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Essays on Public Finance

Tomáš Lichard

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Contents

Abstract

This dissertation analyzes two presently widely discussed topics in Public Finance: relationship between the shadow economy and tax policy, and the effect of financial transaction taxes on the functioning of financial markets.

The first chapter describes presently used estimators of the size of the shadow economy, with a focus on microeconomic estimators. It illustrates problems with assumptions that a vast majority of recent studies use to identify underreporting (mainly the comparison of employed and self-employed) using data from four transition economies as an example. It shows that the most common assumption, that self-employed evade whereas employees do not is probably too strict in less compliant economies, where even employees have opportunities to evade through e.g. under-the-table wages or by moonlighting at unreported jobs.

The second chapter develops an estimator of unreported income that relaxes some of these strict assumptions. Assuming only that tax-evading households have a higher consumption-income gap than non-evaders in surveys, an endogenous switching model with unknown sample separation enables the estimation of both the probability of hiding income and the expected amount of unreported income for each household. Using data from Czech and Slovak household budget surveys, we find the size of the shadow economy to be substantially larger than estimated using other techniques. These results are robust under a number of alternative specifications. Furthermore, we show that since the share of underreported income decreases with income level, true income inequality in these countries is lower than suggested by the reported income.

In the third chapter we analyze the tax evasion response to the introduction of the flat tax in several transition economies. Using the estimator from the previous chapter, we show that in majority of studied countries there was no discernible effect of the flat tax reform on the size of the shadow economy. We argue that this finding is consistent with the tax morale story, as satisfaction with public services and with countries' development in general declined in these countries.

The fourth chapter focuses on financial transaction taxes (FTTs), which have returned to spotlight since the recent economic crisis as a possible means to offset negative risk externalities. However, up-to-date academic research does not provide sufficient insights into the effects of transaction taxes on financial markets, as the literature has heretofore been focused too narrowly on Gaussian variance as a measure of volatility. In this paper, we argue that it is imperative to understand the relationship between price jumps,

Gaussian variance, and FTTs. While Gaussian variance is not necessarily a problem in itself, the non-normality of return distribution caused by price jumps affects not only the performance of many risk-hedging algorithms but directly influences the frequency of catastrophic market events. To study the relationship between FTTs and price jumps, we use an agent-based model of financial markets. Its results show that the relationship is intricate, as the volatility as measured by the standard deviation of prices may rise with increasing tax rate, while, at the same time, the measure of price jumps goes down. This result implies that regulators may face a trade-off between overall variance and price jumps when designing optimal tax.

Abstrakt

Tato dizertace se věnuje dvěma v současnosti často diskutovaným tématům v oblasti veřejných financí: šedé ekonomice (a vlivu, který na ni má zavedení rovné daně) a daním z finančních transakcí.

První kapitola nabízí přehled současně používaných odhadů šedé ekonomiky, a to hlavně odhadů založených na mikroekonomických datech. Ukazuje, že předpoklady, na kterých je založena identifikace zamlčování příjmu ve většině současných studií (hlavně předpoklad, že zaměstnanci svůj příjem nikdy nezamlčují), jsou pravděpodobně příliš přísné. Ilustruje to na datech ze čtyř postkomunistických ekonomik.

Druhá kapitola popisuje odhad šedé ekonomiky, jehož předpoklady jsou flexibilnější než předpoklady předchozích odhadů. Za předpokladu, že domácnosti, které v dotaznících zamlčují část příjmu, mají vyšší mezeru mezi příjmy a výdaji než ty, které uvádějí svůj příjem pravdivě, odhadujeme regresní model s přechodem mezi dvěma stavy (přiznaný a zatajovaný příjem), ve kterém není pravidlo přechodu zcela známo a je endogenní. To nám umožňuje odhadnout pravděpodobnost zatajování příjmu pro každou domácnost zároveň s předpokládanou nepřiznanou částkou. Na datech z České a Slovenské republiky ukazujeme, že takto odhadnutá velikost šedé ekonomiky je větší než u předchozích metodologií. Výsledky jsou robustní vzhledem ke změnám specifikace. Jelikož je zatajovaný příjem klesající funkcí přiznaného příjmu, míra nerovnosti počítaná z odhadnutého skutečného příjmu je v těchto zemích nižší, než jak uvádí oficiální statistika.

