

# The Top (0.4%) Tail of Finland: A Tale of Incomes, Tax Rates, and Elasticities from 2009 to 2013

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## Contents

<b>1</b>	<b>Introduction</b>	<b>2</b>
<b>2</b>	<b>Literature Review</b>	<b>3</b>
<b>3</b>	<b>Our Unique, Tidy, Open, Reproducible Dataset</b>	<b>4</b>
<b>4</b>	<b>Methodology</b>	<b>10</b>
<b>5</b>	<b>Results</b>	<b>11</b>
5.1	Time Series Results . . . . .	11
5.2	Panel Results . . . . .	11
<b>6</b>	<b>Discussion</b>	<b>11</b>
6.1	Data Issues . . . . .	11
6.2	Statistical Issues . . . . .	11
6.3	Issues in Context . . . . .	11
<b>7</b>	<b>Conclusion</b>	<b>11</b>
	<b>References</b>	<b>13</b>

# 1 Introduction

The question about an “optimal” income taxation is always discussed against the background of classic economic theories: Income taxation should maximize a given social welfare function that depicts a societies preference for equality. Furthermore, sacrifice theory of income taxation illustrates that redistribution should take place up to the point where marginal utilities are equalized. However, these theories completely neglect *behavioral responses* to taxation. According to the Laffer-Curve, there comes a point where a further increase of the tax rate would result in a loss in tax revenues due to negative labor supply responses. In a relatively recent work, Saez (2004) identifies additional reasons why trends in top-income shares are correlated with the tax rates: labor supply decisions, evasion/avoidance responses and bargaining responses.

Indeed, the rationale of disruptive changes in income taxation schemes, like heavy reductions in marginal income tax rates in the US of the 1980’s was the logic of almost exclusively the supply side economics: Lower tax rates were believed to trigger important increases in economic activities and therefore higher tax revenues. It is against this background that many researchers focused their analysis only on behavioral responses like labor supply, savings and retirement. The current research frontier challenges this intellectual weight on supply side economics and steps beyond those “conventional” behavioral responses. Saez (2004) states that the discovered behavioral responses, such as tax deductible activities, compensation (e.g. wage versus untaxed fringe), unmeasured efforts, career choices, saving decisions and/or compliances, have “substantial effects on economic activity of high-income earners” (p. 118). Eventually, these determinants of reported incomes lead to more elastic responses with respect to taxation than assumed initially (Piketty and Saez 2014).

According to Giertz (2007) this effect is driven mainly by high income earners: analyzing US tax reforms of the 1980’s provides strong evidence that especially highly paid employers were able to retime (i.e. temporally shift) their compensation, taking advantage of the tax reforms. Moreover, and apparently also related to the behavior of the top tail of the income distribution, the timing of capital gains realizations seems to be highly sensitive to changes in the capital gains tax rates (Auerbach and Poterba 1988). Finally, tax cuts in the top individual taxation to below the corporate tax rate triggered a massive shift of corporate income towards the individual income sector (legal entities that are only taxed at the individual level) (Auerbach and Slemrod 1997). All in all, the data strongly suggests that taxpayers with high incomes are much more responsive to changes than individuals in the middle class.

The relevance of these mechanisms can be illustrated by the actual share of total incomes that the top income earners account for: In the US for example, the top 1% owned almost 20% of total incomes in 2010 (Alvaredo et al. 2013). This elucidates how tax-burden minimizing behavior of ultra wealthy people yields enormous sources inefficiencies for a whole economy. It is our opinion, that these patterns need to be discussed not only in a purely economic rationale (welfare loss spillover effects, etc.), but also raise questions about the equality of income distribution. Therefore, a detailed and well justified analysis of the actual mechanisms is essential.

Whereas poverty is studied extensively in economics through surveys and welfare programs, the current debate still lacks information about the top of the income distribution. The aim of this project is to inspect exactly this upper end of the income distribution. For this, we will analyze micro-level data from Finnish taxpayers from which we have data for 2009 to 2013.

In Finland the tax on earned income is levied according to a progressive tax scale: Each taxpayer has to pay a basic amount dependent on his earned income plus the tax rate within the respective tax bracket. The concrete tax scheme is decided annually by the parliament. The relevant tax rates of the top tax-bracket were levied as follows:

- 2009: 30.5%
- 2010: 30.0%
- 2011: 30.0%
- 2012: 29.75%
- 2013: 31.75%

Against this background, our paper’s purpose is to identify anomalies in the tax patterns of ultra-wealthy Finnish people. In detail, the research question of this paper is: What is the responsiveness of reported taxable income to changes in average tax rates?

