Essays on taxation and income measurement

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Contents

Abstract

The thesis is about household income taxation and consists of three essays.

Chapter 1 investigates the implications of the design of income tax schedules for the distribution of household income and work incentives from the cross-national perspective. Using microsimulation techniques, we evaluate the distributional effects of replacing existing graduated rate schedules in Western European countries with flat tax schemes. Our simulations show that in specific circumstances a revenue neutral flat tax reform can increase income equality and improve work incentives; in most cases, however, there is an equity-efficiency trade-off. We show that the specific flat tax design and the welfare state regime play a key role.

Chapter 2 estimates the determinants and extent of income tax compliance in a novel way, using income survey data linked with tax records at the individual level for Estonia. I model jointly two processes contributing to discrepancies in employment income between these data sources – tax evasion and (survey) measurement error. The results indicate a number of socio-demographic and labour market characteristics which are associated with non-compliance. Overall, about 12% of wages and salaries are underreported, which is very substantial for a major income source subject to third party reporting and tax withholding.

Chapter 3 follows on Chapter 2, extending the scope of analysis from employees to the self-employed. It uses the same data source but an alternative method by Pissarides and Weber (1989), where the scale of income underreporting is inferred from the comparison of income and expenditure patterns across different population groups. Results confirm substantial underreporting of earnings by private employees and indicate large underreporting by the self-employed on the basis of register income, while a much smaller scale of non-compliance is detected for the self-employed and no underreporting for private employees using survey incomes.

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> *It's a dangerous business, Frodo, going out of your door /../ You step into the Road, and if you don't keep your feet, there is no knowing where you might be swept off to.*
>
> – J.R.R. Tolkien, *The Lord of the Rings*

The long journey is over and looking back, I think the comment certain Mssr Baggins gave to his young relative on how one can easily end up in (or be drawn into) long ventures applies equally well to PhD studies. My doctoral studies have been challenging but also very rewarding and educational. I have learned a lot and gained many valuable experiences along the way and I am very grateful to everyone who has travelled the Road with me.

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Declarations

Chapter 1 is joint work with Andreas Peichl and an earlier version was also part of his PhD thesis (2008) at the University of Cologne. Chapter 1 is based on the version published as Paulus, A. and Peichl, A. (2009) 'Effects of flat tax reforms in Western Europe', *Journal of Policy Modeling* 31: 620-636, to which we both contributed equally (50% of each section). Earlier (longer) versions of the essay have appeared in the series of ISER Working Papers (No 2008-06), FiFo-CPE Discussion Papers (No 08-04), EUROMOD Working Papers (EM2/08) and IZA Discussion Papers (No 3721). I have further extended the discussion in Chapter 1 and added more detailed results, partly drawing on additional material in our earlier working papers.

All other work in the thesis is mine alone and has not been submitted to this or any other university for another degree.

Chapter 2 has been published as ISER Working Paper No 2015-10 and Chapter 3 as ISER Working Paper No 2015-15.

In this world nothing can be said to be certain, except death and taxes.

– Benjamin Franklin

There is always time to pay and to die.

– an Italian proverb

Introduction

Modern societies rely to a large extent on taxation: from providing resources for public goods and services to shaping the allocation of economic resources and achieving distributional goals. The design of a tax system and how it affects individual behaviour are therefore of central importance for the society.

The thesis is about household income taxation and consists of three self-contained essays in empirical economics. The first essay, Chapter 1, is concerned with the design of personal income tax – contrasting a graduated rate tax schedule with a schedule featuring a single positive tax rate (the so-called flat tax) – and explores its implications for the distribution of household income and work incentives. The other two essays, Chapter 2 and Chapter 3, deal with tax compliance and measure to what extent incomes are correctly reported by individuals for tax purposes as well as in the survey context. All three studies draw on survey micro-data at the household and individual level, the first chapter in a cross-national setting, the second and the third focusing on a single country (Estonia) and utilising a combined dataset linking survey and administrative information.

The starting point for Chapter 1 is the observation how prevalent flat income taxes became in the Central and Eastern European countries following their transitions from planned to market economies. Within a dozen years, since the mid-1990s, more than ten countries in the region introduced a flat income tax, while Western European countries maintained graduated rate taxes with a brief exception of Iceland. Several more countries joined in the late 2000s though some have also returned to a graduated rate tax since then.

A number of empirical studies have assessed the effects of flat tax reforms, typically in the form of ex ante evaluation for a single country, and suggested that such reforms could improve work incentives and increase labour supply but would lead to greater relative income gains for better off households and, therefore, larger income inequalities. Chapter 1 argues that such findings could be highly dependent on the particular design (tax parameters) chosen for the flat tax and do not need to hold universally. Indeed, theoretical work by Davies and Hoy (2002) has established that there is a continuous set of parameter combinations, which can ensure a budgetary neutral move from a graduated rate schedule to a flat tax scheme, featuring a single marginal rate above a tax-free threshold. Even more importantly, they show that the inequality of post-tax income distribution is decreasing in the flat tax rate and in the tax threshold (for budget-neutral combinations) and there exists a unique combination of flat tax parameters, which can maintain the same level of inequality as with the graduated rate tax. Particular 'break-even' values of parameters would be dependent on a chosen inequality measure, though some additional theoretical regularities have been pointed out by Chiu (2007).

Chapter 1 takes the theoretical predictions into practice by studying the feasibility of flat tax reforms in a comparative setting from the distributional perspective. More specifically, we ask whether existing graduated rate schemes in Western Europe can be replaced with flat taxes without major negative distributional consequences – as generally expected – and to what extent it is possible to limit the perceived trade-off between equity and work incentives? To answer these questions, we assess the effect of various hypothetical flat tax reforms on the household income distribution using fiscal microsimulation techniques (Bourguignon and Spadaro, 2006; O'Donoghue, 2014; Figari et al., 2015). The microsimulation method allows modelling changes in the variable of interest for highly heterogenous individuals, taking into account their characteristics and possible interactions. To obtain consistent and comparable results across countries, we use the EU tax-benefit model EUROMOD (Sutherland and Figari, 2013), which is unique for its multi-country coverage. The model simulates disposable income for nationally representative samples of households under different tax-benefit scenarios and allows us to quantify the first-order effects of tax reforms on the household distribution and work incentives.

Our results generally confirm the equity-efficiency trade-off arising from flat tax reforms though also identify some exceptions. In particular, the Southern European countries are more likely candidates for such reforms. Chapter 1 extends previous empirical literature in two ways: first, by undertaking a systematic approach to assess the relationship between inequality and flat tax parameters, taking guidance from the theoretical insights; and second, by providing an indication of variability and robustness of results on the basis of cross-country evidence.

Chapter 2 and Chapter 3 approach income taxation from a different angle, by concentrating on the question how compliant people are with tax rules – a highly relevant issue to understand the efficacy of tax design. Given its concealed nature, tax non-compliance raises non-trivial challenges for its measurement and it is extremely difficult to provide hard evidence on its scale and incidence. This prompted Slemrod and Weber (2012) to make a call for new innovative empirical strategies to bring greater credibility to the applied work on tax compliance, despite numerous studies attempting to estimate the extent and patterns of tax non-compliance in the past. This is what both chapters aim to achieve by utilising a unique dataset, which links income survey data with tax records for Estonia, to estimate the extent and determinants of individual compliance behaviour. Estonia was the first country to introduce a flat income tax in Eastern Europe. Apart from historic curiosities, this also provides an advantage for the empirical estimation strategy as it allows us to set aside an important but highly endogenous factor – variation in marginal tax rates – and focus on various other household characteristics in a cross-sectional sample.

Chapter 2 and Chapter 3 are related and study the underreporting of employment income by contrasting information from multiple sources at the individual level, but differ for their econometric approach and the sample of interest (employees vs all workers). Chapter 2 proposes a novel econometric method to model income reporting to the tax authority and in the household survey jointly, in both cases allowing the observed values to differ from their underlying true values. The identification strategy is based on the assumption that public sector employees have no opportunities to hide their (public) employment income but are comparable to private sector employees in other respects. Chapter 2 connects the strands of literature on tax evasion and survey measurement error. In fact, linked datasets of a similar nature have been previously used in several measurement error studies (e.g. Kapteyn and Ypma, 2007) but assuming all register incomes to be truthfully reported. Research on tax compliance, on the other hand, is only starting to discover the potential of such information sources.

Chapter 3, in turn, extends and applies the well-known method of Pissarides and Weber (1989) that contrasts household incomes with expenditures. The method assumes that expenditures are accurately reported (in the survey) and have a robust relationship with household incomes. Unusual income-expenditure gaps therefore imply income underreporting. The downside of the method is a less efficient estimation strategy, focused on the aggregate level of non-compliance and offering fewer insights on factors or characteristics associated with non-compliance. Compared to Chapter 2, Chapter 3 extends the analysis to the self-employed, who are commonly assumed to be much less compliant than employees due to the lack of a third-party reporting mechanism. Whereas nearly all previous studies using this method have assumed that employees are fully compliant, I relax the assumption for private sector employees in line with Chapter 2. Furthermore, the method has been previously applied mainly to household survey data, implicitly assuming that household reporting behaviour is similar for tax and survey purposes, while the linked dataset allows me to test this explicitly in Chapter 3.

Findings in Chapter 2 and Chapter 3 consistently point to substantial underreporting of salaries and wages to the tax authority among private sector employees and the aggregate estimates are similar, despite the methodological differences. This challenges the common view in the literature that at most a very marginal proportion of taxes on employment income is evaded. Chapter 3 shows in addition that self-employment income is underreported to an even greater extent, which is in line with other studies. The results contribute to an extension of scarce empirical evidence outside the US and especially among the post-socialist countries.

Information on the prevalence and patterns of non-compliance helps us to understand better its nature and circumstances, which lead to income underreporting and can point to solutions to counterbalance such developments, among others, improving the targeting of tax audits. Tax avoidance and tax evasion have recently come under a very strong spotlight as governments seek ways to bolster public finances and increasingly recognise the financial and political cost associated with non-compliant individuals and corporations.

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Chapter 1

Effects of flat tax reforms in Western Europe*

*The essay is joint work with Andreas Peichl, at the time a PhD student at the University of Cologne, and part of it is based on work carried out during his research visit to the European Centre for Analysis in the Social Sciences (ECASS) at the Institute for Social and Economic Research (ISER), University of Essex, supported by the Access to Research Infrastructures action under the EU Improving Human Potential Programme. The essay has been published as Paulus and Peichl (2009) 'Effects of flat tax reforms in Western Europe', *Journal of Policy Modeling* 31: 620-636. The chapter is based on the published version, further extended with additional discussion and results.

1.1 Introduction†

One of the most striking economic policy developments of recent years has been the large number of countries adopting a flat personal income tax, i.e. broadly speaking a tax with a single positive marginal rate (with or without a tax-free threshold). Although the seminal proposal by Hall and Rabushka (1983, 1985) triggered a lively academic and political debate, before the mid-1990s only a few countries and territories had actually implemented a flat tax, most prominently Hong Kong and the Channel Islands. Since 1994, however, after its introduction in Estonia, many countries have followed suit. At the beginning of 2009, there were nearly thirty countries worldwide with flat tax systems, about half of which were situated in Eastern Europe. Whilst the implementation of such reforms is currently under discussion in several other countries, including many in Western Europe (see, e.g. Keen et al., 2008; Nicodeme, 2007), Iceland has been the only country in the region to adopt a flat tax. Considering the recent success of the flat tax in Eastern Europe, questions arise about whether there is scope for such a policy reform in Western Europe as well.

Potential gains associated with the flat tax include the simplification of tax filing, with proponents dreaming of a tax return fitting on a postcard (Hall and Rabushka, 1985) or a beer coaster (Kirchhof, 2003), which may well lower the costs of tax compliance and administration. By eliminating tax exemptions, distortions in the tax base are reduced.

† We use EUROMOD version C13. EUROMOD is continually being improved and updated and the results presented here represent the best available at the time of writing. We are indebted to all past and current members of the EUROMOD consortium for the construction and development of EUROMOD. This version of EUROMOD relies on micro-data from twelve different sources for fifteen countries. We use data from the European Community Household Panel (ECHP) User Data Base made available by Eurostat; the Austrian version of the EU-SILC made available by Statistik Austria; the Panel Survey on Belgian Households (PSBH) made available by the University of Liège and the University of Antwerp; the Income Distribution Survey made available by Statistics Finland; the public use version of the German Socio Economic Panel Study (GSOEP) made available by the German Institute for Economic Research (DIW), Berlin; the Greek Household Budget Survey by the National Statistical Service of Greece; the Socio-Economic Panel for Luxembourg (PSELL-2) made available by CEPS/INSTEAD; the Socio-Economic Panel Survey (SEP) made available by Statistics Netherlands through the mediation of the Netherlands Organisation for Scientific Research-Scientific Statistical Agency, and the Family Expenditure Survey (FES), made available by the UK Office for National Statistics (ONS) through the Data Archive. Material from the FES is Crown Copyright and is used by permission. Neither the ONS nor the Data Archive bear any responsibility for the analysis or interpretation of the data reported here. An equivalent disclaimer applies for all other data sources and their respective providers.

Also, flat taxes are believed to improve labour supply incentives and reduce tax evasion. The argument for improved compliance is perhaps weaker in developed countries, but it is often central to this kind of reform in developing and transition countries. These arguments point towards possible efficiency gains, in terms of more productive use of resources and increased employment, and potentially higher tax revenues and social welfare. On the other hand, the impact of flat taxes on the distribution of the tax burden may represent a serious drawback and could be the main reason limiting their spread in developed countries with a well established middle class.

However, in the discussion of the flat tax "a notable and troubling feature [...] is that it has been marked more by rhetoric and assertion than by analysis and evidence" (Keen et al., 2008, p. 713). For instance, only a few empirical studies have considered previous reforms in detail. The most attention has been paid to the Russian flat tax reform of 2001 and there is some evidence that it was associated with increased (voluntary) compliance (Gorodnichenko et al., 2009). It was also followed by significant real growth in personal income tax revenue, but there was no strong evidence that this was caused by the reform itself or by improved law enforcement, nor could any positive labour supply responses be identified (Ivanova et al., 2005). In another example, the 2004 reform in Slovakia, income tax revenues declined, however, in the longer term the reform is expected to bring efficiency gains from reduced distortions in the economy and improved incentives to work (Brook and Leibfritz, 2005; Moore, 2005). Furthermore, Saavedra et al. (2007) make a general claim on the basis of cross-country regression models that the flat tax reforms on average affect compliance positively but do not have a significant impact on revenues.

Given that flat taxes have not yet been implemented in Western countries, the potential effects of flat tax reforms in these countries have mainly been studied using simulation models. There have been several previous studies, usually focusing on a single country (see, e.g. Aaberge et al., 2000; Adam and Browne, 2006; Caminada and Goudswaard, 2001; González-Torrabadella and Pijoan-Mas, 2006; Kuismanen, 2000). Overall findings indicate that introducing a flat tax would redistribute in favour of high income households and enhance labour supply (incentives). However, we argue that this could be the outcome of specific parametric reforms rather than a universal feature of the flat tax. This is supported by the findings of Fuest et al. (2008) for Germany and Jacobs et al. (2007) for the Netherlands which show that a flat tax with a high basic allowance and a high rate has less harmful distributional effects than a flat tax with a low rate. However, only the low flat rate led to positive, albeit small, labour supply effects.

The aim of the chapter is to analyse the feasibility of the flat tax policy option for Western Europe, focusing on the distributional aspects which are likely to be more important than in Eastern Europe. We contribute to the existing empirical literature on flat tax reforms in two ways: first, by addressing explicitly the parameterisation of flat tax reforms, and second, by undertaking a comparative analysis of various flat tax designs for selected Western European countries. Davies and Hoy (2002) show that in the case of revenue neutral flat tax reforms there are two sets of critical parameter values: a lower bound of the flat tax rate below which income inequality is always higher compared to a given graduated rate tax, and an upper bound above which inequality is always lower. We rely on these theoretical insights to construct different hypothetical flat tax reform scenarios for which we analyse the distributional and incentive effects. We use EUROMOD, a tax-benefit microsimulation model for the EU countries, to compare the results across countries in a common framework. We also study the effects on polarisation, which can be used as an indicator of the strength of the middle class. We ask whether different combinations of flat tax rates and tax-free thresholds always have positive incentive effects and an adverse effect on the middle class. We concentrate on the short-term static effects assuming that these decide the political feasibility of a tax reform although there are possibly important long-term effects as well.[1]

Our analysis shows that in some cases a revenue neutral flat tax reform can increase income equality and improve work incentives, more often, however, there is an equity-

[1] People judge future gains and losses asymmetrically (see, e.g. Kahneman and Tversky, 1979). Starting from a reference point and given the same variation in absolute values, there is a bigger impact of losses than of gains (loss aversion). Furthermore, people prefer the status quo over uncertain outcomes in the future ("status-quo-bias", see Kahneman et al., 1991). Therefore, short-term losses can have a much stronger impact than (uncertain) future gains. Hence, the short-term effects presented here could be decisive.

efficiency tradeoff. We show that the selection of flat tax parameters and the specific welfare state regime play a key role for the results. Overall, our analysis contributes to explaining why flat taxes have not been politically successful in Western Europe so far and suggests that their implementation is more likely in Mediterranean welfare states with a rather small middle-class and high income polarisation.

The rest of Chapter 1 is organised as follows: Section 1.2 provides a discussion on the flat tax design. Section 1.3 describes EUROMOD and our reform scenarios. Section 1.4 illustrates the distributional effects in terms of inequality, polarisation, winners and losers and labour supply incentive effects. Section 1.5 concludes and discusses the policy implications of our analysis.

1.2 Flat tax design

A flat (income) tax implies that some sort of proportionality is embedded in the income tax system, i.e. incomes are taxed at the same (flat) rate independent of their level. Its design, however, can be very different. Most countries with a flat tax system apply different rates to personal and corporate income, although a common rate has become more popular, and usually, the tax rate does not vary for components of personal income. Tax systems which tax only capital income at a flat rate and levy a progressive rate schedule on labour income (e.g., those in Scandinavian countries) are usually not considered as flat but as dual income tax systems (see, e.g. OECD, 2006). For the tax base one can differentiate between concepts which allow tax concessions (allowances, credits, deductions) and those which do not. Strictly speaking, only a flat rate tax without any tax relief is a 'pure' flat tax as in this case the share of tax payments to income is constant for the whole income range. Such a proportional income tax has only been applied in Georgia and Bulgaria. In all other cases, the tax incidence on incomes is progressive as a single marginal tax rate is combined (at least) with a basic allowance. This is also the concept we focus on in this chapter. A further step towards overall flat tax incidence would be integrating income tax with other taxes and benefits, resulting in a negative income tax at low-income levels (see, e.g. Atkinson, 1995; de Jager et al., 1996).

An important aspect which has rarely been addressed in previous studies is the setting of tax system parameters for the ex ante analysis of hypothetical tax reforms. In our case we are interested in the relationship between flat tax parameters (flat tax rate and basic allowance) and distributional effects. Davies and Hoy (2002) show theoretically that the inequality of after-tax distribution of income is monotonically declining in the flat tax rate and the associated level of basic allowance which generates the same tax yield.[2] Furthermore, for revenue neutral tax reforms, which replace a graduated rate tax with a flat rate tax, they prove the existence of critical flat tax rates such that compared to the (existing) graduated rate tax after-tax income inequality is:

(i) higher (for any inequality index) with any flat tax rate equal to or below a lower bound,

(ii) lower (for any inequality index) with any flat tax rate equal to or above an upper bound,

(iii) the same for a given inequality index at a specific flat tax rate between the two boundaries.

These regularities apply to any inequality measure satisfying the Pigou-Dalton principle of transfers and under the assumption that behaviour is not affected by tax system changes. The lower bound corresponds to the flat tax rate which provides a revenue neutral solution if the basic allowance is kept at the same level as for the graduated rate tax. The upper bound corresponds to the flat tax rate which ensures that a person with the highest income pays the same tax under each scheme. In comparison to the graduated rate schedule, the lower and upper bound should lie between the lowest and highest graduated tax rate.

We rely on these theoretical insights to design our flat tax reform scenarios. However, these theoretical regularities are only approximations for empirical estimation because

[2] Note that as a flat tax schedule has only two parameters – marginal tax rate and basic allowance – it is possible to choose only one freely when imposing revenue neutrality.

existing tax systems are further complicated by the presence of other tax deductions and allowances. Some systems do not even have a (well-defined) basic allowance to start with. Moreover, the definition of revenue neutrality is not straightforward. If revenue neutrality is only limited to income taxes then it might not preserve the mean of the disposable income distribution, as there are often instruments whose eligibility or amount depend on net income after taxes (e.g., means-tested non-taxable benefits) and, therefore, might change their value when tax systems are modified. Furthermore, the premise of ex-ante revenue neutrality (i.e. without behavioural responses) is a rather strong assumption but it is necessary to follow the framework of Davies and Hoy (2002).

1.3 Flat tax simulations

1.3.1 EUROMOD: model and database

We use the microsimulation technique to simulate taxes, benefits and disposable income under different policy scenarios at the household level, on the basis of household micro-data from nationally representative income surveys. Simulation analysis allows conducting a controlled experiment by changing the tax-benefit parameters of interest while holding everything else – i.e. household population and their characteristics – constant. Therefore, the researcher does not have to deal with endogeneity problems when identifying the effects of the policy reform under consideration.

Simulations are carried out using EUROMOD, a static tax-benefit model for the EU countries, which was designed for comparative analysis. Through a common framework, which has a greater flexibility than typical national models to accommodate a range of different tax-benefit systems, it allows the comparison of countries in a consistent way. EUROMOD was originally built in the late 1990s, by a consortium of research institutions from each EU15 country with a good knowledge and expertise in their respective national tax-benefit system, and has been regularly updated since then. The tax-benefit systems included in the model have been validated against aggregated administrative statistics as well as national tax-benefit models (where available)[3], and the robustness checked through numerous applications (see, e.g. Bargain, 2007).

The model can simulate most direct taxes and benefits except those based on previous contributions as this information is usually not available from the cross-sectional survey data used as input datasets. Information on these instruments is taken directly from the original data sources (if available). EUROMOD assumes full benefit take-up and tax compliance, focusing on the intended effects of tax-benefit systems. Although tax compliance is an important aspect of flat tax reforms, we do not consider this here and limit our analysis to the first-order static effects.

The main stages of the simulations are the following. First, household micro-data containing information about households composition, socio-demographic characteristics and gross market incomes are read into the model. The model then constructs corresponding assessment units for each tax and benefit instrument, ascertains which units are eligible for that instrument and determines the amount of benefit or tax liability for each member of the unit. Finally, after all taxes and benefits in question are simulated, disposable income for each household is calculated. Disposable income includes all monetary incomes, except capital gains and irregular incomes. Aggregating household data allows for an analysis at the population (or at some intermediate) level. For further information on EUROMOD, see Sutherland (2001, 2007).

Our analysis is based on the 2003 tax-benefit systems, which is the most recent wave available in EUROMOD for the EU-15 (at the time of writing) but limited to ten countries: Austria (AT), Belgium (BE), Finland (FI), Germany (GE), Greece (GR), Luxembourg (LU), the Netherlands (NL), Portugal (PT), Spain (SP) and the United Kingdom (UK), excluding Denmark, France, Ireland, Italy and Sweden. The input datasets for these countries are summarised in Table 1.A.1 in Appendix 1.A. These are based on various household income or budget surveys (e.g. ECHP, GSOEP, FES), which have been transformed into a suitable format for the model. Where the original data source only

[3]For detailed information on the modelling and validation of each tax-benefit system, see EUROMOD Country Reports at http://www.iser.essex.ac.uk/euromod.

provides the net values of (market) incomes components, their corresponding gross values have also been imputed.[4] (Such net-to-gross conversions are typically done by reversing the tax rules.) The full samples of original surveys are retained, so that EUROMOD input datasets remain nationally representative. The sample sizes vary across countries from less than 2,500 to more than 11,000 households. All monetary variables are updated to the 2003 year using country-specific uprating factors, as the income reference period varies from 1999 to 2003.

1.3.2 Existing tax systems and reform scenarios

In relation to the widely used welfare state typology of Esping-Andersen (1990) and Ferrera (1996) our selection of countries provides at least one example for each welfare type: Continental (AT, BE, GE, LU, NL), Nordic (FI), Anglo-Saxon (UK) and Southern (GR, PT, SP). Indeed, the existing income tax systems in these countries are quite varied. As of 2003, all have graduated rate schedules with a number of tax brackets ranging from 3 (UK) to 16 (Luxembourg) and the highest marginal tax rate from 38% (Luxembourg) to around 55% (Finland, state and local rate combined). All schedules are piecewise linear except that of Germany which has a unique continuous function for tax rates at a range of income levels. All countries provide a general tax concession: seven countries in the form of a basic allowance, often integrated into the tax schedule (as a 0% bracket), the Netherlands and Portugal apply tax credits and Austria uses both elements. About half of the countries tax capital income together with other income while the rest tax it separately by applying a flat rate (of 15-30%). The countries also differ with respect to the unit of assessment. Again, half of them allow only individual taxation, four countries apply either optional or compulsory joint taxation, and one (Belgium) provides limited income sharing for married couples. Table 1.A.2 in Appendix 1.A summarises these characteristics.

In our flat tax reform simulations we modify the current income tax rules (i.e. the baseline) by replacing all existing personal income tax deductions, allowances and credits with a single personal allowance and the existing graduated rate schedule with a flat rate.

[4]Data transformations for each dataset are described in Data Requirement Documents (DRD).

We only keep refundable tax credits on the basis that these are equivalent to benefits.[5] In countries where capital income is currently taxed at a separate rate, we abolish this separate rate and include capital income in the flat tax base.

We re-calculate household disposable income after modifying tax parameters, while other policy parameters in the model (e.g. benefit rules) as well as household characteristics are kept constant. The estimated differences in household disposable income between the baseline and our counterfactual scenarios show the first-order (the so-called morning-after) effects of the flat tax reforms. We do not attempt to model possible behavioural reactions of individuals in the labour market or potential efficiency gains from increased employment, but do assess changes in effective marginal tax rates to reflect how much people's financial work incentives are affected. This means that market incomes and employment statuses in the reform scenarios are the same as in the baseline. Such static calculations are not necessarily restrictive for the purpose of estimating welfare changes, which can be approximated with income changes under certain conditions (especially when changes are small), consistent with the existence of behavioural responses (Bourguignon and Spadaro, 2006). On the other hand, when behavioural changes are expected to be very large, it may raise difficulties for estimating them correctly as resulting predictions could be outside currently observed patterns of labour supply for a large proportion of the sample. Large predicted changes (increases) in labour supply also highlight the role of labour demand as demand-side restrictions could limit the extent to which changes in supply lead to employment changes. Furthermore, as noted earlier, we draw on Davies and Hoy (2002) theoretical framework, which itself assumes that behaviour is unchanged.

Altogether, our reform scenarios have the potential to broaden the tax base, simplify the systems (due to fewer specific deductions) and make them more transparent. We do not attempt to harmonise tax bases across countries and we limit ourselves to personal income taxes, i.e. without modifying existing social insurance contribution schemes (SIC) or corporate income taxes (see, e.g. Agliardi and Agliardi, 2009). One could also carry

[5] Examples include the lone parent tax credit in Austria, the tax credit for families with school children in Greece, working mother tax credit in Spain and working tax credit and child tax credit in the UK.

out an exercise of simply flattening tax rate schedules without adjusting the tax base (see, e.g. Schwarz and Gustafsson, 1991), but this would result in higher revenue neutral flat tax rates due to retained exceptions, therefore, limiting gains for labour supply incentives.

We simulate the following three flat income tax scenarios for each country:

- S1: a revenue neutral flat rate with a basic allowance in the existing (or equivalent) amount,
- S2: a 10 percentage points higher flat rate compared to the first scenario and an increased tax allowance to preserve revenue neutrality,
- S3: a 20 percentage points higher flat rate compared to the first scenario and further increased tax allowance to preserve revenue neutrality.

All scenarios are revenue neutral with the total income tax revenue within $\pm 0.1\%$ limits of its baseline value. In terms of the Davies and Hoy (2002) approach, our first scenario should approximately correspond to the lower bound. Because of additional complexities discussed in Section 1.2 exact lower and upper bounds cannot be identified in a straightforward manner in practice. The ten and 20 percentage point higher tax rate under the second and the third scenario are chosen to provide a wide range of tax rates and cover roughly the existing brackets in order to explore the distributional effects in the likely range of the upper bound.

Figure 1.1 plots the flat tax rate under each scenario and the lowest and highest (positive) tax rate of the existing tax rate schedules. Because of revenue neutrality the tax allowance is not independent of the tax rate (see Table 1.A.3 in Appendix 1.A for corresponding values). There is notable variation in the flat tax rate under the first scenario (from 11.6 to 33.9 percent). This variation results from the combination of the underlying pre-tax income distribution and average effective tax burden under the existing system. This also affects the other two scenarios. However, it turns out that for most countries the range of flat tax rates under the three scenarios is sufficient to roughly match the range of existing tax rates. A notable exception is the Netherlands with a very wide range of graduated tax rates due to the integrated schedule of social insurance contributions and income tax (in the baseline). As expected, flat tax rates under the first scenario are above the lowest rates in the existing schedules with only Portugal having a slightly lower rate, which is possibly due to the elimination of additional tax allowances. Flat tax rates under the third scenario are around the previous highest marginal rates for six countries and below that for the rest.

[FIGURE 1.1 HERE]

1.4 Simulation results

A key aim of our analysis is to explore whether different combinations of tax rates and allowances always have positive incentive effects and an adverse effect on the middle class. We compare the results across countries, first focusing on the measures summarising the changes in the income distribution (e.g., inequality and polarisation). Next we consider redistributive effects in the form of the share of winners and losers. Finally, we analyse how effective marginal tax rates change.[6]

1.4.1 Inequality and polarisation

We compute distributional measures based on equivalised household disposable incomes.[7] Figure 1.2 presents income inequality as measured by the Gini coefficient for each scenario (the underlying values for the Gini coefficient and additionally for the Generalised Entropy measures are provided in Table 1.A.5 in Appendix 1.A). Already distinct differences between the countries in terms of disposable income inequality are noticeable in the baseline scenario and to some extent can be explained by the distribution of gross

[6] We limit the presentation of results in this chapter to the most important findings. More detailed results can be found in an earlier version of the paper (see Paulus and Peichl, 2008).

[7] We use the modified OECD equivalence scale which weights the household head with a factor of 1, household members aged 14 and older with 0.5, and under 14 with 0.3. The household net income is divided by the sum of the individual weights of each member (=equivalence factor) to compute the equivalent household income.

incomes. Two groups can be distinguished: inequality is rather high in Southern European countries (Greece, Portugal and Spain) and the UK, and rather low in Continental Europe (Austria, Germany and the Benelux countries) and Finland.

[FIGURE 1.2 HERE]

Introducing a revenue neutral flat tax increases inequality unambiguously under the first scenario (S1). In the second scenario (S2) inequality decreases relative to the baseline for Finland and the UK (depending on the inequality measure for the latter) and in the third scenario (S3) remains higher compared to the baseline only in Austria and Luxembourg. These differences between countries can be partly explained by different existing tax systems and the resulting distribution of tax payments. For instance, the effective average tax rate varies less across deciles in countries like Belgium, Finland and the UK, where inequality decreases.

The scenarios can be ranked according to the level of inequality as $I(S1) > I(S2) > (S3)$, and this ordering is stable when using different inequality indices (see Table 1.A.5). The fact that inequality levels in the third scenario are below or close to those in the baseline scenario show that corresponding flat tax rates are in the vicinity of the upper boundary.[8] However, recalling from Figure 1.1 that flat tax rates under the third scenario are in several countries very close to the existing highest statutory rates, the political feasibility of this scenario appears low.

An alternative way to compare the feasibility of introducing a flat tax reform in these countries from the distributional perspective is to consider flat tax rates required to achieve not only revenue neutrality but also to keep the inequality level constant (see Table 1.A.4 in Appendix 1.A). As suggested by Davies and Hoy (2002), such double-neutral flat tax rates are uniquely defined but specific to inequality measures (unlike the lower and the upper bound). Furthermore, Chiu (2007) theoretical analysis shows that double-neutral flat tax rates are increasing in the parameter α for the Generalised Entropy measures, $GE(\alpha)$, and this is indeed clearly the case for four countries (GR, NL, SP, UK). In

[8]Inequality in the third scenario is lower for those countries where the flat tax rate for this scenario is close or exceeds previous highest rate (GR, UK, GE, BE, FI), except LU, and additionally for PT.

another three countries (BE, FI, LU) it does not hold but this appears to be at least partly related to a few highly unusual observations, i.e. very low incomes (even negative) and very high incomes. For Austria, Germany and Portugal, the double-neutral tax rates for these inequality indices are very similar and produce no clear ranking among them. On the whole, the range of double-neutral flat tax rates across countries is quite stable for different inequality measures: from 27-28% to 45-52%. The continental countries (LU, BE, GE, AT) feature the highest double-neutral tax rate, while Portugal and the UK the lowest (as well as Finland with the $GE(2)$ measure). There is a clear negative correlation between the baseline level of inequality and the double-neutral flat tax rate: the higher the initial level of inequality, the lower the tax rate. This holds for all four inequality measures considered here. Overall, distributional concerns would seem limiting the scope for flat tax reforms as most of distribution-neutral flat tax rates are rather high by historical standards.[9]

To assess the importance of the middle class we calculate the polarisation index of Schmidt (2004).[10] Highly polarised income distribution implies a small middle class and a large gap between rich and poor. Like inequality, polarisation is high in the Southern European countries and the UK and low in Continental Europe and Finland, and it is decreasing over the scenarios (see Figure 1.3). Interestingly though, there is a relationship between the extent to which the baseline and alternative scenarios differ and the initial level of polarisation (with the exception of Finland and the UK): the lower the initial level of polarisation, the more pronounced are differences between the baseline and the flat tax scenarios.

[FIGURE 1.3 HERE]

[9] Lithuania used to have the highest tax rate (33%) among flat tax countries (see Nicodeme, 2007), before gradually lowering the rate down to 15% in 2006-2009.

[10] Schmidt (2004) creates a polarisation index which in analogy to the Gini index (Lorenz curve) is based on a polarisation curve for better comparability of the results and their interpretations. Generally speaking, polarisation is the occurrence of two antipodes. A rising income polarisation describes the phenomenon of a declining middle class resulting in an increasing gap between rich and poor. The proportion of middle income households is declining while the shares of the poor and the rich are both rising.

This pattern can be explained as follows: when introducing a flat tax, people around the median income face higher tax burdens, whereas low and especially high income households have higher after-tax incomes. The opposite effects on low and middle income households increase the homogeneity within the bottom half of the income distribution. The gains at the top of the distribution increase the heterogeneity between the bottom and the upper half. Both effects lead to higher polarisation. However, if polarisation is already high, the turning-point between gainers and losers occurs higher up in the income distribution. Therefore, fewer people at the top will gain and at the same time more people above the median will lose. This will decrease the homogeneity within the upper group as well as polarisation, counteracting the two polarisation increasing effects. The size of each effect depends on the marginal tax rate and the basic allowance. Therefore, it is a priori unclear if polarisation increases, decreases or remains constant. In our analysis, polarisation is increasing in the first scenarios for all countries (i.e. the first two effects dominate), but it remains practically constant for Greece and Portugal in the second scenario and for three more countries in the third scenario (i.e. the effects balance each other), while Finland and the UK show reduction in these scenarios (i.e. the third effect dominates).

1.4.2 Gainers and losers

The introduction of a revenue neutral tax reform always yields gainers and losers as different groups of taxpayers are affected in a different way by tax schedule flattening and tax base broadening. Figure 1.4 summarises gainers and losers[11] by presenting their share of the population. In the first scenario, there are significantly more losers than winners in every country. Belgium, Finland, Germany and the UK have about the same share of winners and losers in the second scenario; Germany and the UK along with Greece and Portugal also have the most people with unchanged income. In the third scenario, only Austria and Luxembourg still have more losers; Germany, the Netherlands and Portugal

[11]Individuals from households whose disposable income does not change more than 10 euros per month in either direction are regarded as unchanged.

have roughly the same share of those gaining and losing and most people in Greece still remain in the no-change category. Overall, the fraction of winners is increasing over scenarios for most countries (except for Austria, Germany and Greece). In all scenarios, the highest share appears in Belgium and Finland. If disposable income is chosen as the only criterion for an election decision, only the third flat tax scenario would be supported by a majority in most countries.

[FIGURE 1.4 HERE]

In the first scenario with the lowest flat tax rates the gains are solely concentrated in the top 1–2 deciles (extending also to the 7th and 8th decile in Belgium).[12] When increasing the marginal tax rate and basic allowance, low income households start gaining, but fewer high income households gain. Nonetheless, the very top of the distribution still gains in every scenario. The gains in mean disposable income increase (decrease) with flat tax parameters (i.e. marginal tax rate and basic allowance) for low (high) income households. In other words, the lower (higher) the flat tax parameters the higher (lower) are the gains for high income households. In most countries the relative losses in terms of disposable income are high (sometimes even highest) for middle income households in all scenarios. Given that these groups play usually an important role in the political process of a mature welfare state, these effects might explain why a flat tax is not very popular in Western Europe.

1.4.3 Work incentives: effective marginal tax rates

We now turn our attention to the effects of flat tax reforms on the effective marginal tax rates (EMTR) to gauge potential efficiency effects in the labour market. EMTRs reflect financial incentives to work more by quantifying how much of an additional unit of income is lost due to increased taxes or withdrawn (means-tested) benefits. Therefore, changes in effective marginal tax rates are also suggestive of distortions (i.e. substitution

[12] See Paulus and Peichl (2008) for the effect on mean disposable income by deciles. The range of changes is somewhat higher for the first (from -9.7% to +12.1%) and the third scenario (-13.1% to 8.0%) compared with the second scenario (-5.5% to 6.2%).

effects) in the labour supply caused by the tax-benefit system. If policy changes affect work incentive indicators little then it is likely that the changes in labour supply are also small.[13]

We calculate EMTRs for the working age population (those aged 18-64) with positive employment or self-employment income, increasing earnings of each individual in the household in turn by 3% while the change in all benefits and taxes (including social insurance contributions) is observed at the household level: $EMTR_i = 1 - \Delta Y_j / d_i$, where d_i is the increment of gross earnings for individual i and Y_j disposable income of household j to which this individual belongs.

The average EMTRs differ distinctively in the baseline scenario across countries (see Figure 1.5). This can be attributed to several factors such as, for example, the overall size of the government (and therefore the demand for public funds), the general tax mix (e.g., the importance of direct taxes and contributions compared to indirect taxes) as well as economic differences between the countries. Mediterranean countries with the lowest average EMTRs have rather low income levels as well as the lowest relative levels of income taxation and social insurance contributions, resulting in high inequality and polarisation of the income distribution. Finland and the UK which have higher EMTRs on average attribute much more importance to the income tax whereas social insurance contributions are relatively low. These social insurance contributions, however, play an important role in financing the Continental European welfare states where social insurance contributions are as high as income taxes and average EMTRs are highest (except for Luxembourg).

[FIGURE 1.5 HERE]

Effective marginal tax rates on average increase with (statutory) flat tax rates, although revenue is kept constant and, therefore, the scenarios can be ranked in the following way: $EMTR(S1) < EMTR(S2) < EMTR(S3)$. Flat tax rates required to attain revenue neutrality with existing personal allowances (first scenario) lower average EMTRs and improve labour supply incentives in all countries. Results for revenue neutral

[13] More precisely, the expected labour supply reactions of individuals would depend on their effective tax rates and labour supply elasticities.

flat rates necessary to keep the inequality levels close to their baseline values (second and third scenario) depend on the country, but the very fact that there are countries where incentives on average improve even with high flat tax rates (e.g., in Mediterranean and most Continental countries) is still remarkable. This can be explained on the one hand by the fact that even in the third scenario most of the flat tax rates are below the existing top marginal rates. On the other hand, higher basic allowance (compared to the status-quo) increases the share of people with zero tax liability.

Changes in the effective marginal tax rates are explored in further detail in Table 1.A.6 and Table 1.A.7 (Appendix 1.A). Table 1.A.6 shows the distribution of EMTRs, based on various percentile values. The first flat tax scenario (S1) makes generally the distribution of EMTRs more even (see Austria and Portugal, in particular) and the opposite characterises the third scenario (S3), which leads to more unequal and polarised distribution of work incentives (see e.g. Finland, Germany, Spain). Belgium and the UK stand out for the highest top EMTRs (95th percentile) – these are due to low-earners receiving means-tested benefits, and hence also little affected by alternative tax schedules. Note that the percentile values can refer to very different people if there is substantial re-ranking due to the reforms.

The ranking of individuals is preserved in Table 1.A.7, which provides median EMTRs by earnings decile group.[14] We see that EMTRs in the baseline are generally increasing in earnings, except at the very top part of the earnings distribution in countries where there is an upper limit on social insurance contributions or lower SIC rates at the top (Austria, Germany, Greece, Luxembourg). Compared to other countries, the profiles for existing systems are flatter in Belgium, the Netherlands and the UK. Under the flat tax scenarios, the corresponding profiles become visibly piece-wise linear and as such are generally much different from the baselines. (The two exceptions are S2 for Greece and S1 for the UK, which are relatively close to the baseline.) The upper end is again affected by caps on social insurance contributions and now being additionally visible for

[14]That is dividing the working age population (with positive earnings) into ten equal groups based on the ranking of their (gross) earnings.

the Netherlands, Spain and the UK. EMTRs for the bottom earnings decile groups differ between the reform scenarios reflecting the generosity of the tax allowance (i.e. the level at which EMTRs suddenly increase): the larger the tax allowance, the more earners face a zero (or a very low) effective marginal tax rate. Depending on the level of the flat tax allowance, EMTRs either increase for lower decile groups compared to the baseline where incomes become taxable (e.g. Austria), or decrease when the new tax threshold is high enough to exempt them completely (especially notable for Belgium and the UK), so that their tax liability falls despite the higher (statutory) flat tax rate. Therefore, lower earnings decile groups tend to gain with higher flat tax rate combinations. In the case of Portugal and Greece (scenario 3), the threshold is so high that EMTRs increase only from the 8th earnings decile group onwards. For the same reason, there are several cases where the change in the group median EMTR exceeds substantially the difference in flat tax rates between those scenarios (e.g. for the middle decile groups in Finland, Luxembourg, Spain and the UK). Large differences from the baseline also occur at the very top of the earnings distribution under low flat tax rates (e.g. the Netherlands and Portugal). Potential adjustments in labour supply behaviour are likely to be especially difficult to predict for groups which face such a major shift in work incentive indicators.