Ve třetí kapitole využíváme tuto metodologii na odhad vlivu zavedení rovné daně ve vybraných zemích střední a východní Evropy na velikost šedé ekonomiky. Z našich výsledků vyplývá, že ve většině těchto zemí nebyl tento efekt významný. Ukazujeme, že tento výsledek se dá vysvětlit neekonomickými faktory, jelikož v těchto zemích došlo v zkoumaném období k zhoršení více indikátorů spokojenosti s vládou a všeobecným vývojem ve společnosti.

Tématem čtvrté kapitoly jsou daně z finančních transakcí (DFT). DFT se vrátily do středu zájmu po poslední globální finanční krizi jako potenciální způsob omezení negativních externalit na finančních trzích. Současný výzkum však nepřináší dostatečně hluboký náhled na dopad zavedení DFT na fungování trhu, neboť se současná literatura zaměřuje příliš úzce na gaussovskou varianci jakožto míru volatility. Ukazujeme nezbytnost studování vztahu mezi cenovými skoky, gaussovskou variancí a DFT. Zatímco gaussovská variance nemusí být sama o sobě problém, odklony od normality distribuce výnosů způsobené cenovými skoky negativně ovlivňují nejen výkonnost zajišťovacích algoritmů,

ale je přímo spjata s frekvencí katastrofických událostí na trzích. Abychom pochopili výše uvedené vztahy, používáme model finančních trhů založený na multiagentním přístupu. Jeho výsledky ukazují, že vztah mezi těmito veličinami je ambivalentní. Regulátor je tak při nastavování optimální daně postaven před volbu mezi nízkou celkovou volatilitou a nízkým počtem cenových skoků.

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Czech Republic, Prague — Tomáš Lichard
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Preface

This dissertation analyzes two of the most widely-discussed issues in the public finance – shadow economy and financial transaction taxes.

The first issue, the shadow economy (also known as "gray economy" or "underground economy" and by various statistical offices as the "unrecorded economy"), is usually defined as activity hidden from the authorities including transactions that are not illegal per se but which are hidden in order to evade taxes. Given this definition, it is clear that the shadow economy is of significant interest not only to academics, but to governments as well. The shadow economy (i.e. income underreporting) not only reduces tax revenues, but may increase spending on income-conditioned transfer programs. Therefore, it is no surprise that the fight against the shadow economy is at a forefront of many government's agenda. Particularly in an environment of growing budget deficits, policy-makers often believe that better capturing the shadow economy would improve governments' fiscal stance, especially given that increasing tax rates to offset the income lost to evasion can lead to even greater evasion. In addition to tax revenue, there are other issues connected with the shadow economy. One such issue is economic inefficiency. Inefficiency may be caused by diversion of economic activity to the possibly less efficient hidden sector, or unproductive activities connected with income hiding, such effort spent on 'cooking the books'. The desire to avoid attention may also lead to inefficiently small enterprise sizes. Also, cross-country differences in the size of the shadow economy size cause international comparisons of GDP to be biased.

Governments are experimenting with various ways how to decrease tax evasion (see e.g. Muller, Conlon, Lewis, & Mantovani, 2013). Examples of such methods include tax receipt lotteries and cash transaction fiscalization. As these methods are costly, policy makers should require an accurate estimation of potential benefits in order to properly compare them to costs of these measures. For this, they need reliable estimates of the size of the shadow economy.[1] However, estimating the size of the shadow economy is not a straightforward task for various reasons, not the least being that, by definition, individuals tend to hide such activities. As a result, researchers need to make what are sometimes heroic assumptions in order to estimate the extent of the shadow economy. Consequently, as the first chapter argues, up-to-date methods of estimation (both micro and macro) suffer from various problems. The first chapter also practically demonstrates most problematic assumptions, by estimating the size of the shadow economy for four transition countries using a widely used identifying assumption.