In a first step, we will visualize how the share of the top 0.4% (approximately the wealthiest 15,000 individuals) (insert footnote how we roughly calculated this) in total income-tax revenue changes between 2009 and 2013. Following up, with inferential statistics we will dig deeper into income-tax payer’s behavior. With the principle of elasticity of taxable income (ETI) we want to apply a broader measure than only the labor supply elasticity in order to gain a better understanding of efficiency costs of taxation. Finally it is worth mentioning that many of the issues also apply to any tax base (Saez, Slemrod, and Giertz 2012), which makes it an even worthier topic to investigate.

## 2 Literature Review

Since the 1990’s, several researchers analysed the elasticity of taxable income (ETI) in different settings with different data and different methodologies. Most of these analyses on the ETI focus on the United States due to data limitations, nonetheless there are few studies in the literature also about Canada and Western Europe. The following chapter provides an overview, focusing on empirical approaches, the data, and respective findings.

The very first attempt to investigate high income share of reported aggregate income was run by Feenberg and Poterba (1993). By using **aggregated time-series data**, they calculated the adjusted gross income (AGI) owned by the top 0.5 percent of US households in the period from 1951 to 1990. During this span they were able to identify an increase of this share by about 6% in 1970 to more than 12.1% in 1988. They assume that this is due to behavioral responses, since the pattern in the time series is consistent with reductions in the top marginal tax rates around a significant tax reform in 1986.

Following, Slemrod (1996) analyzed inequality for 1954 to 1990 using exactly the same data as Feenberg and Poterba (1993). In his time-series model, Slemrod used the high-income share of AGI and four other components of income as dependent variables. The explanatory variables were measures of one-year lagged and one-year leading top tax rate for both individual income and capital gains. As a control for exogenous income trends he included a control for earnings inequality between the 90th and the 10th percentiles, as well as macroeconomic variables like level of stock prices, etc. Slemrod could not find evidence that the changes in the top tax rate explain the high-income share of AGI until 1985, but rather that the wage inequality seems to be the underlying driver. However, in the period from 1985 until 1990 Slemrod revealed that the high-income share of AGI is most likely caused by changes to the structure of the tax base: different incentives and opportunities to report income were introduced for high income earners.

Saez (2004) uses data from the *Internal Revenue Service* (IRS) from 1960 to 2000 regress the log of average income of the top 1% of the distribution on the log of average net-of-tax rate for the top 1% over the time period. Even though he included time trends and other controls, he found large elasticities. Like Slemrod (1996) he concludes that large proportions of the rise in top incomes can be explained with income shifting. Nonetheless, he was not able to depict the actual degree of top income shares explained by shifting, or if there are other underlying influences of non-tax related increases in earnings.

Whereas the previous paragraphs exclusively presented aggregated time-series methodologies, the following paragraphs lay down the literature using **panel data**. Moffitt and Wilhelm (1998) analyzed the same period around the Tax Reform Act of 1986, but in contrast to previous studies they were one of the first who used panel data. Due to data constraints, their study covered more AGI rather than taxable income. With a two-stage least-squares regression, they included instruments for the change in the net-of-tax rate like education and illiquid assets. Accordingly, these instruments succeeded in distinguishing between high-income and the balance of the population. Taking different controls into account, their major finding was that the high income tax-cut and the respective increase in taxable income of ultra wealthy people in 1986 was **not** accompanied by an increase in hours worked.

Gruber and Saez (2002) wrote a seminal, highly influential paper with a methodological framework used by multiple subsequent papers. Again the period around the Tax Reform Act of 1986 (1979-1990) was subject of the analysis. They examined both broad income responses and taxable income responses for all income levels by measuring behavioral changes over three-year intervals. Moreover they instrumented the net-of-tax rate assuming, that “each filer’s income grows at the rate of overall nominal income growth between the base and the subsequent year” (Saez, Slemrod, and Giertz 2012) and included a rich set of controls like year fixed effects, dummies for marital status, etc. For broad income they estimated an elasticity of 0.12, which is significantly smaller than that of taxable income with 0.65. This result yields that, indeed, much of the taxable income response comes through channels like deductions, exemptions and exclusions. They conclude that this is evidence for significant efficiency costs caused by avoidance opportunities in the current tax system.

Along the same lines, Kopczuk (2005) runs an only slightly different model and found a post-1986 ETI of 0.36. He states that his results imply that the availability of deductions is linked to a behavioral responses. In the absence of being able to have access to deductions, a taxpayer does not respond to changes in tax rates (2005). Giertz (2007) examined a relatively large panel data set from 1979 to 2001, applying the methodology laid down by Gruber and Saez (2002). Again, the empirical evidence for the ETI of broad income (0.12) are significantly lower than of taxable income (0.39) - consistent with Kopczuk (2005) findings that its the availability of deductions and exemptions determining the ETI.

In general one can conclude that these studies found a) patterns in behavioral responses consistent with tax reforms, and that b) those behavioral responses, reflected in high income shares, are not due to labor supply responses but rather due to access to avoidance opportunities. Nonetheless, Saez, Slemrod, and Giertz (2012) outline some overarching methodological issues: The models are not adequately able to control for exogenous income trends, which biases the ETI results. Furthermore the models fail to identify potentially important types of income shifting like between individual and corporate income tax base.

