirical results showed that Dutch taxpayers respond to taxation and adjust their taxable income. For employees, we could identify the mortgage interest deduction as the main channel through which taxable income is adjusted. An adjustment of hours worked could not be inferred from the data, but such real responses and underreporting remain potential channels for those who are self-employed, where income is not reported by a third party.

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# A Appendix

## A.1 Additional Graphs and Tables

Figure A.1: Bunching at the third threshold - single years

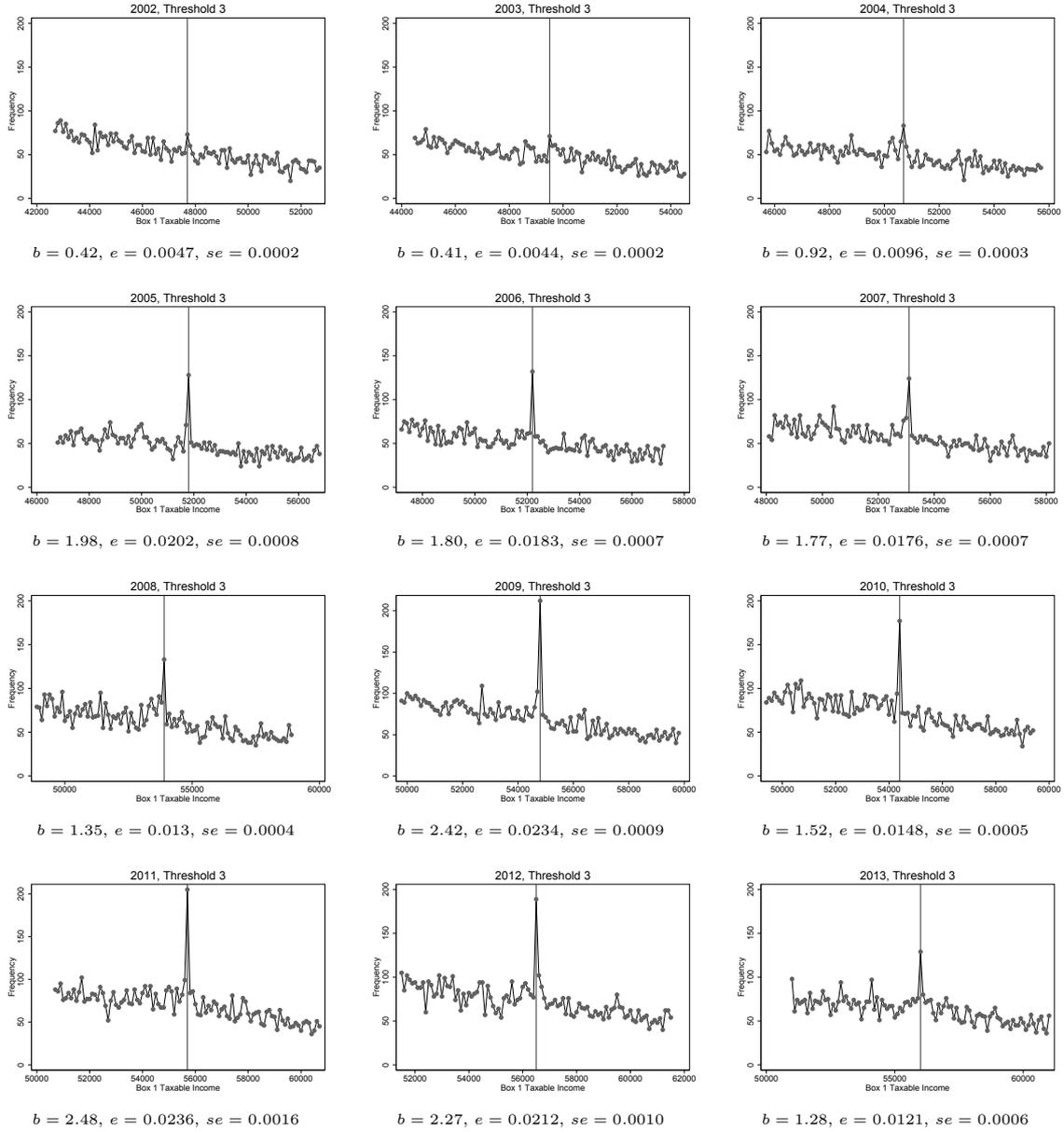
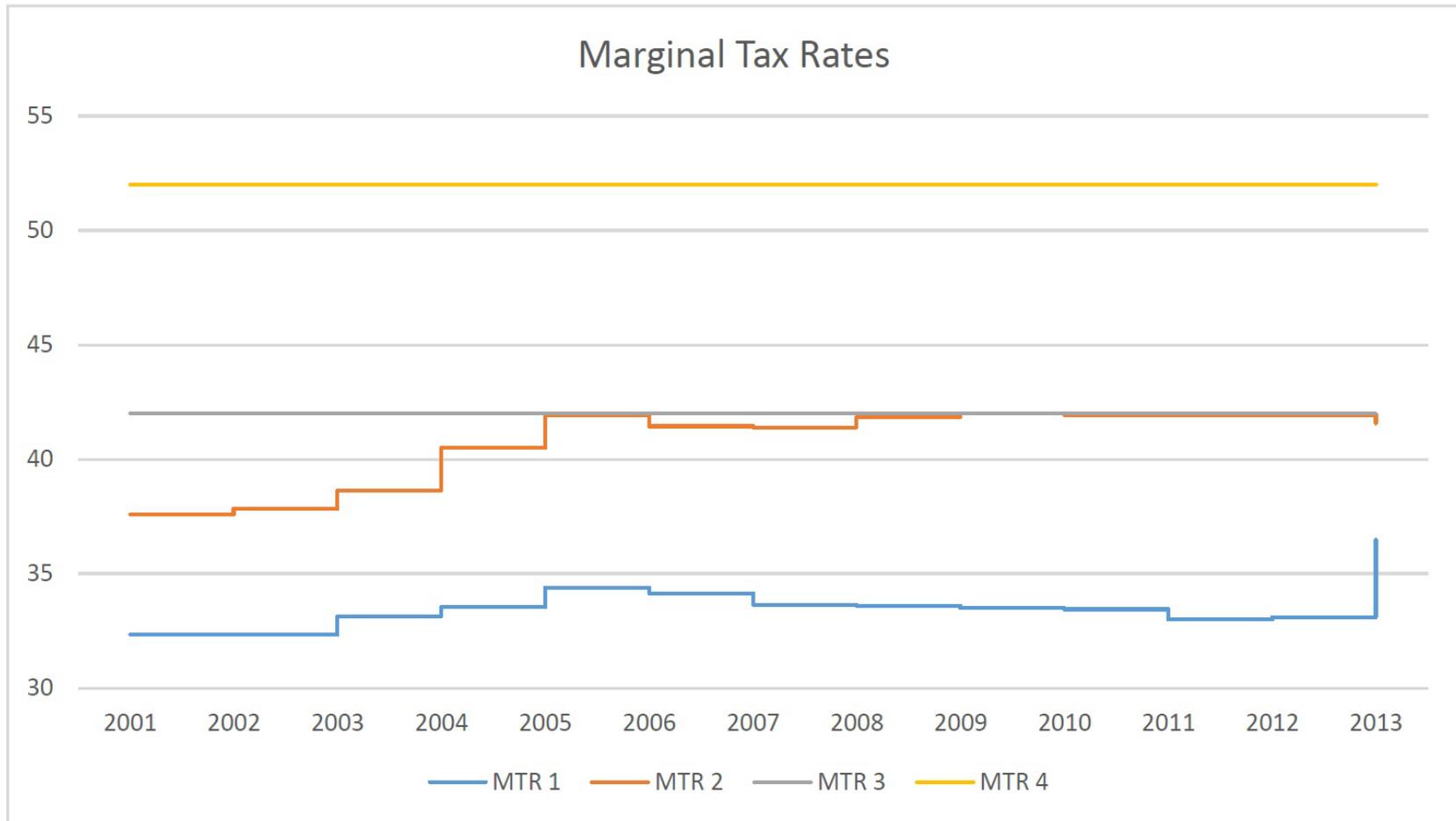