1.5 Conclusion and policy implications

Flat income taxes have become increasingly popular in Eastern Europe. However, this popularity has not yet reached the Western European countries, which have well-established middle classes. Using EUROMOD we provide a microsimulation analysis of various flat tax designs for selected Western European countries in a common framework. Our analysis shows that there are two mutually interdependent dimensions which are decisive for the outcome of flat tax reforms and, therefore, for their political feasibility: first, the flat tax design (i.e. parameters such as flat tax rate and tax-free threshold); and second, the context of the reform (i.e. the underlying income distribution and the institutional background). Table 1.1 summarises the results from our flat tax scenarios across countries.

[TABLE 1.1 HERE]

Different groups of countries can be identified according to the welfare state typology of Esping-Andersen (1990) and Ferrera (1996): in the Nordic and Anglo-Saxon countries inequality increases only in our first scenario. In the Southern European countries inequality increases also in the second scenario, whereas for Continental countries inequality increases in all three scenarios. Incentives improve in all countries in the first and second scenario (except for Finland and the UK) and additionally in the third scenario for Mediterranean and Continental countries. In conclusion, low parameter values that attain revenue neutrality also lower effective marginal tax rates and therefore improve labour supply incentives.[15] This, however, leads to more inequality and polarisation as low rates benefit mainly those with high incomes at the expense of low and middle income households. On the other hand, higher (revenue neutral) flat tax rates can keep the inequality levels unchanged, but in general imply strong disincentive effects.

Exceptions to this equity and efficiency trade-off include all Mediterranean and some Continental countries. A typical Mediterranean welfare state regime provides a rather low level of social security (comparable to the Anglo-Saxon countries) based on low levels of taxes and redistribution (see, e.g. European Commission, 2007). However, they also use Bismarckian social insurance principles providing contributory benefits which entitlement depends on the level of previously earned income (like in the Continental countries). Furthermore, emphasis is put on the role of the family as being a major part of the social care system. As a consequence of its design, the Mediterranean welfare state regime is characterised by high inequality and polarisation of the income distribution, which imply the lack of a well-established middle class. Therefore, the distributional effects of a flat tax reform that burdens the middle class are less severe than in countries with a more equal income distribution and the political feasibility of switching to a flat tax regime is higher.

[15]Note that higher incentives do not necessarily lead to higher labour supply but depend on the respective labour supply elasticities. However, recent studies for the Netherlands by Jacobs et al. (2007) and Germany by Fuest et al. (2008) analyse flat tax reforms similar to our first two scenarios and, in summary, they find an increase in labour supply (and inequality) with a low flat tax rate and allowance, whereas minimising changes in inequality results in negligible labour supply effects.

Note that our analysis focuses on revenue neutral flat tax reforms, while in practice they are usually not designed as such. If we allowed for a loss of tax revenue, implications for work incentives would be different and inequality would change as well. However, the choice of any particular non revenue-neutral scenario would be arbitrary and reduce the comparability of results across countries and with the existing tax systems. Revenue neutrality is also a necessary condition to follow the Davies and Hoy (2002) framework. We also limit ourselves to personal income tax, while acknowledging that this is only part of the tax mix. In particular, we have kept social security contributions unchanged, which represent an additional tax on labour. Moreover, we do not consider effects on investment and capital accumulation, human capital or compliance. When interpreting our results, one has to be aware of the fact that we consider static effects only. Flat taxes are also supposed to have positive dynamic efficiency and growth effects (see, e.g. Cassou and Lansing, 2004; Stokey and Rebelo, 1995), which might make increasing inequality acceptable. However, the short-term distributional effects analysed in this chapter are those most likely to be decisive for the political feasibility of a flat tax reform.

The policy implications of our analysis are the following. The effects of introducing a flat tax depend crucially on the details of the reform and the country under observation. In specific circumstances, there can be scope for a more equitable income distribution and the simultaneous improvement in work incentives. This is more likely for countries with highly polarised income distributions (e.g., the Mediterranean countries). The pattern that emerges suggests that (revenue-neutral) flat tax reforms will always increase the tax burden of the middle class and this is important from a political economy perspective. A strong and politically powerful middle class is a typical characteristic of many Western European countries and the adverse short-term distributional effects imply rather low chances that the flat tax will appeal to these countries. This may also raise doubts about the long-term persistence of the existing flat tax systems in Eastern Europe if middle classes become stronger: the median voter may want to change the present system because in comparison to a graduated tax rate structure it benefits the upper income brackets but burdens the middle of the income distribution. Furthermore, Keen et al.

(2008) have pointed out that the new governments in Eastern Europe may have used (low) flat tax rates as a signal for regime shift towards more market-oriented policies. Therefore, if such a reputation does not need to be acquired (e.g., in Western Europe), a flat tax might be also less appealing.

In summary, implementing a flat tax in Western Europe represents a major challenge in terms of convincing a majority of the population that an immediate redistribution in favour of the highest income deciles is an acceptable means to achieve (uncertain) future economic gains. However, a further movement towards lower (marginal) tax rates with broader tax bases in the form of dual income tax systems (where capital income is taxed at a flat rate and non-capital income at a progressive rate) may be more likely to be observed. This, however, could eventually lead to tax systems moving closer to linearity, albeit without an actual flat tax schedule.

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Figure 1.1: Simulated flat tax rates and existing lowest and highest marginal rate, %

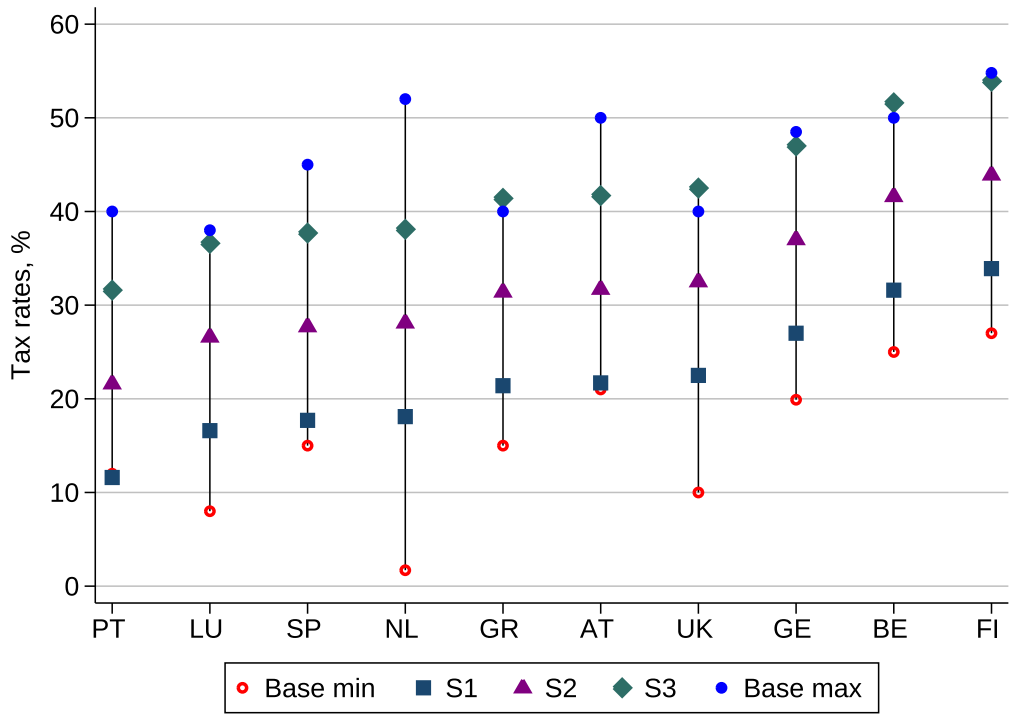

Figure 1.2: Income inequality by the Gini coefficient

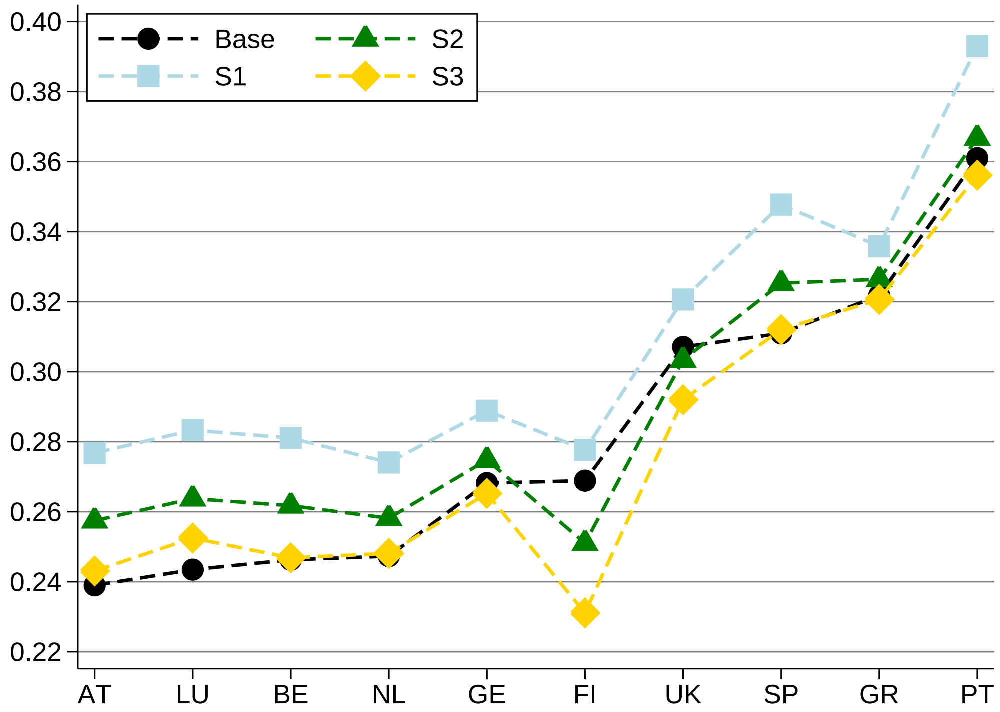

Figure 1.3: Polarisation by the Schmidt index

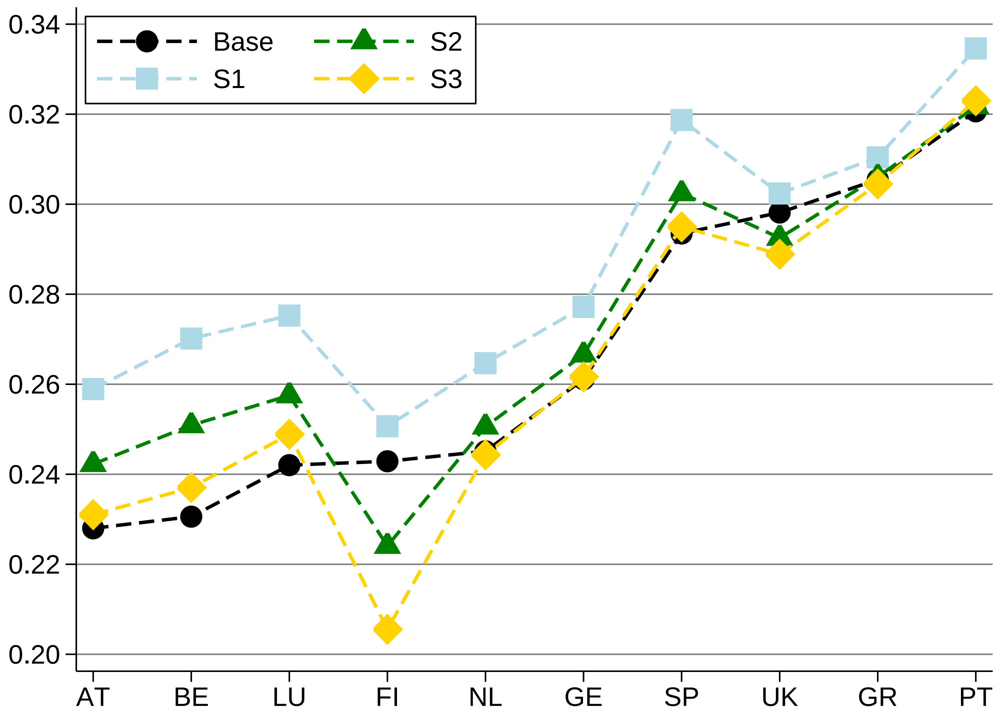

Figure 1.4: Share of gainers (at the top) and losers (at the bottom), %

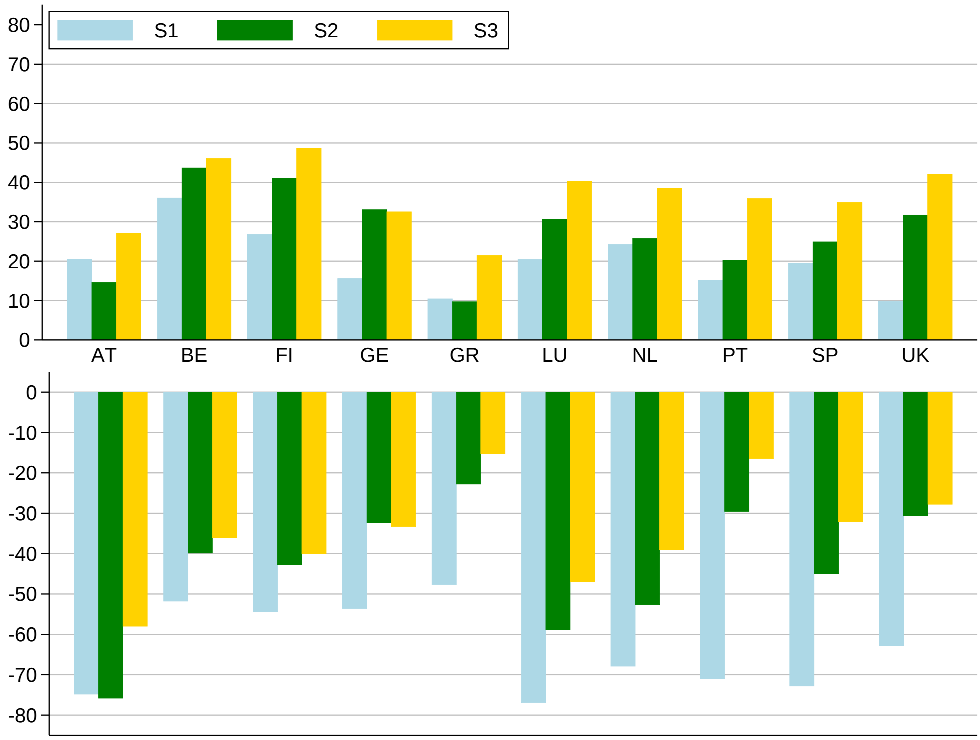

Figure 1.5: Mean effective marginal tax rates, %

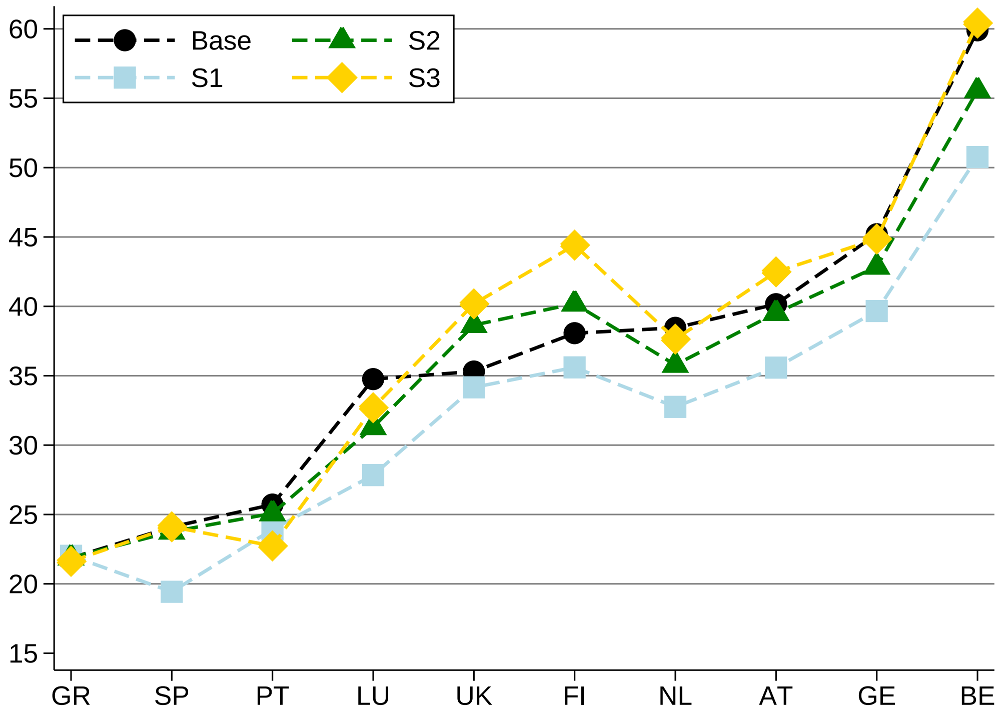

Table 1.1: Summary of simulation results

Country		Inequality			Polarisation			Labour supply incentives		
		S1	S2	S3	S1	S2	S3	S1	S2	S3
Continental	AT	+	+	+	+	+	+	+	+	−
	BE	+	+	∼	+	+	+	+	+	−
	GE	+	+	∼	+	+	+	+	+	+
	LU	+	+	+	+	+	+	+	+	+
	NL	+	+	∼	+	+	∼	+	+	+
Nordic	FI	+	−	−	+	−	−	+	−	−
Anglo-Saxon	UK	+	−	−	+	−	−	+	−	−
Southern	GR	+	+	−	+	∼	−	∼	∼	+
	PT	+	+	−	+	∼	∼	+	+	+
	SP	+	+	∼	+	+	∼	+	+	∼

Note: the symbols have the following meaning: ±: increase (decrease) ∼: no change (or ambiguous results). Scenario S1: low flat tax rate and basic allowance, S2/S3: medium/high parameters; all scenarios produce the same income tax revenue as in the baseline.

Appendix 1.A Supplementary tables

Table 1.A.1: EUROMOD input datasets (version C13)

Country	Dataset	No of households	Date of collection	Reference time period for incomes
AT	Austrian version of EU-SILC	4,521	2004	annual 2003
BE	Panel Survey on Belgian Households	2,975	2002	annual 2001
FI	Income distribution survey	10,736	2001	annual 2001
GE	German Socio-Economic Panel	11,303	2002	annual 2001
GR	Household Budget Survey	6,555	2004/5	annual 2003/4
LU	PSELL-2	2,431	2001	annual 2000
NL	Sociaal-economisch panelonderzoek	4,329	2000	annual 1999
PT	European Community Household Panel	4,588	2001	annual 2000
SP	European Community Household Panel	5,048	2000	annual 1999
UK	Family Expenditure Survey	6,634	2000/1	month in 2000/1

Table 1.A.2: Income tax systems, 2003

Country	No of brackets	Lowest (pos) rate	Highest rate	Form of the main tax relief	Capital taxation	Tax unit
AT	4	21%	50%	0% tax bracket, tax credit	flat tax (25%)	individual
BE	5	25%	50%	tax allowance	optional flat tax (15%)	some sharing
FI	5	state 12%, local 15%	state 35%, local 19.75%	0% tax bracket (state), tax allowance (local)	flat tax (29%)	individual
GE	4	19.9%	48.5%	0% tax bracket	integrated	optional joint
GR	3	15%	40%	0% tax bracket	integrated	individual
LU	16	8%	38%	0% tax bracket	integrated	joint
NL	4	1.7%	52%	tax credit	flat tax (30%)	individual
PT	6	12%	40%	tax credit	flat tax (20%)	joint
SP	5	15%	45%	tax allowance	integrated	optional joint
UK	3	10%	40%	tax allowance	one bracket reduced	individual

Table 1.A.3: Flat tax rates (FTR) and (yearly) basic allowances (FTA)

Country	Scenario 1 (S1)		Scenario 2 (S2)		Scenario 3 (S3)	
	FTR	FTA	FTR	FTA	FTR	FTA
AT	21.7%	3,640	31.7%	9,780	41.7%	13,750
BE	31.6%	5,570	41.6%	10,210	51.6%	13,470
FI	33.9%	5,800	43.9%	9,640	53.9%	12,590
GE	27.0%	7,235	37.0%	14,573	47.0%	19,612
GR	21.4%	8,400	31.4%	12,250	41.4%	15,213
LU	16.6%	9,750	26.6%	21,586	36.6%	29,236
NL	18.1%	9,000	28.1%	16,332	38.1%	21,120
PT	11.6%	1,770	21.6%	6,963	31.6%	11,064
SP	17.7%	3,400	27.7%	9,355	37.7%	13,535
UK	22.5%	4,615	32.5%	10,000	42.5%	13,765

Notes: S1-low flat tax rate and basic allowance, S2/S3-medium/high parameters; all scenarios produce the same income tax revenue as in the baseline. Basic allowance is shown in pounds for the UK and in euros for other countries.

Table 1.A.4: Revenue and inequality-neutral flat tax rates by inequality measure, %

Country	Gini	GE(0)	GE(1)	GE(2)
AT	44.4	45.5	44.7	45.2
BE	50.0	48.4	45.4	40.7
FI	34.2	33.5	32.4	27.0
GE	44.8	45.2	45.2	45.7
GR	37.5	36.9	38.2	38.7
LU	52.2	50.2	47.9	45.7
NL	35.3	35.1	38.6	42.3
PT	28.6	28.7	28.7	28.3
SP	38.7	38.8	39.5	40.9
UK	29.9	30.6	32.5	35.3

Notes: $GE(\alpha)$ denotes Generalised Entropy inequality measure.

Table 1.A.5: Income inequality and polarisation in the baseline and the flat tax scenarios

		Gini	GE(0)	GE(1)	GE(2)	PS
AT	base	0.239	0.095	0.102	0.131	0.228
	S1	0.277	0.127	0.143	0.211	0.259
	S2	0.257	0.110	0.122	0.172	0.242
	S3	0.243	0.099	0.106	0.141	0.231
BE	base	0.246	0.108	0.116	0.196	0.231
	S1	0.281	0.128	0.142	0.237	0.270
	S2	0.262	0.112	0.121	0.189	0.251
	S3	0.247	0.101	0.105	0.150	0.237
FI	base	0.269	0.127	0.175	0.587	0.243
	S1	0.278	0.134	0.186	0.618	0.251
	S2	0.251	0.112	0.151	0.452	0.224
	S3	0.231	0.096	0.122	0.315	0.206
GE	base	0.268	0.119	0.120	0.141	0.261
	S1	0.289	0.137	0.144	0.183	0.277
	S2	0.275	0.125	0.128	0.156	0.267
	S3	0.265	0.117	0.117	0.136	0.262
GR	base	0.322	0.191	0.175	0.209	0.305
	S1	0.336	0.205	0.198	0.258	0.310
	S2	0.326	0.195	0.183	0.228	0.306
	S3	0.321	0.189	0.173	0.205	0.304
LU	base	0.243	0.094	0.099	0.117	0.242
	S1	0.283	0.127	0.139	0.178	0.275
	S2	0.264	0.110	0.119	0.149	0.258
	S3	0.252	0.101	0.107	0.129	0.249
NL	base	0.247	0.103	0.102	0.119	0.245
	S1	0.274	0.126	0.132	0.174	0.265
	S2	0.258	0.113	0.116	0.148	0.251
	S3	0.248	0.105	0.105	0.128	0.244
PT	base	0.361	0.211	0.229	0.313	0.321
	S1	0.393	0.250	0.282	0.416	0.335
	S2	0.367	0.218	0.240	0.337	0.322
	S3	0.356	0.206	0.220	0.292	0.323
SP	base	0.311	0.177	0.167	0.210	0.293
	S1	0.348	0.216	0.216	0.315	0.319
	S2	0.325	0.191	0.188	0.260	0.302
	S3	0.312	0.178	0.169	0.221	0.295
UK	base	0.307	0.153	0.166	0.235	0.298
	S1	0.321	0.167	0.189	0.302	0.302
	S2	0.303	0.151	0.166	0.248	0.293
	S3	0.292	0.140	0.149	0.206	0.289

Notes: $GE(\alpha)$ denotes Generalised Entropy inequality measure and PS the Schmidt polarisation index.

Table 1.A.6: Effective marginal tax rates (%): percentiles and the mean

		p5	p10	p25	p50	p75	p90	p95	mean
AT	base	0.0	17.5	37.7	41.0	47.8	49.5	53.4	40.2
	S1	21.6	21.6	35.0	35.4	35.8	35.8	41.9	35.6
	S2	0.0	17.5	33.4	43.6	44.0	44.0	49.3	39.5
	S3	0.0	17.5	18.1	51.7	52.2	52.2	56.7	42.5
BE	base	32.6	43.9	49.9	51.0	55.3	58.6	100.0	59.9
	S1	31.6	39.2	39.2	40.5	40.5	50.6	100.0	50.8
	S2	13.1	41.6	48.1	49.2	49.2	53.1	100.0	55.6
	S3	13.1	13.1	56.9	57.9	57.9	61.1	100.0	60.4
FI	base	0.0	4.6	29.0	43.4	46.7	51.9	56.9	38.1
	S1	0.0	4.6	38.4	39.6	39.6	39.6	44.6	35.6
	S2	0.0	4.6	45.9	49.2	49.2	49.2	50.6	40.2
	S3	0.0	4.6	9.4	58.7	58.7	58.7	58.7	44.4
GE	base	1.8	19.3	36.4	50.0	54.0	59.5	64.4	45.2
	S1	0.8	3.5	28.5	46.0	49.0	52.6	64.6	39.7
	S2	0.0	1.8	21.0	49.9	59.0	60.0	65.7	42.9
	S3	0.0	1.8	21.0	49.6	68.8	70.6	70.6	44.9
GR	base	0.0	0.0	14.4	19.4	39.8	41.4	43.6	21.9
	S1	0.0	0.0	16.0	21.4	34.1	36.7	36.7	22.0
	S2	0.0	0.0	0.0	19.4	33.3	42.5	44.7	21.9
	S3	0.0	0.0	0.0	19.4	41.4	50.9	50.9	21.6
LU	base	11.7	13.9	22.6	35.5	44.6	46.5	47.8	34.8
	S1	11.7	18.0	26.8	26.9	28.7	28.7	37.1	27.8
	S2	11.7	11.7	13.9	35.9	36.0	37.6	44.4	31.3
	S3	11.7	11.7	13.9	38.5	45.2	46.6	50.4	32.7
NL	base	1.7	25.4	35.0	45.4	46.3	52.0	55.5	38.5
	S1	1.7	18.1	22.9	33.3	51.6	51.6	61.7	32.8
	S2	1.7	24.2	28.1	32.3	57.8	58.5	60.6	35.8
	S3	1.7	24.2	33.3	39.0	42.4	65.5	65.5	37.6
PT	base	7.8	11.0	11.0	23.0	35.0	45.0	45.0	25.7
	S1	11.0	11.0	21.3	21.3	23.2	31.6	31.6	23.9
	S2	10.6	11.0	11.0	21.6	30.2	49.4	49.4	25.1
	S3	0.0	11.0	11.0	11.0	39.1	39.1	67.2	22.7
SP	base	0.0	0.0	18.4	28.8	32.6	37.0	37.0	24.1
	S1	0.0	17.6	17.6	22.9	22.9	22.9	22.9	19.4
	S2	0.0	0.0	27.6	27.6	32.2	32.2	32.2	23.8
	S3	0.0	0.0	6.3	37.6	41.6	41.6	41.6	24.1
UK	base	17.8	23.0	31.4	31.4	37.0	58.0	70.0	35.3
	S1	22.5	23.5	30.5	31.9	33.5	67.5	70.5	34.2
	S2	4.6	9.4	33.5	41.9	43.5	48.0	78.9	38.7
	S3	0.0	9.4	11.0	49.2	51.9	53.5	68.8	40.2

Notes: pX denotes the Xth percentile.

Table 1.A.7: Median effective marginal tax rates (%) by earnings decile group

		1	2	3	4	5	6	7	8	9	10
AT	base	0.0	18.1	38.3	40.0	40.4	42.1	41.0	48.1	49.2	42.6
	S1	21.6	35.8	35.8	35.8	35.8	35.4	35.4	35.4	35.4	22.0
	S2	0.0	18.1	43.6	44.0	44.0	43.6	43.6	43.6	43.6	31.9
	S3	0.0	18.1	18.1	51.9	52.2	51.9	51.9	51.9	51.9	41.9
BE	base	39.4	48.1	55.3	55.8	51.0	51.0	50.8	51.0	54.2	55.2
	S1	40.5	40.5	40.5	40.5	40.5	40.5	40.5	40.5	40.5	40.5
	S2	13.1	49.2	49.2	49.2	49.2	49.2	49.2	49.2	49.2	49.2
	S3	13.1	15.9	57.9	57.9	57.9	57.9	57.9	57.9	57.9	57.9
FI	base	4.6	18.6	26.2	39.0	40.4	45.4	45.7	45.7	50.4	51.6
	S1	4.6	39.6	39.6	39.6	39.6	39.6	39.6	39.6	39.6	39.6
	S2	4.6	4.6	49.2	49.2	49.2	49.2	49.2	49.2	49.2	49.2
	S3	4.6	4.6	4.6	58.7	58.7	58.7	58.7	58.7	58.7	58.7
GE	base	3.5	30.3	44.2	51.1	50.9	52.6	54.3	54.6	50.3	50.7
	S1	1.8	20.1	43.5	52.6	49.5	48.8	47.7	47.1	40.4	28.5
	S2	1.8	3.5	21.0	42.2	60.0	59.4	58.3	57.7	51.0	39.0
	S3	1.8	3.5	21.0	21.0	63.7	69.9	68.8	68.2	61.5	49.6
GR	base	0.0	0.4	16.0	16.3	16.2	19.4	30.0	41.2	40.0	40.0
	S1	0.0	0.0	16.0	19.4	34.0	34.0	34.1	34.1	31.8	21.4
	S2	0.0	0.0	16.0	16.0	16.0	19.4	42.5	42.5	40.5	31.4
	S3	0.0	0.0	16.0	16.0	16.0	16.2	16.2	50.8	49.1	41.4
LU	base	13.9	20.2	24.6	28.2	33.6	39.1	46.3	46.4	46.4	40.0
	S1	11.7	28.7	28.7	26.9	26.9	26.9	26.9	26.9	26.9	18.0
	S2	11.7	13.9	13.9	36.0	36.0	36.0	36.0	36.0	36.0	28.3
	S3	11.7	13.9	13.9	13.9	13.9	45.2	45.2	45.2	45.2	38.5
NL	base	35.0	35.0	25.4	46.3	46.3	46.3	45.4	45.4	44.2	52.0
	S1	33.3	33.3	39.4	51.6	51.6	51.6	23.3	22.9	19.9	18.1
	S2	33.3	33.3	24.2	51.6	58.5	58.5	32.8	32.3	29.7	28.1
	S3	33.3	33.3	24.2	39.0	39.0	65.5	42.3	41.7	39.4	38.1
PT	base	11.0	11.0	23.0	23.0	23.0	25.0	25.0	35.0	35.0	44.6
	S1	11.0	21.3	21.3	21.3	21.3	21.3	21.3	21.3	21.3	21.3
	S2	11.0	11.0	11.0	11.0	20.0	30.2	30.2	30.2	30.2	30.2
	S3	11.0	11.0	11.0	11.0	11.0	11.0	11.0	39.1	39.1	39.1
SP	base	0.0	6.3	20.4	28.8	28.8	28.8	28.8	32.6	32.6	37.0
	S1	0.0	17.6	22.9	22.9	22.9	22.9	22.9	22.9	17.6	17.6
	S2	0.0	0.0	6.3	32.2	32.2	32.2	32.2	32.2	27.6	27.6
	S3	0.0	0.0	6.3	6.3	29.2	41.6	41.6	41.6	37.6	37.6
UK	base	18.0	31.4	31.4	31.4	31.4	31.4	31.4	31.4	29.7	41.0
	S1	22.5	33.5	31.9	31.9	31.9	31.9	31.9	31.9	23.5	23.5
	S2	6.7	11.0	41.9	41.9	41.9	41.9	41.9	41.9	33.5	33.5
	S3	0.0	11.0	9.4	11.0	51.9	51.9	51.9	51.9	43.5	43.5

Notes: decile groups are based on individual gross earnings of the working age population (with positive earnings).

Chapter 2

Tax evasion and measurement error

2.1 Introduction*

Income tax evasion, i.e. a deliberate act of non-compliance with legal requirements to disclose income (obtained by legal means) to tax authorities in order to reduce tax liability, undermines the intended effects of a tax by eroding the tax base and altering the distribution of tax burden among individuals. It also affects labour supply (and demand) behaviour by introducing an additional choice margin in the form of undeclared work as opposed to declared work and, hence, can distort the allocation of economic resources. Furthermore, it increases the costs for the society to enforce tax rules.[1] On the other hand, tax evasion may have not only negative consequences, e.g. (partly) undeclared work could provide the only employment option for the most vulnerable. For this reason and because enforcement is costly, it is neither optimal nor feasible to eliminate tax evasion completely. However, to design optimal tax and enforcement rules one needs to know who evades taxes, their reasons for doing so and the extent of non-compliance.

The main constraint for empirical research on tax evasion is, unsurprisingly, the lack of suitable data, this being especially pronounced for developing countries. To study and explain income tax evasion at the micro-level, one would essentially need a measure of undeclared income for individuals. This kind of data are usually unreliable and very difficult and/or expensive to obtain. There are two main sources: audited tax reports and surveys from which the incidence and the degree of tax evasion can be inferred either directly or indirectly. An alternative to the actual income data is to rely on laboratory experiments. Each of these has its own advantages and disadvantages, which will be explained in more detail in the next section.

As various data sources can complement each other, a combination of them has potential to provide more exhaustive information about non-compliance. In particular, combining survey income data with tax records at the *individual* level offers new possibilities

*The chapter uses the 2008 wave of Estonian Social Survey linked with administrative tax records and made available by Statistics Estonia.

[1]As Shaw et al. (2010) emphasise, enforcement is a true resource cost to a society and it does not produce any resource gains because any resulting increase in tax revenues is a transfer from private citizens.

to study tax evasion. Matching and linking such information is usually very restricted due to privacy concerns and indeed, to the author's knowledge, the only study so far using such data to estimate tax evasion is by Baldini et al. (2009). They compare the two income measures and assuming that people report their true income in the survey, obtain a measure of non-reporting. However, the survey data can often contain notable measurement errors (which they acknowledge but do not deal with in their analysis). In fact, there have been several studies in the measurement error literature[2], which assume that administrative data are error-free and hence differences between survey income and income from the tax records are due to survey measurement error alone, and analyse its determinants, e.g. Bound and Krueger (1991) and Bollinger (1998).[3] Later studies have started to relax this assumption by considering matching errors (Kapteyn and Ypma, 2007; Meijer et al., 2012) or errors in register data (Abowd and Stinson, 2013), but have not attempted to assess the scale and nature of error in administrative data, let alone tax evasion as a possible source.

Chapter 2 provides estimates of the pattern and determinants of tax evasion based on a unique dataset combining a household income survey and tax records for Estonia. The main research questions are: (1) Which individual characteristics contribute to evading taxes on wages and salaries? (2) What is the extent and distribution of undeclared income? Unlike earlier studies attributing income discrepancies between different data sources either to tax evasion or survey measurement error, here both reporting processes are modelled in a joint framework. Focusing on employment income, the key assumption made is that measurement error is unrelated to the sector where the individual works while the same does not hold for tax compliance. Specifically, it is assumed that taxes cannot be evaded in the public sector. This assumption provides some parallels with the methodology pioneered by Pissarides and Weber (1989), where underreported income for

[2]See Bound et al. (2001) and Chen et al. (2011) for surveys of this literature (in economics).

[3]The linked administrative data (referred to as validation data in this literature) could also originate from other sources. For example, Duncan and Hill (1985) and Bound et al. (1994) are based on linked survey and employer reports. Apart from limited representativeness due to a small single firm sample characterising these two examples, there is also an important conceptual difference for studying tax compliance – the information what employers have reported in the validation study is not necessarily identical with that reported to the tax authority.

one population group (like self-employed) is inferred from a comparison with a reference group (e.g. employed), which is assumed to have negligible non-compliance but to be similar in other respects. In addition to different data strategy and econometric model, the assumption used in this study is, arguably, less restrictive as it considers the possibility that (private sector) employees engage in tax evasion as well. Furthermore, Pissarides and Weber (1989) type of studies have assumed implicitly that the underreporting of income in a survey corresponds to the underreporting of income to the tax authority, which is not required here.

We use the Estonian Social Survey, which is the basis for the Estonian component of the European Union Statistics on Income and Living Conditions (EU-SILC) survey, linked to tax records for 2007. As the underlying data linkage has been carried out (legitimately) without the requirement for consent by the survey respondents, this allows us to retain all relevant sample and, more importantly, avoid potential selection biases, which can arise from the consent decision (see e.g. Sakshaug and Kreuter, 2012). This is the main problem for data linkages as they often require respondents' agreement beforehand. For example, previous evidence suggests that consenting can be correlated with income (Jenkins et al., 2006) and as it is conceivable that the consent decision for linking tax records could be influenced by the tax compliance behaviour as well, it is crucial to avoid such sample restrictions.

The chapter extends the empirical tax evasion literature in several ways. First, it proposes a novel econometric model to analyse tax evasion, taking into account potential survey measurement error. As far as the author is aware of, this is the first such attempt. Second, it provides new evidence on non-compliance in a post-socialist country, which extends the rather limited empirical literature on countries other than the US. Third, it studies specifically tax non-compliance related to wages and salaries which has received less attention in the literature, for example, compared to self-employment income.

The estimates show that compliance is associated with a number of socio-demographic and labour market characteristics. Overall, people in the bottom and the top part of earnings distribution are found much less compliant. The results indicate substantial non-reporting of wages and salaries, mainly in the form of partial rather than full evasion. This highlights that third party reporting and tax withholding, which this income source is subject to, have limitations and suggests that tax audits might be less effective in revealing true wages and salaries than previously thought.

The chapter is structured as follows. The next section gives an overview of the relevant tax compliance literature, focusing on previous theoretical and empirical findings on the individual characteristics associated with tax evasion. Section 2.3 provides information on the main aspects of the Estonian income taxes and their administration. Section 2.4 presents the econometric model used to estimate jointly tax compliance and survey measurement error. Section 2.5 gives an overview of the data sources, their linkage and summarises earnings information. Section 2.6 presents and discusses findings, in terms of who is more likely to evade income taxes as well as the extent and pattern of non-compliance, and tests the robustness of results through sensitivity checks. The last section concludes with some policy implications and suggestions for further extensions.

2.2 Related literature

We first review previous work which has provided insights into the factors influencing income tax compliance, both in the form of theoretical predictions and empirical evidence. The focus here is on individuals rather than firms or the tax authority. For more comprehensive recent reviews, see Andreoni et al. (1998), Alm (1999), Slemrod and Yitzhaki (2002), Sandmo (2005), Shaw et al. (2010), Alm (2012), Hashimzade et al. (2013), Pickhardt and Prinz (2014).

2.2.1 Theoretical work on tax evasion

The economic theory of tax evasion has evolved over the past 40 years starting with the seminal paper by Allingham and Sandmo (1972), who provided a relatively simple framework for analysis, but demonstrated the complexity of the subject as they could provide clear predictions only in certain dimensions. Theoretical models have advanced significantly since then, however, as Alm (2012) points out, more complex approaches tend to yield more ambiguous results. For this reason, we start from the standard model.

In the Allingham-Sandmo (A-S) paper, a risk-averse individual maximises expected utility by choosing how much income to report to the tax authority. While non-compliance reduces tax liability (levied at the proportional rate), the individual would have to pay a fine (proportional to the non-reported income) if this was detected. This so-called deterrence model predicts that evasion is decreasing in the probability of detection and the penalty rate but gives ambiguous results in other aspects. The effect of an increase in total income on the fraction of income reported depends on relative risk aversion: the effect is positive (constant or negative) if relative risk aversion is increasing (constant or decreasing). Assuming decreasing absolute risk aversion, which has been generally accepted since then, it can be further shown that the *level* of underreported income increases with total income and that more risk-averse individuals would evade less (Cowell, 1990). An increase in the tax rate has an ambiguous effect on evasion.[4] In a similar model, Srinivasan (1973) analysed generic tax and penalty schedules with a risk-neutral individual and showed that evasion decreases as the probability of detection increases. The effect of an increase in total income on the proportion of income reported depends now on the nature of the tax schedule and the probability of detection: it decreases with a progressive tax if the probability of detection is independent of income, while it increases with a proportional tax if the probability of detection is an increasing function of (total) income.

While the A-S model has been criticised for various reasons, it has remained central in economic analysis with much of the theoretical work maintaining a focus on the rational agent making his decision on the basis of a cost-benefit analysis. The main weakness of the original model is that it seems to predict much lower compliance than the empirical evidence suggests[5] and various additional factors have been proposed to explain

[4]Yitzhaki (1974) pointed out that if instead the penalty is proportional to the evaded *tax* then, surprisingly, a tax increase has a positive effect on compliance (if the individual has decreasing absolute risk aversion).

[5]See Alm (1999) and Slemrod and Yitzhaki (2002) for numeric illustrations.

this, for example, the differences between actual and perceived probabilities of auditing, third party reporting and non-pecuniary costs. The standard economic analysis of tax compliance has also been criticised in other disciplines for overlooking legal issues, e.g. Graetz and Wilde (1985), and for taking taxpayer's motivation as given, e.g. Weigel et al. (1987). Indeed, its focus is mainly on enforcement activities – as Alm (1999) stressed, a person would *only* pay taxes because of the fear of detection and punishment with this approach.