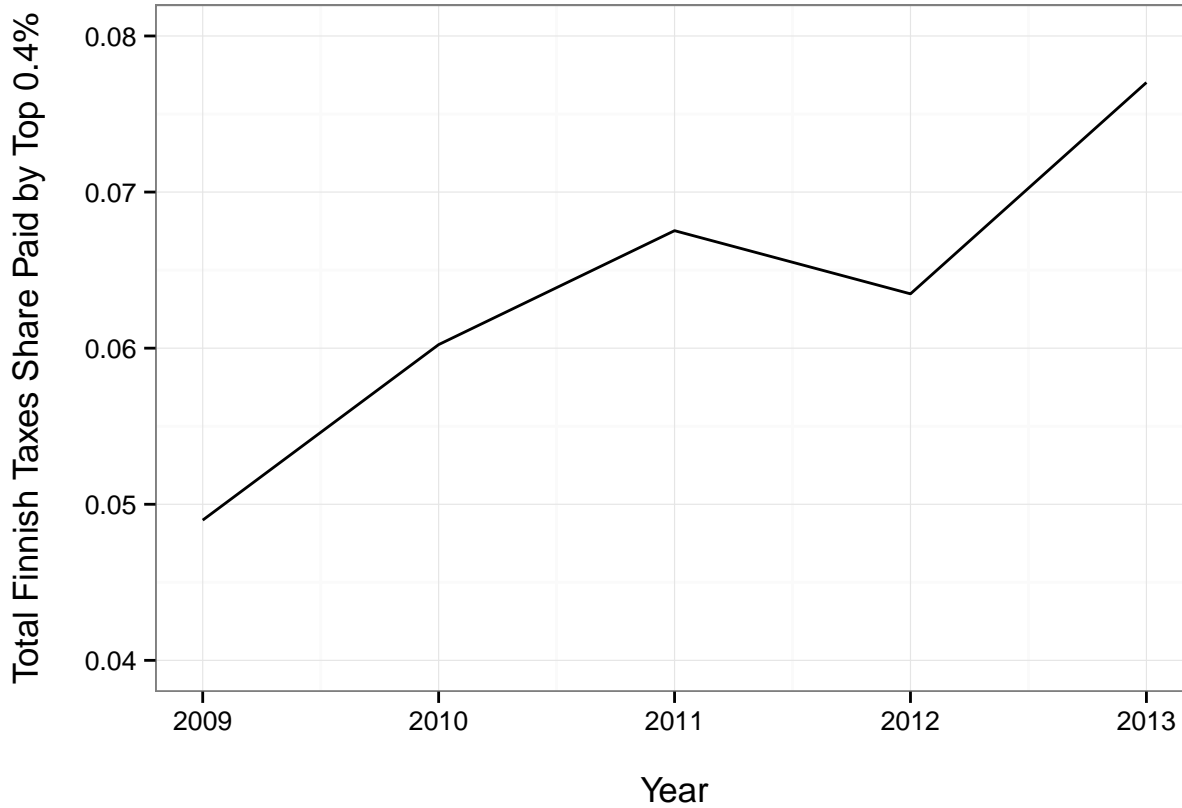
Against the background that this paper’s subject of interest is Finland, it is worth noting that there are two recent papers about Denmark that made use of the especially rich data available in all Scandinavian countries, including a variety of demographic variables that are not available in the US. Another advantage is, that the income distribution in Scandinavia has been relatively stable compared to other parts of the world, which makes it easier to identify effects of income taxation. Jacobsen Kleven and Schultz (2011) analyzed the period from 1984 to 2005, using the methodology of Gruber and Saez (2002) and controlled for a rich set of base-year incomes. Their identified elasticities were modest compared to the previous studies. Nonetheless they observed some important structural behaviors: Elasticities are larger for self-employed than for employees and in high income levels (top quintile) the elasticities are two to three times larger compared to the bottom quintile of the distribution. Finally, Chetty et al. (2011) estimated bunching around kink points, also exploiting population tax files from Denmark. The key finding is that large changes in marginal tax rates are associated with large elasticities, whereas the elasticities are small for small tax changes. They are assuming that this effect is due to large adjustment costs in the Danish tax-scheme.