Table A.1: Bunching window and counterfactual for Figure A.1

Year	Bunching Window	Counterfactual Model
2002	-50 € to +50 €	linear
2003	-50 € to +50 €	linear
2004	-50 € to +50 €	linear
2005	-50 € to +50 €	Third-Order Polynomial
2006	-150 € to +50 €	linear
2007	-150 € to +50 €	linear
2008	-50 € to +50 €	linear
2009	-150 € to +50 €	linear
2010	-50 € to +50 €	linear
2011	-150 € to +250 €	Second-Order Polynomial
2012	-50 € to +250 €	linear
2013	-50 € to +150 €	Second-Order Polynomial

Notes: The table shows the specifications used to obtain the estimates in Figure A.1.

Figure A.2: Development of marginal tax rates



Notes: The figure depicts the changes in the marginal tax rates in the Netherlands from 2001 to 2013.

Table A.2: Comparison of different model specifications

Sample	(1)				(2)				(3)			
	$b$	$e$	$se$	$t$	$b$	$e$	$se$	$t$	$b$	$e$	$se$	$t$
Pooled Sample	2.36	0.0231	0.0017	13.83	2.23	0.0218	0.0087	2.08	1.96	0.0192	0.0035	5.08
Employed	1.77	0.0174	0.0011	15.65	1.85	0.0181	0.0070	2.16	1.61	0.0157	0.0027	5.34
Self-Employed	3.95	0.0387	0.0040	9.68	3.75	0.0367	0.0169	1.83	3.38	0.0331	0.0072	4.18
Men	1.70	0.0166	0.0011	15.59	1.55	0.0152	0.0064	1.99	1.46	0.0143	0.0025	5.30
Women	5.03	0.0492	0.0043	11.54	5.11	0.0499	0.0203	2.04	4.01	0.0392	0.0084	4.21

Notes: (1) represents our model with the endogenous bunching window and the counterfactual model, which is determined by the BIC. (2) show the results for a symmetric bunching window going from -750 € to +750 € and using a 7th order polynomial counterfactual model. (3) show the results for a symmetric bunching window going from -350 € to +350 € and using a 7th order polynomial counterfactual model.  $b$  is the estimated excess mass,  $e$  the corresponding elasticity,  $se$  the standard error obtained from a parametric residual bootstrap procedure and  $t$  is a t-value, obtained by dividing the elasticity by the standard error.





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