Further theoretical work starting with Andersen (1977) and Pencavel (1979) extended the A-S framework with endogenous income where the individual decides jointly with compliance his labour supply. The relationship between the key parameters and evasion, however, becomes even less straightforward in this case. Nevertheless, one relevant insight for our purposes is from Cowell (1985) who points out that one form of cheating involves taking additional jobs. One strand of the subsequent literature focused on the interactions with the tax authority[6], which in general is outside the scope of interest here as they offer little insights on individual characteristics relevant for compliance. Among a few exceptions is a study by Erard and Feinstein (1994) who confirm with a game-theoretic model that evasion (in general) increases with total income. There is also a useful hint on firm characteristics: Kleven et al. (2009) show that in the presence of third-party reporting, it is optimal for large firms to comply fully.

A relatively recent part of the literature considers more realistic behavioural elements like various forms of non-expected utility and social interactions, though the focus often remains on enforcement parameters. See Hashimzade et al. (2013) for a detailed discussion. This branch has considered additional factors such as different subjective costs (feeling guilty or ashamed, stigma, damage to reputation), which can explain why there seem to be fewer non-compliant people than the standard model predicts. While the extent of evasion depends on the utility function in the A-S model, the condition for compliance is determined solely by the audit risk, tax and penalty rate. Adding nonpe-

[6]Two main approaches rely on principal-agent and game-theoretic models. See Andreoni et al. (1998) for a detailed discussion.

cuniary costs to the utility function makes this condition more restrictive, as pointed out by Allingham and Sandmo (1972) themselves[7] and later by Gordon (1989) and Sandmo (2005). The decision to comply is then affected by the extent of disutility from cheating, which naturally varies between individuals. However, these unobservable parameters are difficult to test empirically.

In this chapter, we focus on the association between tax evasion and total income. As explained above, the theory tends to suggest that evasion (in absolute amount) increases with income, while it is inconclusive about the proportion of income evaded. This has great political importance as, for example, if people with higher income were more likely to evade taxes on larger proportions of their income, this would raise important questions about the fairness of tax system. Given the nature of the dataset used (more in Section 2.5), we will not be able to test the effect of risk preferences and enforcement parameters on compliance as these are not observed directly. The probability of auditing/detection is likely to vary, for example, with industry (and occupation) and this we can control for but we have no detailed information about the actual auditing strategy. Furthermore, what is likely to be more important is the *perceived* probability of getting caught.

Due to the flat income tax in Estonia (more in Section 2.3), there is also very little variation in the marginal effective tax rates in the cross-sectional data which does not allow studying their effect on compliance. On the other hand, this can be also a useful feature as it allows us to set aside a component which is generally difficult to identify due to endogeneity.

The broad set of socio-demographic information available in our dataset allows us to identify which personal characteristics are associated with tax compliance. While economic theory remains rather vague in this context, one useful framework has been suggested in the psychology literature by Weigel et al. (1987) where tax evasion behaviour is influenced by social and psychological (or personal) factors. In both cases, they further distinguish between two groups of factors: those instigating tax evasion behaviour

[7]This together with other extensions in their paper – endogenous probability of detection and a dynamic case – seem surprisingly often overlooked in the later literature.

and those that constrain it. Social norms are given as an example of social instigations, while financial difficulties and perceived unfairness of tax laws and authorities are part of personal instigations; access to cash receipts for a given occupation and tax enforcement, among else, operate as social constraints, while the perceived risk of punishment and attitudes towards evasion represent personal constraints. This provides some useful guidelines for selecting specific variables in the econometric model.

2.2.2 Empirical work on tax evasion

We now turn to the empirical literature on tax evasion, retaining the focus on individual. We limit our attention further to studies utilising individual-level income data, grouping these by the type of data source used: audits, surveys and experiments.

Audited tax records

Audited tax returns are considered to offer the most reliable information on tax compliance (Andreoni et al., 1998; Feldman and Slemrod, 2007). On the grounds of cost-efficiency, audits are typically non-random as the cases are already selected based on some predictions of which individuals are more susceptible of evasion, making it difficult if not impossible to generalise findings to the wider population. To overcome this problem, there have been also randomised audits carried out in some countries. These have been most extensive and regular in the US in the form of the Taxpayer Compliance Measurement Program (TCMP) in 1965-88 and the National Research Program (NRP) since 2001.[8] The individual-level data from these audits have been used in several papers, typically regressing the difference between reported income and actual income as established on the basis of an audit against variables such as the marginal effective tax rate, total true income, presence and proportion of particular income sources and the limited socio-demographic information that is available from tax reports (e.g. age group, marital status, region). The first study was by Clotfelter (1983) whose primary interest was the effect of marginal tax rates on evasion. This has been followed with extensions including partial detection (Feinstein,

[8] For an overview of US studies, see Slemrod (2007).

1991), the role of tax practitioners (Erard, 1993, 1997), non-filers (Erard and Ho, 2001) and multi-mode evasion (Martinez-Vazquez and Rider, 2005).

Despite similar sets of regressors, the findings have been surprisingly varied. For the marginal tax rate, Clotfelter (1983) and Martinez-Vazquez and Rider (2005) find a positive effect on non-compliance, while Erard (1997) finds a negative effect (for reports where tax practitioners were used). Feinstein (1991) provides mixed results with a positive effect for each of the two years analysed separately (i.e. as in other studies) but a negative effect for the pooled model. In Erard (1993), the effect of the marginal tax rate is also significant and goes in either direction depending on a particular tax preparation mode.

Findings on the relationship between (true) income and evasion are also mixed. Clotfelter (1983) found that underreporting increases with income[9], which Feinstein (1991) confirmed with single-year audits, while showing an insignificant (and opposite) effect with the pooled model. Martinez-Vazquez and Rider (2005) found a negative effect with the whole sample yet a positive link emerged when the sample was split into three audit classes. Evidence in Erard (1993, 1997) suggests an inverted U-shape for some paid-prepared returns (and non-significant or a negative effect for others). It is even less clear how evasion, measured as the proportion of income not reported, varies across the income distribution. This has been shown in Johns and Slemrod (2010) who analysed the distributional impact of non-compliance. They find that the proportion of *total (true) income* not reported is larger for higher income groups (although peaking between the 90th and 95th percentile), while underreporting of wages and salaries in relative terms declines over the same income groups, and amounts to only about 1% overall.

In terms of other personal characteristics there seems to be evidence that evasion is higher among married people and lower for elderly (Clotfelter, 1983; Feinstein, 1991; Martinez-Vazquez and Rider, 2005). The latter also find that the number of dependents is positively related to non-compliance.

There are several shortcomings commonly acknowledged in the literature concerning audited tax information: even thorough audits are unlikely to detect all income and mod-

[9]He used after-tax income, while later papers have relied on (adjusted) gross income.

els accounting for imperfect detection have been suggested by Alexander and Feinstein (1987) and Feinstein (1991); TCMP/NPR data typically exclude non-filers who have been studied by Erard and Ho (2001) and non-compliance can also include unintentional reporting errors which have been considered by Alexander and Feinstein (1987) and Erard (1997). One critical aspect from our point of view is the lack of socio-demographic variables, though some studies have addressed this by matching audit data with information from other source, see e.g. Witte and Woodbury (1985) and Dubin and Wilde (1988), though using aggregated rather than individual-level data. Furthermore, analyses based on audited returns typically consider all taxable income together which come from very different sources characterised by different opportunities for evasion and potentially different factors influencing compliance decisions. Evasion can also take place in the form of underreporting income or overreporting deductions which have been distinguished only in a few of studies (Feinstein, 1991; Martinez-Vazquez and Rider, 2005). Overall, US audits have suggested very low evasion of incomes from wages/salaries, although this might be underestimated as any undeclared payments could be concealed both by the individual and the employer and, hence, very difficult to detect.

A study by Kleven et al. (2011) for Denmark is a rare one based on random audits outside the US. They find that tax evasion has a statistically significant positive association with being male, a homeowner, working in a small firm and working in sectors like agriculture, construction and real estate. The strongest predictors are, however, variables reflecting the presence and size of self-reported income, and once these are controlled for only gender (and marital status, after changing the sign) remain statistically significant.

Surveys

Surveys can provide wide-ranging information. On the one hand, they can ask respondents directly whether they have engaged in tax evasion activities of various forms, see e.g. Kinsey (1992), Sheffrin and Triest (1992), Forest and Sheffrin (2002). There are also two studies for Estonia which rely on such data to estimate individual determinants for tax evasion/undeclared work (or its proxies). Kriz et al. (2008) use a survey by the Estonian

Institute of Economic Research (*Eesti Konjuktuuriinstituut*, EKI) on the self-reported receipt of undeclared earnings (i.e. the so-called envelope wages) together with two other data sources: non-random tax audits and the Estonian Labour Force Survey (LFS). While the first two sources contain explicit information on whether a person had evaded taxes, the LFS could only provide a proxy in the form of self-reported work under a verbal contract. Using logit models they find higher propensities for being a tax evader for those working in small firms, in construction and agricultural sector; for part-time employees, non-Estonians, men, young and elderly; for those with less education as well as regional differences. Meriküll and Staehr (2010) reach similar conclusions with their estimations for all three Baltic States on the basis of the Working Life Barometer survey for 1998 and 2002. Using a logit model where the dependent variable indicates the self-reported receipt of envelope wages, they confirm earlier findings for Estonia by showing a higher likelihood of tax evasion for people with more than one job, a lower skilled job, working in a smaller firm or expanding firm; and in the construction, trade and agricultural sector. Both studies, however, have limitations due to a small number of cases of tax evasion and/or limited sets of explanatory variables.

The main problem with self-reported data is that it is unclear how truthful respondents are, given the sensitivity of the subject (Weigel et al., 1987; Elffers et al., 1991), even more so when asked about the magnitude of evasion. Such measurement problems with survey data prompted Slemrod and Weber (2012) to even conclude that the empirical research in tax compliance is (largely) yet to experience a ‘credibility revolution’, and to call for more creativity and attention to appropriate econometric techniques. Methods determining the extent of tax non-compliance indirectly from survey data are, however, a step in that direction. For example, several studies have followed the Pissarides and Weber (1989) approach deriving such estimates from the comparison of income and (food) expenditure by contrasting the self-employed with employees as the prevalence of tax evasion is usually lower for the latter, see e.g. Schuetze (2002), Lyssiotou et al. (2004), Engström and Holmlund (2009), Kukk and Staehr (2014) and Hurst et al. (2014). Feldman and Slemrod (2007) take a similar approach but compare claimed tax deductions for different population sub-groups (using unaudited tax returns). However, these studies have offered little insights to the determinants of tax evasion.

Combining survey data with administrative data sources may offer the most promising route, though there are very few previous studies on tax compliance using survey data linked with tax reports and even less with income information from both sources at the individual level. Mork (1975) provides an early example where respondents (Norwegian men) were asked about their income (in intervals). He compared income interval mid-points in the survey with the average declared income for the same persons and found that the ratio of register income to survey income was lower at higher income levels. Elffers et al. (1987) analysed a sample of Dutch taxpayers whose tax returns had been carefully audited (without their knowledge) and then asked to participate in a survey, relying on a complex procedure to link the two data sources while preserving people's anonymity. Participants were asked in the survey whether they had underreported income or overreported deductions, but not about the magnitude of misreporting. Their most important finding is essentially zero correlation between assessed and admitted non-compliance.

Baldini et al. (2009) is apparently the only other study on tax compliance using individual income from linked survey and administrative data.[10] They do acknowledge the presence of measurement errors (potentially in either source) but do not attempt to account for these and attribute all differences between two income measures to tax evasion, assuming that survey income represents true income. Their findings suggest that evasion is higher (both in absolute and relative terms) for higher income groups, people with more education and the self-employed. However, the analysis includes only a few explanatory variables and the data have clear limitations in terms of a relatively small sample (about 1,000 observations), representativeness (as it refers to the residents of Modena in Italy) and accuracy (a period mismatch between the two sources). Most importantly, their finding of (average) register income exceeding (average) survey income at lower survey income levels points to substantial measurement errors in the survey. Hence, an analysis based

[10] See Fiorio and D'Amuri (2005) and Benedek and Lelkes (2011) for examples of studies comparing survey income with administrative records at aggregate levels without involving matching.

on raw differences between two income measures can give a rather misleading picture of evasion.

As discussed in the introduction, linked survey and administrative data are more common in the survey measurement error literature where, in turn, potential misreporting of earnings in tax records due to non-compliance is ignored.

Experiments

Another method is generating data through laboratory experiments, see Alm (1991) and Alm and Jacobson (2007) for relevant reviews. Experiments have confirmed the role of auditing and penalties (though evidence on the effect of marginal tax rates remains mixed), provided useful guidance on various auditing strategies as well as highlighted additional factors influencing compliance decisions. Similar to audited tax returns, only a small number of socio-demographic variables have been examined: older people have been found more compliant (Friedland et al., 1978; Baldry, 1987; Pudney et al., 2000) and males less compliant (Spicer and Becker, 1980; Baldry, 1987; Pudney et al., 2000). There is also evidence that the propensity to evade (Becker et al., 1987; Pudney et al., 2000) increases with true income, but the results for the extent of underreporting are less clear with Baldry (1987) showing a positive effect and Pudney et al. (2000) a negative effect (conditional on evasion).

While experiments can provide unique insights into the behaviour underpinning tax evasion and avoid usual problems with measurement error, the main challenge is its ability to represent individuals' behaviour in the real world and at the population level. Several studies have found notable framing effects (Baldry, 1986; Webley and Halstead, 1986; Schepanski and Kelsey, 1990), meaning that results can be sensitive to how the nature or purpose of the experiment is perceived by the participants. Furthermore, experiments are naturally limited as not all determinants can be (easily) tested in a laboratory setting. For example, all job-related characteristics (e.g. occupation, industry, firm size) are difficult if not possible to relate to the income generated in a lab session. The income distribution arising from a lab experiment is also hardly representative of the actual income distribution and the same applies to the estimates of non-compliance at the aggregate level.

2.3 The institutional setting

Estonia is one of the three Baltic States in the northeastern part of Europe and one of the smallest EU member states with a population of 1.3 million. The Estonian tax system is fairly simple and linear; it was the first country in Europe to (re)introduce flat income tax in 1994. The five largest tax instruments – personal and corporate income taxes, social security contributions, VAT and excises – are all levied at the national level and accounted for about 97% of total tax receipts in 2000-2012 (European Commission, 2014). Property taxes are marginal and there are no wealth taxes. Apart from a modest increase in the share of indirect taxes, the structure of taxes has been broadly stable since 2000.

Personal income tax is applied on comprehensive income, pooling all sources of income including realised capital gains. The main deductions from taxable income are personal allowance, child allowance, pension allowance, mortgage interest payments and education related expenses.[11] This leaves rather limited possibilities for overreporting tax deductions and, hence, non-compliance can mainly take place in the form of underreporting income to the tax authority. A single marginal tax rate (22% in 2007) is applied on the final tax base.[12] Nearly all social insurance contributions (SIC) are paid by employers and consist of the social tax (33% of gross earnings since its introduction in 1994), which funds pension and health care systems, and unemployment insurance contribution (0.3% in 2007). Employees pay only contributions to the funded pension scheme (2% in 2007), which is voluntary for older generations, and unemployment insurance contributions (at twice the rate of employers). This means that the effective marginal tax rate varies very

[11] As of 2007, the personal allowance and the child allowance (per child starting from the second) were both 1,534 EUR per year (24,000 EEK); the pension allowance was 2,301 EUR per year (36,000 EEK) and the upper limit on deductible expenses was 3,196 EUR (50,000 EEK). All applied on individual basis, except the child allowance which can be claimed by one of the parents. For comparison, average gross annual salary was 8,694 EUR in 2007.

[12] Companies only pay corporate income tax on distributed earnings, while retained earnings are not taxed. Dividends are only taxed once and not considered as taxable income for individuals.

little between employees and cannot be an important determinant of non-compliance at the individual level.

The fiscal year is the calendar year and tax reports must be submitted by the end of March next year. Individual declarations are pre-populated with the information received from employers as well as social insurance funds who administer taxable benefits (public pensions, unemployment insurance benefit, parental benefit, sickness pay etc). Married couples can choose to file a joint report, in which case all the income and allowances are considered together. While this would be beneficial only for couples where one spouse has unused allowances, for other couples the joint liability would be the same as the sum of individual liabilities (but never higher). For employment income and taxable benefits, income tax and SIC are withheld at source. As only the personal allowance and the pension allowance can be applied on a monthly basis, individuals entitled to other allowances and deductions need to file a report to benefit from them. The same applies to those who have been employed only part of the year. Otherwise, as of 2007, residents whose taxable income does not exceed the personal allowance[13] or who have no additional tax liability, i.e. final tax liability corresponds to the withholding tax, do not have to file a tax report. A relatively simple personal income tax system places low compliance burden on individuals and little professional assistance is required and used. As the tax authority also offers free phone and email support service, the overall compliance costs for individuals ought to be low.

Due to employers' obligation to report salaries and wages (on a monthly basis), evading taxes on employment income cannot take place without their knowledge and consent. Furthermore, given how the (statutory) tax burden is shared between employees and employers, this provides significant incentives for both sides to evade taxes. The employer would gain from cost reductions, providing an advantage over law-abiding competitors, though it is important to note that such incentives are unlikely to hold for the *public sector* in Estonia. This is supported by the evidence from the Working Life Barometer survey in

[13] Also the pension allowance and the allowance applicable to the compensation for accident at work or occupational disease, if applicable.

the Baltic countries, according to which only 2% of the public sector employees in 2002 admit having received (sometimes) undeclared payments in cash, see Antila and Ylöstalo (2003, p. 128). (The estimate covers wages and salaries from second jobs as well and, hence, does not appear to refer strictly to income from the public sector employment.) Along with potential gains from non-compliance, the employer must consider risks – there is always the possibility that any current or previous employee might tip off the tax authorities, which in Estonia is likely to result in the employer being fined and not the employee. In this respect the risk of being exposed is significantly lower for the self-employed and, arguably, for smaller companies.

The employee in turn might benefit from higher net earnings or having employment at all. There are also significant disadvantages built into the system for those undertaking fully undeclared work as they would not have health insurance coverage, their (expected) future pension would be lower, especially when it comes to the funded scheme (the so-called second pillar), and they would have difficulties getting a mortgage or a loan.[14] Hence, a common practice for tax evasion is believed to entail declaring part of the earnings, e.g. at the level of the legal minimum wage or slightly higher to raise less suspicion. A similar practice is mentioned in Besim and Jenkins (2005) for North Cyprus. They also suggest that by employing people through contracts with smaller firms, larger firms can benefit from tax evasion without increasing the risk of exposure for themselves. They also point out that as firms need to make unrecorded cash sales to pay their employees undeclared income, the evasion of payroll taxes also results in part of value added taxes and, possibly, corporate income tax being evaded.

Overall, it is not obvious whether it is the employee or the employer who has the decisive role in evading income and payroll taxes. Unless one side has a much stronger bargaining position, for example, if the employee has few or no job alternatives and the employer is well aware of that, it is effectively a joint decision.

[14]Given the real estate boom in mid-2000s and a very large increase in mortgage loans to households, this must have become a rather important incentive.

2.4 Model

The general model structure is the following. Let y_i^T denote the true value of earnings of individual i.[15] Employed persons have positive earnings ($y_i^T > 0$) and non-employed people have zero earnings ($y_i^T = 0$). Generally, true earnings are not directly observable and instead each person states her earnings in the survey, y_i^s, which can differ from the actual earnings due to intentional or unintentional misreporting (e.g. recall errors). Hence, there could be individuals with zero true earnings among those reporting positive survey income and such misreporting may have occurred, for example, because of confusing reference time periods or not wanting to reveal the non-employment status. People also choose how much of their actual earnings to declare to the tax authority, which we refer to as register income and denote with y_i^r. We can rule out negative taxable earnings and assume that people do not declare more income to the tax authority than they actually received.[16] Employed individuals have then three choices: full compliance ($y_i^r = y_i^T$), partial evasion ($0 < y_i^r < y_i^T$) or full evasion ($y_i^r = 0$), while non-employed persons always declare zero earnings ($y_i^r = 0$).

Our main interest is an estimate of income not reported to the tax authority, which is the difference between true earnings and declared earnings, $e_i = y_i^T - y_i^r$, and non-negative by assumption. This in turn requires a measure of true earnings and we seek to obtain this from observed survey and register income, assuming both relate to true earnings (and other personal characteristics), in a latent class framework. More specifically, our modelling strategy involves specifying a structural model for true earnings, survey earnings and declared earnings, and estimating it with a parametric method. As the econometric model consists of three separate equations estimated simultaneously while only two dependent variables are observed (y_i^r, y_i^s), we need further restrictions to identify

[15] We focus throughout on wages and salaries and use terms *earnings* and *income* interchangeably.

[16] It is possible to report negative self-employment income in Estonia (similar to many other countries) as related expenses can be deducted from gross self-employment income, but the same does not apply to wages and salaries. Over-reporting of earnings could happen in practice, although one might expect this to be not very common. For example, Clotfelter (1983) shows evidence for the US that the proportion of people understating their taxable income greatly exceeds the proportion of people overstating their income.

all model parameters. Given the discussion about incentives to evade in Section 2.3, our key *identifying assumption* is that people working in the public sector are constrained in their choice and cannot evade taxes, i.e. $y_i^r = y_i^T$, while there are no systematic differences between the public and private sector employees with respect to (true) earnings formation and measurement error in the survey data. (In the empirical analysis, we are actually able to relax the latter assumption by allowing some key parameters to differ between the two sectors.) This means that for a part of the sample, i.e. public sector employees, we observe true earnings as well and can therefore identify parameters for all three earnings equations.

Focusing on the sample of people with reported (full-time) employment and hence positive earnings in the survey ($y_i^s > 0$), we proceed by specifying the exact structure for each earnings function.[17] With probability p, an individual i in our sample is truly employed and has log-normally distributed true earnings:

$$\ln y_i^T = x_i \beta^T + \varepsilon_i^T \tag{2.1}$$

where x_i are her characteristics determining the log income and $\varepsilon_i^T \sim N(0, \sigma_T^2)$ is a random term. With probability $1-p$, the employment status is misreported in the survey and the person has actually no earnings ($y_i^T = 0$) – assuming this could happen equally among those claiming to be working in the public sector and those in the private sector. We constrain the probability to be fixed, though this could be relaxed by allowing the probability to vary according to personal characteristics. We have chosen not to complicate the model structure with this as it seems to concern relatively few cases. The probability density of true earnings, conditional on having positive earnings, is:

$$f(y_i^T | x_i, y_i^T > 0) = \frac{1}{\sigma_T y_i^T} \phi \left(\frac{\ln y_i^T - x_i \beta^T}{\sigma_T} \right) \tag{2.2}$$

where $1/y_i^T$ is the Jacobian term and $\phi(.)$ is the probability density function of the stan-

[17]Note that we maintain a wider scope compared with several previous studies on measurement error using linked data as their focus is typically limited to cases where positive earnings are reported in *both* sources. See, for example, Bound and Krueger (1991) and Kapteyn and Ypma (2007).

dard normal distribution.

To reflect multiple choices of compliance, we model declared earnings (y_i^r) as a *fraction* of true income, using a two-limit Tobit model and a latent variable r_i^* ('the propensity to comply'):

$$y_i^r = \begin{cases} 0 & \text{if } y_i^T = 0 & \text{(no earnings)} \\ 0 & \text{if } y_i^T > 0 \text{ and } r_i^* \leq 0 & \text{(full evasion)} \\ r_i^* \cdot y_i^T & \text{if } y_i^T > 0 \text{ and } 0 < r_i^* < 1 & \text{(partial evasion)} \\ y_i^T & \text{if } y_i^T > 0 \text{ and } r_i^* \geq 1 & \text{(no evasion)} \end{cases} \tag{2.3}$$

where

$$r_i^* = \theta^r y_i^T + x_i\beta^r + \varepsilon_i^r \quad \text{if } y_i^T > 0 \tag{2.4}$$

and $\varepsilon_i^r \sim N(0, \sigma_r^2)$. Assuming ε_i^T and ε_i^r to be independent, the probability density of declared earnings, conditional on true earnings, is the following:

$$f(y_i^r|x_i, y_i^T) = \begin{cases} \Pr(y_i^r = 0|y_i^T = 0) &=& 1 & \\ \Pr(y_i^r = 0|x_i, y_i^T) &=& \Phi\left(-\frac{\theta^r y_i^T + x_i\beta^r}{\sigma_r}\right) & \forall y_i^T > 0 \\ f(y_i^r|x_i, y_i^T) &=& \frac{1}{\sigma_r y_i^T}\phi\left(\frac{y_i^r/y_i^T - \theta^r y_i^T - x_i\beta^r}{\sigma_r}\right) & \forall y_i^T > 0 \\ \Pr(y_i^r = y_i^T|x_i, y_i^T) &=& 1 - \Phi\left(\frac{1 - \theta^r y_i^T - x_i\beta^r}{\sigma_r}\right) & \forall y_i^T > 0 \end{cases} \tag{2.5}$$

We refer to this as the *multiplicative* model and additionally consider declared earnings in an *additive* form, where θ^r and β^r-s are interpreted in levels rather than the ratio of declared earnings.[18] The probability density function of declared earnings is very similar in the two cases. As a characteristic of the Tobit model, both specifications combine the extensive and intensive margin of decision making – whether to underreport incomes

[18]Specifically:

$$y_i^r = \begin{cases} 0 & \text{if } y_i^T = 0 & \text{(no earnings)} \\ 0 & \text{if } y_i^T > 0 \text{ and } y_i^{*r} \leq 0 & \text{(full evasion)} \\ y_i^{*r} & \text{if } y_i^T > 0 \text{ and } 0 < y_i^{*r} < y_i^T & \text{(partial evasion)} \\ y_i^T & \text{if } y_i^T > 0 \text{ and } y_i^{*r} \geq y_i^T & \text{(compliance)} \end{cases}$$

where

$$y_i^{*r} = \theta^r y_i^T + x_i\beta^r + \varepsilon_i^r \quad \text{if } y_i^T > 0$$

to the tax authority at all and, if so, to what extent. Modelling each choice margin explicitly would provide more flexibility but also further complicate the model structure and its identification. We have therefore opted for testing these two alternative Tobit specifications instead.

The multiplicative model combines the overall compliance decision (i.e. extensive margin) with underreporting in relative terms and part of its structure is akin to the model of fractional detection of income tax evasion in Feinstein (1991). The additive model combines the compliance decision with underreporting in absolute terms. While both types of model allow studying how compliance in *relative* terms varies across the income distribution (i.e. one of our main research questions), a slight advantage of the multiplicative model is that its parameter θ^r provides (some) direct insights into that. More specifically, θ^r provides a clear indication of the effect of true earnings on the latent variable. (The link with the censored variable is non-linear and depends on the values of other covariates as well.) With the additive model, θ^r reflects both the level of true resources and their effect on compliance, though it may capture more adequately the existence of a tax-free threshold.[19] The additive model could also reflect better the nature of compliance decisions if there are fixed costs involved and non-compliance is not deemed worthwhile unless the amount of evaded taxes is substantial enough. On the other hand, the cost of compliance could be correlated with true earnings (for example, potential damage to reputation may increase with true earnings) for which the multiplicative model would be then more appropriate. Overall, it is difficult to establish a priori which specification is more relevant and people's actual behaviour could be more complex and involve elements

and $\varepsilon_i^r \sim N(0, \sigma_r^2)$. The probability density of declared earnings, conditional on true earnings:

$$f(y_i^r|x_i, y_i^T) = \begin{cases} \Pr(y_i^r = 0|y_i^T = 0) & = & 1 & \\ \Pr(y_i^r = 0|x_i, y_i^T) & = & \Phi\left(-\frac{\theta^r y_i^T + x_i\beta^r}{\sigma_r}\right) & \forall y_i^T > 0 \\ f(y_i^r|x_i, y_i^T) & = & \frac{1}{\sigma_r}\phi\left(\frac{y_i^r - \theta^r y_i^T - x_i\beta^r}{\sigma_r}\right) & \forall y_i^T > 0 \\ \Pr(y_i^r = y_i^T|x_i, y_i^T) & = & 1 - \Phi\left(\frac{(1-\theta^r)y_i^T - x_i\beta^r}{\sigma_r}\right) & \forall y_i^T > 0 \end{cases}$$

[19] However, the threshold applies only to the personal income tax while employer social contributions are paid on all gross earnings (see Section 2.3). Furthermore, as we are focusing on full-time employees and the legal minimum wage exceeds substantially the tax-free threshold, we have decided not to model the threshold explicitly.

of each. We therefore estimate both models to see which one fits the data better.

Finally, conditional on $y_i^s > 0$, log survey income y_i^s is modelled as a function of log true earnings and individual characteristics x_i, assuming ε_i^T and ε_i^s to be independent, and including a separate dummy in the case true earnings are zero:

$$\ln y_i^s = \theta^s \ln y_i^T \cdot 1(y_i^T > 0) + \theta_0^s \cdot 1(y_i^T = 0) + x_i\beta^s + \varepsilon_i^s \tag{2.6}$$

where $1(\cdot)$ is an indicator function and $\varepsilon_i^s \sim N(0, \sigma_s^2)$.[20] The probability density of survey income, conditional on reporting employment in the survey, is

$$f(y_i^s|x_i, y_i^T, y_i^s > 0) = \frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s \ln y_i^T \cdot 1(y_i^T > 0) - \theta_0^s \cdot 1(y_i^T = 0) - x_i\beta^s}{\sigma_s}\right) \tag{2.7}$$

where $1/y_i^s$ is another Jacobian term. (Given our sample of interest, we omit the condition $y_i^s > 0$ below.)

The overall probability density function (PDF) for a pair of observed earnings measures (y_i^r, y_i^s) for individual i can be written conditional on true earnings, with the latter integrated out over its plausible range, i.e. any amount equal to or larger than declared earnings:

$$f(y_i^r, y_i^s|x_i) = f(y_i^T = y_i^r|x_i) f(y_i^r, y_i^s|x_i, y_i^T = y_i^r) + \int_{y_i^r}^{\infty} f(y^T|x_i) f(y_i^r, y_i^s|x_i, y^T)\, \mathrm{d}y^T \tag{2.8}$$

Assuming that, conditional on true earnings and other covariates, the statements of register and survey income are independent of each other, i.e. the error terms (ε_i^r, ε_i^s) are uncorrelated, this can be simplified further as

$$\begin{aligned} f(y_i^r, y_i^s|x_i) =& f(y_i^T = y_i^r|x_i) \Pr(y_i^r = y_i^T|x_i, y_i^T) f(y_i^s|x_i, y_i^T = y_i^r) \\ &+ \int_{y_i^r}^{\infty} f(y^T|x_i) f(y_i^r|x_i, y^T) f(y_i^s|x_i, y^T)\, \mathrm{d}y^T \end{aligned} \tag{2.9}$$

[20] We also experimented with survey earnings in levels but the model fit to the data was much poorer. The log form of earnings has been also commonly used in the measurement error literature, where the focus is typically on the sample of people with positive earnings in both data sources.

Among those with positive survey income, we can distinguish between two sets of observational outcomes, depending on whether register income is zero (A_{0s}) or positive (A_{rs}).[21] In the case of observations in set A_{0s}, the PDF combines the possibility of true earnings being zero and true earnings being positive and entirely undeclared. For observations in set A_{rs}, the PDF combines the possibility of all or part of earnings being declared, as positive register income implies that true earnings are also positive given our assumption of $y_i^r \leq y_i^T$:

$$f(y_i^r, y_i^s|x_i) = \begin{cases} f(\text{no earnings}) + f(\text{full evasion}) & \text{if } y_i^r = 0 \\ f(\text{compliance}) + f(\text{partial evasion}) & \text{if } y_i^r > 0 \end{cases} \tag{2.10}$$

The log likelihood function of the sample is

$$\ln L = \sum_{i \in A_{0s}} \ln f_{0s}(y_i^r, y_i^s|x_i) + \sum_{i \in A_{rs}} \ln f_{rs}(y_i^r, y_i^s|x_i) \tag{2.11}$$

We estimate the parameters p, β-s, θ-s and σ-s with the maximum likelihood method and use the Gauss-Hermite quadrature to evaluate the integrals numerically. Detailed components of the likelihood function for the multiplicative and the additive model are provided in Appendix 2.A.

Model identification is based on the assumption that public employees are constrained in their choice to be compliant, hence determining a priori some of those who are fully compliant (or actually non-employed). As true earnings are then directly observed for public employees in the tax records, their sample drives the identification of parameters in the true earnings equation and also in the survey earnings equation. The sample of private sector employees, in turn, identifies parameters in the declared earnings equation. Survey earnings are instrumental in establishing to what extent observed income dispar-

[21] There is also a small group of people who reported zero survey earnings and positive register income (see Section 2.5). These cases point to a specific type of survey measurement error and appear to be associated with very marginal employment, therefore, having less relevance for our purposes as we shall be focusing on full-time employees. Furthermore, as employment characteristics on which we draw in the analysis are only available in the survey data and cannot be established for this group, we have excluded such observations from the analysis. This is common in survey-based empirical literature on labour market behaviour in general, though typically the same choice is made implicitly there.

ities between the constrained and unconstrained employees are due to non-compliance rather than differences in their true earnings. Hence, a partial model omitting survey earnings and covering only true earnings (y_i^T) and register income (y_i^r), is likely to result in downward biased estimates of the scale of non-compliance. Intuitively, on the basis of register income alone, there would be weaker evidence to suggest that the actual level of earnings among unconstrained employees may be above what is recorded in the tax records and comparable to that for public employees or, possibly, even higher. As long as part of private sector employees are fully compliant, some (indirect) evidence is still present. At extreme, if *all* private sector employees unreported the same amount of income or the same proportion of their true income, then it would not be possible to separate it from differences in true earnings compared with public sector employees, using a single observed measure of income. Estimating a system of equations with two income measures, ensures that parameter estimates agree with both sets of observations.[22] We illustrate the importance of having two income measures by estimating also a partial model as part of the sensitivity analysis.

In principle, the model can be estimated with an identical set of covariates (x_i) for all three income equations (as shown later in the sensitivity analysis), but in order to improve the identification we have made some exclusion restrictions. For example, interview characteristics are only included in the survey earnings equation, while it excludes job characteristics present in other two equations. The full list is given in Section 2.6. In terms of identification, there are no substantial differences between the multiplicative and the additive model.

[22]This is of course useful only if survey earnings are indeed strongly correlated with true earnings, otherwise they would give misleading information. The latter would have wider implications as it would call then into a question the reliability of income surveys in general.

2.5 Data

2.5.1 Data sources and linkage

The analysis is based on the Estonian Social Survey 2008 (*Eesti Sotsiaaluuring*, ESU) linked to administrative tax records. ESU is a household income survey, carried out annually since 2004 by Statistics Estonia. It is based on a rotating panel where each household is surveyed for four waves and one fourth of the sample is replaced in every wave. (Only cross-sectional information is used in this essey.) Basic demographic information is collected for all household members, while detailed person interviews are conducted with those aged 16 or over. ESU is also used as the basis for the Estonian component in the European Union Statistics on Income and Living Conditions (EU-SILC) database.

Information from administrative tax records is based on individual tax declarations (FID), if available, or (employer) tax withholding reports (TSD), hence covering all residents.[23] Although individual and employer reports differ in their structure, this has little importance in our case, not least because individual reports are pre-populated with the information from employers. Both provide detailed income information, with the main (yet minor) difference that the TSD forms exclude income earned abroad as reporting is limited to resident firms. Where only information from TSD is available this means that neither the joint reporting for married couples was used nor additional tax allowances claimed (even if applicable). For each individual, income is provided separately by type and provider, e.g. the employer or a government institution administrating a given benefit. This is also the case for joint reporting affecting certain aggregates like total income, total income tax, total allowances and total deductions, which are then summed for the couple (and not needed in the analysis).

Individual records in the two data sources have been linked using a unique personal identification number (PIN). This is officially assigned to each person and included in the Population Registry which provides the sample frame. PIN is therefore known for

[23] This is different from studies on the US where non-filers are usually missing from administrative data (hence referred to as 'ghosts'). Erard and Ho (2001) is one of the very few exceptions.

all sampled individuals, while asked for other household members during the interview in return for excluding them from the sample frame while participating in the ESU panel, so that they would not have to take part in other surveys conducted by Statistics Estonia at the same time. Those who did not provide a PIN were matched with the Population Register using their address and individual characteristics (as the Population Register does not provide information about household composition).[24] This resulted eventually in only a very few people without a match and, hence, without an identified PIN. It is also possible that the matching involved some error with incorrect PINs being assigned, although it is likely to be negligible. All data linkage was carried out by Statistics Estonia without a requirement to inform sample members or obtain their consent on the basis of the legislation governing its activities.[25] This characteristic is very important as consenting could be systematically affected by factors which are of key interest in this context: for example, income in general, or tax compliance behaviour in particular. The final dataset used here is anonymised with people's names, addresses etc removed.

The initial sample for ESU 2008 included 14,942 individuals of whom only 71 could not be identified in the tax register (see Table 2.1). Omitting people younger than 16, who are not subject to a person interview, reduces the sample size to 12,699 persons. Of those, 1,910 did not respond to the survey (12.8% of the initial sample)[26] and another 87 people had no person interview carried out. A further 465 cases are omitted due to missing earnings information in ESU (mainly those who reported their earnings on an interval scale), which leaves 10,237 people with known survey earnings (including zero values).

[TABLE 2.1 HERE]

Essentially, we are interested in all individuals with (paid) employment in the income reference period but focus on those with more substantial employment experience

[24] Seven out of 11 digits of the PIN are determined by person's gender and the date of birth.

[25] In comparison, 24-89% consent rate was achieved in studies summarised in Sakshaug and Kreuter (2012, Table 1) where respondents' agreement for linkage was required.

[26] For newly-added sample members, the number of non-respondents refers to sampled people only without other household members (as they remain unknown).

to achieve greater sample homogeneity. For that purpose, we first exclude those who have *never* had a regular job, that is any full- or part-time work which lasted for at least 6 months. We then limit our sample to those employed, i.e. with positive survey earnings (5,500 people).[27] Besides *current* labour market characteristics (at the time of the interview), ESU also collects information about the *main* activity in any month of the income reference period, which is the previous calendar year before the survey interview, i.e. 2007. On this basis, we further select those who reported part- or full-time employment as the main activity at least for one month in the income reference period (5,327 cases).

In the final step, we limit our sample to 4,121 individuals who worked full time for the whole income reference period as a way to increase robustness with respect to potential measurement error in the number of months worked information. (This will be relaxed as part of sensitivity testing in Section 2.6.4, adjusting earnings with the number of months in receipt.) We also distinguish between people working in the constrained and in the unconstrained sector reflecting people's opportunities to engage in tax evasion. Following our key assumption, the *constrained sector* refers to people working in the public sector, but excluding those with a second job or who have changed jobs to take a more conservative approach. They account for about 29% of the final sample and are primarily located in set A_{rs}. Everyone else is assigned to the *unconstrained sector*, including those with missing employer status. As part of robustness checks, we will also test alternative definitions.

2.5.2 Earnings information

The version of ESU used here includes all the income variables from the standard release as well as variables with *original values* before imputations by Statistics Estonia, i.e. incomes as they were reported (either net or gross, monthly or annual), including missing values. This allows us to avoid relying on the imputations in the standard release.

[27] There are also 343 cases where people (with regular job experience) have positive earnings in the tax records but zero earnings in ESU. These appear to represent very marginal employment, as reflected in the much lower average earnings compared to the main sample – see Table 2.2. Nearly 60% of these are old age or disability pensioners according to their labour market status.

Among 5,500 individuals who reported positive earnings in ESU (Table 2.1), 95% stated earnings in monthly terms (rather than annual) and in 91% of cases net of (withheld) employee social contributions and income tax.[28] As derivation of gross values from net (or vice versa) is also affected by tax evasion, we keep the extent of such imputations for ESU data to a minimum by using the original net values in the subsequent analysis. Imputations are then only needed to obtain net values for cases where gross values were initially reported in the survey (about 10% of the sample). We carry out our own imputations drawing on the self-reported information about whether the employer (withheld and) paid social insurance contributions and income tax and whether a person participates in the funded pension scheme. Given the sensitivity of the question about withheld taxes, this is likely to overestimate compliance but provides nevertheless a better approximation compared to assuming full (or no) compliance. Among those who reported a gross income figure, nearly 97% said that income tax was fully paid and under 3% that taxes were not paid.[29] As part of sensitivity analysis in Section 2.6.4, the model is also estimated on a sample excluding all observations with imputed values.

The tax records indicate gross annual earnings together with withheld income tax and contributions, therefore, it is possible to construct an equivalent measure of net earnings. While there is only a single individual-level variable for wages and salaries in ESU (separate from self-employment income), earnings in the tax records are known in great detail, distinguishing payments by employer and type (as well as tax treatment).[30] On the other hand, unlike in ESU the number of months paid is not available in our

[28]When asked about non-regular payments and bonuses, about 20% of people reported additional (net) remuneration, which they had omitted from their earnings reported initially.

[29]The proportion of those reporting that employee SIC (i.e. unemployment insurance contribution) had been fully paid was somewhat lower, about 90%. This is because less people are liable to pay this (e.g. it excludes those who have reached the legal retirement age or are receiving an early retirement pension) but also likely due to less awareness of that particular contribution (as it was introduced only in 2002). The same proportions are slightly lower for those who reported a net income figure, 92% for income tax and 87% for employee SIC, mainly due to higher prevalence of individuals who said they did not know or did not answer the question.

[30]The following type of payments have been included in the constructed earnings measure to match the content of the ESU earnings variable as closely as possible: salaries and wages, board member fees, compensation for termination of employment or service, remuneration or service fees paid on the basis of a contract for services (*töövõtuleping*). Payments to compensate loss of earnings due to health-related absence from work (by the Health Insurance Fund) or unemployment (by the Unemployment Insurance Fund) have been excluded.

dataset and we rely on corresponding information from ESU.

Table 2.2 shows mean log earnings in ESU and in the tax records (the annual net figure is divided by 12), distinguishing between non-respondents and respondents in ESU and in which of the two sources positive earnings were reported. There are several important features. First, a comparison of the mean value of log earnings in the tax records for ESU (unit) non-respondents (8.46) and respondents (8.33), see panel (a), shows that non-respondents' earnings are somewhat higher on average (the difference is non-zero with $p = 0.035$) and suggests that those with higher (register) income may be less likely to participate in the survey.[31] This is not necessarily a concern for our model estimates, as long as non-response patterns are the same for public and private sector employees. Though we are unable to investigate non-response in much detail (due to the lack of information on non-respondents), the distribution of register earnings – not shown here – appears very similar for non-respondents and respondents.