### 3 Our Unique, Tidy, Open, Reproducible Dataset

The Nordic countries of Finland, Sweden and Norway have a tradition of publishing everyone’s income and tax details every year. Whereas in Sweden and Norway this data is only accessible to citizens and after pulling an official request, in Finland top income tax earners are public figures as a result of heightened media scrutiny on top income tax earners. Finland’s largest business online daily newspaper Taloussanommat published the figures in a suitable format for our purpose: The top 15,000 income earners over the age of 18 are displayed on yearly basis from 2009 to 2013, including their name, total income (income, profits, and capital gains), taxed paid and average tax rate. In a first step we scraped the data from their [dedicated website](#). Since there are some observations missing in the first three years (2009 to 2011), the final data set contains 70,402 observations. The variables given by our scraped data are as follows: full name, total income (in euros), total taxes paid (in euros), average tax rate (in percent), and the tax year. We also created a couple of new variables that are helpful for our analysis: the rank based on the income of each individual

in a given year and the share of total income-revenues that the top 15,000 tax payers pay. Furthermore, we created two different datasets for analysis, a time-series and a panel-dataset (more in the methodology) section. The panel dataset uses the given names of the taxpayers as unique identifiers and therefore we are able to track 4,867 individuals across all 5 years.

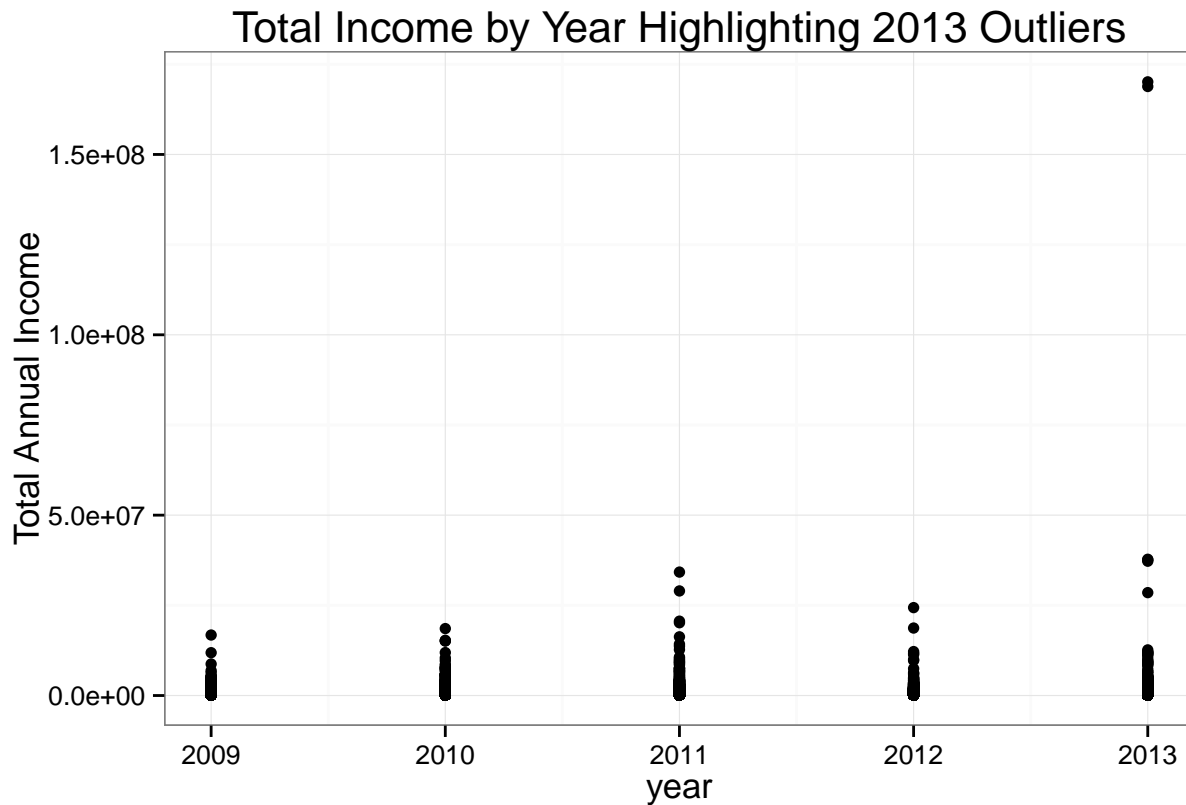
In order to derive an estimate of the share of the population that our top-tailed income earners comprise, we looked at data from (“OECD Stats: Population 2009-2013”) to determine the working population in a given year in Finland (in 2009 it was 3,547,335 and shrinking to 3,508,645 by 2013). From this we divided the number of observations in our dataset in a given year by the working population in given year. Thus, we arrive at a dataset consisting of the top 0.4% income earners in Finland each year (make this a footnote: note that for 2009 there are missing observations, so the total observations is low resulting in a population share of 0.34%). Moreover, we are able to track the development of the share of the total income tax revenue paid by the top 0.4 percent over our time period. In the figure below, the share increases from 5 percent to almost 8 percent over the course of five years. In each year we can nicely observe the changes in the top income tax rate changes which likely resulted in the reflected changes in tax revenue collected by the top 0.4 percent. Most importantly for our analysis, from this graph we can clearly see a start shift in the share from 2012 to 2013 (the year of the tax reform). This provides simple, yet powerful graphical analysis in our attempt to flesh out latent underpinnings in taxpayers behavior given our dataset.