The second chapter therefore develops a novel estimator that aims to relax some of the strictest assumptions in current microeconomic methods. In contrast to heavily-used macroeconomic methods, we do not employ aggregate indicators, but rather microeconomic data on households. Therefore, this estimator does not suffer from the potential endogeneity problems associated with such measures. The advantages of our estimator are twofold. Firstly, compared to previous methods based on microeconomic data, we avoid ex ante assumptions about which households evade and which do not.[2] Secondly, we employ broadly collected household budget surveys that are available on a standardized basis across many countries. We demonstrate the proposed method by using data from Czech and Slovak household budget surveys and show that the size of the shadow economy is substantially larger than estimates derived using other techniques. Moreover, these results are robust to a number of alternative specifications and identification restrictions. We also show that the hidden activity can have profound implications for inequality, as, at least for the countries studied, the extent of the shadow economy is negatively correlated with household income. Therefore, in these countries, the degree of inequality is overestimated when using the reported income to compute its measure.

One of the oft-quoted remedies for tax evasion is the introduction of a flat (or more precisely uniform) tax rate. The intuition is that high earners in an economy with a flat tax rate have less incentive to hide the part of their income that would, within progressive

[1]As Slemrod (2007) puts it: "The mere presence of tax evasion does not imply a failure of policy. Just as it is not optimal to station a police officer at each street corner to eliminate robbery and jaywalking completely, it is not optimal to eliminate tax evasion." (p. 43)

[2]The most common groups in these roles are self-employed and employed, respectively.

taxation, fall into a higher tax bracket.[3] However, only a handful of studies tried to verify this claim. The third chapter thus builds on the methodology described in the second part of the dissertation to estimate the effect of introduction of a flat tax on a selected group of CEE countries. As we show, the evidence on the effect of the flat tax is not unambiguous. We argue that these results can be explained by the relative importance of non-economic factors (tax morale).

The fourth chapter offers new insights into another problem in public finance – financial transaction taxes (FTTs). These are also sometimes called Tobin taxes, as it was James Tobin who first proposed a tax on spot conversions of one currency into another (Tobin, 1978; Eichengreen, Tobin, & Wyplosz, 1995) as a way to mitigate short-term financial round-trip excursions into another currency. The name 'Tobin tax' is today often used to denote not only foreign exchange transaction taxes, but FTTs in general. Therefore, this text uses these terms interchangeably.

The debate on the merits of Tobin-like taxes has not so far reached a definite conclusion.[4] Proponents of the tax claim that increased transaction costs affect short-term high volume trading (speculation) more than long-term positions, decreasing market volatility and thus potential for crashes. In this regard, the tax can be thought of as a Pigovian tax on a negative risk externality, as market instability can adversely affect the real economy and lead to welfare losses. Opponents of the Tobin tax generally claim that it can, in fact, increase volatility by decreasing market liquidity, or that speculative trading serves to stabilize prices around the long-run fundamental price. Although recently the debate has been gaining new traction in political circles, it is often driven more by ideology and politics than by rigorous academic research. The academic debate has been historically driven mostly by theoretical models, although more recently, simulation and empirical studies have been gaining some ground. However, both theoretical predictions and empirical evidence are so far mixed. The main point of the fourth chapter is that studies about FTTs have focused on conditional Gaussian variance as a measure of volatility. They ignore an additional source of volatility—price jumps. The literature (such as Merton, 1976, and Giot, Laurent, & Petitjean, 2010) suggests that the volatility of most financial instruments can be decomposed into two parts: a regular Gaussian component and a price

[3]Thus, from the political economy point of view, it is perhaps no surprise that it is the CEE region where the flat tax rate is most prevalent, as these countries are not only estimated to have higher shadow economies, but often experience higher levels of corruption (as measured by Transparency International's Corruption Perception Index). Furthermore, historically they have often lacked the technical capacities for more sophisticated policies.

[4]For an overview, see McCulloch and Pacillo (2011), or Matheson (2012).

jump component. Many models that aim to estimate conditional variance, such as various GARCH models[5], ignore the price jump component while allowing the realized variance to deviate from the Gaussian distribution. However, as we show in this chapter, the link between price jumps and conditional variance is not entirely straightforward—the measure of one may rise while the measure of the other decreases. While Gaussian variance is not necessarily a problem in itself, the non-normality of return distribution caused by price jumps affects not only the performance of many risk-hedging algorithms, but directly influences the frequency of catastrophic market events.