[TABLE 2.2 HERE]

Second, there is a small group of people who reported zero earnings in ESU but had positive earnings in the tax records. The average value of their log register income (6.28) is much lower, see panel (b), which implies very marginal (formal) employment with a particular recall error. We therefore conclude that this group is rather specific and its omission (see previous sub-section) should not be problematic from the viewpoint of tax compliance. In contrast, mean log survey earnings are much more similar among those with no earnings in the tax records (8.54) and those with earnings in both sources (8.72).

Third, for those with positive earnings in both sources (A_{rs}), the difference in the mean log value of survey and register income is a modest 0.1. However, when distinguishing between those in the *constrained sector* and those in the *unconstrained sector*, a very clear

[31] Toomse (2010) uses an earlier wave of the same data (ESU 2007), extended with additional information from the sample frame, to analyse non-response in depth. She finds that, conditional on making a contact, those living in the capital region and urban settlements, younger people and males were less likely to take part in the survey, while income (salary quintile) was not relevant for the probability to co-operate. However, income was significant for some particular modes of refusal and co-operation as high salary earners were more likely to firmly refuse at the first contact and more likely to be respondents requiring larger number of calls after the first contact.

pattern emerges. Mean log earnings in the tax records (8.84) exceed mean log earnings in ESU (8.77) in the constrained sector, which by our assumption means their true earnings are on average underreported in the survey. But it is the opposite in the unconstrained sector, where mean log earnings in the tax records (8.55) are lower than mean log survey earnings (8.70). Assuming that survey earnings are similarly underreported by this group, this indicates substantial underreporting of earnings to the tax authority. Note also that the difference in mean log survey earnings between the two sectors is statistically significant only at the 10% level ($p = 0.068$). The same pattern holds for the final estimation sample, see panel (c). Similarly, Kapteyn and Ypma (2007, p. 524) report that the mean difference between survey and administrative earnings (for A_{rs}) in their data is positive, while survey earnings are smaller than administrative earnings in most cases. More generally, measurement error studies (based on linked data) have commonly found very similar mean earnings in survey and administrative sources but significant differences at the individual level, in either direction (see Bound et al., 2001). It appears that no distinction has been made between private and public sector in this literature though.

Figure 2.1 provides further details by showing the full distribution of each earnings variable for the final sample (excluding zero register incomes and some very high incomes for a better overview). While the overall shape of the distribution is similar for the two earnings measures, earnings reported in the survey have a number of pikes at round income levels (e.g. 5, 6, 7, 8, 10, 15 thousand EEK), which is a sign of a particular type of measurement error called heaping: a tendency to report rounded-off values. Earnings reported in the tax records show a much smoother distribution. It has been shown that heaping can cause notable problems in some applications, for example, for modelling the dynamics of (self-reported) household consumption (Pudney, 2008). Pischke (1995) noted the same feature in the US income survey (PSID 1983 and 1987) linked with employer reports. He imposed similar rounding pattern to register incomes and found only little correlation with the actual measurement error (defined as the difference between earnings in the survey and the employer records), suggesting that this is perhaps not a critical issue in our context. As our econometric approach is already quite complicated, we therefore chose not to model this feature explicitly.

[FIGURE 2.1 HERE]

As the final sample contains only people who (according to ESU) worked full time during the whole income reference period, in principle, there should not be anyone below the minimum wage level (denoted by the vertical lines in Figure 2.1). This does not hold strictly, especially for register income. It could mean either that survey information on work duration is not completely accurate and/or part of earnings have been unreported to the tax authority. As the distribution of log earnings (not shown here) is close to a normal distribution and there is no obvious spike at the minimum wage level as, for example, demonstrated for Hungary by Elek et al. (2012), we do not model possible censoring of true earnings at the level of minimum wage. This also means that (despite of anecdotal evidence) there is little trace of a particular form of non-compliance, where only a part of earnings *equal* to the minimum wage is reported to the tax authority and taxes evaded on the rest of income. We therefore do not account explicitly for this case of non-compliance, preferring instead a more generic model set out in Section 2.4.

Figure 2.2 gives an overview of the correspondence between two earnings measures at the individual level, separately for the constrained and the unconstrained sector. (Again for the final sample excluding those with zero register income and some very high incomes.) The two groups of individuals reveal a similar pattern with most of the observations appearing around the 45-degree line, though survey earnings tend to exceed earnings in the tax records in cases where the latter have low values, and the opposite when the latter have high values. This is also reflected by the slope of a linearly fitted line which is about 0.65 for both sectors. The same pattern has been also found in the studies on survey measurement error (e.g. Bound and Krueger, 1991; Bound et al., 1994; Bollinger, 1998), where this has been interpreted as a negative correlation between the measurement error in the survey data and the true value of earnings – recall that these studies have commonly assumed earnings in the administrative data to reflect true values – though Kapteyn and Ypma (2007) show that this pattern can also occur without 'true' mean reversion. Additionally, there is visibly more variation in the unconstrained sector compared to the constrained sector and a greater mass of observations in the upper left region as one would expect in the presence of tax evasion (if earnings in the survey are disclosed more truthfully). This is also illustrated by a locally weighted regression line which has a U-shape at the low values of register earnings.

[FIGURE 2.2 HERE]

Finally, Table 2.3 shows (unweighted) sample means by sector for all the explanatory variables used in subsequent regression models. These are mostly dummy and categorical variables and provide information about socio-demographic and work characteristics as well as interview related aspects. Note that some labour market variables contain a few missing values and these observations are omitted at the estimation stage. The age variable has been centered around its mean (and re-scaled) to avoid linear correlation between the age and the age-squared variable. Furthermore, in several cases, the categories have been joined to avoid having very few observations in any subgroup.[32] There are some differences in the composition of people working in two sectors. In comparison with the unconstrained sector, there are less men in the constrained sector, they tend to be more educated and work primarily in the field of education, health and public administration; there is also a larger proportion of professionals but fewer craft workers and machine operators.

[TABLE 2.3 HERE]

[32] Various groupings for the industry variable were tested and the final version chosen on the basis of similar tax compliance behaviour based on the modelling results.

2.6 Findings

2.6.1 Model estimates

The model is estimated both in the multiplicative and the additive form on the sample described in Table 2.1. (The effective sample has about 120 observations less due to item non-response.) The semi-infinite integrals (for true earnings) were solved numerically using Gauss-Hermite quadrature with the nodes and the weights as calculated in Steen et al. (1969). The log-likelihood functions (see Appendix 2.A) were programmed in Stata 12 and estimated using 15 quadrature points. In addition to the main results discussed below, Section 2.6.4 provides an overview of results from a sensitivity analysis.

The following explanatory variables are included in all three earnings equations: age, age squared, gender, nationality and education. Further demographic characteristics (marital status, region, rural area, dummy for studying) and job characteristics (industry, occupation, number of employees, hours in the main job, dummy for the second job, hours in the second job) are included in the true earnings equation and in the declared earnings equation but not in the survey earnings equation as they are expected to have a negligible effect on the latter. Each equation also includes certain covariates which are excluded from the other two equations to improve identification: health status in the true earnings equation, a mortgage and a lease dummy in the declared earnings equation and interview characteristics (month, people present, rating, response mode, wave) in the survey earnings equation. Having a mortgage and/or a lease loan is assumed to be associated with higher compliance (other things equal) as in order to successfully apply for either of these, one needs to have earnings (in sufficient amount) deposited directly to a bank account on a regular basis. As such this creates an incentive to have a higher proportion of earnings declared if access to credit is desired (see also Section 2.3). Finally, our baseline model specification allows certain parameters to differ between the unconstrained and the constrained sector: the intercept and variance for the true earnings and survey earnings equations as well as θ^s.

The results for all three equations (with robust standard errors) are presented in

Table 2.4 for the multiplicative model and in Table 2.5 for the additive model. Most covariates for log true earnings ($\ln y^T$) are statistically significant at the 1% level and with expected signs. Earnings are higher for males, Estonian nationals and more educated people; they are higher in the northern (capital) region and notably lower in the north-east region.[33] Age has an inverted U-shape effect on the size of earnings, peaking at 40 years where the age premium is about 17% compared to people aged 20 and 60. There is also a statistically significant positive relationship with health status, job skill level (i.e. occupation), the size of firm and hours worked. Compared to employees in education, health and public administration – reflecting largely public sector employment – earnings are higher in construction, wholesale trade, transportation, professional services and finance. It is somewhat surprising that the sector premium is highest in construction, though the data refer to 2007 which marked the height of the boom in the real estate and construction sector. Finally, while the dummy for the constrained sector is very close to zero (and statistically non-significant), variance (σ_T^2) estimates are clearly higher for the unconstrained sector. Results with the additive model for the true earnings equation are very similar except for slightly larger coefficients for nationality, education, firm size and occupation.

[TABLE 2.4 AND 2.5 HERE]

In the case of declared earnings (y^r), the raw coefficients show the effect of independent variables on the latent dependent variable, while our key interest is the effect on the censored dependent variable. For that purpose, raw estimates are useful only to the extent of showing which covariates are statistically significant and the sign of the effect on the censored variable. Marginal effects on the (censored) declared earnings are provided in the next subsection.

Conditional on true earnings, declared earnings have a statistically significant positive association with age, Estonian nationality, education, studying, the size of the firm and whether the household has a mortgage or a lease loan. Having a mortgage has lower

[33] The gender earnings gap is very large at 39%, calculated as $\exp(\hat{\beta}_{\text{male}}) - 1$. Estonia has the highest (unadjusted) gender earnings gap among the EU countries, see Eurostat indicator *tsdsc340*.

statistical significance and one explanation for this is that people interested in mortgage could be less constrained by lower declared earnings if they can compensate this by using (accumulated) undeclared earnings to make a larger downpayment. People requiring a lease loan are presumably less likely to have substantial savings of any form and, hence, the size of declared earnings is more important.

Declared earnings are lower for men and for non-married, in particular those who are separated, divorced or widowed. The north-east region, which has several specific characteristics, also stands out for a negative coefficient. First, it has suffered from the highest unemployment rate compared to other regions since the beginning of the 1990s (following the collapse of heavy industry which was central to the local labour market), at times even up to twice higher than in others. Second, with the highest share of non-Estonians, the region is ethnically much less homogenous and this may affect the overall level of trust in public institutions and tax morale. Across sectors, declared earnings are lower in construction, transportation (combined with storage and courier services), hotels and restaurants, and finance (combined with real estate and administrative support) in comparison with education, health and public administration as well as manufacturing, mining and utilities. Occupations associated with higher declared earnings are clerks as well as service and sales workers, while skilled agricultural workers and blue-collar workers have lower earnings. The results for declared earnings are well in line with findings in Kriz et al. (2008) and Meriküll and Staehr (2010) based on self-reported compliance for Estonia, and also with the (few) general patterns found in the literature (e.g. gender and age – see Section 2.2.2). The main exception concerns marital status as being married has been found associated with *more* evasion in the previous audit-based US studies, though Kleven et al. (2011) also find a link with less evasion like we do.

Again, in terms of statistical significance and the sign of coefficients, results for the additive model are very similar. The values and units of coefficients naturally differ given how declared earnings are specified, most notably for parameter θ^r, i.e. the coefficient of true earnings in the declared earnings equation, which is negative with the multiplicative model and positive with the additive model. But the interpretation of θ^r differs between the two models: unlike for the multiplicative model, it combines the effect of true earnings on declared earnings in levels and relative terms in the additive model.

Finally, conditional on true earnings, survey earnings are higher for males, Estonian nationals, and those more educated. The dummy for working in the constrained sector is not statistically significant. There is also a positive link with the timing of interview[34] and its rating, while the number of waves has a negative effect on earnings reported in the survey. Survey earnings are higher when the interview was responded by another household member, however, there is no statistically significant relationship with who was present at the interview. The coefficient of true earnings (θ^s) is highly significant and in the range of 0.6-0.7, being slightly higher for the unconstrained sector.

For the model as a whole, both the AIC and the BIC statistic favour the multiplicative form.

2.6.2 Marginal effects on declared earnings

To give a quantitative interpretation for the effects of the independent variables in the declared earnings equation (y^r), we estimate their marginal effects on the probability of compliance and the size of declared earnings, conditional on true earnings, as well as the elasticity of declared earnings with respect to true earnings. The underlying formulae are derived in Appendix 2.B.

Figure 2.3 shows marginal effects of age, gender, education, region, industry and firm size on the probability of compliance, conditional on being truly employed.[35] It focuses on covariates for which estimated coefficients were statistically significant and relatively large in absolute size. Marginal effects are estimated at the sample means and modes of, respectively, continuous and discrete variables for a wide range of values of true earnings: from near 0 up to 25 thousand EEK per month, roughly 3 times the average value of earnings in the sample for the unconstrained sector.

[34] The interviews usually take place around the time when annual tax reports are due (i.e. the end of March) to reduce recall errors.

[35] That is $\partial \Pr(y_i^r = y_i^T | x_i, y_i^T)/\partial x_k$ in case x_k is a continuous variable ($\forall y_i^T > 0$). This equals $\frac{\beta_k^r}{\sigma_r}\phi\left(\frac{\theta^r y_i^T + x_i\beta^r - 1}{\sigma_r}\right)$ with the multiplicative model and $\frac{\beta_k^r}{\sigma_r}\phi\left(\frac{x_i\beta^r - (1-\theta^r)y_i^T}{\sigma_r}\right)$ with the additive model.

[FIGURE 2.3 HERE]

Figure 2.3 shows that, based on the multiplicative model, the estimated probability of full compliance is up to 5 percentage points higher for an additional 10 years of age, increasing in true earnings. Depending on the level of true earnings, the probability of compliance is up to 10-11 percentage points (pp) higher for females and people with tertiary education relative to those with basic education (or less). Similarly, the probability is up to 10 pp lower for the north-east region relative to the north, and as much as 24 pp lower for construction, relative to the pooled sectors of manufacturing, mining and utilities, and 28 pp lower for firms with 1-10 employees relative to firms with 50 or more employees.

In comparison, the additive model shows effects of similar magnitude with the exception of effects for region and firm size which are smaller. The plotted curves for the additive model also exhibit more curvature, reflecting greater sensitivity to the level of true earnings. Among else, the effects for industry and firm size are not monotonically increasing in the covered range of true earnings – the highest effect is shown around the level of 20 thousand EEK (per month).

The marginal effects on the probability of full and partial evasion are not shown as the estimated probability of full evasion is low and varies rather little with true earnings. Therefore, the effect on the probability of partial evasion basically mirrors that on the probability of full compliance. The marginal effect on *full* evasion is most notable in the case of construction and small firms where the probability is up to 6-7 pp higher.

Figure 2.4 shows the marginal effect on the expected value of declared earnings for the same characteristics, conditional on true earnings. Overall, this gives a very similar picture in terms of direction and relative magnitude of effects. The key difference is that results for the multiplicative and additive model are now very similar, meaning that the marginal effects on the expected value of declared earnings are much more robust to the model specification than the marginal effects on the probabilities of full compliance.

[FIGURE 2.4 HERE]

Finally, to understand how the level of true earnings itself affects compliance (holding other characteristics constant), we consider the elasticity of the expected value of declared earnings with respect to true earnings. The mean elasticity across all employees in the unconstrained sector, calculated at predicted individual true earnings (conditional on being truly employed)[36], is 0.91-0.92 depending on the type of the model. This means that on average a 1% increase in (predicted) true earnings would result in a 0.9% increase in the expected value of declared earnings.

Figure 2.5 shows elasticity estimates for a person with sample mean/mode characteristics, varying one characteristic at a time and across the same range of true earnings. In all cases, elasticity estimates are below 1. Furthermore, elasticity estimates are lower at higher levels of true earnings, indicating that there is a negative association between compliance and true earnings (other things being equal).

[FIGURE 2.5 HERE]

Elasticity estimates for a person with sample mean/mode characteristics and true earnings at average declared (net) earnings in the sample (8,000 EEK), is 0.97. At this level of true earnings, estimates for the multiplicative and the additive model are basically the same and remain in a narrow range of 0.96-0.98 when varying key characteristics like age, gender, education and region. The estimates are slightly smaller (0.92-0.93) for construction sector and small firms.

Elasticity estimates for true (net) earnings at their mean estimated value in the unconstrained sector (10,000 EEK), are in the range of 0.94-0.97 for most cases in Figure 2.5. At higher levels of true earnings, the gap between two model estimates increases, exceeding 10 percentage points at 25,000 EEK in the case of construction and small firms.

2.6.3 Extent of tax evasion

As a last indicator, we provide (aggregate) estimates for the extent of tax evasion. Each individual is characterised by one of the four activities: $S \in \{$no income, partial evasion,

[36] That is $\mathrm{E}(y_i^T | x_i, y_i^T > 0) = \mathrm{E}[\exp(x_i\beta^T + \varepsilon_i^T) | x_i, y_i^T > 0] = \exp(x_i\beta^T)\exp(\sigma_T^2/2)$.

full evasion, compliance}. Applying Bayes's law on equation (2.10), the probability of being engaged in activity s for an individual i (observed in set k) can be expressed as

$$\Pr(s_i|y_i^r, y_i^s, x_i) = f_k(s_i)/f_k \qquad \text{where } s_i \in S \tag{2.12}$$

The proportion of the sample with outcome s can be estimated as

$$\frac{1}{N}\left[\sum_{i\in A_{0s}} \Pr(s_i|y_i^r, y_i^s, x_i) + \sum_{i\in A_{rs}} \Pr(s_i|y_i^r, y_i^s, x_i)\right] \qquad \text{where } s_i \in S \tag{2.13}$$

where N is the number of individuals in the sample. Additionally, we can estimate the amount of undeclared earnings and their share in total earnings. The expected value of undeclared earnings e_i for individual i is

$$\mathrm{E}[e_i|y_i^r, y_i^s, x_i] = \begin{cases} \mathrm{E}[y_i^T - y_i^r|y_i^r, y_i^s, x_i, y_i^T > y_i^r] \cdot \Pr(\text{full evasion}) & \text{if } y_i^r = 0 \\ \mathrm{E}[y_i^T - y_i^r|y_i^r, y_i^s, x_i, y_i^T > y_i^r] \cdot \Pr(\text{partial evasion}) & \text{if } y_i^r > 0 \end{cases} \tag{2.14}$$

which can be rewritten as

$$\frac{1}{f_k}\int_{y_i^r}^{\infty} (y^T - y_i^r) f(y^T|x_i, y_i^T > 0) f(y_i^r|x_i, y^T) f(y_i^s|x_i, y^T)\,\mathrm{d}y^T \qquad \forall i \in A_k \tag{2.15}$$

The aggregate share of undeclared earnings in total earnings is then[37]

$$\frac{1}{N}\frac{\sum_i E[e_i|y_i^r, y_i^s, x_i]}{\sum_i (y_i^r + E[e_i|y_i^r, y_i^s, x_i])} \tag{2.16}$$

Estimated proportions are given in Table 2.6 (panel a). With both types of model, the estimated share of people in the unconstrained sector with no income is less than 1% and the share of people not reporting any earnings about 3%. The estimated share of people declaring only part of their true earnings exceeds 20% and differs more between the models (28% with the multiplicative and 23% with the additive model), leaving about 70%

[37] More specifically, this is in terms of total *net* earnings. To obtain estimates in terms of total *gross* earnings, taxes paid (as they appear in the tax records) have been added to the denominator.

of private sector employees estimated to be fully compliant (68% with the multiplicative and 73% with the additive model). On the other hand, the difference between the two models is only marginal when comparing the estimates of non-compliance in monetary terms: the aggregate share of undeclared earnings in total (gross) earnings is 15-16% in both cases (panel b). The table also provides estimates for the whole sample as the extent of non-compliance would be typically considered at the population level. Because employees in the constrained sector cannot evade taxes by assumption, the share of compliant individuals in the whole sample is naturally higher than for the unconstrained sample alone (75-80%), while the aggregate share of undeclared earnings is about 12%.

In comparison, a recent audit-based study by Johns and Slemrod (2010) for the US estimated that only 1% of wages and salaries are unreported. Similarly, Kleven et al. (2011) find from audited reports for Denmark that 1% of personal income (comprising labor income, transfers and pensions) is unreported and attribute this to third-party reporting. It is important to note though that unlike most other countries, Denmark has very high effective income tax rates in combination with very low social contribution rates for the employer, hence, the financial incentives implied by the statutory tax burden are very different from that in Estonia.

[TABLE 2.6 HERE]

Finally, we consider the extent of non-compliance over the (true) income distribution. Table 2.6 (panel b) shows undeclared earnings as a share of total (gross) earnings by income decile groups and the pattern which emerges is similar for both types of model. The share is higher for the bottom and the top decile group: 17-24% of total earnings in the unconstrained sector and 13-18% for the whole sample are estimated to be undeclared, yielding a gently sloping U-shape profile. For the multiplicative model, the share of undeclared earnings for the bottom decile group exceeds that of the top decile group, while the opposite is the case for the additive model. This is further illustrated in Figure 2.6, which also shows the scale of measurement error by decile group.

[FIGURE 2.6 HERE]

The pattern of measurement error is clearly different from that of non-compliance showing a very substantial overreporting of survey earnings for the bottom decile group (20-40% of true earnings), a small overreporting for the second decile group and increasing underreporting for higher decile groups, reaching 15-20% of true earnings in the top decile group. Estimated misreporting of survey earnings in the unconstrained sector follows closely what is found for the constrained sector (by assumption), with the main exception of the bottom decile group where misreporting for the constrained sector is notably larger. Our findings therefore support previous evidence on mean reverting survey measurement error, which stemmed from studies assuming administrative data to be error-free. Largely opposite patterns of non-compliance and measurement error may also explain why differences in mean values of survey and administrative earnings have been found to be rather muted in the measurement error literature.

2.6.4 Sensitivity analysis

The sensitivity of the main estimates presented above has been tested by estimating the multiplicative and the additive model (i) on alternative samples (models 1 to 3), (ii) with alternative definitions for the constrained sector (models 4 and 5), (iii) with different sets of covariates or parameter constraints (models 6 to 12), (iv) with modifications to the model specifications (models 13 to 15), and (v) taking into account survey design elements, i.e. weights and clustering (model 16).

Table 2.7 and Table 2.8 summarise the estimates of the key parameters and overall model fit as measured by the AIC and BIC statistics. These show that results are fairly robust to extending the sample with part-time employees (model 1), which was discussed in Section 2.5.[38] Increased sample heterogeneity mainly affects parameter estimates for the constrained sector, resulting in a higher estimate of the variance of true earnings ($\hat{\sigma}_T^2$) and a smaller coefficient of true earnings in the survey earnings equation ($\hat{\theta}^s$). Estimates are also similar when the sample includes everyone who reported survey earnings for 12 months, i.e. also those whose main activity was not paid employment (model 2), or when

[38]In this case, the earnings variables are adjusted with the number of months paid.

applying more conservative sample restrictions, i.e. excluding those with self-employment income or who reported earnings in ESU in gross terms (model 3). The latter finding helps to confirm that the gross-to-net imputations, which were needed for a small sub-sample (see Section 2.5), have no substantial impact on estimates.

More relaxed definitions for the constrained sector, such as assuming that everyone working in large firms (model 4) or utilities, public administration, education and health (model 5) are also constrained, result in poorer model fit, especially for model 4 where the constrained sector becomes much more heterogeneous as a result (cf. $\hat{\sigma}_T^2$ and $\hat{\sigma}_s^2$). Unfortunately, the categorical variable for firm size makes it impossible to test the relevance of any other criteria for a large firm.

[TABLE 2.7 AND 2.8 HERE]

Next, we test alternative sets of covariates and parametric restrictions. Model fit and the estimates of the key parameters are relatively robust to omitting covariates for the declared earnings (y^r) equation (model 6) or the survey earnings (y^s) equation (model 7), i.e. imposing all $\beta^r = 0$ and $\beta^s = 0$ (apart from the intercept), respectively. The same applies to restricting the intercept β_0^T and σ_T^2 (model 8) or β_0^s, θ^s and σ_s^2 (model 9) to be the same for the constrained and the unconstrained sector, i.e. the parameters that are allowed to differ between the two sectors in the baseline model. As the main difference between the sectors concerns $\hat{\sigma}_T^2$, which is nearly two times larger for the unconstrained sector, the model fit is worse with model 8. Compared to the baseline, including additional covariates (model 10 and 11) improves the model fit according to AIC, though BIC indicates the opposite. Model 10 adds to the survey earnings equation (y^s) demographic and job characteristics, which were previously included only in the other two equations (marital status, region, industry, occupation etc), while model 11 includes all covariates in all three equations. In both cases, the key parameters change little.

Across models 1 to 11, the estimates of the coefficient of true earnings in the declared earnings equation ($\hat{\theta}^r$) are rather stable with the multiplicative type of models (ranging from -0.02 to -0.03) and always statistically highly significant. It varies more with the additive type of models (ranging from 0.05 to 0.6) and is not always statistically significant (cf. model 4). This implies that θ^r for the additive type of model is more sensitive and cannot be estimated so precisely. The estimates of another key parameter, the coefficient of true earnings in the survey earnings equation ($\hat{\theta}^s$), are similar for the two types of models ranging from 0.42 to 0.75 in these scenarios.

We also test alternative model specifications (besides the multiplicative and the additive form for the y^r equation). Most importantly, we assess the added value of having income also reported in the survey and not only in the tax records by estimating a partial model which contains the true earnings (y^T) equation and the declared earnings (y^r) equation and leaves the survey earnings (y^s) equation aside (model 13). This is equivalent to imposing $\theta^s = 0$ and $\theta^s_0 = 0$ in the survey earnings equation (model 12) such that any direct link between the true earnings and survey earnings is ignored. The latter approach demonstrates how the overall model fit becomes much poorer with these restrictions and, hence, confirms the importance of combining two sets of income observations for estimating true earnings (see also discussion in Section 2.4). It is notable how much the estimates of θ^r for model 12 and 13 differ from other models. Second, we estimate a (sub)model using only the sample of employees with both positive survey and declared earnings (model 14) and here too we observe a sizeable effect on the estimate of θ^r. Third, assuming that everyone has declared their earnings correctly to the tax authority (model 15), we estimate a model based only on simplified likelihood functions (see equations 2.A.3 and 2.A.4 in Appendix 2.A – in this case there is no difference between the multiplicative and the additive form). Much poorer model fit confirms that this is clearly an unrealistic assumption. Without the possibility of underreporting y^r, estimated variance of true earnings and survey earnings ($\hat{\sigma}^2_T, \hat{\sigma}^2_s$) increase greatly and the link between true earnings and survey earnings becomes weaker (i.e. $\hat{\theta}^s$ decreases).

Finally, estimations with survey weights, which account for the sample design and non-response, and clustering at the household level (model 16), confirm their negligible effect on parameter estimates.

The second part of the sensitivity analysis focuses on the estimates of the extent of non-compliance under various scenarios. These are summarised in Table 2.9, both in terms of the proportion of sample and unreported earnings as a share of total earnings. The share of compliant people is between 72-82% with the multiplicative type of models (leaving aside model 15 where evasion is ruled out by assumption), while it is slightly more varying with the additive type of models (69-85%). It is notable that the estimated share of full evaders is highest when the sample includes part-time employees (model 1 and 2). Across models 1-11, the estimated share of undeclared earnings is quite stable ranging between 9-14% of total income for the multiplicative and the additive types, the latter often yielding marginally higher estimates. Among these models, the share of undeclared earnings is the lowest when the constrained sector is extended to include employees in large firms (model 4) and the highest with the extended sample used for model 2. The proportion of undeclared earnings is only 6% with the partial models (12 and 13), where true earnings are estimated solely on the basis of declared earnings, ignoring survey earnings.

[TABLE 2.9 HERE]

Among models 1-11, non-compliance is higher in the bottom and the top decile group, and to some extent in the 2nd and the 9th decile group, hence, providing further support for the overall U-shape. The U-shape is especially pronounced for model 1 and model 2, which are estimated on extended samples including also individuals with lower work intensity (as employees). The estimates by decile groups are more robust for the multiplicative models.

The partial models (12 and 13), however, exhibit a different profile: the share of undeclared earnings is the highest for the bottom decile group(s) (14-25%), then decreases smoothly across the estimated true income distribution and is only 1-2% for the top decile group. This illustrates how on the basis of declared earnings alone and without a secondary income measure, it is not possible to detect all undeclared earnings as the estimates of true earnings, especially at higher income levels, remain too conservative.[39] A declining ratio of unreported wages and salaries across the true income distribution is also

[39]That is unless there are no earnings differences between the constrained and the unconstrained sector at any income level which would be a very strong assumption.

shown in Johns and Slemrod (2010) based on audited reports and, in the light of evidence above, could therefore indicate limited success of audits to uncover non-compliance for earnings at higher levels. The structure of multiplicative model 13 is similar to Feinstein (1991) who modelled income underreporting and its partial detection by auditors using also audit data. Without means to identify absolute detection rates, he interpreted his estimates of non-compliance as if all auditors had the same detection rates as estimated for the best performers and our findings essentially confirm his intuition. Our empirical findings are also in line with recent work in the measurement error literature where Meijer et al. (2012), generalising the Kapteyn and Ypma (2007) model, demonstrate that the best predictors of true earnings are those combining survey and register income measures.[40]

Finally, as with the previous table, taking survey design into account (model 16) has only a limited effect on the estimates – the biggest change occurs in the top decile group where the estimated share of underreported earnings decreases by 2-4 percentage points.

2.7 Conclusions

The chapter uses income survey data linked with tax records at the individual level for Estonia to estimate the determinants and extent of income tax compliance in a novel way. We propose and estimate an econometric model with three simultaneous equations for true income, register income and survey income. Unlike previous approaches in the tax compliance and survey measurement error literature, our model allows income to be misreported *both* in the survey and in the tax records. Focusing on employment income (i.e. wages and salaries), we model register and survey earnings conditional on true earnings and other personal characteristics. Our key identifying assumption is that people working in the public sector are constrained in their choice and cannot evade taxes, while there are essentially no systematic differences in true earnings and survey measurement error between public and private sector employees (after controlling for

[40]In this case, the source of error in the administrative values is only due to mismatch in record linkage. Interestingly, Meijer et al. (2012) highlight unreported earnings in the register data when discussing potential reasons for the latter to perform relatively poorly.

individual characteristics). This enables us to observe true earnings for part of the sample.

Besides proposing a novel econometric model and identification strategy, the chapter extends the empirical tax evasion literature by providing new evidence of non-compliance in a post-socialist country. High-quality data sources for studying tax compliance are very rare, especially in other than major developed countries; the dataset used here is also unique for not requiring respondents' consent for linkage, which could result in a serious sample selection bias. A long-term characteristic of Estonia is its flat income tax due to which cross-sectional variation in effective marginal tax rates is very limited. Our study is therefore unable to shed light on the effect of marginal tax rates on compliance, but also avoids related endogeneity problems as progressive tax rates would be highly correlated with declared income.

The main findings are the following. First, our estimates show that, conditional on true earnings, earnings declared to the tax authority are positively associated with age, education levels, Estonian nationality, studying, the size of the firm and having a mortgage or a lease loan. Compliance is lower for men, non-married and for people living in the north-east region. There are also notable sectoral and occupational differences and, importantly, our results indicate a negative association between compliance and true earnings (other things being equal). In general, our estimates appear to be in line with findings in the previous literature. Second, we find substantial non-compliance with respect to wages and salaries overall. While the share of fully non-compliant employees is marginal (2-3%), our estimates show that more than 20% of employees underreport part of their earnings and about 12% of total employment income (and 15-16% of total income in the unconstrained sector) is not declared to the tax authority. Third, there are significant differences across the estimated true income distribution with much lower compliance among the people in the bottom and the top earnings decile group. Fourth, there are substantial measurement errors in survey income. These exhibit a mean-reverting pattern with large over-reporting at low values of true earnings and moderate under-reporting at medium and high values of true earnings.

In times when researchers are increasingly gaining access to linked survey and administrative data, our model represents a new improved method for studying prevalence and determinants of tax compliance as well as survey measurement error. Our analysis also highlights limitations for detecting non-compliance on the basis of audited tax reports alone, even with partial detection methods (commonly used by the US tax authority), as the resulting estimates are likely to be too conservative.

Our findings have also several important policy implications. Rather sizable under-reporting of earnings, despite all such income being in principle subject to third-party reporting and tax withholding, highlights the limitations of such procedures to avoid non-compliance and confirms the (continuing) need for other measures as well to counter evasion. It also raises questions about the common view in the literature that there is very little evasion of taxes on wages and salaries in the first place and about the ability of (randomised) audits, on which previous findings are mainly based, to capture non-declared earnings. This suggests that more attention to employment income by the tax authorities could be warranted. Finally, there are implications for the progressivity and redistributive aspects of the tax system. The overall pattern of non-compliance across the income distribution could induce more people to perceive that their effective tax burden is higher compared to those who are better off and subsequently weaken their motives to be compliant.

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Table 2.1: Evolution of the sample

Sample	Number of persons Total	A_{0s}	A_{rs}	Omitted at each step
Initial sample of ESU 2008	14,942	-	-	-
Linked with tax records	14,871	-	-	71
Aged 16 or older[a]	12,699	-	-	2,172
Respondent household[b]	10,789	-	-	1,910
Respondent individual	10,702	-	-	87
Complete earnings information	10,237	-	-	465
Ever had a regular job	8,587	-	-	1,650
Employed (positive survey earnings)	5,500	294	5,206	3,087
Employment main activity[c]	5,327	249	5,078	173
Full time employment[d]	4,121	138	3,983	1,206
- constrained sector[e]	921	12	909	-
- unconstrained sector	3,200	126	3,074	-

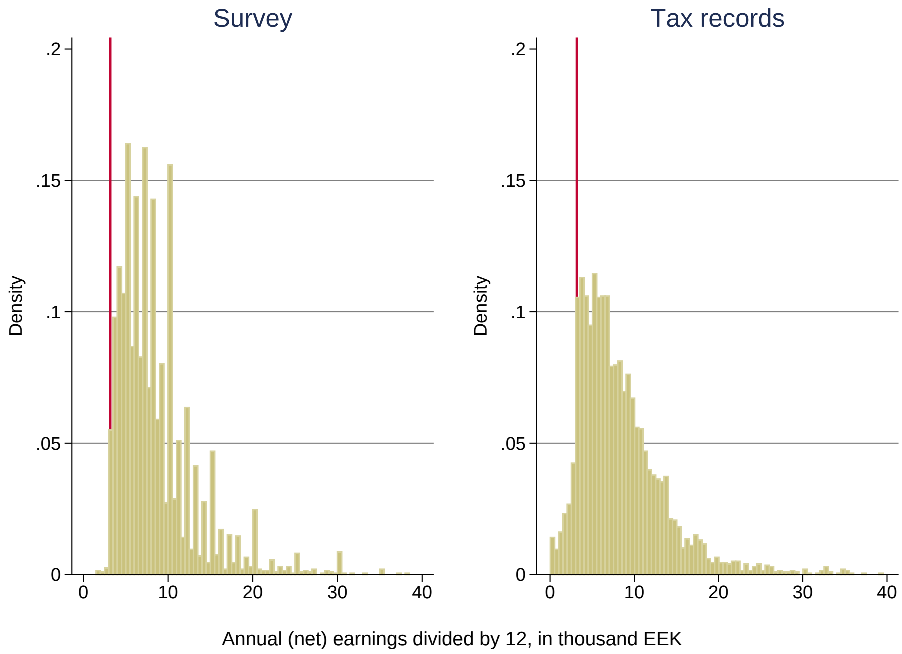
Notes: [(a)] subject to a personal interview in the survey; [(b)] for new sample members the number of non-respondents includes only sampled persons without other household members; [(c)] part- or full-time employment reported as the main activity at least for one month in the income reference period; [(d)] full-time employment reported as the main activity (and employment income received) for 12 months in the income reference period; [(e)] constrained sector sub-sample includes public sector employees, except those who changed jobs or have a second job.

Table 2.2: Mean log survey and register income

Sample	$\ln y^s$ b	se	$\ln y^r$ b	se	Difference b	se	N
(a) All (adults) with positive earnings in the tax records							
ESU non-respondents	-	-	8.46	0.06	-	-	1,114
ESU respondents	-	-	8.33	0.03	-	-	6,698
(b) ESU respondents – intermediate sample							
Positive earnings in the tax records (A_{r0})	-	-	6.28	0.14	-	-	343
Positive earnings in ESU (A_{0s})	8.54	0.09	-	-	-	-	294
Positive earnings in both sources (A_{rs})	8.72	0.02	8.61	0.02	0.10	0.01	5,206
- constrained sector	8.77	0.03	8.84	0.03	-0.07	0.02	1,040
- unconstrained sector	8.70	0.02	8.55	0.02	0.16	0.02	4,166
(c) ESU respondents – final estimation sample							
Positive earnings in ESU (A_{0s})	8.99	0.07	-	-	-	-	138
Positive earnings in both sources (A_{rs})	8.92	0.01	8.84	0.02	0.08	0.01	3,983
- constrained sector	8.87	0.03	8.95	0.03	-0.08	0.02	909
- unconstrained sector	8.93	0.01	8.80	0.02	0.14	0.02	3,074

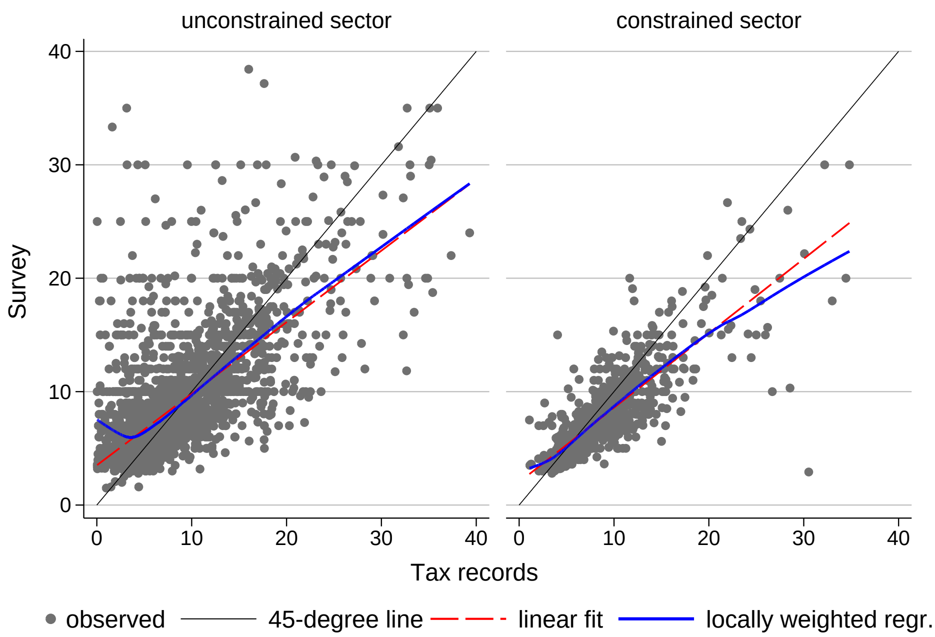
Notes: annual (net) earnings in EEK divided by 12, in log terms; estimates take into account design weights and clustering at the household level; intermediate sample contains respondent individuals with complete earnings information and who have had a regular job; final estimation sample contains full-time employed; constrained sector sub-sample includes public sector employees, except those who changed jobs or have a second job.

Figure 2.1: Distribution of survey and register income



Notes: final estimation sample (i.e. full-time employed) excluding those with zero earnings or monthly earnings above 40 thousand EEK (N=3,964); bandwith=0.5; vertical line shows the monthly minimum net wage (3,175 EEK).

Figure 2.2: Survey and register income by sector



Notes: annual (net) earnings divided by 12, in thousand EEK; final estimation sample (i.e. full-time employed) excluding those with zero earnings or monthly earnings above 40 thousand EEK (N = 3,964); constrained sector sub-sample includes public sector employees, except those who changed jobs or have a second job.

Table 2.3: Sample means

Variable	Uncon-strained	Con-strained	All	N
Monthly (net) earnings in tax report, thousand EEK	8.09	8.76	8.24	4,121
Monthly (net) earnings in ESU, thousand EEK	8.94	7.85	8.69	4,121
Age[a]	-0.10	0.33	-0.01	4,121
Age[a] squared	1.36	1.23	1.33	4,121
Gender=male	0.56	0.30	0.50	4,121
Nationality=Estonian	0.73	0.79	0.74	4,121
Education=basic or less	0.11	0.05	0.10	4,121
Education=secondary	0.63	0.45	0.59	4,121
Education=tertiary	0.25	0.50	0.31	4,121
Marital status=single	0.16	0.12	0.15	4,121
Marital status=married	0.54	0.56	0.54	4,121
Marital status=cohabiting	0.19	0.15	0.18	4,121
Marital status=divorced, widow or separated	0.11	0.17	0.12	4,121
Dummy for studying	0.03	0.05	0.04	4,121
Region=north	0.30	0.26	0.29	4,121
Region=central	0.14	0.12	0.14	4,121
Region=north-east	0.10	0.12	0.10	4,121
Region=west	0.17	0.17	0.17	4,121
Region=south	0.28	0.32	0.29	4,121
Area=rural	0.41	0.40	0.41	4,121
Occupation=senior managers, legislators	0.11	0.12	0.11	4,120
Occupation=professionals	0.09	0.36	0.15	4,120
Occupation=technicians, associate professionals	0.11	0.14	0.11	4,120
Occupation=clerks	0.05	0.06	0.05	4,120
Occupation=service and sales workers	0.10	0.13	0.11	4,120
Occupation=skilled agricultural workers	0.02	0.01	0.01	4,120
Occupation=craft and related trade workers	0.22	0.04	0.18	4,120
Occupation=plant and machine operators	0.22	0.05	0.19	4,120
Occupation=elementary occupations	0.08	0.10	0.09	4,120
Industry=agriculture, forestry	0.06	0.02	0.05	4,028
Industry=manufacturing, mining, utilities	0.32	0.05	0.26	4,028
Industry=construction	0.15	0.01	0.12	4,028
Industry=wholesale trade, motor vehicles	0.06	0.00	0.05	4,028
Industry=retail trade	0.09	0.00	0.07	4,028
Industry=transportation, storage, courier	0.09	0.07	0.08	4,028
Industry=hotels, restaurants	0.04	0.01	0.03	4,028
Industry=prof. services, information, communication	0.04	0.02	0.04	4,028
Industry=finance, real estate, admin/support	0.07	0.01	0.05	4,028
Industry=education, health, public admin.	0.08	0.80	0.25	4,028

Notes: unweighted means for the final estimation sample (i.e. full-time employed); [a] constructed as $(age-43)/10$, where 43 is (unweighted) sample mean.