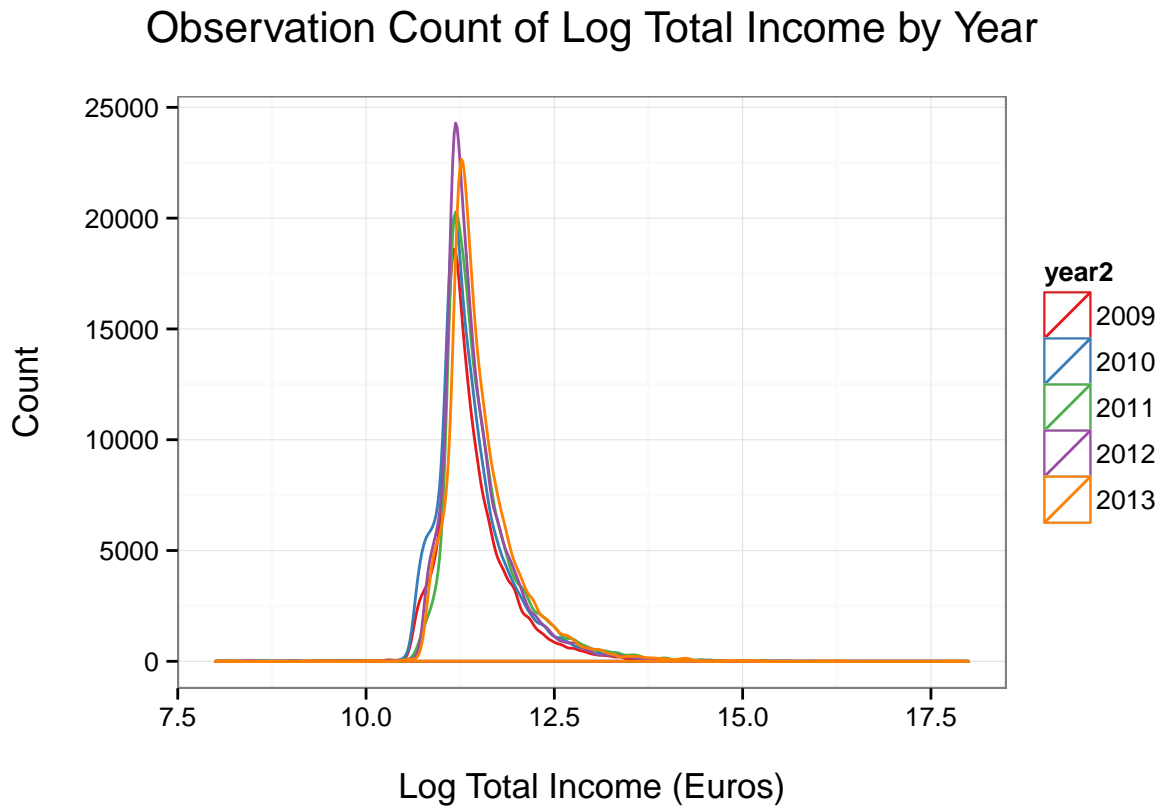
Year	N	Ave Inc (E)	Med Inc (E)	Ave Paid (E)	Med Paid (E)	Mean Tax (%)	Med Tax (%)
2009	12134	283245	199020	106996	80653	40	43
2010	14290	305270	201964	111710	80336	39	42
2011	13978	350746	219372	128043	87256	40	44
2012	15000	285234	202520	112169	83368	41	43
2013	15000	347759	213323	136092	89515	42	44
All	70402	315287	207456	119433	84494	40	43

The table above provides a quick overview of the mean and median of relevant variables by each year. As

expected, all of the median income and taxes paid fall below the median indicating that high income earners (and taxpayers) skew the data. Only in 2013 do we observe two extreme outliers (see figure below), two tech multi-millionaires working for a iOS [video game developer](#) which currently has the two top grossing iPad games in 122 countries.