Therefore, the fourth chapter's aim is to analyze the relationship between price jumps and variance, and how transaction taxes affect them – a point that has been so far rather ignored in the literature. To do this, we employ a methodology of agent-based models (ABMs), which, although still not universally accepted in economics, have been recently gaining recognition. In the words of Trichet (as cited in Hommes, 2013, p. 2):

> The atomistic, optimising agents underlying existing models do not capture behaviour during a crisis period. We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents. We need to entertain alternative motivations for economic choices. Behavioural economics draws on psychology to explain decisions made in crisis circumstances. Agent-based modeling dispenses with the optimization assumption and allows for more complex interactions between agents. Such approaches are worthy of our attention.

ABMs allow explicit modelling of interactions between numerous, potentially heterogenous, autonomous agents, who can choose to interact with each other and the environment based on different dynamic behavioral rules that can diverge from rational optimization. Each of these agents is represented as an individual object. Thus, it is possible to introduce agent-level heterogeneity in information sets, wealth, and expectations, or other behavioral and institutional imperfections, which is not possible with the top-down approach historically used in economics. These local interactions give rise to emergent behavior at the macro level that cannot be directly explained by the micro properties. Not having to impose market clearing conditions with corresponding prices, ABMs also enable researchers to study of out-of-equilibrium behavior. This bottom-up approach is in contrast with top-bottom approach historically used in economics, where a Walrasian

[5] For an overview see Hamilton (1994).

auctioneer insures that there is no excess demand or supply.[6] Thus, ABMs allow for more realistic models that are not solvable using a well defined set of equations with a closed form solution. As such, ABMs are useful in the study of complex systems, such as markets and economic systems in general.[7]

The results of our agent-based model suggest that the relationship of Gaussian variance, price jumps, and liquidity is not straightforward. While Gaussian variance is not necessarily a problem in itself, the non-normality of return distribution caused by price jumps affects not only the performance of many risk-hedging algorithms but directly influences the frequency of catastrophic market events. To study the aforementioned relationship, we use an agent-based model of financial markets. We show that while volatility (as measured by standard deviation of prices) can go down with changes in the tax rate at the same time as the number of price jumps increases. This result implies that regulators may face a trade-off between overall variance and price jumps when designing optimal tax.

[6]For a more profound discussion of ABMs and complex systems in economics, see Tesfatsion and Judd (2006)

[7]Tesfatsion (2006) defines a complex system as having the following characteristics: 1) it is composed of interacting units, and 2) it exhibits emergent properties, i.e. properties arising from interaction of units that are not properties of the units themselves.

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Chapter 1

Overview of Shadow Economy Estimators: Good Case of Bad Econometrics?

Abstract

This chapter offers an overview of current methods used to estimate the size of shadow economies size, with a focus on microeconomic methods. It discusses critical drawbacks of their identifying assumptions, including the assumption that employees do not evade taxes, while the self-employed do. The chapter then goes on to practically illustrate the use of this assumption (and its cons) by estimating the size of the shadow economy for four transition countries: the Czech Republic, Russia, Slovakia and Ukraine. Results show that the method yields an unrealistically low estimate for all countries (1-3%), which I attribute to the failure of the ex ante assumption about evading and non-evading groups that drives the identification.

1.1 Introduction

In recent years, as many countries have faced growing budget challenges, governments have sought adjustments that will both increase tax revenue and reduce income-conditioned transfer programs. Policy-makers often believe that better capturing the shadow economy[1] will contribute to such goals (see e.g. Muller, Conlon, Lewis, & Mantovani, 2013). However, governments that try to offset the income lost to evasion by increasing tax rates can find themselves in a "vicious cycle" (Lyssiotou, Pashardes, & Stengos, 2004, p.622) in which rising tax rates create incentives for even greater evasion. In response, countries often introduce measures to induce or enforce tax compliance. Such measures, including tax receipt lotteries (e.g. China, Portugal, Slovakia, Taiwan), or methods of strict oversight of realized cash turnovers (e.g. the requirement that all vendors use cash registers in Croatia and the Czech Republic), are, however, costly.[2] Therefore, policy makers need an accurate estimation of the potential benefits (beginning with more accurate estimates of the size of the shadow economy) before implementing such policy changes.