(Table continues on next page)

Table 2.3 continues

Variable	Unconstrained	Constrained	All	N
Dummy for constrained sector[b]	0.00	1.00	0.22	4,121
No of employees=1-10	0.20	0.14	0.19	4,019
No of employees=11-19	0.17	0.16	0.16	4,019
No of employees=20-49	0.22	0.26	0.23	4,019
No of employees=50 or more	0.37	0.42	0.38	4,019
No of employees=uncertain (more than 10)	0.04	0.03	0.04	4,019
Number of hours in main job (usual per week)	40.84	40.03	40.66	4,024
Dummy for second job	0.07	0.00	0.05	4,028
Number of hours in second job (usual per week)	0.86	0.00	0.67	4,028
Health=very good	0.08	0.07	0.08	4,120
Health=good	0.59	0.58	0.59	4,120
Health=neither good or bad	0.30	0.32	0.30	4,120
Health=poor or very poor	0.03	0.03	0.03	4,120
Dummy for health problems limiting work/study	0.15	0.14	0.15	4,121
Dummy for HH having a mortgage	0.25	0.20	0.24	4,110
Dummy for HH having a lease	0.25	0.23	0.25	4,121
Month of interview (since Feb)	1.65	1.53	1.62	4,121
Dummy for young child at interview	0.04	0.03	0.03	4,121
Dummy for older child at interview	0.09	0.12	0.09	4,121
Dummy for spouse at interview	0.29	0.28	0.29	4,121
Dummy for other relative at interview	0.10	0.07	0.09	4,121
Interview rating=very well	0.63	0.63	0.63	4,121
Interview rating=well	0.32	0.30	0.31	4,121
Interview rating=ok	0.06	0.06	0.06	4,121
Interview responded=alone	0.84	0.89	0.85	4,121
Interview responded=with someone's help	0.03	0.02	0.03	4,121
Interview responded=by other HH member	0.13	0.09	0.13	4,121
Number of waves	2.14	2.19	2.15	4,121

Notes: [(b)] constrained sector sub-sample includes public sector employees, except those who changed jobs or have a second job.

Table 2.4: Estimates for the multiplicative model

	Dependent variable					
	$\ln y^T$		y^r		$\ln y^s$	
	coef.	se	coef.	se	coef.	se
Age[a]	-0.025***	0.008	0.073***	0.021	-0.027***	0.004
Age[a] squared	-0.039***	0.005	0.021	0.015	-0.007**	0.003
Male	0.327***	0.018	-0.181***	0.055	0.089***	0.014
Estonian nationality	0.166***	0.024	0.230***	0.055	0.044***	0.011
Education (ref=basic or less)						
- secondary	0.066**	0.026	0.168***	0.056	0.051***	0.016
- tertiary	0.223***	0.030	0.331***	0.079	0.136***	0.019
Marital status (ref=married)						
- single	-0.042*	0.024	-0.128**	0.065		
- cohabiting	-0.011	0.020	-0.165***	0.051		
- divorced/widow/separated	-0.021	0.022	-0.267***	0.069		
Region (ref=north)						
- central	-0.141***	0.025	0.080	0.063		
- north-east	-0.228***	0.027	-0.146**	0.066		
- west	-0.146***	0.024	0.097	0.061		
- south	-0.172***	0.022	0.025	0.053		
Rural area	-0.020	0.016	-0.043	0.044		
Studying	0.006	0.036	0.418**	0.169		
Industry (ref=edu/health/pub.adm)						
- agriculture/forestry	0.008	0.043	-0.085	0.146		
- manufacturing/mining/utilities	0.054*	0.030	-0.006	0.116		
- construction	0.323***	0.039	-0.364***	0.116		
- wholesale trade	0.199***	0.044	0.002	0.131		
- retail trade	0.054	0.034	-0.223	0.137		
- transportation/storage/courier	0.235***	0.036	-0.334***	0.120		
- hotels/restaurants	0.046	0.044	-0.386***	0.139		
- prof. services/inform./commun.	0.160***	0.046	-0.104	0.139		
- finance/real estate/admin-support	0.128***	0.043	-0.437***	0.129		
Occupation (ref=clerks)						
- senior managers	0.409***	0.039	-0.127	0.134		
- professionals	0.345***	0.037	-0.207	0.148		
- technicians/associate prof.	0.227***	0.038	-0.163	0.134		
- service/sales workers	-0.065*	0.039	-0.104	0.156		
- skilled agricultural workers	0.139*	0.082	-0.617***	0.191		
- craft/trade workers	0.119***	0.041	-0.323**	0.129		
- plant/machine operators	0.039	0.037	-0.318**	0.128		
- elementary	-0.205***	0.038	-0.268*	0.142		

Notes: [(a)] constructed as $(age - 43)/10$, where 43 is (unweighted) sample mean. Robust standard errors shown. * p<0.1, ** p<0.05, *** p<0.01

(Table continues on next page)

Table 2.4 continues

	Dependent variable					
	$\ln y^T$		y^r		$\ln y^s$	
	coef.	se	coef.	se	coef.	se
Constrained sector[b]	0.003	0.024			0.062	0.055
No of employees (ref=1 to 10)						
- 11 to 19	0.107***	0.025	0.110**	0.052		
- 20 to 49	0.162***	0.023	0.339***	0.057		
- 50 or more	0.273***	0.022	0.416***	0.055		
- uncertain (more than 10)	0.246***	0.051	0.159*	0.086		
Hours in main job	0.013***	0.002	-0.005	0.003		
Second job	0.109*	0.057	-0.016	0.155		
Hours in second job	0.004	0.003	0.002	0.007		
Health status (ref=neutral)						
- very good	0.183***	0.031				
- good	0.077***	0.018				
- poor/very poor	-0.082*	0.046				
Health affected work/studying	-0.055***	0.021				
HH has a mortgage			0.077*	0.043		
HH has a lease			0.154***	0.041		
Number of waves					-0.020***	0.004
Month of interview (since Feb)					0.008**	0.003
Interview rating (ref=very well)						
- well					-0.014	0.010
- ok					-0.051**	0.023
Interview responded (ref=alone)						
- with someone's help					-0.045	0.030
- by other HH member					0.037**	0.016
At interview: young child					0.030	0.028
At interview: older child					-0.012	0.013
At interview: spouse					0.012	0.010
At interview: other relative					0.004	0.018
Intercept	0.934***	0.095	1.646***	0.240	0.479***	0.039
p	0.993***	0.002				
θ (unconstrained sector)			-0.024***	0.004	0.689***	0.018
θ (constrained sector)					0.642***	0.025
θ_0					1.113***	0.084
σ (unconstrained sector)	0.474***	0.015	0.583***	0.035	0.247***	0.008
σ (constrained sector)	0.354***	0.014			0.233***	0.012
Sample size	4,006					
AIC	39,017					
BIC	39,741					

Notes: [b] constrained sector sub-sample includes public sector employees, except those who changed jobs or have a second job. Robust standard errors shown. * p<0.1, ** p<0.05, *** p<0.01

Table 2.5: Estimates for the additive model

	Dependent variable					
	$\ln y^T$		y^r		$\ln y^s$	
	coef.	se	coef.	se	coef.	se
Age[a]	-0.024***	0.009	1.180***	0.319	-0.028***	0.004
Age[a] squared	-0.038***	0.005	0.356*	0.215	-0.008**	0.003
Male	0.329***	0.018	-2.911***	0.820	0.095***	0.014
Estonian nationality	0.182***	0.025	2.740***	0.898	0.041***	0.011
Education (ref=basic or less)						
- secondary	0.071***	0.027	1.961**	0.773	0.049***	0.016
- tertiary	0.232***	0.032	4.531***	1.311	0.133***	0.019
Marital status (ref=married)						
- single	-0.045*	0.025	-1.528	0.962		
- cohabiting	-0.013	0.021	-2.446***	0.845		
- divorced/widow/separated	-0.029	0.023	-3.525***	1.022		
Region (ref=north)						
- central	-0.145***	0.025	0.942	0.964		
- north-east	-0.233***	0.028	-1.428	0.975		
- west	-0.150***	0.025	1.158	0.940		
- south	-0.178***	0.023	0.546	0.833		
Rural area	-0.021	0.017	-0.367	0.661		
Studying	0.007	0.036	4.940*	2.769		
Industry (ref=edu/health/pub.adm)						
- agriculture/forestry	0.008	0.044	-2.094	2.309		
- manufacturing/mining/utilities	0.062**	0.031	-1.077	1.948		
- construction	0.340***	0.042	-6.985***	2.014		
- wholesale trade	0.203***	0.047	-0.587	2.239		
- retail trade	0.052	0.036	-4.713**	2.161		
- transportation/storage/courier	0.249***	0.038	-6.500***	2.080		
- hotels/restaurants	0.027	0.044	-6.009***	2.322		
- prof. services/inform./commun.	0.173***	0.048	-3.275	2.360		
- finance/real estate/admin-support	0.123***	0.045	-7.685***	2.206		
Occupation (ref=clerks)						
- senior managers	0.429***	0.041	-2.589	2.000		
- professionals	0.349***	0.038	-3.647	2.276		
- technicians/associate prof.	0.234***	0.039	-3.198	1.989		
- service/sales workers	-0.065	0.040	-1.655	2.193		
- skilled agricultural workers	0.110	0.083	-9.570***	2.919		
- craft/trade workers	0.108**	0.042	-5.282***	1.941		
- plant/machine operators	0.031	0.038	-4.815**	1.921		
- elementary	-0.208***	0.039	-3.886*	2.078		

Notes: [(a)] constructed as $(age - 43)/10$, where 43 is (unweighted) sample mean. Robust standard errors shown. * p<0.1, ** p<0.05, *** p<0.01

(Table continues on next page)

Table 2.5 continues

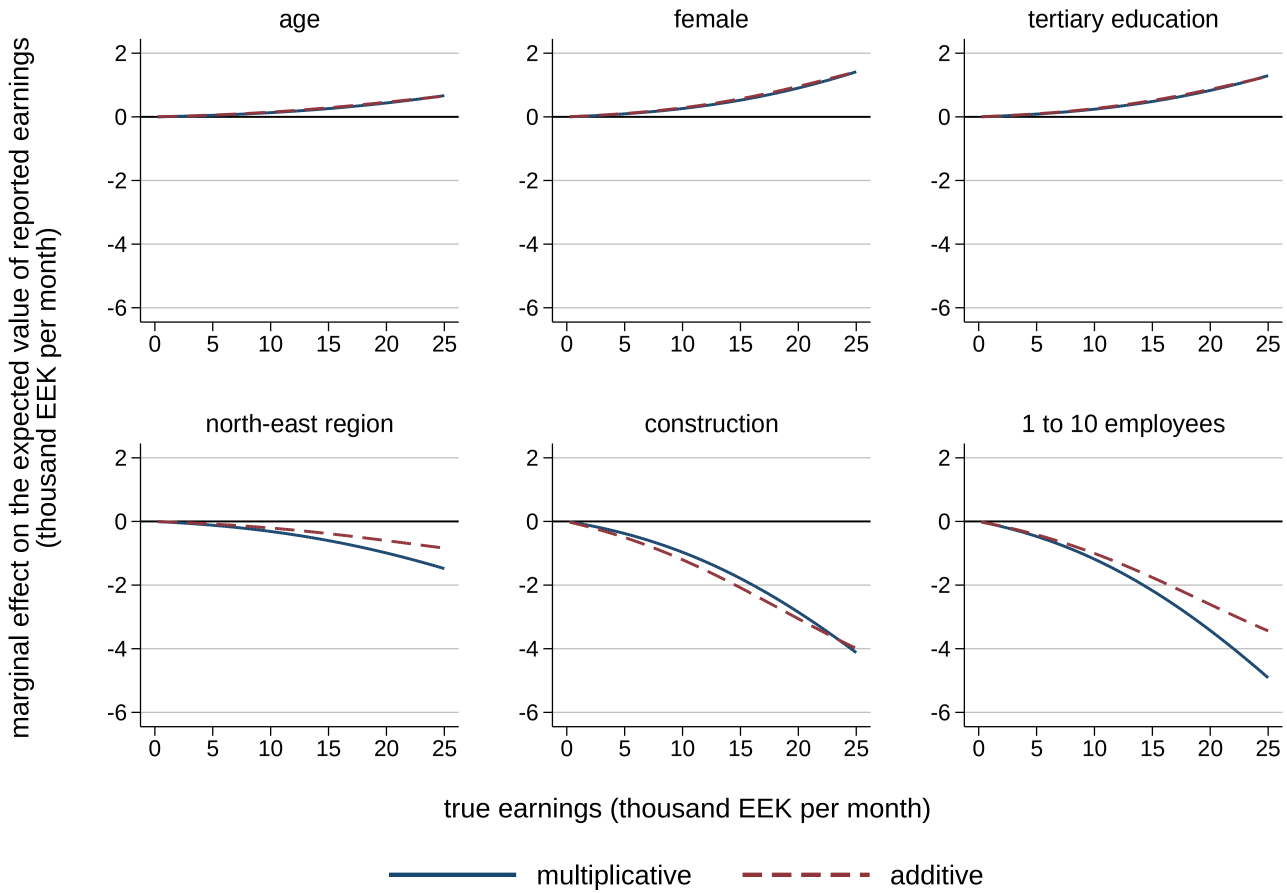
	Dependent variable					
	$\ln y^T$		y^r		$\ln y^s$	
	coef.	se	coef.	se	coef.	se
Constrained sector[b]	0.017	0.024			-0.021	0.057
No of employees (ref=1 to 10)						
- 11 to 19	0.119***	0.026	1.089	0.795		
- 20 to 49	0.181***	0.024	4.199***	0.993		
- 50 or more	0.295***	0.023	5.191***	1.054		
- uncertain (more than 10)	0.263***	0.053	0.843	1.355		
Hours in main job	0.013***	0.002	-0.124**	0.059		
Second job	0.118*	0.061	-0.400	2.408		
Hours in second job	0.005	0.004	-0.023	0.110		
Health status (ref=neutral)						
- very good	0.183***	0.032				
- good	0.077***	0.019				
- poor/very poor	-0.085*	0.046				
Health affected work/studying	-0.053**	0.022				
HH has a mortgage			0.750	0.650		
HH has a lease			2.099***	0.653		
Number of waves					-0.021***	0.004
Month of interview (since Feb)					0.008**	0.003
Interview rating (ref=very well)						
- well					-0.015	0.010
- ok					-0.046**	0.023
Interview responded (ref=alone)						
- with someone's help					-0.050*	0.030
- by other HH member					0.043***	0.016
At interview: young child					0.036	0.028
At interview: older child					-0.007	0.014
At interview: spouse					0.011	0.010
At interview: other relative					0.004	0.018
Intercept	0.860***	0.100	20.137***	4.301	0.567***	0.037
p	0.996***	0.001				
θ (unconstrained sector)			0.300**	0.108	0.653***	0.018
θ (constrained sector)					0.642***	0.026
θ_0					1.129***	0.099
σ (unconstrained sector)	0.478***	0.019	8.553***	0.944	0.254***	0.008
σ (constrained sector)	0.354***	0.014			0.233***	0.012
Sample size	4,006					
AIC	39,189					
BIC	39,913					

Notes: $^{(b)}$ constrained sector sub-sample includes public sector employees, except those who changed jobs or have a second job. Robust standard errors shown. * p<0.1, ** p<0.05, *** p<0.01

Figure 2.3: Marginal effect on the probability of full compliance, conditional on true earnings

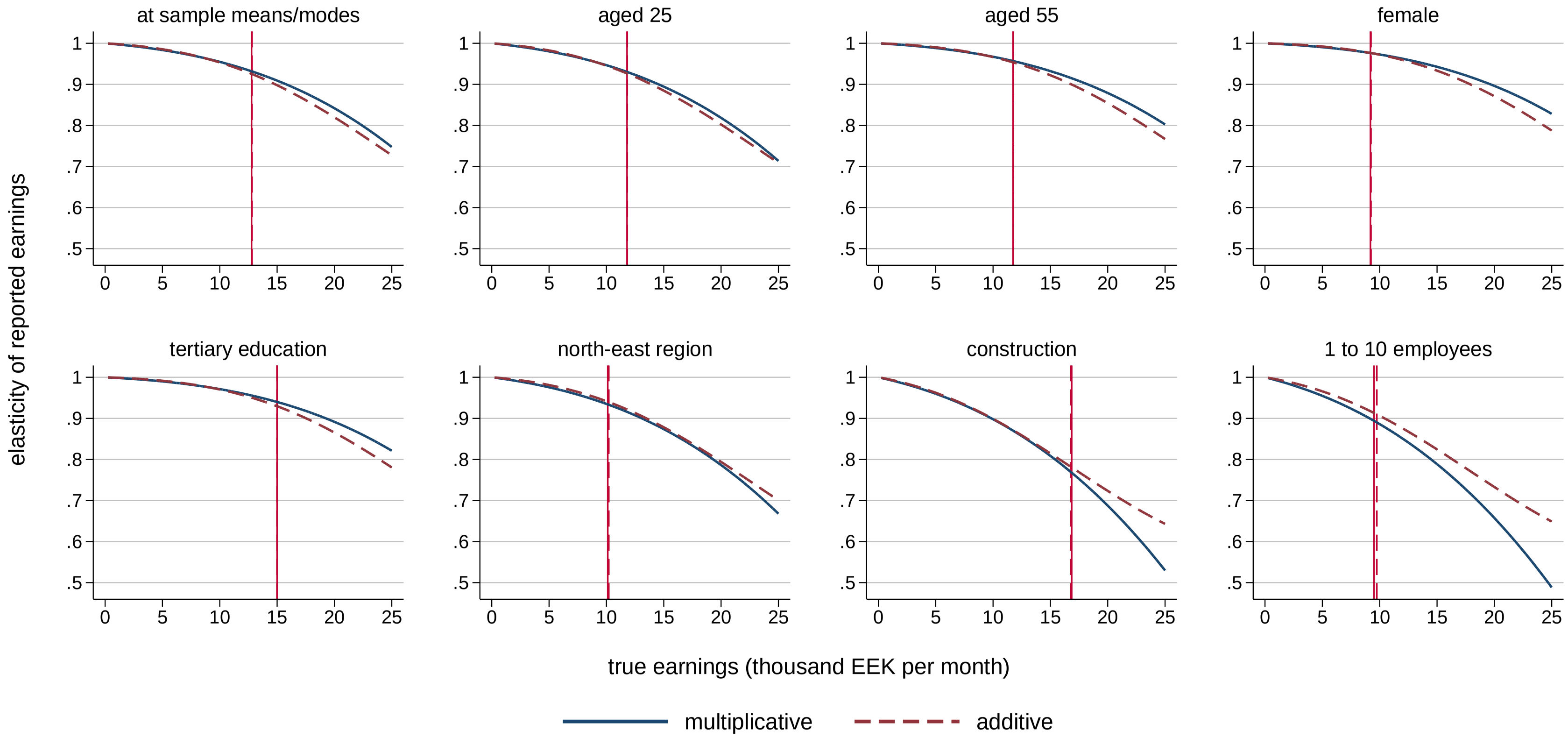
Notes: Calculated as the partial derivative for age ($\Delta = 10$ years) and as a discrete change in the outcome for categorical variables. Assessed at the sample means/modes, i.e. for a 43 year old married Estonian male with secondary education who is living in an urban area in North-Estonia; working 40 hours per week in manufacturing in the private sector, in a firm with 50 or more employees, whose occupation is plant/machine operator, who does not have a second job and is not studying; is in good health and has no health conditions affecting working; does not have a mortgage or a lease loan; participates for the first time in the survey, was interviewed in February, responded alone with no other people present at the interview and the interview went very well.

Figure 2.4: Marginal effect on the expected value of declared earnings ($\mathrm{E}[y^r|x, y^T]$)



Notes: Calculated as the partial derivative for age ($\Delta = 10$ years) and as a discrete change in the outcome for categorical variables. Assessed at the sample means/modes, i.e. for a 43 year old married Estonian male with secondary education who is living in an urban area in North-Estonia; working 40 hours per week in manufacturing in the private sector, in a firm with 50 or more employees, whose occupation is plant/machine operator, who does not have a second job and is not studying; is in good health and has no health conditions affecting working; does not have a mortgage or a lease loan; participates for the first time in the survey, was interviewed in February, responded alone with no other people present at the interview and the interview went very well.

Figure 2.5: Elasticity of expected value of declared earnings ($\mathrm{E}[y^r|x, y^T]$) with respect to true earnings (y^T)



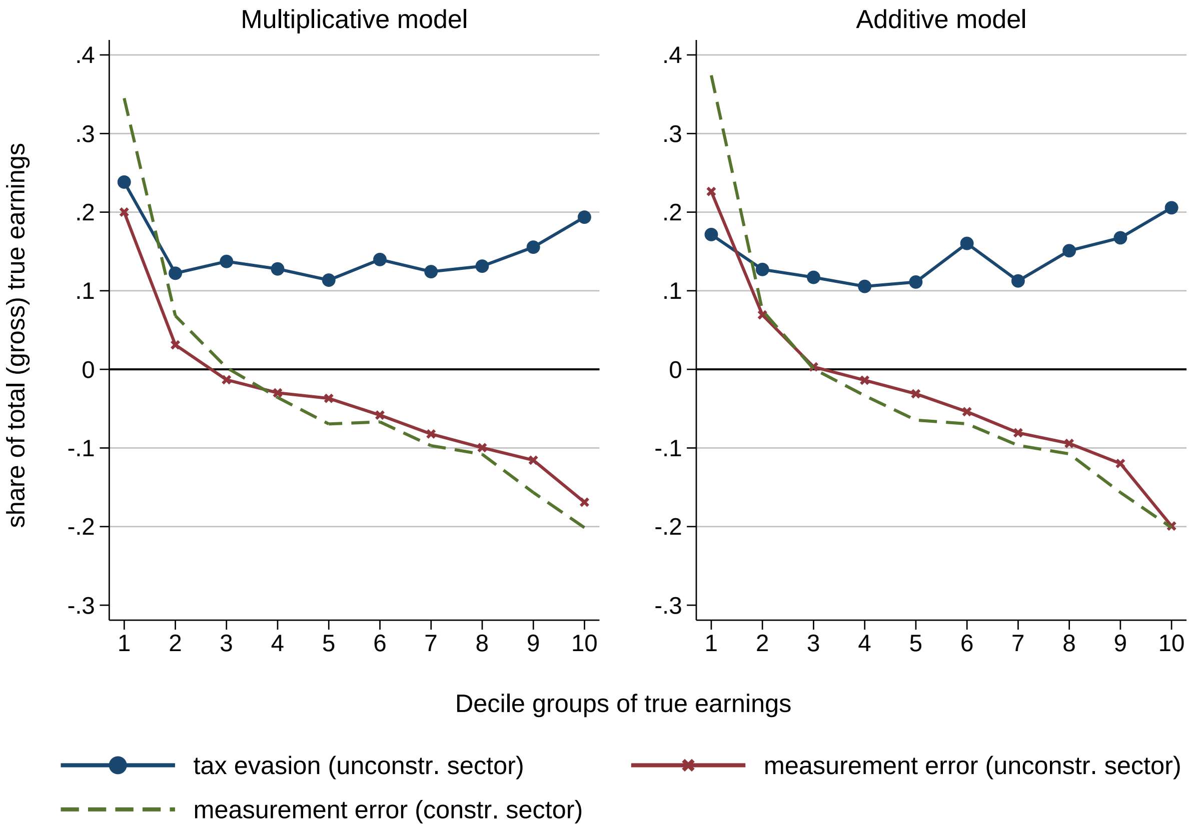
Notes: The first plot is assessed at the sample means/modes, i.e. for a 43 year old married Estonian male with secondary education who is living in an urban area in North-Estonia; working 40 hours per week in manufacturing in the private sector, in a firm with 50 or more employees, whose occupation is plant/machine operator, who does not have a second job and is not studying; is in good health and has no health conditions affecting working; does not have a mortgage or a lease loan; participates for the first time in the survey, was interviewed in February, responded alone with no other people present at the interview and the interview went very well.. In other plots, one characteristic is adjusted in comparison with the first plot. Vertical lines show predicted true (net) earnings (conditional on being positive), $\mathrm{E}[y^T|x, y^T > 0]$, for a person with corresponding characteristics.

Table 2.6: Estimation of tax non-compliance

	Unconstrained sector		Whole sample	
	Multiplicative	Additive	Multiplicative	Additive
(a) Proportion of sample, %				
no income	0.5	0.2	0.7	0.4
full evaders	3.1	3.5	2.4	2.7
part evaders	28.2	22.9	21.8	17.7
compliant	68.2	73.4	75.1	79.2
(b) Undeclared earnings as a share of total gross true earnings, %				
All	15.4	15.8	12.1	12.5
Decile 1	23.8	17.2	17.4	12.9
Decile 2	12.2	12.7	9.7	10.2
Decile 3	13.7	11.7	11.1	9.4
Decile 4	12.8	10.6	10.2	8.3
Decile 5	11.4	11.1	8.9	8.8
Decile 6	14.0	16.0	10.1	11.6
Decile 7	12.4	11.3	8.8	7.8
Decile 8	13.1	15.1	9.4	10.8
Decile 9	15.6	16.7	12.5	13.4
Decile 10	19.4	20.6	16.9	18.0
	N = 3,093		N = 4,006	

Notes: deciles are constructed on the basis of estimated gross true earnings using the whole estimation sample.

Figure 2.6: Tax evasion and measurement error by decile groups



Notes: *tax evasion* = the aggregate gap of estimated true earnings and register income, $\sum_i \left(\hat{y}_i^T - y_i^r\right)$; *measurement error* = the aggregate gap of survey income and estimated true earnings, $\sum_i \left(y_i^s - \hat{y}_i^T\right)$; both shown as a share of total estimated gross true earnings by sector (constrained/unconstrained) and decile group; deciles are constructed on the basis of estimated gross true earnings using the whole estimation sample.

Table 2.7: Sensitivity analysis: selected parameter estimates for alternative multiplicative model specifications

	Multiplicative models																
	base	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
p	0.993	0.990	0.992	0.996	0.985	0.993	0.990	0.992	0.993	0.993	0.993	0.994	0.992	0.992		0.968	0.992
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		(0.003)	(0.003)
θ^r	-0.024	-0.020	-0.020	-0.024	-0.030	-0.025	-0.023	-0.020	-0.021	-0.023	-0.028	-0.026	0.016	0.016	-0.010		-0.018
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.012)	(0.012)	(0.002)		(0.004)
θ^s (unconstr.)	0.689	0.687	0.715	0.693	0.651	0.677	0.679	0.754	0.694	0.681	0.630	0.621	0.000		0.676		0.671
	(0.018)	(0.016)	(0.016)	(0.021)	(0.020)	(0.020)	(0.019)	(0.016)	(0.019)	(0.016)	(0.022)	(0.022)	(.)		(0.020)		(0.026)
θ^s (constrained)	0.642	0.584	0.657	0.644	0.426	0.613	0.637	0.721	0.644	0.681	0.571	0.556	0.000		0.646	0.353	0.594
	(0.025)	(0.034)	(0.024)	(0.029)	(0.036)	(0.036)	(0.025)	(0.024)	(0.025)	(0.016)	(0.028)	(0.029)	(.)		(0.026)	(0.021)	(0.044)
θ^s_0	1.113	1.039	1.159	1.304	0.927	1.050	1.060	1.231	1.116	1.150	0.970	0.941	0.000			0.778	1.150
	(0.084)	(0.078)	(0.081)	(0.084)	(0.089)	(0.092)	(0.080)	(0.094)	(0.087)	(0.082)	(0.084)	(0.101)	(.)			(0.070)	(0.109)
β^T_0 x constrained	0.003	-0.008	0.012	-0.024	-0.110	0.026	-0.001	-0.011	0.000	-0.007	0.009	0.014	0.059	0.059	-0.006		0.024
	(0.024)	(0.025)	(0.024)	(0.025)	(0.027)	(0.027)	(0.024)	(0.024)	(.)	(0.023)	(0.024)	(0.025)	(0.028)	(0.028)	(0.024)		(0.031)
β^s_0 x constrained	0.062	0.186	0.094	0.072	0.499	0.114	0.056	0.041	0.066	0.000	0.095	0.111	-0.064		0.034		0.127
	(0.055)	(0.066)	(0.053)	(0.063)	(0.069)	(0.075)	(0.055)	(0.060)	(0.056)	(.)	(0.059)	(0.060)	(0.015)		(0.060)		(0.094)
σ_T (unconstr.)	0.474	0.482	0.486	0.473	0.490	0.478	0.474	0.469	0.446	0.479	0.476	0.473	0.424	0.424	0.458		0.470
	(0.015)	(0.013)	(0.014)	(0.017)	(0.017)	(0.016)	(0.016)	(0.015)	(0.013)	(0.016)	(0.014)	(0.014)	(0.013)	(0.013)	(0.017)		(0.021)
σ_T (constrained)	0.354	0.427	0.375	0.355	0.502	0.386	0.353	0.356	0.446	0.354	0.353	0.351	0.353	0.353	0.354	0.554	0.389
	(0.014)	(0.023)	(0.015)	(0.016)	(0.027)	(0.017)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.029)
σ_r	0.583	0.630	0.623	0.591	0.530	0.593	0.720	0.538	0.600	0.551	0.623	0.617	0.725	0.725	0.397		0.608
	(0.035)	(0.037)	(0.033)	(0.036)	(0.036)	(0.038)	(0.051)	(0.031)	(0.036)	(0.033)	(0.040)	(0.039)	(0.095)	(0.095)	(0.017)		(0.054)
σ_s (unconstr.)	0.247	0.273	0.262	0.239	0.257	0.249	0.251	0.248	0.253	0.242	0.245	0.242	0.429		0.248		0.251
	(0.008)	(0.007)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.006)		(0.008)		(0.011)
σ_s (constrained)	0.233	0.269	0.249	0.236	0.321	0.260	0.233	0.245	0.233	0.242	0.224	0.223	0.354		0.231	0.356	0.262
	(0.012)	(0.012)	(0.011)	(0.013)	(0.012)	(0.017)	(0.012)	(0.012)	(0.012)	(0.007)	(0.012)	(0.013)	(0.010)		(0.012)	(0.007)	(0.021)
AIC	39,017	47,594	44,521	34,220	40,715	39,285	39,485	39,213	39,112	39,032	38,855	38,734	41,917	21,369	37,299	42,258	.
BIC	39,741	48,340	45,259	34,929	41,433	40,009	39,951	39,836	39,824	39,737	39,787	39,868	42,622	21,948	38,007	42,674	.
N total	4,006	4,853	4,545	3,515	4,006	4,006	4,016	4,006	4,006	4,006	4,006	4,006	4,006	4,006	3,881	4,016	4,006
N constrained	3,093	3,807	3,558	2,742	1,958	2,816	3,100	3,093	3,093	3,093	3,093	3,093	3,093	3,093	2,980	0	3,093

Notes: robust standard errors are shown in parentheses under parameter point estimates. Alternative model specifications as follows. **Alternative samples:** (1) include those working part-time or working less than 12 months, (2) survey earnings reported for 12 months, (3) exclude those with survey self-employment income or survey earnings reported in gross terms. **Alternative definitions for the constrained sector:** (4) include private sector workers in large firms (50+ employees), (5) include private sector workers in utilities, public administration, education and health. **Alternative set of co-variates or constraints:** (6) no co-variates in the register income (y^r) equation, (7) no co-variates in the survey income (y^s) equation, (8) common parameters (intercept, σ^2_T) for the constr./unconstr. sector in the true income (y^T) equation, (9) common parameters (intercept, θ^s, σ^2_s) for the constr./unconstr. sector in the survey income (y^s) equation, (10) extended co-variates in the survey income (y^s) equation, (11) same co-variates in all earnings equations, (12) true income omitted among covariates in the survey income equation ($\theta^s = 0$). **Alternative model specifications:** (13) partial model without the survey income (y^s) equation, (14) limit to those with positive earnings in both sources, i.e. set A_{rs} only, (15) everyone assumed constrained, i.e. no evasion. **Other:** (16) survey design (weights, clustering) taken into account.

Table 2.8: Sensitivity analysis: selected parameter estimates for alternative additive model specifications

	Additive models																
	base	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
p	0.996	0.995	0.989	0.990	0.988	0.996	0.988	0.996	0.989	0.996	0.996	0.989	0.991	0.991		0.968	0.994
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)		(0.003)	(0.002)
θ^r	0.300	0.385	0.519	0.500	0.048	0.268	0.465	0.353	0.618	0.283	0.229	0.603	1.090	1.090	0.541		0.433
	(0.108)	(0.078)	(0.057)	(0.082)	(0.116)	(0.120)	(0.074)	(0.084)	(0.104)	(0.099)	(0.150)	(0.116)	(0.080)	(0.080)	(0.037)		(0.099)
θ^s (unconstr.)	0.653	0.642	0.636	0.624	0.610	0.640	0.597	0.712	0.617	0.652	0.598	0.545	0.000		0.618		0.624
	(0.018)	(0.016)	(0.019)	(0.024)	(0.018)	(0.019)	(0.023)	(0.018)	(0.022)	(0.017)	(0.021)	(0.023)	(.)		(0.024)		(0.029)
θ^s (constrained)	0.642	0.584	0.724	0.695	0.425	0.613	0.708	0.724	0.715	0.652	0.571	0.625	0.000		0.647	0.353	0.616
	(0.026)	(0.035)	(0.026)	(0.031)	(0.037)	(0.037)	(0.027)	(0.025)	(0.027)	(0.017)	(0.028)	(0.030)	(.)		(0.026)	(0.021)	(0.052)
θ^s_0	1.129	1.051	2.035	2.260	0.922	1.060	1.954	1.269	2.004	1.125	0.976	1.790	0.000			0.778	1.357
	(0.099)	(0.108)	(0.139)	(0.122)	(0.114)	(0.108)	(0.117)	(0.119)	(0.127)	(0.093)	(0.090)	(0.133)	(.)			(0.070)	(0.269)
β^T_0 x constrained	0.017	0.002	0.016	-0.022	-0.094	0.039	-0.007	-0.002	0.000	0.005	0.031	0.041	0.060	0.060	-0.022		0.032
	(0.024)	(0.025)	(0.025)	(0.026)	(0.027)	(0.028)	(0.028)	(0.024)	(.)	(0.024)	(0.024)	(0.024)	(0.027)	(0.027)	(0.027)		(0.031)
β^s_0 x constrained	-0.021	0.090	-0.209	-0.179	0.409	0.030	-0.261	-0.061	-0.249	0.000	0.016	-0.220	-0.064		-0.078		-0.022
	(0.057)	(0.070)	(0.060)	(0.074)	(0.072)	(0.078)	(0.065)	(0.063)	(0.064)	(.)	(0.060)	(0.066)	(0.015)		(0.062)		(0.121)
σ_T (unconstr.)	0.478	0.494	0.488	0.465	0.515	0.484	0.476	0.473	0.434	0.484	0.480	0.455	0.423	0.423	0.470		0.476
	(0.019)	(0.016)	(0.017)	(0.023)	(0.020)	(0.021)	(0.021)	(0.019)	(0.016)	(0.020)	(0.019)	(0.017)	(0.014)	(0.014)	(0.021)		(0.026)
σ_T (constrained)	0.354	0.428	0.376	0.357	0.502	0.386	0.354	0.357	0.434	0.355	0.353	0.350	0.353	0.353	0.356	0.554	0.391
	(0.014)	(0.023)	(0.015)	(0.016)	(0.027)	(0.016)	(0.014)	(0.014)	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.029)
σ_r	8.553	7.498	5.629	5.713	8.395	8.701	6.346	7.636	5.294	8.218	9.697	5.882	3.670	3.670	3.895		7.541
	(0.944)	(0.658)	(0.493)	(0.500)	(0.762)	(1.098)	(0.681)	(0.782)	(0.437)	(0.936)	(1.105)	(0.552)	(0.563)	(0.563)	(0.379)		(0.969)
σ_s (unconstr.)	0.254	0.282	0.275	0.248	0.259	0.255	0.262	0.254	0.267	0.245	0.253	0.261	0.429		0.257		0.259
	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.006)		(0.008)		(0.010)
σ_s (constrained)	0.233	0.269	0.266	0.248	0.321	0.260	0.249	0.245	0.249	0.245	0.224	0.239	0.354		0.231	0.356	0.263
	(0.012)	(0.012)	(0.013)	(0.015)	(0.012)	(0.017)	(0.013)	(0.012)	(0.014)	(0.007)	(0.012)	(0.014)	(0.010)		(0.012)	(0.007)	(0.021)
AIC	39,189	47,774	44,749	34,322	40,804	39,445	39,637	39,391	39,297	39,206	39,036	38,948	41,913	21,365	37,409	42,258	.
BIC	39,913	48,520	45,488	35,031	41,522	40,169	40,103	40,014	40,008	39,911	39,967	40,081	42,618	21,945	38,117	42,674	.
N total	4,006	4,853	4,545	3,515	4,006	4,006	4,016	4,006	4,006	4,006	4,006	4,006	4,006	4,006	3,881	4,016	4,006
N constrained	3,093	3,807	3,558	2,742	1,958	2,816	3,100	3,093	3,093	3,093	3,093	3,093	3,093	3,093	2,980	0	3,093

Notes: robust standard errors are shown in parentheses under parameter point estimates. Alternative model specifications as follows. **Alternative samples:** (1) include those working part-time or working less than 12 months, (2) survey earnings reported for 12 months, (3) exclude those with survey self-employment income or survey earnings reported in gross terms. **Alternative definitions for the constrained sector:** (4) include private sector workers in large firms (50+ employees), (5) include private sector workers in utilities, public administration, education and health. **Alternative set of co-variates or constraints:** (6) no co-variates in the register income (y^r) equation, (7) no co-variates in the survey income (y^s) equation, (8) common parameters (intercept, σ^2_T) for the constr./unconstr. sector in the true income (y^T) equation, (9) common parameters (intercept, θ^s, σ^2_s) for the constr./unconstr. sector in the survey income (y^s) equation, (10) extended co-variates in the survey income (y^s) equation, (11) same co-variates in all earnings equations, (12) true income omitted among covariates in the survey income equation ($\theta^s = 0$). **Alternative model specifications:** (13) partial model without the survey income (y^s) equation, (14) limit to those with positive earnings in both sources, i.e. set A_{rs} only, (15) everyone assumed constrained, i.e. no evasion. **Other:** (16) survey design (weights, clustering) taken into account.