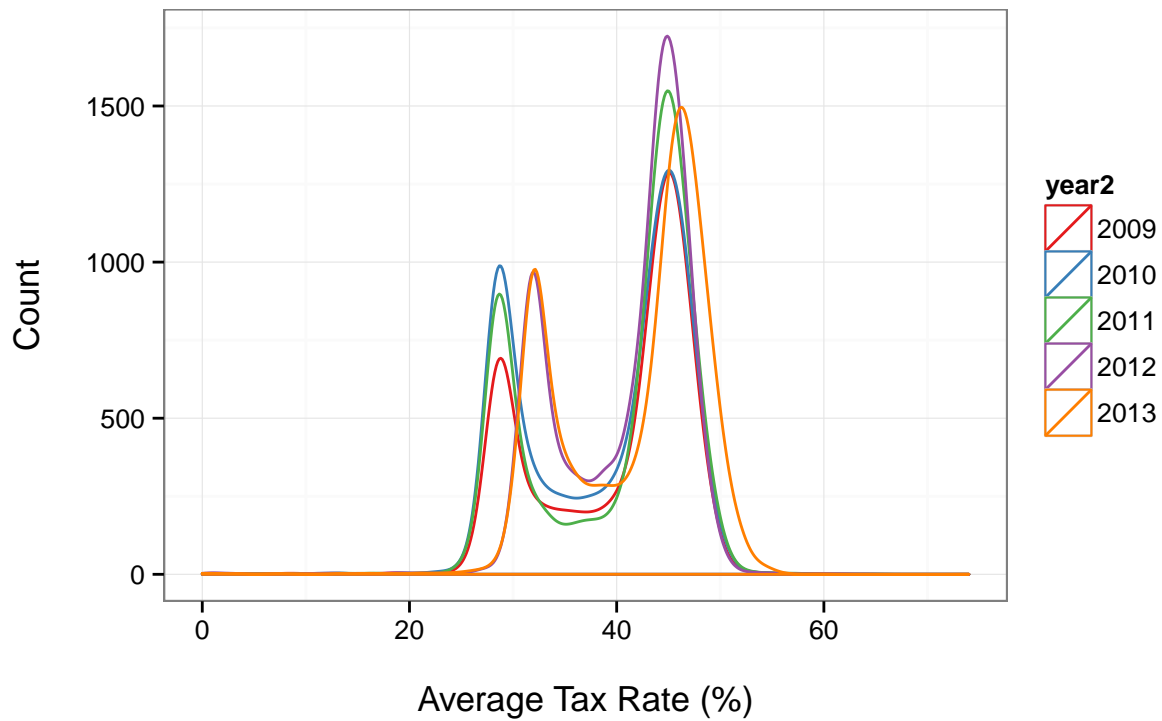


For our analysis, we took the natural log of reported taxable income in order to obtain a more normal distribution. The plot below shows that across all five years, the logged incomes follow a similar distribution (albeit not as normal as we would like – however we are working with a specific subset, namely the ultra wealthy, so it is expected that our data does not follow a normal distribution).



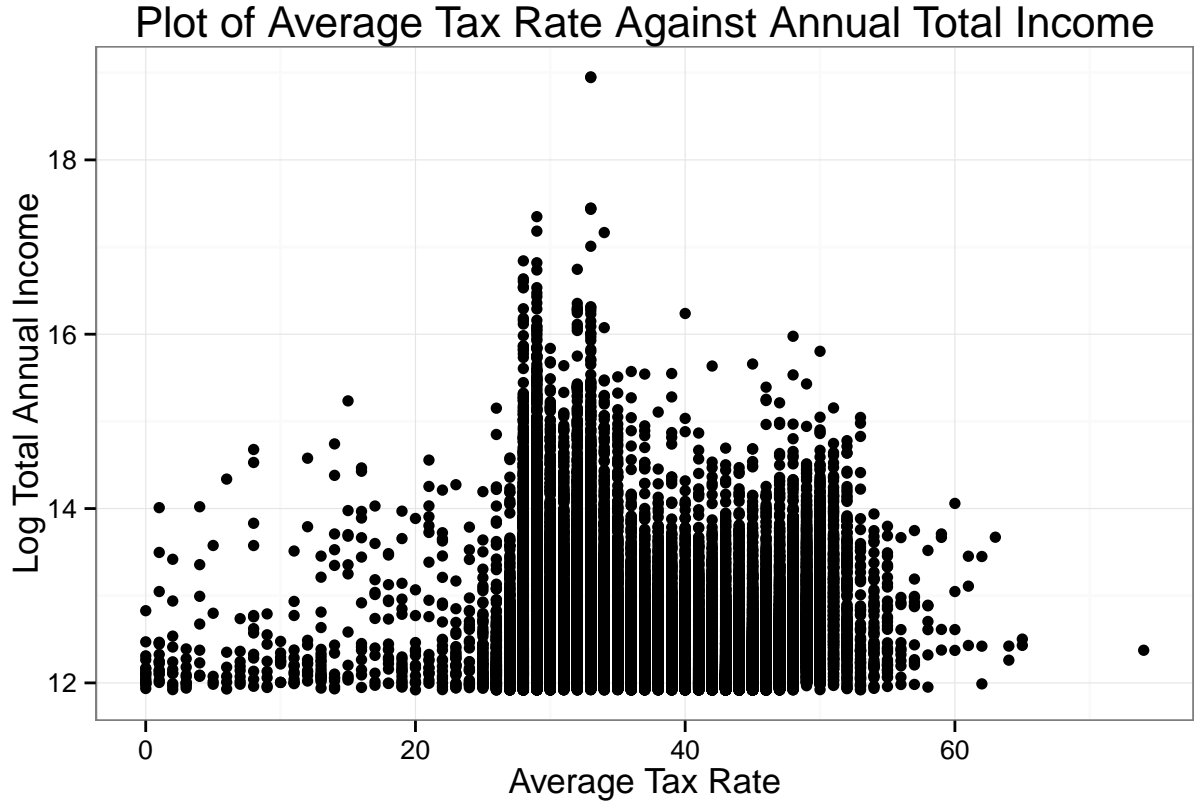
The figure below shows observation counts of the average tax rate paid across the five years of our data. It is interesting to note a parallel trend in all five years, with two bimodal peaks centered around 30 and 47 percent, respectively. We cannot disentangle behavioral response from this graph alone, because we are not privy to the sources of our taxpayers taxable income. However, it is interesting to note that we can already see that in the first peak 2012 and 2013 look identical, despite that fact of the tax reform starting January 1, 2013. More interesting is that 2012 has the highest number of observations at the second peak.