There are multiple reasons in addition to tax revenue issues why estimation of the size of the shadow economy is policy-relevant. In general, a larger shadow economy is believed to increase public debt and lead to suboptimal macroeconomic policies. Standard methods of estimating deadweight loss (such as Harberger, 1964) understate the inefficiencies caused by tax systems and economic regulations if they do not reflect the diversion of economic activity into a possibly less efficient hidden sector.[3] Prado (2011) reports that inefficiencies due to distortions into informality account for approximately the same share of cross-national income differences as differences in savings rates. Changes in the propensity to hide income can also reconcile the empirical observations that estimates of the elasticity of labor supply in response to tax increases are close to zero, while those of the elasticity of taxable income with respect to the same tax increases range from 0.25 up to 2.0 (see Saez, Slemrod, & Giertz, 2012).

The link between institutional quality and measured output differences becomes weaker

[1]Also known as the "gray economy" or "underground economy" and by various statistical offices as the "unrecorded economy", this sector can be defined as activity hidden from the authorities, including transactions that are not illegal per se but are hidden in order to evade taxes.

[2]As Slemrod (2007) puts it: "The mere presence of tax evasion does not imply a failure of policy. Just as it is not optimal to station a police officer at each street corner to eliminate robbery and jaywalking completely, it is not optimal to eliminate tax evasion." (p. 43)

[3]Such inefficiencies might be caused by resources being used in evasion efforts instead of in productive activities. They might also arise because the need to avoid drawing attention from authorities results in inefficiently small enterprise sizes.

when controlling for unreported income. Thus weak institutions may not hamper economic productivity so much as divert output from recorded to unrecorded channels. Additionally a loss of social welfare may arise because misreported incomes inhibit implementation of "first-best" social assistance programs, by systematically violating the principle of treating equals equally, undermining public support for otherwise desirable policies. Globally, allocations of foreign assistance and investment capital flows may be distorted by differences in the size of the shadow economy across countries, which make international comparisons based on recorded per capita income and its growth rate inaccurate.

Despite the critical policy importance of obtaining accurate estimates of the size, change, and distribution of the shadow economy across countries and over time, current methods of estimation suffer from various methodological issues – ranging from overly strict assumptions to unclear identification and potential endogeneity. Various assumptions such as constant velocity of money or no difference in the composition of output or production efficiency, etc., between the shadow economy and recorded economy are questionable. They are also intertwined with studied country characteristics.

Allingham and Sandmo (1972) provided a basic framework for rigorously thinking about the shadow economy theoretically, but estimating its size empirically is notoriously difficult for numerous reasons, not least of which is that, by definition, individuals are attempting to hide such activities. It is hard to imagine that surveys and other direct inquiries about people's tax evasion are of much use. Individuals who do not report all or part of their income on tax returns or other official records are unlikely to reveal their full income or evasion status in a survey, even if the survey promises anonymity. Even if this problem is properly addressed by a good survey design, it is difficult if not impossible to keep surveys consistent across years and countries. If nothing else, memories or records of income reported to the tax authorities provide an easy reference point when answering survey questions.

Thus most measures of the size of the shadow economy have relied on what Slemrod and Weber (2012) aptly refer to as "traces of true income." These indirect methods can be divided into two groups: those that use aggregate data and those based on household or firm level data. Macroeconomic methods are of several types, including:

1. National accounting approaches focusing on the discrepancy between national accounting source and use data;

2. Monetary approaches focusing on cash velocity and transaction demand; and

3. Physical input approaches, often focusing on electricity consumption.

Relatively coherent macroeconomic methods of estimating the size of the shadow economy have a long tradition, but have often been criticized for lacking an underlying theory, relying on implausible assumptions, and employing flawed econometric techniques (see Hanousek & Palda, 2006 and Thomas, 1999) including inadequately controlling for endogeneity. The assumption of constant velocity of money underlying many papers using the monetary method is suspect,[4] while changes in electricity demand inherently confound changes in the size of the shadow economy with changes in the composition of output or production efficiency. Even more limiting, many approaches require an assumed-accurate measure of the initial size of the shadow economy and merely try to capture its change in size overtime. Combining several macroeconomic indicators of the size of the shadow economy into a single estimating equation (the so called Multiple Indicators-Multiple Causes (MIMIC) technique) does not help since such techniques are sensitive to the choice of variables and their transformations (see e.g. Breusch, 2005).