Table 2.9: Sensitivity analysis: estimation of tax compliance (whole sample)

	Multiplicative models																
	base	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(a) Proportion of sample, %																	
no income	0.7	0.9	0.8	0.4	1.5	0.7	1.0	0.8	0.7	0.7	0.7	0.6	0.8	0.8	0.0	3.2	0.8
full evaders	2.4	3.1	3.2	2.7	1.6	2.4	2.2	2.4	2.4	2.4	2.4	2.5	2.3	2.3	0.0	0.0	2.5
part evaders	21.8	22.9	24.0	22.3	15.5	20.4	20.7	24.5	21.2	23.5	19.8	19.6	14.9	14.9	28.6	0.0	22.0
compliant	75.1	73.1	71.9	74.6	81.4	76.5	76.1	72.3	75.6	73.3	77.1	77.3	82.0	82.0	71.4	96.8	74.7
(b) Undeclared earnings as a share of total gross true earnings, %																	
All	12.1	12.6	13.6	13.0	8.9	11.8	11.5	13.1	11.4	13.0	11.3	11.3	6.3	6.3	10.1	0.0	11.7
Decile 1	17.4	26.7	25.2	16.2	11.9	16.5	19.9	17.2	17.4	17.6	16.4	17.2	14.5	14.5	11.3	0.0	17.0
Decile 2	9.7	14.0	15.3	11.6	6.5	9.7	10.6	11.3	10.4	10.4	12.0	11.3	16.2	16.2	9.8	0.0	12.4
Decile 3	11.1	14.8	13.5	11.2	8.1	10.5	10.0	9.7	11.1	11.5	9.4	9.7	17.6	17.6	10.0	0.0	11.2
Decile 4	10.2	11.2	12.5	10.3	6.9	9.3	9.1	10.7	10.4	9.6	11.2	9.9	12.4	12.4	8.8	0.0	10.6
Decile 5	8.9	10.8	10.1	9.3	6.2	9.1	7.6	10.6	9.3	9.8	8.1	9.5	12.4	12.4	10.4	0.0	11.2
Decile 6	10.1	9.3	10.6	10.3	7.0	9.4	9.8	10.3	10.0	9.5	9.9	9.6	7.6	7.6	8.8	0.0	9.5
Decile 7	8.8	11.0	11.2	10.2	6.9	8.4	8.7	10.4	8.8	10.1	8.9	8.8	6.0	6.0	8.5	0.0	9.6
Decile 8	9.4	9.7	10.0	8.8	7.1	9.2	8.4	10.5	9.2	10.0	8.0	7.7	3.8	3.8	8.7	0.0	11.0
Decile 9	12.5	11.8	13.4	13.7	9.7	12.2	11.9	14.4	12.0	13.5	10.9	11.3	1.8	1.8	11.4	0.0	12.8
Decile 10	16.9	15.4	17.4	18.8	12.5	16.5	15.9	17.7	14.0	18.7	15.3	15.2	0.8	0.8	11.4	0.0	12.9
	Additive models																
	base	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(a) Proportion of sample, %																	
no income	0.4	0.5	1.1	1.0	1.2	0.4	1.2	0.4	1.1	0.4	0.4	1.1	0.9	0.9	0.0	3.2	0.6
full evaders	2.7	3.5	3.0	2.1	1.9	2.7	2.0	2.7	2.0	2.7	2.7	2.0	2.2	2.2	0.0	0.0	2.7
part evaders	17.7	20.0	26.2	24.1	11.5	16.6	24.0	21.1	23.5	19.3	14.6	18.7	20.8	20.8	31.2	0.0	21.4
compliant	79.2	76.0	69.7	72.8	85.4	80.3	72.8	75.8	73.3	77.5	82.3	78.2	76.0	76.0	68.8	96.8	75.3
(b) Undeclared earnings as a share of total gross true earnings, %																	
All	12.5	13.8	14.5	13.1	9.4	12.2	12.3	14.2	11.0	13.7	10.8	8.9	6.2	6.2	13.1	0.0	13.2
Decile 1	12.9	19.2	21.9	12.4	11.4	13.4	16.8	13.0	14.5	13.5	12.9	13.7	24.9	24.9	8.5	0.0	12.6
Decile 2	10.2	13.3	14.2	11.1	5.7	9.0	13.1	10.6	12.9	9.9	10.0	13.0	18.1	18.1	8.7	0.0	10.9
Decile 3	9.4	14.0	15.8	11.7	5.7	9.3	13.7	8.6	12.1	9.6	8.3	11.4	15.1	15.1	8.5	0.0	11.9
Decile 4	8.3	12.1	12.9	10.7	6.4	8.0	10.7	10.3	9.7	9.0	10.3	9.7	10.1	10.1	9.4	0.0	10.7
Decile 5	8.8	9.2	13.8	11.7	5.3	8.6	11.3	10.2	12.9	8.9	6.8	11.2	8.3	8.3	11.2	0.0	11.8
Decile 6	11.6	11.3	13.6	13.0	7.3	10.4	8.5	10.8	11.4	11.2	10.1	9.7	6.5	6.5	10.2	0.0	11.7
Decile 7	7.8	11.9	10.2	11.0	6.2	8.0	9.0	11.2	8.6	9.2	7.5	7.1	4.6	4.6	10.8	0.0	11.2
Decile 8	10.8	10.6	11.7	11.1	7.4	10.4	10.7	12.0	9.7	12.2	9.7	8.7	3.9	3.9	12.5	0.0	10.8
Decile 9	13.4	13.8	14.6	12.9	8.9	12.9	10.7	16.0	10.7	14.0	10.7	6.3	2.6	2.6	13.9	0.0	14.7
Decile 10	18.0	18.0	17.3	16.7	15.8	18.0	16.2	20.3	11.6	20.9	14.8	8.4	2.1	2.1	18.5	0.0	16.3
Sample size	4,006	4,853	4,545	3,515	4,006	4,006	4,016	4,006	4,006	4,006	4,006	4,006	4,006	4,006	3,881	4,016	4,006

Notes: deciles are constructed on the basis of estimated gross true earnings using the whole estimation sample. Alternative model specifications as follows. **Alternative samples:** (1) include those working part-time or working less than 12 months, (2) survey earnings reported for 12 months, (3) exclude those with survey self-employment income or survey earnings reported in gross terms. **Alternative definitions for the constrained sector:** (4) include private sector workers in large firms (50+ employees), (5) include private sector workers in utilities, public administration, education and health. **Alternative set of co-variates or constraints:** (6) no co-variates in the register income (y^r) equation, (7) no co-variates in the survey income (y^s) equation, (8) common parameters (intercept, σ_T^2) for the constr./unconstr. sector in the true income (y^T) equation, (9) common parameters (intercept, θ^s, σ_s^2) for the constr./unconstr. sector in the survey income (y^s) equation, (10) extended co-variates in the survey income (y^s) equation, (11) same co-variates in all earnings equations, (12) true income omitted among covariates in the survey income equation ($\theta^s = 0$). **Alternative model specifications:** (13) partial model without the survey income (y^s) equation, (14) limit to those with positive earnings in both sources, i.e. set A_{rs} only, (15) everyone assumed constrained, i.e. no evasion. **Other:** (16) survey design (weights, clustering) taken into account.

Appendix 2.A Detailed presentation of the model

The likelihood function

The multiplicative model

Recall from Section 2.4 that $\Pr(y_i^T > 0) = p$ and $\Pr(y_i^r = 0 | y_i^T = 0) = 1$ by assumption. For the unconstrained employees (U), probability density functions are the following:

$$
\begin{aligned}
f_{0s}^U &= f_{0s}^U(y_i^r, y_i^s | x_i) = f_{0s}^U(\text{no earnings}) + f_{0s}^U(\text{full evasion}) \\
&= \Pr(y_i^T = 0) \Pr(y_i^r = 0 | x_i, y_i^T = 0) f(y_i^s | x_i, y_i^T = 0) \\
&\quad + \Pr(y_i^T > 0) \int_0^\infty f(y^T | x_i, y_i^T > 0) \Pr(y_i^r = 0 | x_i, y^T) f(y_i^s | x_i, y^T) \, \mathrm{d}y^T \\
&= (1-p) 1 \frac{1}{\sigma_s y_i^s} \phi\left(\frac{\ln y_i^s - \theta_0^s - x_i\beta^s}{\sigma_s}\right) \\
&\quad + p \int_0^\infty \frac{1}{\sigma_T y^T} \phi\left(\frac{\ln y^T - x_i\beta^T}{\sigma_T}\right) \Phi\left(-\frac{\theta^r y^T + x_i\beta^r}{\sigma_r}\right) \\
&\qquad \cdot \frac{1}{\sigma_s y_i^s} \phi\left(\frac{\ln y_i^s - \theta^s \ln y^T - x_i\beta^s}{\sigma_s}\right) \mathrm{d}y^T
\end{aligned} \tag{2.A.1}
$$

$$
\begin{aligned}
f_{rs}^U &= f_{rs}^U(y_i^r, y_i^s | x_i) = f_{rs}^U(\text{partial evasion}) + f_{rs}^U(\text{full compliance}) \\
&= \Pr(y_i^T > 0) f(y_i^T = y_i^r | x_i, y_i^T > 0) \Pr(y_i^r = y_i^T | x_i, y_i^T) f(y_i^s | x_i, y_i^T = y_i^r) \\
&\quad + \Pr(y_i^T > 0) \int_{y_i^r}^\infty f(y^T | x_i, y_i^T > 0) f(y_i^r | x_i, y^T) f(y_i^s | x_i, y^T) \, \mathrm{d}y^T \\
&= p \frac{1}{\sigma_T y_i^r} \phi\left(\frac{\ln y_i^r - x_i\beta^T}{\sigma_T}\right) \left[1 - \Phi\left(\frac{1 - \theta^r y_i^r - x_i\beta^r}{\sigma_r}\right)\right] \frac{1}{\sigma_s y_i^s} \phi\left(\frac{\ln y_i^s - \theta^s \ln y_i^r - x_i\beta^s}{\sigma_s}\right) \\
&\quad + p \int_{y_i^r}^\infty \frac{1}{\sigma_T y^T} \phi\left(\frac{\ln y^T - x_i\beta^T}{\sigma_T}\right) \frac{1}{\sigma_r y^T} \phi\left(\frac{y_i^r / y^T - \theta^r y^T - x_i\beta^r}{\sigma_r}\right) \\
&\qquad \cdot \frac{1}{\sigma_s y_i^s} \phi\left(\frac{\ln y_i^s - \theta^s \ln y^T - x_i\beta^s}{\sigma_s}\right) \mathrm{d}y^T
\end{aligned} \tag{2.A.2}
$$

In the case of constrained employees (C), $\Pr(y_i^r = y_i^T) = 1$, and their probability density functions simplify to:

$$
f_{0s}^C = (1-p) \frac{1}{\sigma_s y_i^s} \phi\left(\frac{\ln y_i^s - \theta_0^s - x_i\beta^s}{\sigma_s}\right) \tag{2.A.3}
$$

$$
f_{rs}^C = p \frac{1}{\sigma_T y_i^r} \phi\left(\frac{\ln y_i^r - x_i\beta^T}{\sigma_T}\right) \frac{1}{\sigma_s y_i^s} \phi\left(\frac{\ln y_i^s - \theta^s \ln y_i^r - x_i\beta^s}{\sigma_s}\right) \tag{2.A.4}
$$

The additive model

For the unconstrained employees (U), probability density functions are the following. First

$$
\begin{aligned}
f_{0s}^U = (1-p)1\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta_0^s - x_i\beta^s}{\sigma_s}\right) \\
+ p\int_0^\infty \frac{1}{\sigma_T y^T}\phi\left(\frac{\ln y^T - x_i\beta^T}{\sigma_T}\right)\Phi\left(-\frac{\theta^r y^T + x_i\beta^r}{\sigma_r}\right) \\
\cdot \frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s \ln y^T - x_i\beta^s}{\sigma_s}\right)\mathrm{d}y^T \qquad (2.A.5)
\end{aligned}
$$

which is the same as for the multiplicative model (equation 2.A.1), and then

$$
\begin{aligned}
f_{rs}^U = p\frac{1}{\sigma_T y_i^r}\phi\left(\frac{\ln y_i^r - x_i\beta^T}{\sigma_T}\right)\left[1-\Phi\left(\frac{(1-\theta^r)y_i^r - x_i\beta^r}{\sigma_r}\right)\right]\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s \ln y_i^r - x_i\beta^s}{\sigma_s}\right) \\
+ p\int_{y_i^r}^\infty \frac{1}{\sigma_T y^T}\phi\left(\frac{\ln y^T - x_i\beta^T}{\sigma_T}\right)\frac{1}{\sigma_r}\phi\left(\frac{y_i^r - \theta^r y^T - x_i\beta^r}{\sigma_r}\right) \\
\cdot \frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s \ln y^T - x_i\beta^s}{\sigma_s}\right)\mathrm{d}y^T \qquad (2.A.6)
\end{aligned}
$$

For the constrained employees (C), both probability density functions are the same as with the multiplicative model, see equation (2.A.3) and (2.A.4).

Log likelihood function with the application of Gauss-Hermite quadrature

The multiplicative model

First, rewrite the integral for f_{0s}^U in equation (2.A.1) by making the substitution $u = \frac{\ln y^T}{\sqrt{2}\sigma_T}$, implying $y^T = \exp(\sqrt{2}\sigma_T u)$ and $\mathrm{d}y^T = \sqrt{2}\sigma_T\exp(\sqrt{2}\sigma_T u)\,\mathrm{d}u$:

$$
\begin{aligned}
&\int_0^\infty \frac{1}{\sigma_T y^T}\phi\left(\frac{\ln y^T - x_i\beta^T}{\sigma_T}\right)\Phi\left(-\frac{\theta^r y^T + x_i\beta^r}{\sigma_r}\right)\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s \ln y^T - x_i\beta^s}{\sigma_s}\right)\mathrm{d}y^T \\
&= \int_0^\infty \frac{1}{\sigma_T\exp(\sqrt{2}\sigma_T u)}\frac{1}{\sqrt{2\pi}}\exp\left[-\frac{1}{2\sigma_T^2}(\sqrt{2}\sigma_T u - x_i\beta^T)^2\right]\Phi\left(-\frac{\theta^r\exp(\sqrt{2}\sigma_T u) + x_i\beta^r}{\sigma_r}\right) \\
&\quad\cdot\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s\sqrt{2}\sigma_T u - x_i\beta^s}{\sigma_s}\right)\sqrt{2}\sigma_T\exp(\sqrt{2}\sigma_T u)\,\mathrm{d}u \\
&= \int_0^\infty \frac{1}{\sigma_T}\frac{1}{\sqrt{2\pi}}\exp\left[-u^2 + \frac{\sqrt{2}u}{\sigma_T}x_i\beta^T - \frac{1}{2\sigma_T^2}(x_i\beta^T)^2\right]\Phi(\cdot)\frac{1}{\sigma_s y_i^s}\phi(\cdot)\sqrt{2}\sigma_T\,\mathrm{d}u \\
&= \frac{1}{\sigma_T}\phi\left(\frac{x_i\beta^T}{\sigma_T}\right)\int_0^\infty \exp(-u^2)\exp\left(\frac{\sqrt{2}u}{\sigma_T}x_i\beta^T\right)\Phi(\cdot)\frac{1}{\sigma_s y_i^s}\phi(\cdot)\sqrt{2}\sigma_T\,\mathrm{d}u \qquad (2.A.7)
\end{aligned}
$$

This semi-infinite integral can be approximated using the Gauss-Hermite quadrature rule

$$\int_0^{\infty} \exp\left(-u^2\right) f(u)\, \mathrm{d}u \simeq \sum_{j=1}^{n} \omega_j f(\tau_j) \tag{2.A.8}$$

as follows

$$\begin{aligned} &\sum_{j=1}^{n} \omega_j \exp\left(\frac{\sqrt{2}\tau_j}{\sigma^T} x_i\beta^T\right) \Phi\left(-\frac{\theta^r \exp(\sqrt{2}\sigma_T\tau_j) + x_i\beta^r}{\sigma_r}\right) \\ &\cdot \frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s\sqrt{2}\sigma_T\tau_j - x_i\beta^s}{\sigma_s}\right)\sqrt{2}\sigma_T \end{aligned} \tag{2.A.9}$$

using the nodes τ_j and the weights ω_j as calculated in Steen et al. (1969). Finally, the log likelihood of observation i in set A_{0s} is:

$$\begin{aligned} \ln f_{0s}^U = \ln \Bigg\{ &(1-p)\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta_0^s - x_i\beta^s}{\sigma_s}\right) + p\frac{1}{\sigma_T}\phi\left(\frac{x_i\beta^T}{\sigma_T}\right)\sum_{j=1}^{n}\omega_j \exp\left(\frac{\sqrt{2}\tau_j}{\sigma_T}x_i\beta^T\right) \\ &\cdot\Phi\left(-\frac{\theta^r\exp(\sqrt{2}\sigma_T\tau_j) + x_i\beta^r}{\sigma_r}\right)\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s\sqrt{2}\sigma_T\tau_j - x_i\beta^s}{\sigma_s}\right)\sqrt{2}\sigma_T \Bigg\} \end{aligned} \tag{2.A.10}$$

In analog the integral for f_{rs}^U in (2.A.2) is rewritten by making the substitution $u = \frac{\ln y^T - \ln y^r}{\sqrt{2}\sigma_T}$, implying $y^T = \exp(\sqrt{2}\sigma_T u + \ln y^r)$ and $\mathrm{d}y^T = \sqrt{2}\sigma_T \exp(\sqrt{2}\sigma_T u + \ln y^r)\, \mathrm{d}u$:

$$\begin{aligned} &\int_{y_i^r}^{\infty} \frac{1}{\sigma_T y^T}\phi\left(\frac{\ln y^T - x_i\beta^T}{\sigma_T}\right)\frac{1}{\sigma_r y^T}\phi\left(\frac{y_i^r/y^T - \theta^r y^T - x_i\beta^r}{\sigma_r}\right) \\ &\quad\cdot\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s \ln y^T - x_i\beta^s}{\sigma_s}\right)\mathrm{d}y^T \\ &= \int_0^{\infty}\frac{1}{\sigma_T}\frac{1}{\sqrt{2\pi}}\exp\left[-\frac{1}{2\sigma_T^2}(\sqrt{2}\sigma_T u + \ln y^r - x_i\beta^T)^2\right]\frac{\phi(\cdot)}{\sigma_r\exp(\sqrt{2}\sigma_T u + \ln y^r)}\frac{\phi(\cdot)}{\sigma_s y_i^s}\sqrt{2}\sigma_T\,\mathrm{d}u \\ &= \frac{1}{\sigma_T}\phi\left(\frac{\ln y^r - x_i\beta^T}{\sigma_T}\right)\int_0^{\infty}\exp(-u^2)\exp\left(-\frac{\sqrt{2}u}{\sigma_T}(\ln y^r - x_i\beta^T)\right) \\ &\quad\cdot\frac{\phi(\cdot)}{\sigma_r\exp(\sqrt{2}\sigma_T u + \ln y^r)}\frac{\phi(\cdot)}{\sigma_s y_i^s}\sqrt{2}\sigma_T\,\mathrm{d}u \\ &\simeq \frac{1}{\sigma_T}\phi\left(\frac{\ln y^r - x_i\beta^T}{\sigma_T}\right)\sum_{j=1}^{n}\omega_j\exp\left(-\frac{\sqrt{2}\tau_j}{\sigma_T}(\ln y^r - x_i\beta^T)\right) \\ &\quad\cdot\frac{\phi(\cdot)}{\sigma_r\exp(\sqrt{2}\sigma_T\tau_j + \ln y^r)}\frac{\phi(\cdot)}{\sigma_s y_i^s}\sqrt{2}\sigma_T \end{aligned} \tag{2.A.11}$$

Unlike with $\ln f_{0s}^U$, taking the logarithm of f_{rs}^U allows us to separate several terms:

$$
\begin{aligned}
\ln f_{rs}^U = & \ln p - \ln \sigma_T - \frac{1}{2}\ln(2\pi) - \frac{1}{2}\left(\frac{\ln y_i^r - x_i\beta^T}{\sigma_T}\right)^2 \\
& + \ln\Bigg\{ \frac{1}{y_i^r}\left[1 - \Phi\left(\frac{1 - \theta^r y_i^r - x_i\beta^r}{\sigma_r}\right)\right]\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s \ln y_i^r - x_i\beta^s}{\sigma_s}\right) \\
& \quad + \sum_{j=1}^n \omega_j \exp\left[-\frac{\sqrt{2}\tau_j}{\sigma_T}(\ln y_i^r - x_i\beta^T)\right]\frac{1}{\sigma_r \exp(\sqrt{2}\sigma_T\tau_j + \ln y_i^r)} \\
& \quad \cdot \phi\left(\frac{y_i^r / \exp(\sqrt{2}\sigma_T\tau_j + \ln y_i^r) - \theta^r \exp(\sqrt{2}\sigma_T\tau_j + \ln y_i^r) - x_i\beta^r}{\sigma_r}\right) \\
& \quad \cdot \frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s(\sqrt{2}\sigma_T\tau_j + \ln y_i^r) - x_i\beta^s}{\sigma_s}\right)\sqrt{2}\sigma_T \Bigg\}
\end{aligned}
\tag{2.A.12}
$$

The additive model

The log likelihood of an observation i in set A_{0s} is identical to (2.A.10):

$$
\begin{aligned}
\ln f_{0s}^U = \ln \Bigg\{ & (1-p)\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta_0^s - x_i\beta^s}{\sigma_s}\right) + p\frac{1}{\sigma_T}\phi\left(\frac{x_i\beta^T}{\sigma_T}\right)\sum_{j=1}^n \omega_j \exp\left(\frac{\sqrt{2}\tau_j}{\sigma_T}x_i\beta^T\right) \\
& \cdot\Phi\left(-\frac{\theta^r \exp(\sqrt{2}\sigma_T\tau_j) + x_i\beta^r}{\sigma_r}\right)\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s\sqrt{2}\sigma_T\tau_j - x_i\beta^s}{\sigma_s}\right)\sqrt{2}\sigma_T \Bigg\}
\end{aligned}
\tag{2.A.13}
$$

In analog the integral for f_{rs}^U in (2.A.6) is rewritten by making the substitution $u = \frac{\ln y^T - \ln y^r}{\sqrt{2}\sigma_T}$:

$$
\begin{aligned}
& \int_{y_i^r}^{\infty} \frac{1}{\sigma_T y^T}\phi\left(\frac{\ln y^T - x_i\beta^T}{\sigma_T}\right)\frac{1}{\sigma_r}\phi\left(\frac{y_i^r - \theta^r y^T - x_i\beta^r}{\sigma_r}\right)\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s \ln y^T - x_i\beta^s}{\sigma_s}\right)\mathrm{d}y^T \\
& = \int_0^{\infty} \frac{1}{\sigma_T}\frac{1}{\sqrt{2\pi}}\exp\left[-\frac{1}{2\sigma_T^2}(\sqrt{2}\sigma_T u + \ln y^r - x_i\beta^T)^2\right]\frac{1}{\sigma_r}\phi(\cdot)\frac{1}{\sigma_s y_i^s}\phi(\cdot)\sqrt{2}\sigma_T\,\mathrm{d}u \\
& \simeq \frac{1}{\sigma_T}\phi\left(\frac{\ln y_i^r - x_i\beta^T}{\sigma_T}\right)\sum_{j=1}^n \omega_j \exp\left[-\frac{\sqrt{2}\tau_j}{\sigma_T}(\ln y_i^r - x_i\beta^T)\right]\frac{1}{\sigma_r}\phi(\cdot)\frac{1}{\sigma_s y_i^s}\phi(\cdot)\sqrt{2}\sigma_T
\end{aligned}
\tag{2.A.14}
$$

The log likelihood of an observation i in set A_{rs} is:

$$\begin{aligned}\ln f_{rs}^U =& \ln p - \ln\sigma_T - \frac{1}{2}\ln(2\pi) - \frac{1}{2}\left(\frac{\ln y_i^r - x_i\beta^T}{\sigma_T}\right)^2 \\ &+ \ln\Bigg\{\frac{1}{y_i^r}\left[1-\Phi\left(\frac{(1-\theta^r)y_i^r - x_i\beta^r}{\sigma_r}\right)\right]\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s\ln y_i^r - x_i\beta^s}{\sigma_s}\right) \\ &+ \sum_{j=1}^{n}\omega_j\exp\left[-\frac{\sqrt{2}\tau_j}{\sigma_T}(\ln y_i^r - x_i\beta^T)\right]\frac{1}{\sigma_r}\phi\left(\frac{y_i^r - \theta^r\exp(\sqrt{2}\sigma_T\tau_j + \ln y_i^r) - x_i\beta^r}{\sigma_r}\right) \\ &\cdot\frac{1}{\sigma_s y_i^s}\phi\left(\frac{\ln y_i^s - \theta^s(\sqrt{2}\sigma_T\tau_j + \ln y_i^r) - x_i\beta^s}{\sigma_s}\right)\sqrt{2}\sigma_T\Bigg\} \end{aligned} \tag{2.A.15}$$

Appendix 2.B Model interpretation

The multiplicative model

Expected value of y^r, conditional on true employment

Let us define $a = -(\theta^r y^T + x\beta^r)/\sigma_r$ and $b = (1 - \theta^r y^T - x\beta^r)/\sigma_r$, omitting the subscript i. For any positive y^T, the probability of full evasion is $\Phi(a)$, the probability of full compliance $[1-\Phi(b)]$ and the probability of partial evasion $[\Phi(b) - \Phi(a)]$. The expected value of the *truncated* reported earnings is (for any $y^T > 0$):[41]

$$\begin{aligned}\mathrm{E}\left[y^r\middle|0<y^r<y^T,x,y^T\right] =& \mathrm{E}\left[r^*y^T\middle|0<r^*<1,x,y^T\right] \\ =& y^T(\theta^r y^T + x\beta^r) + y^T\sigma_r\mathrm{E}\left[\frac{\varepsilon^r}{\sigma_r}\middle|a<\frac{\varepsilon^r}{\sigma_r}<b,x,y^T\right] \\ =& y^T\sigma_r(-a) + y^T\sigma_r\int_a^b\left(\frac{\varepsilon^r}{\sigma_r}\right)\frac{f\left(\frac{\varepsilon^r}{\sigma_r}\middle|x,y^T\right)}{\Pr\left(a<\frac{\varepsilon^r}{\sigma_r}<b\middle|x,y^T\right)}\,\mathrm{d}\frac{\varepsilon^r}{\sigma_r} \\ =& y^T\sigma_r(-a) + y^T\sigma_r\int_a^b\left(\frac{\varepsilon^r}{\sigma_r}\right)\frac{\phi\left(\frac{\varepsilon^r}{\sigma_r}\right)}{\Phi(b)-\Phi(a)}\,\mathrm{d}\frac{\varepsilon^r}{\sigma_r} \\ =& y^T\sigma_r(-a) + y^T\sigma_r\frac{\phi(a)-\phi(b)}{\Phi(b)-\Phi(a)}\end{aligned} \tag{2.B.1}$$

[41]To solve the integral, note that $\mathrm{d}\phi(x) = -x\phi(x)\,\mathrm{d}x$.

The expected value of the *observed* reported earnings (for any $y^T > 0$):

$$\begin{aligned}
\mathrm{E}(y^r|x, y^T) =& 0 \cdot \Pr(y^r = 0|x, y^T) + y^T \cdot \Pr(y^r = y^T|x, y^T) \\
&+ \mathrm{E}\left[y^r \middle| 0 < y^r < y^T, x, y^T\right] \cdot \Pr(0 < y^r < y^T|x, y^T) \\
=& y^T[1 - \Phi(b)] + \left[y^T \sigma_r(-a) + y^T \sigma_r \frac{\phi(a) - \phi(b)}{\Phi(b) - \Phi(a)}\right][\Phi(b) - \Phi(a)] \\
=& y^T \Phi(-b) + y^T \sigma_r(-a)[\Phi(b) - \Phi(a)] + y^T \sigma_r[\phi(a) - \phi(b)] \qquad (2.B.2)
\end{aligned}$$

Partial effects for $\mathrm{E}(y^r)$

If x_k is a continuous variable then (for any $y^T > 0$):

$$\begin{aligned}
\frac{\partial \mathrm{E}(y^r|x, y^T)}{\partial x_k} =& \; y^T \phi(-b) \left(\frac{\beta_k^r}{\sigma_r}\right) + y^T \beta_k^r[\Phi(b) - \Phi(a)] + y^T \sigma_r(-a) \left[\phi(b) - \phi(a)\right] \left(-\frac{\beta_k^r}{\sigma_r}\right) \\
&+ y^T \sigma_r \left[\phi(a)(-a) - \phi(b)(-b)\right] \left(-\frac{\beta_k^r}{\sigma_r}\right) \\
=& \; y^T \beta_k^r[\Phi(b) - \Phi(a)] + y^T \phi(a) \left(-\frac{\beta_k^r}{\sigma_r}\right)[-\sigma_r(-a) + \sigma_r(-a)] \\
&+ y^T \phi(b) \left(-\frac{\beta_k^r}{\sigma_r}\right)[-1 + \sigma_r(-a) - \sigma_r(-b)] \\
=& \; y^T \beta_k^r[\Phi(b) - \Phi(a)] \qquad (2.B.3)
\end{aligned}$$

If x_k is a dichotomous variable (for any $y^T > 0$):

$$\frac{\Delta \mathrm{E}(y^r|x, y^T)}{\Delta x_k} = \mathrm{E}(y^r|x, y^T, x_k = 1) - \mathrm{E}(y^r|x, y^T, x_k = 0) \qquad (2.B.4)$$

Finally, differentiate with respect to y^T (for any $y^T > 0$):

$$\begin{aligned}
\frac{\partial \mathrm{E}(y^r|x, y^T)}{\partial y^T} =& \; \Phi(-b) + y^T \phi(-b) \left(\frac{\theta^r}{\sigma_r}\right) + [\sigma_r(-a) + y^T \theta^r][\Phi(b) - \Phi(a)] \\
&+ y^T \sigma_r(-a) \left[\phi(b) - \phi(a)\right] \left(-\frac{\theta^r}{\sigma_r}\right) + \sigma_r[\phi(a) - \phi(b)] \\
&+ y^T \sigma_r \left[\phi(a)(-a) - \phi(b)(-b)\right] \left(-\frac{\theta^r}{\sigma_r}\right) \\
=& \; \Phi(-b) + [\sigma_r(-a) + \theta^r y^T][\Phi(b) - \Phi(a)] + \sigma_r[\phi(a) - \phi(b)] \\
&+ \phi(a) \left(-\frac{\theta^r}{\sigma_r}\right) \left[-y^T \sigma_r(-a) + y^T \sigma_r(-a)\right] \\
&+ \phi(b) \left(-\frac{\theta^r}{\sigma_r}\right) \left[-y^T + y^T \sigma_r(-a) - y^T \sigma_r(-b)\right] \\
=& \; \Phi(-b) + [\sigma_r(-a) + \theta^r y^T][\Phi(b) - \Phi(a)] + \sigma_r[\phi(a) - \phi(b)] \qquad (2.B.5)
\end{aligned}$$

Elasticity of $\mathrm{E}(y^r)$

Combining equation (2.B.2) and (2.B.5), the elasticity of $\mathrm{E}(y^r)$ with respect to y^T (for any $y^T > 0$):

$$\begin{aligned}\frac{\partial \mathrm{E}(y^r|x,y^T)/\partial y^T}{\mathrm{E}(y^r|x,y^T)/y^T} &= \frac{\Phi(-b)+[\sigma_r(-a)+\theta^r y^T][\Phi(b)-\Phi(a)]+\sigma_r[\phi(a)-\phi(b)]}{y^T\Phi(-b)+y^T\sigma_r(-a)[\Phi(b)-\Phi(a)]+y^T\sigma_r[\phi(a)-\phi(b)]}y^T \\ &= 1+\frac{\theta^r y^T[\Phi(b)-\Phi(a)]}{\Phi(-b)+\sigma_r(-a)[\Phi(b)-\Phi(a)]+\sigma_r[\phi(a)-\phi(b)]} \qquad (2.B.6)\end{aligned}$$

The additive model

Expected value of y^r, conditional on true employment

Define now $a = -(\theta^r y^T + x\beta^r)/\sigma_r$ and $b = (y^T - \theta^r y^T - x\beta^r)/\sigma_r$, omitting again the subscript i. The expected value of the *truncated* reported earnings (for any $y^T > 0$):

$$\begin{aligned}\mathrm{E}\left[y^r \middle| 0<y^r<y^T,x,y^T\right] =&\mathrm{E}\left[y^{*r}\middle|0<y^{*r}<y^T,x,y^T\right] \\ =&\theta^r y^T + x\beta^r + \sigma_r \mathrm{E}\left[\frac{\varepsilon^r}{\sigma_r}\middle| a<\frac{\varepsilon^r}{\sigma_r}<b,x,y^T\right] \\ =&\sigma_r(-a)+\sigma_r\int_a^b \left(\frac{\varepsilon^r}{\sigma_r}\right)\frac{f\left(\frac{\varepsilon^r}{\sigma_r}\middle|x,y^T\right)}{\Pr\left(a<\frac{\varepsilon^r}{\sigma_r}<b\middle|x,y^T\right)}\mathrm{d}\frac{\varepsilon^r}{\sigma_r} \\ =&\sigma_r(-a)+\sigma_r\int_a^b \left(\frac{\varepsilon^r}{\sigma_r}\right)\frac{\phi\left(\frac{\varepsilon^r}{\sigma_r}\right)}{\Phi(b)-\Phi(a)}\mathrm{d}\frac{\varepsilon^r}{\sigma_r} \\ =&\sigma_r(-a)+\sigma_r\frac{\phi(a)-\phi(b)}{\Phi(b)-\Phi(a)} \qquad (2.B.7)\end{aligned}$$

The expected value of the *observed* reported earnings (for any $y^T > 0$):

$$\begin{aligned}\mathrm{E}(y^r|x,y^T) =&0\cdot\Pr(y^r=0|x,y^T)+y^T\cdot\Pr(y^r=y^T|x,y^T) \\ &+\mathrm{E}\left[y^r\middle|0<y^r<y^T,x,y^T\right]\cdot\Pr(0<y^r<y^T|x,y^T) \\ =&y^T[1-\Phi(b)]+\left[\sigma_r(-a)+\sigma_r\frac{\phi(a)-\phi(b)}{\Phi(b)-\Phi(a)}\right][\Phi(b)-\Phi(a)] \\ =&y^T\Phi(-b)+\sigma_r(-a)[\Phi(b)-\Phi(a)]+\sigma_r[\phi(a)-\phi(b)] \qquad (2.B.8)\end{aligned}$$

Partial effects for $\mathrm{E}(y^r)$

If x_k is a continuous variable then (for any $y^T > 0$):

$$\begin{aligned}
\frac{\partial \mathrm{E}(y^r|x,y^T)}{\partial x_k} &= y^T\phi(-b)\left(\frac{\beta_k^r}{\sigma_r}\right) + \beta_k^r[\Phi(b)-\Phi(a)] + \sigma_r(-a)\left[\phi(b)-\phi(a)\right]\left(-\frac{\beta_k^r}{\sigma_r}\right) \\
&\quad + \sigma_r\left[\phi(a)(-a)-\phi(b)(-b)\right]\left(-\frac{\beta_k^r}{\sigma_r}\right) \\
&= \beta_k^r[\Phi(b)-\Phi(a)] + \phi(a)\left(-\frac{\beta_k^r}{\sigma_r}\right)\left[-\sigma_r(-a)+\sigma_r(-a)\right] \\
&\quad + \phi(b)\left(-\frac{\beta_k^r}{\sigma_r}\right)\left[-y^T+\sigma_r(-a)-\sigma_r(-b)\right] \\
&= \beta_k^r[\Phi(b)-\Phi(a)]
\end{aligned} \tag{2.B.9}$$

If x_k is a dichotomous variable then (for any $y^T > 0$):

$$\frac{\Delta \mathrm{E}(y^r|x,y^T)}{\Delta x_k} = \mathrm{E}(y^r|x,y^T,x_k=1) - \mathrm{E}(y^r|x,y^T,x_k=0) \tag{2.B.10}$$

Finally, differentiation with respect to y^T (for any $y^T > 0$) yields:

$$\begin{aligned}
\frac{\partial \mathrm{E}(y^r|x,y^T)}{\partial y^T} &= \Phi(-b) + y^T\phi(-b)\left(-\frac{1-\theta^r}{\sigma_r}\right) + \theta^r[\Phi(b)-\Phi(a)] \\
&\quad + \sigma_r(-a)\left[\phi(b)\left(\frac{1-\theta^r}{\sigma_r}\right) - \phi(a)\left(-\frac{\theta^r}{\sigma_r}\right)\right] \\
&\quad + \sigma_r\left[\phi(a)(-a)\left(-\frac{\theta^r}{\sigma_r}\right) - \phi(b)(-b)\left(\frac{1-\theta^r}{\sigma_r}\right)\right] \\
&= \Phi(-b) + \theta^r[\Phi(b)-\Phi(a)] \\
&\quad + \phi(a)\left(-\frac{\theta^r}{\sigma_r}\right)\left[-\sigma_r(-a)+\sigma_r(-a)\right] + \phi(b)\left(\frac{1-\theta^r}{\sigma_r}\right)\left[-y^T+\sigma_r(-a)-\sigma_r(-b)\right] \\
&= \Phi(-b) + \theta^r[\Phi(b)-\Phi(a)]
\end{aligned} \tag{2.B.11}$$

Elasticity of $\mathrm{E}(y^r)$

Combining equation (2.B.8) and (2.B.11), we can express the elasticity of $\mathrm{E}(y^r)$ with respect to y^T (for any $y^T > 0$):

$$\begin{aligned}
\frac{\partial \mathrm{E}(y^r|x,y^T)/\partial y^T}{\mathrm{E}(y^r|x,y^T)/y^T} &= \frac{y^T\Phi(-b) + \theta^r y^T[\Phi(b)-\Phi(a)]}{y^T\Phi(-b) + \sigma_r(-a)[\Phi(b)-\Phi(a)] + \sigma_r[\phi(a)-\phi(b)]} \\
&= 1 - \frac{x\beta^r[\Phi(b)-\Phi(a)] + \sigma_r[\phi(a)-\phi(b)]}{y^T\Phi(-b) + \sigma_r(-a)[\Phi(b)-\Phi(a)] + \sigma_r[\phi(a)-\phi(b)]}
\end{aligned} \tag{2.B.12}$$

Chapter 3

Income underreporting based on income-expenditure gaps

3.1 Introduction*

Reliable empirical evidence on tax non-compliance is difficult to obtain due to the very nature of the phenomenon. Apart from costly tax audits, various statistical methods have been developed to estimate income underreporting using micro-data from diverse sources. In this chapter, we estimate the extent of income underreporting for Estonia following the approach in a well-known study by Pissarides and Weber (1989), PW for short. They seek to detect unreported income on the basis of consumption propensities, contrasting a particular population group with another for which incomes are assumed to be accurately measured. More specifically, using survey data PW estimate the extent of income underreporting among the self-employed in the UK, taking employees as a reference group and comparing their food expenditure. Their key assumptions are that both groups report their food expenditure correctly in the survey, survey income corresponds to the income reported to the tax authority, employees report their income accurately in the survey and that the marginal propensity to consume with respect to (permanent) income does not differ between the two groups (after controlling for household characteristics).

We improve on the Pissarides and Weber (1989) method in two ways. First, as demonstrated in Chapter 2, a substantial part of salaries and wages can also be underreported, and hence, the original PW approach should be interpreted as estimating underreporting of income by the self-employed *relative* to employees, rather than in absolute terms. Instead of relying on all wage earners, as is commonly done in previous studies, we base our reference group on public sector employees, allowing us to estimate income underreporting not only for the self-employed but also for employees working in the private sector. Besim and Jenkins (2005) were the first to try this for North Cyprus in a simplified approach (with survey data), while we introduce this extension in the full PW framework. Second, to interpret income underreporting in a survey more broadly as tax non-compliance, it needs to be established that there is no systematic variation between different population groups in the way their income in the survey compares to incomes in the tax reports. We

*The chapter uses the 2007 and 2008 wave of the Estonian Social Survey linked with administrative tax records and made available by Statistics Estonia.

explore the validity of the latter assumption by estimating income underreporting both with survey incomes and incomes declared to the tax authority (or register income), using a dataset for Estonia which links these two sources for the same individuals. While the PW method has been applied before to register incomes[1], to the author's knowledge, this is the first analysis carried out with a dataset containing both types of income and, hence, is able to offer a direct comparison of results.[2] We further extend the empirical literature on tax non-compliance geographically with evidence for an Eastern European country, complementing a recent study by Kukk and Staehr (2014) who assess underreporting of self-employment income using the Estonian Household Budget Survey. Whereas previous studies have relied mainly on food expenditure, due to data limitations, we use instead information on housing related consumption expenditure (mostly utilities). We believe our results are not critically affected by this, for reasons discussed below.

Our results show large underreporting of earnings by the self-employed and also substantial underreporting of earnings by private sector employees on the basis of housing expenditures and *register income*, while a much smaller scale of non-compliance is detected for the self-employed and no underreporting for private employees using *survey incomes*. This suggests that previous studies applying the PW methodology to survey data may have underestimated the extent of non-compliance.

The chapter proceeds as follows. The next section explains the methodology, starting with the Pissarides and Weber (1989) approach and modifications in later studies, before presenting our approach. Section 3.3 provides an overview of the data sources, sample selection, expenditure and income information, and descriptive statistics. Section 3.4 presents findings and Section 3.5 concludes.

[1]Feldman and Slemrod (2007) use only information from tax returns for the US. Johansson (2005) and Engström and Holmlund (2009) use household surveys for Finland and Sweden, respectively, where income information has been added from administrative sources.

[2]Linking survey data with tax records also helps to overcome a serious limitation of the latter arising from generally very limited socio-demographic information.

3.2 Methodology

We first provide a methodological overview, outlining the original approach by Pissarides and Weber (1989) (Section 3.2.1) and discussing alternative specifications used in later applications (Section 3.2.2). Different approaches have yielded similar or even identical measures of income underreporting, but it is important to understand differences in their underlying assumptions when comparing results. We base our approach (Section 3.2.3) on the PW model, but estimate a slightly different measure of income underreporting following Hurst et al. (2014). We show that this particular form (applied to the standard PW model) is preferable to the one PW used as its estimation requires fewer assumptions. We then explore some of the main assumptions in more detail (Section 3.2.4).