## Observation Counts of Average Tax Rate by Year



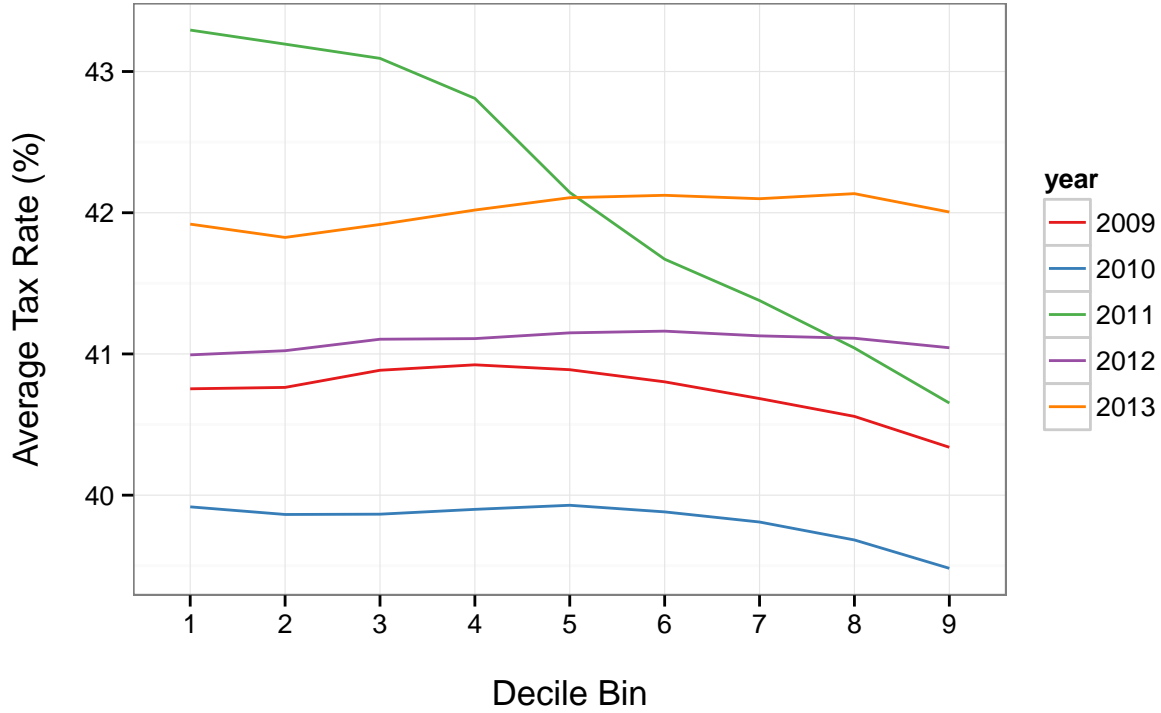
The next figure plots the log total annual income against the average tax rate. This figure provides a good visual outlook of our data, since we are interested in observing patterns between these two key variables. There are clearly multiple instances where higher income individuals have a small average tax rate (even instances where individuals have an average tax rate of zero), which is likely due to taking advantages of deductions or even worse potential tax avoidance like for example, shifting income to capital gains.





Finally, inspired by the methodology of Riihelä, Sullström, and Tuomala (2010), we look at the mean of the average tax rate by income decile bins across five years. With the exception of 2011, the mean holds stable across all deciles. We cannot explain why 2011 has decrease as the income grows. However, we are most interested in the between year comparisons. The average tax rates for 2009 and 2010 always fall below the mean rates for 2012 and 2013 with 2013, as expected having the highest mean across all deciles. In order to dig deeper into the data, we present our methodology and results as follows.