3.2.1 The Pissarides-Weber approach

The general idea behind the Pissarides and Weber (1989) method is to infer income underreporting from contrasting expenditure and income patterns for different population subgroups, assuming that marginal consumption propensities are identical and the reference group reports income correctly. Intuitively, one population group is used to estimate an expenditure function, which is then inverted to predict incomes for another group and compared with their reported incomes. PW studied income underreporting by the self-employed in the UK using food expenditure.[3]

The starting point is an expenditure function (Engel curve), relating log consumption expenditure on particular goods or services (c_i) by household i to household log *permanent* income (y_i^P) and a vector of household characteristics (z_i):

$$\ln c_i = z_i\alpha + \beta \ln y_i^P + \epsilon_i \tag{3.1}$$

where α is a vector of parameters, β the elasticity of consumption with respect to per-

[3] Similarly, (food) Engel curves have been used in other contexts, for example, to measure biases in consumer price indices (Hamilton, 2001) and purchasing power parities (Almås, 2012), impute total expenditure into income surveys (Blundell et al., 2008) and estimate household material living standards (Larsen, 2009).

manent income and ϵ_i a random term with zero mean and constant variance. Household *current* (true) income y_i^T fluctuates around the permanent income and is usually not (directly) observed:

$$y_i^T = p_i y_i^P \tag{3.2}$$

Instead, households report a measure of their current income (in the survey), which can differ from its true value:

$$k_i y_i = y_i^T \tag{3.3}$$

with k_i denoting the adjustment (or scaling) factor needed to obtain the true income from the reported income. It is further assumed that p_i and k_i are stochastic terms distributed log-normally, that is

$$\ln p_i = \mu_p + u_i \tag{3.4}$$

$$\ln k_i = \mu_k + v_i \tag{3.5}$$

where μ_p and μ_k are mean log values, and u_i and v_i have zero means and constant variances σ_u^2 and σ_v^2. Combining equations (3.2) to (3.5), we obtain

$$\ln y_i = (\mu_p - \mu_k) + (u_i - v_i) + \ln y_i^P \tag{3.6}$$

Substituting this into (3.1) leads to

$$\ln c_i = z_i\alpha + \beta \ln y_i - \beta(\mu_p - \mu_k) - \beta(u_i - v_i) + \epsilon_i \tag{3.7}$$

The identification strategy is based on the assumption that one can distinguish between two population sub-groups: individuals in group A (e.g. employees) report all their income truthfully, that is $k_i = 1\ \forall i \in A$ (and hence $\mu_{k_A} = 0$ and $\sigma_{v_A}^2 = 0$), while individuals in group B (e.g. self-employed) may underreport (or overreport) their income. It is also assumed that parameters α and β in the expenditure function and the mean of p_i (i.e. $\bar{p}_A = \bar{p}_B$) are the same for two groups. Given the properties of the log-normal distribution,

$\ln \bar{p} = \mu_p + \frac{1}{2}\sigma_u^2$, this yields

$$\mu_{p_A} - \mu_{p_B} = \frac{1}{2}(\sigma_{u_B}^2 - \sigma_{u_A}^2) \tag{3.8}$$

Note that we can expect the current income of the self-employed to be more volatile than that of employees, that is $\sigma_{u_B}^2 > \sigma_{u_A}^2$. Using an indicator variable D_i, which takes a value of 1 for individuals in group B and 0 otherwise, these assumptions can be incorporated in (3.7):

$$\begin{aligned}\ln c_i &= z_i\alpha + \beta \ln y_i + \beta(\mu_{k_A} - \mu_{p_A}) + \beta D_i \left[(\mu_{k_B} - \mu_{p_B}) - (\mu_{k_A} - \mu_{p_A})\right] + \eta_i^{PW} \\ &= -\beta\mu_{p_A} + z_i\alpha + \beta \ln y_i + \gamma^{PW} D_i + \eta_i^{PW} \end{aligned} \tag{3.9}$$

where $\gamma^{PW} = \beta\left[\mu_{k_B} + \frac{1}{2}(\sigma_{u_B}^2 - \sigma_{u_A}^2)\right]$ and $\eta_i^{PW} = \epsilon_i - \beta(u_i - v_i)$. The error term η_i^{PW} is heteroskedastic due to the assumed differences in the variance of u_i and v_i between group A and B. Furthermore, as $\ln y_i$ and η_i^{PW} are correlated[4], income is instrumented with a set of x (we discuss the choice of instruments in Section 3.4):

$$\ln y_i = z_i\delta_z + \delta_d D_i + x_i\delta_x + \xi_i \tag{3.10}$$

It follows that the average adjustment factor for group B is

$$\bar{k}_B^{PW} = \exp\left[\mu_{k_B} + \frac{1}{2}\sigma_{v_B}^2\right] = \exp\left[\frac{\gamma^{PW}}{\beta} + \frac{1}{2}(\sigma_{v_B}^2 + \sigma_{u_A}^2 - \sigma_{u_B}^2)\right] \tag{3.11}$$

To obtain variance estimates in (3.11) note that ξ_i in (3.10) absorbs u_i and v_i as well as any unexplained variation in y_i^P (cf. equation 3.6). By its nature, permanent income is not correlated with shocks in current and reported income. Assuming also that the unexplained variation in permanent income is the same for two groups of individuals, the

[4] It follows from equation (3.6) that $\mathrm{E}[\ln y_i \eta_i^{PW}] \neq 0$.

difference in residual variation (σ^2_ξ) between the two groups can be expressed as

$$\sigma^2_{\xi_B} - \sigma^2_{\xi_A} = \sigma^2_{u_B} + \sigma^2_{v_B} - 2\,\mathrm{Cov}(u_B, v_B) - \sigma^2_{u_A} \tag{3.12}$$

While combining (3.11) with (3.12) is not sufficient to obtain an identifiable point estimate of $\bar{k}^{PW}_B$, PW discuss its plausible range by making the following arguments. Assuming that u and v are uncorrelated, the lower bound is obtained with the lowest σ_{v_B} value (zero, i.e. everyone in group B misreport their income by the same proportion) and the upper bound with the lowest σ_{u_B} value (equal to σ_{u_A}, i.e. current incomes in group B are no more volatile than current incomes in group A). With these additional assumptions, the range of $\bar{k}$ can be expressed as

$$\bar{k}^{PW}_B = \exp\left[\frac{\gamma^{PW}}{\beta} \pm \frac{1}{2}\left(\sigma^2_{\xi_B} - \sigma^2_{\xi_A}\right)\right] \tag{3.13}$$

PW further show that allowing for small positive correlation between u and v, does not have a large effect on the estimated range of $\bar{k}$ in the UK context.

3.2.2 Alternative specifications

The PW approach has been applied in its original form by Schuetze (2002) and Johansson (2005). There have been also several attempts to obtain a point estimate instead of bounds by utilising various proxies for permanent income or relying on different assumptions, which we summarise in this section.

Kim, Gibson, and Chung (2009) use *average* log income over time for the same household, i.e. $\overline{\ln y_{it}} = (1/T)\sum_{t=1}^{T} \ln y_{it}$, constructed from panel data. They argue that this eliminates variation in p_i, hence, yielding $\gamma^{KGC} = \beta\mu_{k_B}$ in an equivalent expression to (3.9). Taking into account that (3.12) is now reduced to $\sigma^2_{\xi_B} - \sigma^2_{\xi_A} = \sigma^2_{v_B}$, the average adjustment factor becomes

$$\bar{k}^{KGC}_B = \exp\left[\frac{\gamma^{KGC}}{\beta} + \frac{1}{2}\sigma^2_{v_B}\right] = \exp\left[\frac{\gamma^{KGC}}{\beta} + \frac{1}{2}\left(\sigma^2_{\xi_B} - \sigma^2_{\xi_A}\right)\right] \tag{3.14}$$

This is numerically identical to the upper bound in the PW approach (cf. equation 3.13), which involved slightly weaker assumptions of $\sigma^2_{u_A} = \sigma^2_{u_B}$ and $\text{Cov}(u_B, v_B) = 0$. The approach by Kim et al. (2009) raises however a question whether such 'between estimates' should also balance out variation in the reported income (σ^2_v), which the authors do not address.

Kukk and Staehr (2014) draw on data where people report both their current and regular income, and use the latter as a direct measure of permanent income. This allows them to rely explicitly on $y_i^P = k_i y_i$ instead of (3.2) and (3.3) above, and leads to

$$\ln c_i = z_i\alpha + \beta \ln y_i + \gamma^{KS} D_i + \eta_i^{KS} \tag{3.15}$$

where $\gamma^{KS} = \beta\mu_{k_B}$ and $\eta_i^{KS} = \epsilon_i + \beta v_i$. As with Kim et al. (2009), the average adjustment factor is

$$\bar{k}_B^{KS} = \exp\left[\frac{\gamma^{KS}}{\beta} + \frac{1}{2}(\sigma^2_{\xi_B} - \sigma^2_{\xi_A})\right] \tag{3.16}$$

Hurst, Li, and Pugsley (2014) assume instead of $\bar{p}_A = \bar{p}_B$ that the transitory income component is the same for the two groups after controlling for their characteristics, i.e. $\ln p_i = z_i\psi + \nu_i$. Unlike other studies, Hurst et al. (2014) focus on the proportion of true income which is reported, $\kappa_i = 1/k_i$, rather than k_i, and assume it is constant for group B (self-employed). Due to this assumption, κ and k are entirely equivalent in their application. However, the choice between the two indicators does matter for the standard PW approach as we will show in the next subsection.[5] Noting that z_i does not include the group indicator D_i, this leads to

$$\ln c_i = z_i(\alpha - \beta\psi) + \beta \ln y_i + \gamma^{HLP} D_i + \eta_i^{HLP} \tag{3.17}$$

[5] Hurst et al. (2014) do not elaborate on this and their study appears to be the only one, which estimates the average proportion of reported income ($\bar{\kappa}$) instead of average adjustment factor ($\bar{k}$).

where $\gamma^{HLP} = -\beta \ln \kappa_B$ and $\eta_i^{HLP} = \epsilon_i - \beta\nu_i$. Their equivalent to (3.11) is the average proportion of income reported for group B, which is straightforward to estimate:

$$\bar{\kappa}_B^{HLP} = \exp\left(-\frac{\gamma^{HLP}}{\beta}\right) \tag{3.18}$$

Compared to the other methods discussed so far, the Hurst et al. (2014) approach is based on the set of strongest assumptions, effectively combining the assumptions behind the PW lower and upper bound. To see this, substitute both $\sigma_{v_B}^2 = 0$ (lower bound) and $\sigma_{u_A}^2 = \sigma_{u_B}^2$ (upper bound) into (3.11), yielding an equivalent expression to (3.18).

Besim and Jenkins (2005) and Engström and Holmlund (2009) estimate $\bar{k}_B = \exp(\gamma/\beta)$, which equals $1/\bar{\kappa}_B^{HLP}$ in equation (3.18), but they only discuss reduced-form estimation without elaborating on the underlying structural model. Similarly, Feldman and Slemrod (2007) focus directly on current income rather than permanent income and assume that a given income source is underreported by the same proportion.[6] This simplifies the model as in Hurst et al. (2014). But they also distinguish between multiple income sources, allowing each to have a separate adjustment factor k, which results in a non-linear system and is estimated with non-linear least squares.

Lyssiotou, Pashardes, and Stengos (2004) estimate a complete demand system instead of a single expenditure function. They argue that this avoids mistaking preference heterogeneity for income effects and classifying households according to their main source of income, which can be rather arbitrary. On the other hand, their demand system makes simplifications in other dimensions as they also ignore the transitory component of current income and assume that self-reported income is underreported by a constant fraction. Furthermore, the demand system is potentially more sensitive to the measurement error in consumption data and they additionally include income in quadratic terms. They also provide a non-parametric (single equation) estimate, which seems to suggest that a linear functional form for food expenditure may cause a downward bias. A non-parametric method is also used in Tedds (2010) to avoid imposing the functional form a

[6]Using current income could make more sense in their case as they relate charitable contributions to taxable income using income tax returns.

priori. Her analysis for Canada suggests, however, that the reporting function is indeed linear although it also includes a constant.

For further details on previous studies estimating income underreporting on the basis of expenditure and income micro-data, see Table 3.A.1 in Appendix 3.A. Besides summarising methodological aspects, the table also covers key estimates obtained in these studies. To offer a better comparison with earlier studies and demonstrate the sensitivity of results to the model specification, in the empirical part we estimate the Pissarides and Weber (1989) and Hurst et al. (2014) type of measures alongside with our preferred specification, which is explained next.

3.2.3 Current approach

Our approach follows the PW model but seeks to estimate the average proportion of true income which is reported, $\bar{\kappa}$, as in Hurst et al. (2014). It does not matter whether the model is specified in terms of κ_i or k_i, as one can be substituted with the other, but as we see below calculating $\bar{\kappa}$ requires fewer assumptions than $\bar{k}$. While $\kappa_i = 1/k_i$, in general, $\bar{k} \neq 1/\bar{\kappa}$. In the case of Hurst et al. (2014), $\bar{k} = 1/\bar{\kappa}$ as they assume the fraction of underreporting to be constant (i.e. $\sigma_v^2 = 0$), which we do not impose here by following the original PW framework.

Instead of (3.3), we now have $y_i = \kappa_i y_i^T$ and if k_i is log-normally distributed, so is κ_i. For convenience, we re-define equation (3.5) as

$$\ln \kappa_i = \mu_\kappa + v_i \tag{3.19}$$

Equation (3.6) and (3.7) then become

$$\ln y_i = (\mu_p + \mu_\kappa) + (u_i + v_i) + \ln y_i^P \tag{3.20}$$

$$\ln c_i = z_i \alpha + \beta \ln y_i - \beta(\mu_p + \mu_\kappa) - \beta(u_i + v_i) + \epsilon_i \tag{3.21}$$

Substituting (3.8) into (3.21) and using again the indicator D_i, we obtain

$$\ln c_i = -\beta\mu_{p_A} + z_i\alpha + \beta \ln y_i + \gamma D_i + \eta_i \tag{3.22}$$

where $\gamma = -\beta\left[\mu_{\kappa_B} + \frac{1}{2}(\sigma^2_{u_A} - \sigma^2_{u_B})\right]$ and $\eta_i = \epsilon_i - \beta(u_i + v_i)$. We can express the average proportion of true income reported by group B as

$$\bar{\kappa}_B = \exp\left[\mu_{\kappa_B} + \frac{1}{2}\sigma^2_{v_B}\right] = \exp\left[-\frac{\gamma}{\beta} + \frac{1}{2}(\sigma^2_{v_B} + \sigma^2_{u_B} - \sigma^2_{u_A})\right] \tag{3.23}$$

where the σ^2_u terms appear with opposite signs compared to (3.11). Combining (3.23) with (3.12), which remains the same (apart from the sign for the covariation term), and assuming as PW that u_B and v_B are uncorrelated, allows us to write $\bar{\kappa}_B$ in a form, which can be estimated without further assumptions:

$$\bar{\kappa}_B = \exp\left[-\frac{\gamma}{\beta} + \frac{1}{2}(\sigma^2_{\xi_B} - \sigma^2_{\xi_A})\right] \tag{3.24}$$

The lower bound for the adjustment factor in equation (3.13) is numerically equal to $1/\bar{\kappa}_B$ in (3.24), but unlike $\bar{\kappa}_B$ it is obtained with a strong assumption that everyone in group B misreports their income in the same proportion ($\sigma^2_{v_B} = 0$). We expect $\bar{\kappa}_B < 1$, meaning that individuals in group B on average underreport their income.

One of the central aims of the chapter is to establish whether income differences between population subgroups in the survey indeed correspond to how they declare their incomes to the tax authority. It is not obvious that the PW assumption about survey reporting is correct and to assess this, we estimate equation (3.22) in turn with the survey income ($y_i = y_i^s$) and the register income ($y_i = y_i^r$), available for each individual in the dataset. If people from type B households report consistently to the tax authority and in the survey, i.e. $\kappa_i^B(y_i^r) \simeq \kappa_i^B(y_i^s)$, then we would expect to find a similar extent of underreporting with either income concept. If people are (more) truthful in the survey, i.e. $\kappa_i^B(y_i^s) \simeq 1$, then estimation with the survey income should yield no substantial underreporting even if the estimation with the register income does.

Another extension relevant in our context concerns the composition of the reference group, which typically comprises all employees. Depending on opportunities for employees to collude with their employers to circumvent the third party reporting requirements, there can also be underreporting of wages and salaries. Therefore, it makes sense to distinguish between public sector and private sector employees as, in principle, there should be little (if any) possibility for the former to engage successfully in tax evasion activities due to the lack of incentives on the side of employers in the public sector. This requires extending the model as follows.

Starting from equation (3.21), define three subgroups: group A (public sector employees), group B (private sector employees) and group C (self-employed). As before, we assume that group A reports correctly ($\kappa_i = 1 \; \forall i \in A$) and the expected current income, conditional on permanent income, is the same for all groups (i.e. $\bar{p}_A = \bar{p}_B = \bar{p}_C$). Hence, we can rewrite equation (3.8) as

$$\mu_{p_A} - \mu_{p_j} = \frac{1}{2}(\sigma^2_{u_j} - \sigma^2_{u_A}) \quad \text{where} \quad j = B, C \tag{3.25}$$

and equation (3.22) becomes

$$\ln c_i = -\beta\mu_{p_A} + z_i\alpha + \beta \ln y_i + \sum_{j=B,C} \gamma^j D^j_i + \eta_i \tag{3.26}$$

where $\gamma^j = -\beta \left[\mu_{\kappa_j} + \frac{1}{2}(\sigma^2_{u_A} - \sigma^2_{u_j})\right]$ and $\eta_i = \epsilon_i - \beta(u_i + v_i)$. Given the differences in the variance of the residual term ξ_i between the groups (if u and v are uncorrelated):

$$\sigma^2_{\xi_j} - \sigma^2_{\xi_A} = \sigma^2_{u_j} + \sigma^2_{v_j} - \sigma^2_{u_A} \tag{3.27}$$

the average proportion of true income reported by group j is now

$$\begin{aligned}\bar{\kappa}_j = \exp\left[\mu_{\kappa_j} + \frac{1}{2}\sigma^2_{v_j}\right] &= \exp\left[-\frac{\gamma^j}{\beta} + \frac{1}{2}(\sigma^2_{v_j} + \sigma^2_{u_j} - \sigma^2_{u_A})\right] \\ &= \exp\left[-\frac{\gamma^j}{\beta} + \frac{1}{2}(\sigma^2_{\xi_j} - \sigma^2_{\xi_A})\right] \quad \text{where} \quad j = B, C \end{aligned} \tag{3.28}$$

Following the same logic, the framework can be easily extended to N type of households, for example, allowing for different types of private employees and self-employed. In the empirical part, we additionally estimate equation (3.26), both with survey and register income, to see how much such a breakdown affects results.

3.2.4 Main assumptions

Having laid out the PW framework and various modifications, we now consider the main (parametric) assumptions in more detail and discuss their implications.

First, what happens if the assumption about the reference group (i.e. employees) reporting correctly is not valid? The original PW framework has been extended to such a case by Martinez-Lopez (2013), showing that this affects primarily the interpretation of estimates, which then indicate the scale of underreporting relative to the reference group. We demonstrate it for our main specification. The term μ_{κ_A} is now retained in (3.22) with $\gamma = -\beta\left[(\mu_{\kappa_B} - \mu_{\kappa_A}) + \frac{1}{2}(\sigma^2_{u_A} - \sigma^2_{u_B})\right]$ and equation (3.23) becomes:

$$\bar{\kappa}_B = \exp\left[-\frac{\gamma}{\beta} + \frac{1}{2}(\sigma^2_{v_B} + \sigma^2_{u_B} - \sigma^2_{u_A}) + \mu_{\kappa_A}\right] \tag{3.29}$$

Equation (3.12) includes additional terms as well:

$$\sigma^2_{\xi_B} - \sigma^2_{\xi_A} = \sigma^2_{u_B} + \sigma^2_{v_B} + 2\,\mathrm{Cov}(u_B, v_B) - \left[\sigma^2_{u_A} + \sigma^2_{v_A} + 2\,\mathrm{Cov}(u_A, v_A)\right] \tag{3.30}$$

which combined with (3.29) (and assuming zero covariance terms) yields:

$$\begin{aligned}\bar{\kappa}_B &= \exp\left[-\frac{\gamma}{\beta} + \frac{1}{2}(\sigma^2_{\xi_B} - \sigma^2_{\xi_A}) + \mu_{\kappa_A} + \frac{1}{2}\sigma^2_{v_A}\right] \\ &= \exp\left[-\frac{\gamma}{\beta} + \frac{1}{2}(\sigma^2_{\xi_B} - \sigma^2_{\xi_A})\right]\bar{\kappa}_A \end{aligned} \tag{3.31}$$

This corresponds to equation (3.24) adjusted with the average proportion of reported income for group A. In other words, if equation (3.24) is estimated when group A also misreports on average ($\bar{\kappa}_A \neq 1$) then the result for group B cannot be interpreted in absolute terms but *relative* to the level of misreporting by group A (and vice versa). It is not possible in this case to estimate misreporting for any group in absolute terms. This underlines the need to find a reference group characterised by minimal misreporting and ideally with $\bar{\kappa} \simeq 1$, which we hope to have achieved by focusing on public employees.

Second, PW and most of later studies have relied on the traditional demand function relating log expenditure to log income (see eq. 3.1). This functional form implies quite restrictive assumptions on consumer preferences (see e.g. Blundell, 1988): it links substitution effects strictly to income effects and demand is characterised by constant income elasticities. More flexible forms with a budget share as the dependent variable have been used instead by Lyssiotou et al. (2004) and Kim et al. (2009) in the same framework. On the other hand, the Working-Leser/AIDS type of functional form does not restrict the budget share to increase monotonically in overall budget and hence it may not be possible to invert the Engel curve for all values (see e.g. Tedds, 2010). We are not able to construct budget shares in our case as the dataset at our disposal does not contain information on total expenditure (more in Section 3.3). In some instances, if savings can be ignored, one might use total income as a proxy for total expenditure to derive budget shares but this would appear highly problematic in our context, where incomes are thought to be misreported (and expenditure not). In fact, this seems to be an overlooked aspect in Lyssiotou et al. (2004) when they set up a household expenditure function with the dependent variable (budget share) defined in terms of total expenditure, while using true income as the budget constraint on the right hand side.[7] This potential inconsistency is avoided with the usual log-log specification of expenditure function, which we consider as a sufficient approximation for modelling demand.

Another assumption concerns the variable p_i, which determines how current income is related to permanent income. This is modelled independently of household characteristics

[7] Starting from a household cost function, Lyssiotou et al. (2004, p. 625) derive a household expenditure function where the dependent variable, $w_i(p, U)$, is the share of total expenditure allocated for good i (p and U denote prices and utility). When they subsequently substitute U for the indirect utility function V and use true income as the budget constraint, they keep budget shares as they are. This would be strictly correct only if true income equals total expenditure (which they observe in their dataset), in which case it would be very straightforward to calculate misreported income.

(equation 3.4), while there could be for example age-related patterns with permanent income exceeding current income for young people ($p_i < 1$) and the opposite for the middle-aged group. The approach is less restrictive, however, than it initially appears. Hurst et al. (2014) allow $\log p_i$ to explicitly depend on household characteristics ($z_i\psi$) but consequently the additional parameters are absorbed in the general vector of household characteristics, $z_i(\alpha - \beta\psi)$; see equation (3.17). What matters is the potential difference in the intercept for the two groups, which is captured in the original version by allowing μ_p to differ between the groups.

The assumption that all α-s and β-s are the same for the two groups could be more restrictive. Lyssiotou et al. (2004) point out that one of the key advantages of their complete demand system approach over the PW single-equation method is that it avoids confusing preference heterogeneity with income underreporting. They show that not accounting for preference heterogeneity can bias the estimate of underreporting downwards. While data constraints allow us only to estimate a single demand equation, we limit our sample to more homogenous households (couples with the head working full-time) similar to other studies. As part of the sensitivity analysis, we also test some additional sample restrictions.

3.3 Data

3.3.1 Data sources and linkage

We use the Estonian Social Survey (*Eesti Sotsiaaluuring*, ESU), linked with individual tax records. ESU is an annual household income survey, which also provides the Estonian component in the European Union Statistics on Income and Living Conditions (EU-SILC) database. It has a rotating sample design where households are followed in four consecutive waves and a quarter of the sample is replaced in every wave. The survey collects basic demographic information for all household members and detailed information for persons aged 16 or over, with a particular focus on their incomes. Interviews are carried out in the first half of year and the overlap with the end period for submitting annual tax reports (i.e. end of March) is thought to reduce recall errors.[8]

ESU has been linked with individual tax records allowing us to apply the method presented in the previous section both on survey and register income data for the same sample. The data linkage is based on the unique personal identification code, which is assigned to every person[9], and was legally carried out by Statistics Estonia without being required to inform sample members and obtain their consent. This is an important feature as it avoids the potential problem where those who are less compliant might be more likely to refuse data linkage, therefore, leading to a biased sample. Tax records refer either to a personal tax declaration or an (employer) tax withholding report, if the former was not submitted, and match the income reference period in ESU (i.e. the previous calendar year). Note that registered self-employed people are required to file a tax report.[10] Despite the different structure of personal and employer declarations, the informational content is broadly similar, and the tax withholding reports are also used to pre-populate individual tax reports. Both types of report show income by type and provider – employer or government institution administrating a given benefit. While tax records exclude not taxable income sources (such as private transfers between households, the child benefit and the subsistence benefit), the share of such income components in aggregate disposable income is very small (about 2% according to ESU) and we are anyway mainly focusing on household earnings, which are not affected by this.[11]

We use the pooled 2007 and 2008 waves to increase the number of observations and

[8]For detailed information, see the national quality reports for the Estonian SILC at http://ec.europa.eu/eurostat/web/income-and-living-conditions/quality/national-quality-reports (or starting from Eurostat's main page, follow Topic: Population and social conditions – Income, Social Inclusion and Living Conditions – Quality – National quality reports).

[9]The personal identification code is known for all sampled individuals from the Population Register and asked for other household members during the interview. The remaining individuals were matched with the Population Register using their characteristics (e.g. gender and the date of birth determine seven numbers of 11-digit personal identification code) and the address. Nearly all people were matched and while the matching may have involved some error, this is likely to be insignificant. The final dataset used here is anonymised, without names, addresses etc.

[10]A personal tax declaration is also required to claim additional tax allowances, if applicable, and to benefit from optional joint assessment for married couples.

[11]On the other hand, benefit receipt tends to be generally underreported in survey datasets (Bound et al., 2001; Meyer et al., 2009).

reduce sensitivity to outliers in a given year.[12] The combined waves contain nearly 10,000 household observations (see Table 3.1). 98.6% of these had all household members identified in the tax register (no matter whether they had taxable income or not). Excluding households with zero housing expenditure (see the next subsection) has also a negligible effect on the sample size, while excluding households with no earnings (employment and self-employment income[13]) leaves about 7,400 households. We further focus on households whose *head* has positive earnings (95% of all households with positive earnings) so that we can include head characteristics as covariates in the regression analysis. We select the head of household among the persons who state to be responsible for accommodation (or their partners), prioritising the one with the highest earnings[14], as the income position of that person is likely to have the largest influence on total housing related expenses.

[TABLE 3.1 HERE]

Among household heads with earnings we distinguish between public employees, private employees and the self-employed. All household heads reporting (either full-time or part-time) self-employment as their main activity in any month of the income reference period (previous year) or working specifically as a (registered) sole proprietor[15] are considered as the self-employed in the main analysis. In the sensitivity analysis we also consider alternative definitions for the self-employed where household-level information or earnings related to activities as a sole proprietor are additionally taken into account.[16] There are 643 households whose head is self-employed and reported positive earnings in ESU and 568

[12] For example, Kim et al. (2009) demonstrate substantial year-to-year variation in their estimate of income underreporting for Korea in 2000-2005.

[13] Throughout we exclude net losses from (registered) self-employment from our survey income measure to be consistent with income information in the tax reports. The number of affected households is less than 50 in each wave.

[14] To ensure a unique match, additional criteria include being the oldest and, finally, being male. By default, the head of household is defined as the person with the highest income in ESU.

[15] Respectively, ESU variables G35* and H22.

[16] Sole proprietors (FIE) pay both employer contributions and personal taxes, but can deduct related business expenses from their taxable income. (Employer contributions are further deducted from their tax base for the income tax purposes.) People not registered as sole proprietors but engaged in individual work activities (e.g. private consultancy) are liable to declare and pay taxes on such income similar to salaries and wages. ESU further distinguishes earnings related to non-FIE self-employment, which we consider for total earnings but not for determining the self-employment status to be consistent with the tax records.

households whose head is self-employed and reported positive earnings in the tax records. Other household heads with earnings are classified as employees, distinguishing further between heads employed in the public sector and in the private sector. In ESU, people are asked about the proprietor of the enterprise where they work (state/municipality vs private individual/entity). As this refers to their current status rather than the income reference period, we consider those household heads who have changed jobs (after the income reference period and before the survey interview) or have multiple jobs (or unspecified affiliation) as private employees. On the other hand, tax records allow us to distinguish between earnings received from private and public entities. Here, we consider those household heads as public employees who have received payments only from public entities, non-profit organisations or foundations. Household heads classified as private employees account for 73% of all heads with positive earnings, public employees 19-20% and self-employed 7-8% (the share varying only slightly depending on whether ESU or MTA information is used). These proportions are also very similar across the two waves.

There is no sufficiently detailed information on work intensity to account for its impact on the variation in households' earnings. ESU indicates people's *main* activity in every month of the income reference period, distinguishing between working full-time and part-time but not in greater detail (weeks, hours), and the tax records do not contain any information about work intensity. We therefore limit our sample further to the household heads who have indicated in ESU working the whole year full-time as an employee or a self-employed. While the resulting sample is not representative of the whole working population, it still accounts for about 80% of all households with earnings. We relax this criterion as part of the sensitivity analysis.

Finally, as consumption patterns are strongly influenced by household structure, we focus on couples (both with and without children) who account for about 60% of the remaining sample. This is a similar approach to most previous studies (see Table 3.A.1 in Appendix 3.A). Another selection criterion commonly used is to limit the sample to working age people, which we test as part of the sensitivity analysis. The final effective sample contains just over 3,400 households.

3.3.2 Expenditure and income information

The main disadvantage of ESU for this analysis is very limited expenditure data. While previous studies applying the PW method have relied primarily on food expenditure, this is not available in our dataset. Instead, this chapter uses household costs of running the home. Our measure of housing related costs includes heating and power consumption (central heating, electricity, gas, other fuels); water, sewerage and other services; home insurance; housing maintenance and regular repairs – all collected separately in ESU. We exclude payments for housing per se in the main analysis as this is observed in the form of rent and mortgage interest payments for relatively few households: only 10% of households rent their accommodation and just 19% of homeowners report mortgage interest payments. (See Table 3.A.2 in Appendix 3.A for descriptive statistics for all non-monetary variables used.) Most households own their house and have no mortgage, in which case the cost of housing is implicit and can only be estimated indirectly (see e.g. Frick et al., 2010). The high proportion of owner-occupation is largely a result of housing privatisation in the early 1990s (see e.g. Pichler-Milanovich, 2001). In the sensitivity analysis, we also consider our measure of 'housing costs' with rent and mortgage interests payments.[17]

It is not clear without a direct comparison, how modelling based on housing costs (utilities) rather than food expenditure might affect results. Importantly, both consumption items are necessities and represent a substantial part of the total household budget. For example, Blundell et al. (1993, 1998) provide evidence for the UK on food and domestic fuel having similar relationship with household total expenditure. While food expenditure might offer more variability and hence potentially better identification, housing costs could have a more stable relationship with permanent income. Expenditures on utilities depend largely on the choice of dwelling, which is made for a longer period ahead – typically for a year at least – compared with choices related to food consumption and therefore should better reflect income potential in the medium term. Blundell et al. (1998) provide

[17] In comparison, the COICOP category for housing expenditure includes electricity, gas and other fuels; water, sewage and other services; maintenance and repairs as well as actual and imputed rent but not housing-related insurance and mortgage interest payments.

also evidence for domestic fuel being less sensitive to household composition than food and hence our approach could be more robust to potential specification errors.

There is also no particular reason for information on housing expenditure to be more problematic in terms of potential measurement errors. Housing costs may even have smaller recall errors due to involving less transactions (in a given reference period) and transactions being made on a more regular basis. The survey is also carried out when heating costs – the key component of our housing cost variable – are seasonally high and therefore amounts spent are likely to gain more attention by households.[18] While systematic measurement errors in expenditure would bias the coefficient for permanent income (for example, tendency to underreport expenditure would result in a downward bias), what would be more critical for our estimation strategy are differences in systematic measurement errors in expenditure between employees and the self-employed. It is not obvious why this should be the case. A potential scenario could involve the self-employed reporting some of housing costs under business expenses rather than personal consumption. Fortunately, ESU collects information on non-cash income from self-employment and the share of self-employed who report that their business expenses include utilities is very marginal (about 2%).[19] What is perhaps the most reassuring evidence supporting our expenditure measure is that Hurst et al. (2014) obtain very similar results of income underreporting by the self-employed in the US both with food and utilities.

Table 3.2 provides the first look at how household expenditure and income compare across different types of households. It shows the (unconditional) mean of log expenditure (housing related costs) and earnings, separately for the 2007 and 2008 wave. As part of the sensitivity analysis, we also use net total household income and housing related expenses together with rent and mortgage interests.

[TABLE 3.2 HERE]

[18]For example, recommendations made by Browning et al. (2003) for improving the measurement of total household expenditure in general purpose surveys include asking specifically questions about food and utilities, followed by housing costs (rent and interest payments).

[19]In comparison, the most common items (motor fuel and mobile phone services) were reported by about 10-15% of the self-employed.

We can see that mean (log) consumption is highest for the self-employed in both waves and the differences with other two groups are statistically significant. Mean consumption is also somewhat higher for private employees compared to public employees but not significantly so at the 95% level. The same ranking emerges for survey earnings (y^s) in the 2008 wave (with a very marginal difference between private employees and the self-employed), while the 2007 wave exhibits a different pattern: mean (log) survey earnings of private employees still exceed that of public employees, but it is the self-employed who have the lowest mean earnings. However, earnings in the tax records (y^r) show exactly the opposite ranking to consumption levels, with mean income being the highest for public employees and the lowest for the self-employed – consistently across two waves (the differences between public and private employees are again not statistically significant though).[20]

As a consequence, the ratio of mean consumption to mean income (reflected in the difference in mean logs, Δ) varies across household types, being notably higher for self-employed household heads. This is robust to both waves and data sources, though the difference with other household types is larger with earnings in the tax records. The latter also indicate a higher consumption-to-income ratio for private employees compared to public employees, while it is the opposite with survey earnings. As such it provides preliminary evidence for income underreporting by the self-employed and possibly by private employees.

3.4 Estimation and results

We now proceed with the econometric analysis. For a comparison with previous studies, we first estimate equation (3.22), distinguishing between wage earners and the self-employed. In the second stage, we distinguish also between public and private employees,

[20] We use gross earnings from the tax records and survey earnings in net terms, which is how most survey respondents have stated them. This is to minimise the share of sample for which we have to rely on incomes derived from corresponding gross or net values. We do not expect it to have much impact on our comparison of income underreporting in the survey and in the tax records due to the flat income tax with a constant marginal rate above a relatively low income threshold, resulting in a fairly proportional tax system in Estonia.

estimating equation (3.26) with three groups of households.

It follows from the structural model that current observed income ($\ln y_i$) is endogenous and needs exclusion restrictions (i.e. instruments) to be properly identified in the consumption equation. Suitable instruments in this context are variables relevant for the income generation process but with no direct effect on housing expenditure, with various proxies for human capital or work effort being natural candidates.[21] We use dummies for the education level, occupation and industry of the household head as instruments in our case, on the basis that these are strong income predictors and there is no obvious reason why these should affect our measure of housing related costs except through income. With a single endogenous regressor and multiple instruments, the model is over-identified. In the sensitivity analysis, we also test a reduced set of instruments containing only information on the head's education, which is the variable most often used in earlier studies. Other covariates (z_i), used in both consumption and income equation, include household head characteristics (gender, age, age squared, nationality, marital status), household characteristics (number of children and other adults, region, rural area, survey wave) and housing characteristics (type, year of construction, number of rooms, size in m^2, type of ownership).

Model estimates are obtained with the maximum likelihood method using survey weights and robust standard errors with clustering at the household level.[22] On this basis we calculate the average proportion of reported income $\bar{\kappa}$ (equation 3.24), which is our main measure of income misreporting. In addition, we calculate $\bar{\kappa}$ according to Hurst et al. (2014) (equation 3.18) as well as the lower and the upper bound for the average adjustment factor $\bar{k}$ according to Pissarides and Weber (1989) (equation 3.13). This allows us to assess the sensitivity of results to additional assumptions underlying

[21] Instrumental variables used in the previous studies vary markedly. For example, Pissarides and Weber (1989), Schuetze (2002), Lyssiotou et al. (2004) and Johansson (2005) use a rather extensive set of instruments including head's education and/or work intensity for one or both spouses, physical assets and interactions of the self-employment status with other characteristics. Kukk and Staehr (2014) employ education level, gender and nationality of the household head as well as regional dummies. On the other hand, Engström and Holmlund (2009) rely only on income from capital and property taxes and Hurst et al. (2014) on dummies for educational attainment.

[22] Using `sem` command in Stata 12 and restricting coefficients in both equations to be the same for different groups, apart from intercepts, variances and covariances which are allowed to differ.

these approaches (see Section 3.2.2) and compare our results with previous estimates in the literature. In all cases, we present results in terms of the proportion of *underreported income* for an easier comparison.[23] The standard errors for all statistics are calculated using the delta method. We also include estimates of the income elasticity (β), dummies for self-employed and private employees (γ), and variances of the first stage error terms (σ_ξ^2).

3.4.1 Employees vs self-employed

Table 3.3 shows the estimated results for misreporting among the self-employed compared to employees. As explained in Section 3.2.4, the results should be interpreted relative to the level of reporting by employees (which could be also incomplete). Consider first results with the survey income (first two columns). The instrumental variable (IV) estimate of 0.308 for the income elasticity of housing expenditure (β) (column 2) is statistically highly significant and notably higher than the estimate without instrumenting income (0.121, column 1), showing the extent of bias when income endogeneity is ignored. Our estimate is also consistent with those in the previous studies cited here which are mostly in the range of 0.2-0.4.[24]

The residual variance from the (reduced-form) income regression (σ_ξ^2) is also substantially higher for the self-employed as expected, and the shift parameter for the self-employed households (γ) is positive and highly significant. The estimate of income underreporting ($1 - \bar{\kappa}_B$) suggests that, on average, 20% of household (net) earnings are underreported by households whose head is self-employed. Our estimate of the standard PW range is 20-44% and overlaps with those obtained in the earlier studies, shown in terms of the average proportion of underreported income in Table 3.A.1 in Appendix 3.A. There is substantial variation, however, among earlier studies and about half of them

[23] That is $1 - \bar{\kappa}$ and $1 - 1/\bar{k}$, bearing in mind that generally $\bar{k} \neq 1/\bar{\kappa}$.

[24] The exceptions are Besim and Jenkins (2005), Feldman and Slemrod (2007) and Kukk and Staehr (2014) whose estimate of β is higher, about 0.5-0.6. Besim and Jenkins (2005) do not use instrumental variables and have the smallest sample, among else. Feldman and Slemrod (2007) use very different income and expenditure data (declared incomes and charitable contributions in the tax records). Kukk and Staehr (2014) use a measure of regular income, arguably less affected by transitory movements in income.

do not provide a measure of statistical precision for their estimates of income underreporting. The point estimate of 62% underreporting for the self-employed by Kukk and Staehr (2014), using the Estonian Household Budget Survey, is the main exception which is difficult to reconcile not only with our estimates but also with other studies. Their approach is unique for relying on a self-reported measure of regular income as a proxy for permanent income, though without a direct comparison with estimates based on the usual measure of current income it is not possible to ascertain whether this is indeed the primary source of differences.

[TABLE 3.3 HERE]

The last two columns in Table 3.3 report equivalent estimates using register income. Not only are all estimates highly statistically significant but they also reveal much larger income underreporting on average. Our main estimate ($\bar{\kappa}_B$) indicates that 48% of household (gross) earnings are underreported by households with a self-employed head, the PW upper bound 71% and the HLP measure 61% (column 4). This is due to the estimate of income elasticity (β) being smaller and the estimated shift parameter (γ) being larger compared to the IV estimates with survey income (column 2), though this is partly counterbalanced by larger differences in variance estimates between the two groups (cf. equation 3.24). The variance estimates themselves are almost twice as large compared to estimates from survey income. The fact that register data allow us to detect substantially larger income underreporting suggests that the self-employed are more truthful in reporting their income in the survey compared to the tax declarations.

The bottom section of Table 3.3 shows typical diagnostic tests for our instruments.[25] For both data sources, the endogeneity test rejects the null hypothesis that household earnings are exogenous.[26] Furthermore, partial R^2 and the F-test of excluded instruments confirm that instruments are reasonably strong in all models. Finally, the Hansen J-

[25]These are estimated with the help of `ivreg2` package in Stata. While this also supports (limited-information) maximum likelihood estimation method with cluster-robust variance estimates, it does not allow specifying the model structure in the same detail as `sem` (e.g. different σ_ξ^2 by subgroups). Nevertheless, we consider these test diagnostics to represent our main model sufficiently accurately.

[26]The test statistic is defined as the difference of two Sargan-Hansen statistics.

statistic fails to reject the null hypothesis that these are valid instruments in the case of survey incomes, while it raises some doubt for register incomes. It appears to be of limited importance though as in subsequent specifications, the test is passed for both income sources. We also get very similar estimates for β and γ when using only dummies for educational attainment as instruments, in which case the p-value for the Hansen statistic is about 0.4. Hence, without instrumenting earnings, we would obtain biased estimates of income underreporting, indicating much larger income underreporting than is actually the case.

3.4.2 Public employees vs private employees and self-employed

Until now we have estimated income underreporting among the self-employed using (all) employees as the reference group as in previous studies using the same method, apart from Besim and Jenkins (2005), but, as demonstrated in Chapter 2, there can be substantial non-compliance also among employees. In the next step, we further distinguish between households whose head works in the public sector and the private sector, and assume that only the latter have opportunities to underreport their income. The results are shown in Table 3.4.

[TABLE 3.4 HERE]

Similar to Table 3.3, estimates with survey income (column 2) detect income underreporting for households with self-employed heads, now to a slightly larger extent (25%). The estimates also show a modest underreporting for households whose head is a private sector employee (7%), though these are not statistically significant and hence do not suggest substantial differences between public and private sector employees when it comes to income reporting. Estimates from register income (column 4) on the other hand, yield strong evidence for substantial income underreporting among households with privately employed heads (23%), while the estimate for households with self-employed heads is now 56%. The PW upper bound implies average underreporting of 34% and 78% among the two groups. There are also notable differences between estimates from survey income and register income for the residual income variance of households whose head is a private employee: while survey data do not suggest much difference with households whose head is a public employee, estimates with register data show a much higher variance for private employees which exceeds that of public employees by almost two-fold.[27] The income elasticity (β) estimates are essentially not affected by distinguishing between the three groups of households rather than two, and the model fit (according to the AIC and BIC statistics) improves for estimates from either data source. As before, the IV estimation leads to lower underreporting compared to estimation without instruments. The results and conclusions of diagnostic tests for instrumental variables in Table 3.4 are also very similar to those discussed above for Table 3.3.

The estimate of underreporting for private sector employees from register income (23%) is of similar magnitude to the one estimated in Chapter 2 (16%), noting that the first estimate is the average scale of underreporting while the other is the share of undeclared earnings in total earnings (i.e. the aggregate scale). Besides this, the two approaches also differ for the overall method, the unit of analysis (household vs individual) and sample (households of couples whose head is working full-time vs employees working full-time).

On the other hand, our estimates differ substantially from Besim and Jenkins (2005) which is the only other PW-type of study that distinguishes between public sector and private sector employees as well as self-employed. Their estimates of underreporting for the self-employed (10-11%) are the lowest among all the studies considered here and, surprisingly, even slightly lower than that for private employees (13%). Taken together with unusually high β estimates, their results warrant extra caution. There are several different methodological choices, which could limit the comparability of their results with other studies. First, they estimate the extent of underreporting at the average income level (rather than the average rate of misreporting). Second, they employ the OLS estimation. Third, they have the smallest sample among such studies and impose very few sample restrictions. For example, studies relying on food expenditure typically exclude households

[27] As another sensitivity check, we excluded all households with self-employed heads and estimated the model for employees only. The results with both survey and register income changed only marginally for the private sector employees (relative to the public sector employees). See Table 3.A.3 in Appendix 3.A.

engaged in agricultural production as their food purchases might be strongly affected. Based on our own sensitivity analysis (see the next subsection), there can be also variation in consumption patterns due to differences in household structure (e.g. singles vs couples) and a very heterogenous sample might render the estimates of income underreporting unstable.