## Average Tax Rate by Deciles



## 4 Methodology

The methodology in this paper is in general derived by the literature described above, but especially using the methodological framework of Saez (2004) for a time-series model and Giertz (2007) for a panel analysis. Since both approaches are quite relevant in the latest literature and we were not sure how sensitive our data is to the respective model, we decided to include both models in our paper. Due to data constraints, we had to adjust these models slightly suiting our capabilities, explained in the following paragraph.

In our **time-series model** we simply regress the log of average income for the top 15,000 Finnish income earners on the log of the average *net-of-tax rate* in percent over the given time period 2009-2013 (5 observations). Whereas the *net-of-tax rate* depicts the rate of total income after taxes ( $\text{net-of-tax rate} = 1 - \text{average tax}$ ). Saez (2004) wrote about his model: “A simple OLS regression of log average incomes on the log of the net-of-tax rate, always displays insignificant elasticity coefficients. Therefore, the aggregate data display no evidence of significant behavioral responses of reported incomes relative to changes in the average marginal tax rate” (p. 138). Thus, in order to control for exogenous real income growth, we also added a time control capturing year-specific effects.

For our **panel analysis** we used exactly the model laid down by Giertz (2007), exploiting the panel advantage comparing only individuals who filed their tax returns in all subsequent years and also were part of the top 15,000 income earners from 2009 to 2013. In detail, here we are observing 4,867 individuals. The dependent variable in this model is the log of total income in the future year ( $\text{income } t+2$ ) divided by income in the base year ( $\text{income } t$ ), where the future year is two years after the base year. Thus, we end up observing three pairs of years (2009/2011, 2010/2012, 2011/2013). The key independent variable is the log of the average net-of-tax rate in the future year ( $t+2$ ) divided by the average net-of-tax rate in the base year ( $t$ ). We use these time-differences in our variables to avoid endogeneity between the tax rate and income.

$$\ln\left(\frac{income_{t+3}}{income_t}\right) = \alpha_t + \xi \cdot \ln\left(\frac{1 - taxrate_{t+3}}{1 - taxrate_t}\right)$$

(Image Source: Giertz (2007))

Our panel-model differs from the original as such, that we use two instead of three future years for the sake of an additional year pair. Moreover, Giertz (2007) used several control variables like *marital status* that we are not able to obtain due to data constraints.

Again we run two different versions of this model, first simple pooled OLS, but due to the presence of unobserved, time invariant effect also a within estimation (fixed effects). One of the most limiting constraints of this project is the limited time-span available relatively to previous research, which entirely focuses on long-term behavioral elasticities. Here we are only able to observe short term elasticities. Moreover, we are limited to only one income group, namely the top-tax bracket. Consequences of those limitations will be discussed in the *Discussion* section.

## 5 Results

### 5.1 Time Series Results

Regressing the time series model without time control provides an ETI of -0.035, highly significant at the 1% level (with a confidence interval between -0.040 and -0.029). Interestingly the sign of this effect changes, when including the time control (consistent with the literature). Moreover, the effect dampens to an ETI of 0.009, which is still significant at the 1% level (with a confidence interval between 0.003 and 0.014). In detail, this yields that a 1% increase in average tax rate would lead to an 0.009% increase in reported taxable income, *ceteris paribus*. The time trend which is meant to capture all exogenous income growth is also significant at the 1% level and increases the adjusted R squared from 0.002 to 0.246.

### 5.2 Panel Results

## 6 Discussion

### 6.1 Data Issues

### 6.2 Statistical Issues

### 6.3 Issues in Context

## 7 Conclusion

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Final word count:

This project used RStudio (2014) to create this assignment.

Table 1: Time Series Elasticities

	<i>Dependent variable:</i>	
	Log of Average Taxable Income	
	Without Time Trend	With Time Trend
	(1)	(2)
Elasticity	−0.035*** (0.003)	0.009*** (0.003)
Time Trend		0.033*** (0.0002)
Constant	12.639*** (0.002)	−53.855*** (0.440)
Observations	70,402	70,402
R <sup>2</sup>	0.002	0.247
Adjusted R <sup>2</sup>	0.002	0.246
Residual Std. Error	0.093 (df = 70400)	0.081 (df = 70399)
F Statistic	133.426*** (df = 1; 70400)	11,516.240*** (df = 2; 70399)
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01

Table 2: Panel Elasticities

	<i>Dependent variable:</i>	
	Log of Average Taxable Income	
	<i>OLS</i>	<i>panel linear</i>
	(1)	(2)
Elasticity	0.105*** (0.033)	0.640*** (0.131)
Constant	0.016 (0.018)	
Observations	14,580	14,580
R <sup>2</sup>	0.001	0.002
Adjusted R <sup>2</sup>	0.001	0.002
Residual Std. Error	0.449 (df = 14578)	
F Statistic	10.172*** (df = 1; 14578)	23.788*** (df = 1; 9718)
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01

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