3.4.3 Sensitivity analysis

We explore the sensitivity of our results to alternative sample and variable definitions. Table 3.A.4 in Appendix 3.A summarises estimates of β, γ and our principal measure of income underreporting, along with diagnostic indicators, for the base scenario (column 1) and for alternative configurations: an alternative set of instruments (column 2), expanded samples (columns 3-5); narrower samples (columns 6-9); alternative expenditure and income measures (columns 10-11); and alternative self-employment definitions (columns 12-13).

Model (2) shows that very similar results to the baseline are obtained when the set of instrumental variables is limited to the dummies for the head's education (though inevitably this reduces the explanatory power of instruments). Model (3) expands the sample to include those households whose head worked part-time or part-year (about an 8% increase) and the results are also affected very little. Models (4) and (5) are based on samples combining couples with single households and other type of households, respectively. Here, we see slightly more variation in results with some estimates becoming less precise, and more so when single households are included (model 4), though the estimates remain broadly similar.

Models (6) and (7) focus on more homogenous samples by restricting the age range of the household head to 25-55 years, and excluding those with earnings reported only in one data source, respectively. The sample for model (6) is about 80% of the main sample and, while estimates of underreporting with survey income change very little, estimates with register income become significantly larger: 33% and 64% on average for households whose head is, respectively, a private employee and a self-employed. The sample for model (7) is only slightly smaller compared to the main sample, indicating that the latter contains relatively few people with positive earnings in one data source and not in the other, and results are just marginally different from the baseline. Models (8) and (9) provide estimates for the 2007 and 2008 wave separately. Splitting the sample obviously increases standard errors (which is the very reason for using pooled waves in the main analysis) though point estimates are generally quite similar, apart from the dummy for self-employed heads (γ_C) for survey income and the dummy for head in the private sector (γ_B) for register income.

Model (10) employs a measure of housing costs, which includes rent and mortgage interest payments and model (11) uses a broader income measure (total household income) instead of earnings.[28] The alternative expenditure measure is limited, however, to actual expenses only and does not consider implicit rent for homeowners. In both cases, the estimate of the income elasticity of housing expenditure (β) is higher than in the baseline, which is expected as rent and mortgage interests ought to be more elastic than utilities, and total income potentially more relevant for household expenses than earnings alone. However, the model fit to the data (based on AIC and BIC) becomes poorer with model (10) for both survey and register income, and $\bar{\kappa}_B$ becomes even higher than one, implying that households whose heads are private employees *overreport* their income on average, though this estimate is not statistically significant. Estimates of income underreporting with model (11) are slightly lower compared to the baseline, which is expected as reporting accuracy for other income components, which are now included (e.g. public pensions and other social transfers), should not be affected by the type of household.[29] However, the estimates of underreporting do not decrease much as earnings are the dominant source of income for this sample of households. Although the model fit is improved when using total household income, the reason for not choosing model (11) as the baseline is because

[28]The total income in the tax records is limited to taxable incomes only. See Section 3.3.

[29]In the case of survey data, other income sources (even if non-taxable) are still likely to be measured imperfectly due to, for example, recall errors, social stigmas related to the receipt of welfare benefits etc, but it is not obvious why this should vary systematically between public employees, private employees and the self-employed.

of our explicit focus on underreporting of earnings.

Finally, models (12) and (13) test alternative definitions for self-employed households, the former considers a household self-employed if *any* of its members is working as a self-employed (not specifically the head of household) and the latter extends the number of self-employed households by including heads who have not indicated self-employment status (in ESU) but reported income related to registered self-employment income. This expands their numbers when using register income as the reported self-employment status and income are already aligned for survey income based sample. The estimates for model (12) and (13) with survey income differ only marginally from the baseline; the same applies to model (13) with register income, while model (12) estimates of underreporting are slightly smaller.

3.5 Conclusions

In this chapter we extended the method of Pissarides and Weber (1989) for estimating income underreporting and apply this to a household income survey linked with individual tax records for Estonia. This allows us to explore the validity of the two main assumptions underlying this method: that employees are fully compliant and patterns of survey income reporting correspond to the way incomes are declared to the tax authority (i.e. the actual tax compliance behaviour). As a further methodological contribution, we identify a way to obtain a point estimate of underreporting with fewer assumptions. We also review other studies applying this kind of method to provide an overview of their methodological differences. Similar to Besim and Jenkins (2005), but in a more rigourous framework, we distinguish between public sector and private sector employees, relaxing the assumption of full income reporting by the latter.

Our key findings are the following. We detect large underreporting of earnings by couples whose head is a self-employed (56% on average) and also substantial underreporting of earnings by households whose head is a private sector employee (23%) on the basis of (housing related) expenditures and incomes in the tax records. However, the scale of underreporting by the self-employed and private employees is estimated to be much smaller with survey incomes (respectively, 25% and 7%) and the latter estimate is also not statistically significant. Importantly, this suggests that people are more truthful in the surveys than often assumed and previous studies using this method may have underestimated the extent of non-compliance by a substantial margin. Moreover, an obvious advantage of using tax records is that this allows us to attribute income underreporting to non-compliance with much greater certainty compared to survey data where misreporting may also occur due to recall errors, stigma effects etc.

There are several possible policy implications. Higher reporting of wages and salaries compared to self-employment income is an indication that third-party reporting reduces non-compliance substantially. However, what is equally important to emphasise is that it does not rule out tax evasion altogether as the employee and the employer can still collude. Furthermore, in absolute terms, much more tax revenue is lost through the underreporting of employment income compared to the underreporting of self-employment income as the latter accounts for only a marginal share of total earnings (less than 2-4% according to ESU, without corrections for underreporting). Hence, the underreporting of wages and salaries by a small proportion can in monetary terms easily exceed underreported self-employment income even if the latter was entirely concealed.

Despite utilising a rich and novel data source in the field of tax compliance and among the PW-type of studies in particular, Chapter 3 was limited to a cross-sectional analysis and to a single type of expenditure. More waves and larger samples are required to take the analysis further by utilising the panel data element and studying specific subgroups in more detail. Richer consumption data would also allow us to estimate more complex demand systems.

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Table 3.1: Sample size

	Number of households			
	Total	Public	Private	Self-empl.
All survey respondents	9,890			
Matched with tax records	9,754			
Household with non-zero consumption	9,728			
Household with positive earnings				
in the survey	7,457			
in the tax records	7,426			
Head with positive earnings				
in the survey	7,064	1,289	5,132	643
in the tax records	7,038	1,449	5,021	568
Head worked full-time (for whole year)				
in the survey	5,954	1,175	4,251	528
in the tax records	5,789	1,101	4,219	469
Couples (with or without children)				
in the survey	3,498	595	2,549	354
in the tax records	3,413	598	2,502	313

Notes: ESU 2007 and 2008 waves pooled; *public/private* = household head is employed in the public/private sector and not considered a self-employed; (employees in ESU who have multiple jobs or unspecified affiliation or switched jobs are included among private employees, public employees in the tax records include those with earnings only from a public entity, an NGO or a foundation); *self-employed* = household head worked as a self-employed in the income reference period (based on ESU).

Table 3.2: Mean household expenditure and income

	Survey income			Register income		
	$\ln c$	$\ln y^s$	Δ	$\ln c$	$\ln y^r$	Δ
			2007 wave			
Public	7.074	9.295	-2.221	7.082	9.527	-2.444
	(0.026)	(0.042)	(0.040)	(0.027)	(0.049)	(0.047)
	324	324		317	317	
Private	7.121	9.426	-2.305	7.122	9.475	-2.352
	(0.015)	(0.022)	(0.022)	(0.015)	(0.027)	(0.026)
	1,307	1,307		1,280	1,280	
Self-employed	7.228	9.223	-1.996	7.232	8.995	-1.763
	(0.039)	(0.083)	(0.082)	(0.042)	(0.098)	(0.093)
	178	178		160	160	
N total	1,809			1,757		
			2008 wave			
Public	7.257	9.472	-2.215	7.208	9.750	-2.543
	(0.024)	(0.045)	(0.046)	(0.029)	(0.046)	(0.052)
	271	271		281	281	
Private	7.307	9.586	-2.279	7.324	9.690	-2.366
	(0.013)	(0.020)	(0.020)	(0.012)	(0.026)	(0.025)
	1,242	1,242		1,222	1,222	
Self-employed	7.440	9.594	-2.154	7.440	9.357	-1.917
	(0.039)	(0.077)	(0.077)	(0.042)	(0.113)	(0.106)
	176	176		153	153	
N total	1,689			1,656		

Notes: estimated using survey weights on a sample of couple households whose head has positive earnings and worked full-time (2007-08 waves pooled); standard errors (shown in parantheses) are clustered at the household level; c = hh monthly housing costs (excl. rent and mortgage interests) in EEK; y^s = hh net earnings in the survey in EEK (annual amount divided by 12); y^r = hh gross earnings in the tax records in EEK (annual amount divided by 12); Δ = difference in mean log values; *public/private* = household head is employed in the public/private sector and not considered a self-employed; *self-employed* = household head worked as a self-employed in the income reference period (based on ESU).

Table 3.3: Estimates of the model with employees (A) and self-employed (B)

	Survey income		Register income	
	(1) ML	(2) ML-IV	(3) ML	(4) ML-IV
β	0.121***	0.308***	0.078***	0.187***
	(0.018)	(0.054)	(0.014)	(0.036)
γ_B	0.087***	0.123***	0.121***	0.177***
	(0.032)	(0.036)	(0.036)	(0.040)
$\sigma^2_{\xi_A}$	0.190***	0.190***	0.326***	0.326***
	(0.008)	(0.008)	(0.024)	(0.024)
$\sigma^2_{\xi_B}$	0.536***	0.536***	0.904***	0.908***
	(0.168)	(0.169)	(0.183)	(0.184)
$1-\bar{\kappa}_B$	0.421**	0.202**	0.717***	0.481***
	(0.182)	(0.101)	(0.142)	(0.113)
$1-1/\bar{k}_B^{PW_l}$	0.421**	0.202**	0.717***	0.481***
	(0.182)	(0.101)	(0.142)	(0.113)
$1-1/\bar{k}_B^{PW_u}$	0.590***	0.436***	0.841***	0.710***
	(0.127)	(0.095)	(0.083)	(0.073)
$1-\bar{\kappa}_B^{HLP}$	0.513***	0.329***	0.788***	0.612***
	(0.146)	(0.082)	(0.107)	(0.084)
# of employees (A)	3,017	3,017	2,975	2,975
# of self-employed (B)	345	345	306	306
Total obs	3,362	3,362	3,281	3,281
AIC	13,840,023	13,836,263	13,666,398	13,663,828
BIC	13,840,439	13,836,692	13,666,813	13,664,255
Partial R^2		0.1323		0.1572
F-test for excluded instr.-s		19.14		26.35
Endogeneity test (p-value)		0.0000		0.0004
Hansen J-test (p-value)		0.4467		0.0459

Notes: estimated using survey weights on a sample of couple households whose head has positive earnings and worked full-time (2007-08 waves pooled); standard errors (shown in parantheses) are clustered at the household level; *dependent variable* = ln housing costs; *income* = ln earnings; *instruments* = head education level, occupation and industry; *covariates* = head gender, age (centered), age squared, nationality, marital status; no of children and (other) adults in the hh, region, rural area, wave and housing characteristics (type, year of construction, no of rooms, size in m2, ownership); *self-employed* = household head worked as a self-employed in the income reference period (based on ESU); * p<0.1, ** p<0.05, *** p<0.01.

Table 3.4: Estimates of the model with public employees (A), private employees (B) and self-employed (C)

	Survey income		Register income	
	(1) ML	(2) ML-IV	(3) ML	(4) ML-IV
β	0.121***	0.302***	0.080***	0.215***
	(0.020)	(0.054)	(0.012)	(0.034)
γ_B	0.018	0.023	0.049**	0.073***
	(0.022)	(0.022)	(0.023)	(0.024)
γ_C	0.102***	0.141***	0.163***	0.253***
	(0.038)	(0.041)	(0.040)	(0.046)
$\sigma^2_{\xi_A}$	0.181***	0.181***	0.200***	0.199***
	(0.013)	(0.013)	(0.015)	(0.015)
$\sigma^2_{\xi_B}$	0.192***	0.192***	0.354***	0.355***
	(0.007)	(0.007)	(0.017)	(0.017)
$\sigma^2_{\xi_C}$	0.535***	0.536***	0.906***	0.909***
	(0.168)	(0.169)	(0.184)	(0.184)
$1-\bar{\kappa}_B$	0.132	0.068	0.414**	0.232***
	(0.161)	(0.069)	(0.177)	(0.088)
$1-1/\bar{k}_B^{PW_l}$	0.132	0.068	0.414**	0.232***
	(0.161)	(0.069)	(0.177)	(0.088)
$1-1/\bar{k}_B^{PW_u}$	0.141	0.078	0.498***	0.343***
	(0.160)	(0.069)	(0.152)	(0.076)
$1-\bar{\kappa}_B^{HLP}$	0.137	0.073	0.458***	0.290***
	(0.160)	(0.068)	(0.164)	(0.081)
$1-\bar{\kappa}_C$	0.485***	0.250**	0.812***	0.561***
	(0.186)	(0.110)	(0.106)	(0.095)
$1-1/\bar{k}_C^{PW_l}$	0.485***	0.250**	0.812***	0.561***
	(0.186)	(0.110)	(0.106)	(0.095)
$1-1/\bar{k}_C^{PW_u}$	0.638***	0.474***	0.907***	0.784***
	(0.130)	(0.097)	(0.054)	(0.054)
$1-\bar{\kappa}_C^{HLP}$	0.568***	0.372***	0.868***	0.692***
	(0.151)	(0.090)	(0.075)	(0.066)
# of public employees (A)	580	580	579	579
# of private employees (B)	2,437	2,437	2,396	2,396
# of self-employed (C)	345	345	306	306
Total obs	3,362	3,362	3,281	3,281
AIC	13,241,775	13,238,113	12,662,605	12,658,765
BIC	13,242,216	13,238,572	12,663,044	12,659,222
Partial R^2		0.1325		0.1502
F-test for excluded instr.-s		19.33		23.71
Endogeneity test (p-value)		0.0000		0.0000
Hansen J-test (p-value)		0.5083		0.1582

Notes: estimated using survey weights on a sample of couple households whose head has positive earnings and worked full-time (2007-08 waves pooled); standard errors (shown in parantheses) are clustered at the household level; *dependent variable* = ln housing costs; *income* = ln earnings; *instruments* = head education level, occupation and industry; *covariates* = head gender, age (centered), age squared, nationality, marital status; no of children and (other) adults in the hh, region, rural area, wave and housing characteristics (type, year of construction, no of rooms, size in m2, ownership); *public/private* = household head is employed in the public/private sector and not considered a self-employed; *self-employed* = household head worked as a self-employed in the income reference period (based on ESU); * p<0.1, ** p<0.05, *** p<0.01.

Appendix 3.A Supplementary tables

Table 3.A.1: Studies on income underreporting based on income-expenditure gap

Study	Country	Data source	Data type	Sample selection	Sample size
Pissarides and Weber (1989)	UK	FES 1982	cross	couples; head working male	2,208
Schuetze (2002)	Canada	FES 1969, 1974, 1984, 1986, 1990, 1992	pooled	urban couples; head male, aged 25-64, worked full-time/full-year, non-farmer	8,463
Lyssiotou et al. (2004)	UK	FES 1993	cross	married couples; head employed	1,750
Johansson (2005)	Finland	HBS 1994-1996 (income from register)	pooled	couples; head aged < 64, worked full year, non-farmer	2,053
Besim and Jenkins (2005)	North-Cyprus	HCES 1998/99	cross	head/spouse: 1 type of empl. income	907
Feldman and Slemrod (2007)	US	unaudited income tax returns 1999	cross	taxpayers with itemised deductions	76,647
Engström and Holmlund (2009)	Sweden	HBS 1999-2004 (except 2002)	pooled	couples (one/both working), non-farmers	4,600-6,000
Kim et al. (2009)	Korea	KLIPS 2000-2005	panel (average)	urban couples aged 20-65,	6,593
	Russia	RLMS 1994-2000	panel (average)	male head	5,243
Tedds (2010)	Canada	FES 1982, 1986, 1992, 1996	pooled	married couples (no children) aged 25-64, head employed and non-farmer	3,880
Martinez-Lopez (2013)	Spain	HBS 2006-2009	pooled	non-farmers	13,158-16,451
Hurst et al. (2014)	US	CES 1980-2003	pooled	head male, aged 25-55, 30h+, 40 weeks, non-farmer	27,219
		PSID 1980-1997 (except 1988-89)	pooled, panel (3y average)		36,434/18,233
Kukk and Staehr (2014)	Estonia	HBS 2002-2007	pooled	couples: head active	6,016

Notes: FES=Family Expenditure Survey(s), HBS=Household Budget Survey, HCES=Household Consumption Expenditure Survey, KLIPS=Korea Labor Income Panel, RLMS=Russian Longitudinal Monitoring Survey, CES=Consumer Expenditure Survey, PSID=Panel Study of Income Dynamics.

Table continues on the next page.

Table 3.A.1 continues

Study	Group def	Expenditure	Income	Method	Estimation	Results
Pissarides and Weber (1989)	SE ($\geq$ 25% THI)	food	net HE	k bands (EC)	IV-2SLS	white collar 22-35%, blue collar 34-39%
Schuetze (2002)	SE ($\geq$ 30% THI)	food	net THI	k bands (EC)	IV-2SLS	6-22% (across years)
Lyssiotou et al. (2004)	SE (main income), SE income	food, DS	HE	k bands (EC), NP	IV-2SLS, GMM	white collar 8-20%, NP 32%*, DS 39%*; blue collar 27-29%, NP 43%*, DS 54%*
Johansson (2005)	SE ($\geq$ 6 months)	food	net THI (R)	k bands (EC)	(OLS), IV-2SLS	9-19% (head SE), 27-32% (couple SE)
Besim and Jenkins (2005)	SE (income), private EE (reported)	food	net THI	k point	OLS	10-11% (self-empl.), 13% (priv. empl.)
Feldman and Slemrod (2007)	tax schedules (C-F)	charitable contributions	taxable income (R) by schedules	k point	NLS	15-65%* (across schedules)
Engström and Holmlund (2009)	SE (reported)	food	net THI (R)	k point	OLS, IV	14-15% (incorp.), 33% (unincorp.)
Kim et al. (2009)	SE (main job), SE (reported)	food share	THI	k bands (EC), k point (EC)	between OLS, (FE)	38%* (Korea) 47%* (Russia)
Tedds (2010)	SE ($>$ 0% THI)	food	net THI + savings	NP	LOWESS	20%*
Martinez-Lopez (2013)	SE (reported)	food	net THI/THHI	k bands (EC)	IV-2SLS	15-25%
Hurst et al. (2014)	SE (reported)	food, total, non-durables	gross/net THI	κ point	OLS, IV	19-32%* (CES) 28-32%* (PSID)
Kukk and Staehr (2014)	SE ($\geq$ 20% THI)	food	regular net THI	k point (EC)	IV-GMM	62%*

Notes: all results shown in terms of underreporting ($1-\bar{\kappa}$ and $1-1/\bar{k}$), * estimates with t-values or standard errors; SE=self-employed, TH(H)I=total household (head) income, HE=household earnings, R=register-based; EC=(with) error correction, DS=demand system, NP=non-parametric.

Table 3.A.2: Descriptive statistics for non-monetary variables

	mean	st.dev.	N
Education=basic or less	0.07	0.26	4,014
Education=secondary	0.56	0.50	4,014
Education=tertiary	0.37	0.48	4,014
Occupation=senior managers, legislators	0.20	0.40	3,983
Occupation=professionals	0.15	0.35	3,983
Occupation=technicians, associate professionals	0.11	0.32	3,983
Occupation=service/sales workers	0.07	0.25	3,983
Occupation=craft/related trade workers	0.20	0.40	3,983
Occupation=clerks, plant/machine operators	0.20	0.40	3,983
Occupation=agricultural workers, elementary occupations	0.06	0.24	3,983
Industry=agriculture, forestry, fishing	0.05	0.21	3,938
Industry=manufacturing, mining, electricity, gas, water supply	0.25	0.43	3,938
Industry=construction	0.15	0.36	3,938
Industry=trade, hotels, restaurants, transport, communication	0.26	0.44	3,938
Industry=finance, real estate, renting, business activities	0.10	0.29	3,938
Industry=public admin, education, health; own production	0.20	0.40	3,938
Age (centered)	-0.00	1.13	4,014
Age (centered) squared	1.28	1.50	4,014
Gender=male	0.72	0.45	4,014
Nationality=Estonian	0.71	0.45	4,014
Marital status=married	0.73	0.44	4,014
Region=north	0.40	0.49	4,014
Region=central	0.11	0.31	4,014
Region=north-east	0.11	0.32	4,014
Region=west	0.13	0.33	4,014
Region=south	0.24	0.43	4,014
Area=rural	0.29	0.45	4,014
No of persons aged 15+ in the hh (other than couple)	0.45	0.75	4,014
No of children aged 14 or younger in the hh	0.69	0.88	4,014
Housing type=house	0.33	0.47	4,013
Housing type=flat	0.67	0.47	4,013
Construction period=before 1946	0.14	0.35	3,957
Construction period=1946-1960	0.09	0.28	3,957
Construction period=1961-1970	0.17	0.38	3,957
Construction period=1971-1980	0.25	0.43	3,957
Construction period=1981-1990	0.22	0.41	3,957
Construction period=1991-1999	0.05	0.23	3,957
Construction period=2000 or later	0.08	0.27	3,957
Housing size (m2, capped at 450)	75.45	42.57	3,988
Housing ownership=owned	0.90	0.30	4,014
Housing ownership=rented	0.10	0.30	4,014
No of rooms (capped at 6)	3.10	1.18	4,014
2008 wave	0.51	0.50	4,014

Notes: ESU 2007 and 2008 waves pooled; estimated using survey weights on a sample of couple households whose head has positive earnings (in either data source) and worked full-time; person characteristics refer to the head of household; age variable is centered at sample mean (and divided by 10).

Table 3.A.3: Estimates of the model with public employees (A) and private employees (B)

	Survey income		Register income	
	(1) ML	(2) ML-IV	(3) ML	(4) ML-IV
β	0.132***	0.306***	0.081***	0.214***
	(0.018)	(0.058)	(0.015)	(0.038)
γ_B	0.017	0.022	0.050**	0.074***
	(0.021)	(0.021)	(0.023)	(0.023)
$\sigma^2_{\xi_A}$	0.181***	0.181***	0.199***	0.198***
	(0.014)	(0.014)	(0.019)	(0.019)
$\sigma^2_{\xi_B}$	0.192***	0.192***	0.354***	0.355***
	(0.008)	(0.008)	(0.021)	(0.021)
$1-\bar{\kappa}_B$	0.119	0.064	0.417**	0.234***
	(0.139)	(0.064)	(0.173)	(0.085)
$1-1/\bar{k}_B^{PW_l}$	0.119	0.064	0.417**	0.234***
	(0.139)	(0.064)	(0.173)	(0.085)
$1-1/\bar{k}_B^{PW_u}$	0.128	0.074	0.501***	0.345***
	(0.138)	(0.064)	(0.148)	(0.074)
$1-\bar{\kappa}_B^{HLP}$	0.123	0.069	0.461***	0.292***
	(0.138)	(0.064)	(0.160)	(0.079)
# of public employees (A)	580	580	579	579
# of private employees (B)	2,437	2,437	2,396	2,396
Total obs	3,017	3,017	2,975	2,975
AIC	11,935,962	11,933,260	11,519,963	11,516,532
BIC	11,936,371	11,933,681	11,520,371	11,516,951
Partial R^2		0.1319		0.1563
F-test for excluded instr.-s		18.53		21.13
Endogeneity test (p-value)		0.0000		0.0001
Hansen J-test (p-value)		0.6236		0.1744

Notes: estimated using survey weights on a sample of couple households whose head has positive earnings and worked full-time (2007-08 waves pooled); standard errors (shown in parantheses) are clustered at the household level; *dependent variable* = ln housing costs; *income* = ln earnings; *instruments* = head education level, occupation and industry; *covariates* = head gender, age (centered), age squared, nationality, marital status; no of children and (other) adults in the hh, region, rural area, wave and housing characteristics (type, year of construction, no of rooms, size in m2, ownership); *public/private* = household head is employed in the public/private sector and not considered a self-employed; * p<0.1, ** p<0.05, *** p<0.01.

Table 3.A.4: Sensitivity analysis

	Estimates with survey income												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
β	0.302***	0.329***	0.281***	0.313***	0.301***	0.293***	0.294***	0.273***	0.297***	0.452***	0.362***	0.295***	0.302***
	(0.054)	(0.064)	(0.046)	(0.042)	(0.051)	(0.060)	(0.052)	(0.064)	(0.077)	(0.064)	(0.061)	(0.048)	(0.052)
γ_B	0.023	0.025	0.030	0.035*	0.026	0.020	0.027	0.018	0.026	-0.057*	0.018	0.022	0.024
	(0.022)	(0.021)	(0.020)	(0.020)	(0.018)	(0.022)	(0.021)	(0.034)	(0.032)	(0.030)	(0.021)	(0.020)	(0.025)
γ_C	0.141***	0.145***	0.133***	0.152***	0.140***	0.136***	0.132***	0.179***	0.100**	0.102*	0.119***	0.124***	0.142***
	(0.041)	(0.041)	(0.037)	(0.040)	(0.038)	(0.037)	(0.038)	(0.054)	(0.050)	(0.053)	(0.038)	(0.033)	(0.044)
$1-\bar{\kappa}_B$	0.068	0.072	0.096	0.091	0.078	0.063	0.084	0.039	0.098	-0.140*	0.034	0.068	0.066
	(0.069)	(0.058)	(0.067)	(0.057)	(0.059)	(0.070)	(0.065)	(0.120)	(0.092)	(0.077)	(0.058)	(0.064)	(0.078)
$1-\bar{\kappa}_C$	0.250**	0.214**	0.256**	0.237**	0.235**	0.251**	0.242**	0.350**	0.189	0.048	0.203**	0.258***	0.250**
	(0.110)	(0.095)	(0.101)	(0.093)	(0.107)	(0.102)	(0.097)	(0.140)	(0.129)	(0.114)	(0.090)	(0.084)	(0.110)
# of public employees (A)	580	582	634	843	882	414	577	315	265	580	580	514	556
# of private employees (B)	2,437	2,498	2,625	3,087	3,410	2,020	2,341	1,258	1,179	2,437	2,437	2,263	2,461
# of self-employed (C)	345	347	390	399	462	295	316	174	171	345	345	585	345
Total obs	3,362	3,427	3,649	4,329	4,754	2,729	3,234	1,747	1,615	3,362	3,362	3,362	3,362
AIC	13,238,113	13,030,728	14,609,185	20,963,726	18,091,817	9,976,054	12,717,809	6,261,371	6,253,333	13,439,434	13,135,990	13,248,323	13,268,314
BIC	13,238,572	13,031,121	14,609,651	20,964,229	18,092,328	9,976,498	12,718,266	6,261,770	6,253,727	13,439,893	13,136,449	13,248,782	13,268,773
Partial R^2	0.1325	0.0562	0.1293	0.1666	0.1148	0.1224	0.1405	0.1413	0.1315	0.1325	0.1253	0.1341	0.1333
F-test for excluded instr.-s	19.33	47.07	20.13	33.97	22.67	13.84	19.67	12.85	13.34	19.33	18.82	19.63	19.42
Endogeneity test (p-value)	0.0000	0.0003	0.0000	0.0000	0.0000	0.0004	0.0000	0.0006	0.0019	0.0000	0.0000	0.0000	0.0000
Hansen J-test (p-value)	0.5083	0.4835	0.4685	0.5283	0.0991	0.2233	0.6322	0.4654	0.7607	0.6435	0.5391	0.4609	0.5069
	Estimates with register income												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
β	0.215***	0.228***	0.190***	0.237***	0.209***	0.203***	0.216***	0.201***	0.222***	0.293***	0.228***	0.201***	0.217***
	(0.034)	(0.041)	(0.031)	(0.034)	(0.033)	(0.038)	(0.036)	(0.049)	(0.051)	(0.044)	(0.037)	(0.034)	(0.035)
γ_B	0.073***	0.073***	0.071***	0.051**	0.056***	0.096***	0.073***	0.043	0.098***	0.005	0.069***	0.066***	0.073***
	(0.024)	(0.024)	(0.022)	(0.021)	(0.021)	(0.025)	(0.022)	(0.036)	(0.036)	(0.032)	(0.023)	(0.022)	(0.023)
γ_C	0.253***	0.258***	0.243***	0.229***	0.226***	0.275***	0.245***	0.256***	0.243***	0.247***	0.244***	0.186***	0.245***
	(0.046)	(0.052)	(0.040)	(0.054)	(0.042)	(0.052)	(0.042)	(0.068)	(0.064)	(0.063)	(0.045)	(0.036)	(0.045)
$1-\bar{\kappa}_B$	0.232***	0.213***	0.251***	0.145*	0.171*	0.325***	0.231***	0.125	0.306***	-0.061	0.207**	0.224**	0.233***
	(0.088)	(0.081)	(0.089)	(0.074)	(0.091)	(0.093)	(0.085)	(0.165)	(0.112)	(0.114)	(0.085)	(0.088)	(0.086)
$1-\bar{\kappa}_C$	0.561***	0.519***	0.595***	0.423***	0.518***	0.639***	0.558***	0.593***	0.529***	0.386***	0.546***	0.498***	0.538***
	(0.095)	(0.097)	(0.099)	(0.124)	(0.100)	(0.122)	(0.105)	(0.132)	(0.127)	(0.118)	(0.093)	(0.098)	(0.098)
# of public employees (A)	579	589	648	803	837	440	579	307	272	579	579	503	577
# of private employees (B)	2,396	2,449	2,575	3,049	3,395	1,969	2,396	1,233	1,163	2,396	2,396	2,213	2,366
# of self-employed (C)	306	307	343	363	405	262	284	156	150	306	306	565	338
Total obs	3,281	3,345	3,566	4,215	4,637	2,671	3,259	1,696	1,585	3,281	3,281	3,281	3,281
AIC	12,658,765	12,853,090	13,998,692	20,473,284	17,464,964	9,535,421	12,588,820	6,114,329	6,024,277	12,846,529	12,613,991	12,731,497	12,659,990
BIC	12,659,222	12,853,482	13,999,155	20,473,785	17,465,473	9,535,863	12,589,276	6,114,726	6,024,669	12,846,986	12,614,448	12,731,954	12,660,447
Partial R^2	0.1502	0.0750	0.1414	0.1220	0.1232	0.1502	0.1474	0.1551	0.1504	0.1502	0.1512	0.1571	0.1520
F-test for excluded instr.-s	23.71	67.08	24.27	19.11	25.08	18.23	23.05	16.00	15.13	23.71	23.11	25.18	24.03
Endogeneity test (p-value)	0.0000	0.0001	0.0000	0.0000	0.0000	0.0007	0.0000	0.0007	0.0017	0.0000	0.0000	0.0001	0.0000
Hansen J-test (p-value)	0.1582	0.4859	0.2574	0.6819	0.0296	0.0578	0.1380	0.4199	0.2601	0.3902	0.1603	0.1050	0.1668

Notes: model (1) estimated using survey weights on a sample of couple households whose head has positive earnings and worked full-time (2007-08 waves pooled); standard errors (shown in parantheses) are clustered at the household level; *dependent variable* = ln housing costs; *income* = ln earnings; *instruments* = head education level, occupation and industry; *covariates* = head gender, age (centered), age squared, nationality, marital status; no of children and (other) adults in the hh, region, rural area, wave and housing characteristics (type, year of construction, no of rooms, size in m2, ownership); *public/private* = household head is employed in the public/private sector and not considered a self-employed; *self-employed* = household head worked as a self-employed in the income reference period (based on ESU); sensitivity tests: (2) only head's education level used as instruments, (3) sample also includes hh heads working part-time/part-year, (4) also single households, (5) also other (non-single) households, (6) only hh heads aged 25-55, (7) only hh heads with positive earnings in both data sources, (8) 2007 wave only, (9) 2008 wave only, (10) housing cost includes rent and mortgage interests payments, (11) total household income (instead of earnings), (12) also self-employed hh if non-head hh member working as a self-employed, (13) also self-employed hh if head has self-employment income;
* p<0.1, ** p<0.05, *** p<0.01.

Summary and further research

The thesis focuses on various aspects of household income taxation, using economic modelling to investigate policy relevant issues. Chapter 1 studied the scope for flat income taxes in Western European countries with an emphasis on the distributional implications. With Chapter 2 and Chapter 3, I estimated the prevalence and determinants of income underreporting for tax purposes in Estonia. The econometric analysis in Chapter 2 also accounts for measurement errors in survey income and the distinct feature of Chapter 3 is its broader scope, which includes not only employed workers but also self-employed.

Using microsimulation techniques and the EU tax-benefit model EUROMOD, Chapter 1 sought to assess systematically how interdependent dimensions – the flat tax design, the underlying income distribution and the institutional context – relate to the outcomes of flat tax reforms. We do this by estimating the distributional and work incentive effects of a range of hypothetical revenue-neutral flat tax reforms in several Western European countries, varying the level of flat tax rates and tax-free allowance with guidance from the theoretical framework of Davies and Hoy (2002).

Our findings confirm the general pattern that lower flat tax parameters strengthen work incentives but tend to benefit high income households at the expense of low and middle income households and, therefore, lead to a less equal income distribution. Higher flat tax parameters, on the other hand, can maintain the observed levels of inequality but usually exhibit substantial disincentive effects. The results are in line with earlier single-country empirical studies while our broader scope offers more generic insights as well as helps to identify a few exceptions. A common and consistent modelling framework further allows us to note some cross-country patterns along the welfare state typology of Esping-Andersen (1990) and Ferrera (1996). In particular, the Mediterranean (or Southern) welfare regimes show some scope for flat tax reforms with little tradeoff between equity and efficiency considerations. In other words, this shows that the effective tax burden resulting from their existing income tax systems is less different from that of a pure flat tax schedule than in other countries.

There are several possibilities for extending the research in Chapter 1. First of all, cross-country variability could be summarised with alternative scenarios. One particular option – which we are already pursuing in a separate paper – is to consider 'double neutral' flat tax parameters in the sense of achieving not only revenue neutrality but also keeping the level of inequality constant. Such a combination of parameters would be unique for a given measure of inequality and therefore could provide a useful step towards a better understanding of the characteristics of a tax-benefit system determining the intensity of equity-efficiency trade-off.

Second, the analysis in Chapter 1 abstracts from wider effects on the economy and focuses on the first-order effects alone, even though these are likely to be decisive for the political feasibility of a flat tax reform. Changes in work incentive indicators can be seen at best as an approximation to potential labour supply effects. A step forward would be to use large-scale comparative estimates of labour supply elasticities (e.g. Bargain et al., 2014) or to model labour market behaviour explicitly. Discrete labour supply models with static tax-benefit models embedded (see Creedy and Kalb, 2005) are well established and widely used to assess the behavioural reactions to changes in the tax-benefit system, though linking these with labour demand models remains a key challenge. There have been also attempts to link computable general equilibrium (CGE) models with microsimulation models to combine their advantages. While the resulting micro-macro frameworks can be very complex, it is less of a conceptual or a computational problem than an issue of calibrating such models, given the increasing number of parametric combinations (Bourguignon and Bussolo, 2013).

Third, there is clearly scope to complement ex ante analysis based on simulation methods with ex post evaluations of flat tax reforms given their wide implementation in Europe and the first reversals in recent years (e.g. in the Czech Republic and the Slovak Republic). Among such reforms, the one in Russia in 2001 has attracted the most attention so far (see Ivanova et al., 2005; Gorodnichenko et al., 2009; Duncan, 2014) while others largely remain to be studied. In several cases, though, the limited progress can be explained by the lack of suitable micro-data or the specifics and context of the reform, making it difficult to come up with credible identification strategies.

The aim of Chapter 2 was to uncover the extent and patterns of income tax evasion on the basis of income survey data combined with information from administrative tax records at the individual level – a novel and promising data source in the context of tax compliance literature. I propose a multi-equation econometric model to capture income reporting decisions of employees for tax and survey purposes conditional on (latent) true earnings. To identify such a model, my key assumption is that public sector employees are constrained in their choice to evade taxes and their earnings are correctly reported to the tax authority, while there are no systematic differences (after controlling for individual characteristics) between them and private sector employees regarding income reporting in the survey.

I use the Estonian Social Survey (i.e. the Estonian component of the EU-SILC), which has been linked with official tax records using individual ID-s and, remarkably, without the requirement to seek the respondents' explicit consent. The unique properties of linkage ensure its high quality and achieve matches for virtually everyone. Compared to previous empirical studies relying on (audited) tax records only, I have a much richer set of explanatory variables and having a pair of income observations provides better means to estimate true earnings. Compared to studies based on survey data alone, I do not need to make strong (implicit) assumptions about reporting in the survey corresponding to income reporting for the tax purposes and can account for potential measurement error in the survey data.

My results indicate a number of socio-economic and demographic characteristics, which strongly influence tax compliance behaviour, in line with (limited) previous evidence and general expectations. The model allows me to quantify their marginal effects on reported earnings and, therefore, reveal their economic impact as well. I show a negative association between income reporting and the level of true earnings, ceteris paribus, with the mean elasticity among unconstrained employees around 0.9. Overall, I estimate that more than 20% of all employees underreport their earnings – most of them partially – and about 12% of total employment income is not declared in the tax reports. This is a substantial proportion and challenges the common view in the literature that the underreporting of wages and salaries is very low because of third party reporting. I also show variation in reporting patterns across the estimated true income distribution with lower compliance at the bottom and the top range of incomes, and substantial measurement errors in survey income of a mean-reverting nature: large over-reporting at low values of true earnings and moderate under-reporting at medium and high values of true earnings. My findings are robust to a range of sensitivity tests, illustrating the importance of combining register and survey information even if survey incomes are measured with errors.

Chapter 2 is the first attempt to model tax evasion and measurement error jointly and as such there is scope for further improvements and extensions. For example, it might be desirable to introduce additional elements into the modelling framework to reflect the reporting process more flexibly: allow different factors to affect the decision to underreport income and the extent of underreporting, allow for correlation between unobserved factors affecting income reporting in the two cases (i.e. error terms) and distinguish between intentional and unintentional misreporting.

It would be also useful to test the new method on other countries to check its robustness and whether it can confirm in a systemic way a larger scale of underreporting of wages and salaries than previously thought. A particular extension could be for countries with progressive tax schedules, giving explicit attention to the role of marginal effective tax rates which vary very little cross-sectionally in the case of Estonia. As the marginal effective tax rate depends on income reported to the tax authority, it is an endogenous factor in the reporting process and would require careful handling.

Finally, one could seek possibilities to model interactions between employees and employers leading to compliance decisions. While there is no doubt about the nature of the process being non-trivial and modelling involving great challenges, not least because of additional data requirements, such a feature would represent another important step closer to the reality and better understanding of the key determinants of income tax evasion.

Similar to Chapter 2, Chapter 3 deals with income underreporting and utilises the same dataset. It differs however in two important aspects. First, it uses a different method, following a well-known approach by Pissarides and Weber (1989), which contrasts household income and expenditure to recover underreported income. Second, it extends the analysis to the self-employed. As with the model developed in Chapter 2, the Pissarides-Weber method relies on having a group of people who are assumed to report their incomes correctly. Typically, these have been taken to be (all) employees and the method has been applied to survey data on income and food expenditure to study income underreporting among the self-employed. The results of Chapter 2 offer insights for improving on their approach as well. Specifically, in Chapter 3, I limit the assumption of compliant people to public employees only and estimate income underreporting simultaneously for private employees and the self-employed. I also apply their method separately to survey incomes and register incomes to show the implications of their underlying assumption that income reporting in the survey corresponds to reporting for tax purposes. Even though information on expenditures in the SILC is limited and does not cover food, it includes housing related expenses (essentially utilities) which I use instead.

Applying the method in a standard way – using all employees as the reference group and relying on survey income information – leads to the detection of sizeable income underreporting by the self-employed (20-25% on average). My key findings, however, indicate that the extent of underreporting is much higher with register income (48-56%) and also substantial among private employees (23%). Despite different methods (and samples), the latter estimate is of similar magnitude compared to that from Chapter 2 where it was estimated that *private* employees underreport 15-16% of their total employment income. In other words, my findings indicate that people are much more truthful in the survey and the results based on survey data alone do not reveal the full scale of tax non-compliance.

Further research could test assumptions about functional specifications with non-parametric methods (see Tedds, 2010) and seek comprehensive expenditure data (linked with register incomes) to estimate a more complete demand system (cf. Lyssiotou et al., 2004). The size of the sample, which was already boosted by pooling two waves, limits the analysis here to the main types of workers while larger samples would allow relevant characteristics for income underreporting to be explored in more detail. Moving from the cross-sectional setting to panel data could offer even greater advantages by providing explicit information on income variation.

Although we cautioned against treating the estimates of income underreporting based on survey data alone as an indicator of tax evasion, such approach can still enhance income measurement in surveys where one group of respondents is systematically underreporting (or overreporting) income. For the EU-SILC, which is a multi-country survey, this could represent a way to enhance cross-national comparability as reporting behaviour for the same type of people may vary substantially across countries. There is also an increasing number of countries, which by relying on administrative records to provide information on certain income components in the EU-SILC, can offer further research possibilities. Overall, the potential of linked survey and administrative data sources is increasingly recognised and is likely to lead to better availability of information from the combined data sources such as those used in the thesis.

Building on work done in all chapters, my further ambition is to introduce tax compliance into empirical models of labour supply. This would extend current approaches with an important additional channel through which taxes can affect people's labour market behaviour. As I showed in Chapter 2 most tax non-compliance takes place in the form of partial rather than complete evasion and points to people combining declared and undeclared work instead of entirely switching between formal and informal labour markets. From society's perspective, the fact that some people (among those with similar characteristics) are not fully compliant with the tax laws represents a failure of the horizontal equity principle and we need more insights into how the design of tax system influences labour market decisions in the world without full compliance. A choice between flat taxes and graduated rate taxes is one relevant aspect for consideration here.

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