Microeconomic methods, on the other hand, are somewhat less common although more prevalent than indicated by Schneider (2014), who refers to them in a single footnote. In a pioneering work, Pissarides and Weber (1989) (PW) use self-employment status to identify households that might underreport income. They then estimate food Engel curves for the employed from the UK 1982 family expenditure survey and invert these to predict income for the self-employed based on the assumption that households which are similar in demographic characteristics should have similar levels of food expenditures. The difference between the predicted income and the reported income of the self-employed is interpreted as the size of the "black economy." Since then, numerous studies have used similar identification (see, as examples, Schuetze, 2002, Engström & Holmlund, 2009, Ekici & Besim, 2014, and Kukk & Staehr, 2014), often trying to improve other aspects of the estimation. Lyssiotou et al. (2004) extend the PW framework by estimating a complete demand system. Tedds (2010) uses the same identifying assumption, but with a nonparametric method. To account for transitory income variation, Kim, Gibson, and Chung (2015, forthcoming) employ between estimates in panel data settings. Artavanis, Morse, and Tsoutsoura (2015) replace observed food consumption with awarding of credit by bank managers. All continue to rely on the basic and critical assumption that researchers must specify in advance a subset of the population—usually wage and

[4]See Anderson, Bordo, & Duca, 2016 for the evolution of money velocity in the US.

salaried workers—who always fully report their incomes, and another—self-employed individuals—who may underreport. In a novel approach, Braguinsky, Mityakov, and Liscovich (2014) use data on new car ownership matched with data on incomes from a different source and estimate that 80 percent of the total earnings of car-owning employees in Russia is unrecorded. They also rely, however, on an *a priori* and *ad hoc* mechanism for assigning the probability of evasion, although in this case based on a worker's sector of employment and the ownership structure of his or her firm.[5]

The intuition behind the assumption of no employee evasion is that salaried workers have much less opportunity to evade, because their income is often reported by a third-party – their employer. These *a priori* simplifying assumptions are, however, weak both theoretically (see Kolm & Nielsen, 2008 for a model that includes concealment of income by firms and salaried workers) and empirically. Analysis of the 2007 Eurobarometer survey (European Commission, 2007) finds that 5.5 percent of respondents in the EU admit that they received unreported "envelope" wages over and above their reported wages from their formal employer in the preceding 12 months. National values of the percentage of workers reporting that some wages from their main employer went undeclared range substantially, from a high of 23 percent in Romania to a low of 1 percent in France, Germany, Luxembourg and the UK. The Czech and Slovak Republics, which we analyze below, are at 3 and 7 percent, respectively. Among those receiving envelope wages, the share of gross income reported as undeclared also varied substantially, ranging from 10 percent in the UK to 86 percent in Romania. The Czech Republic and Slovakia stand at 14 and 17 percent.[6] For the three Baltic countries, Putniņš and Sauka (2015) report that such undeclared employee wages range from 10 to 16 percent of total economic activity. Braguinsky et al. (2014) also argue that a large portion of employee income in Russia (especially in the trade and services sector where cash flows are easier to manipulate) is

[5]Although Martinez-Lopez (2012) relies on the classical Pissarides and Weber method for separating workers into evading and non-evading, he cleverly compares results across several alternative assumptions about who does not evade, to obtain some clues about the possibility of evasion in the "non-evasion" group. One of the studies that did not use this identifying assumption is Gorodnichenko, Martinez-Vazquez, and Peter (2009), who used the 2001 flat tax reform in Russia as a natural experiment that produced a "control group" consisting of part of the population for whom the marginal tax rate did not change, whose income underreporting (also assumed unchanged) could be compared with a "treatment group" of individuals for whom the marginal tax fell. However, they could estimate only the change in the shadow economy after the reform, not its overall size.

[6]These numbers, however, should be taken only as an indication. As the European Commission (2007) phrased it: "In view of the sensitivity of the subject, the pilot nature of the survey and the low number of respondents who reported having carried out undeclared work or having received 'envelope wages', results should be interpreted with great care" (p.3).

hidden from the authorities.

To illustrate the main idea behind the identification based on the self-employment status, the following section will describe the seminal work that used this assumption (Pissarides & Weber, 1989) in greater detail.

1.2 Methodology

The seminal Pissarides and Weber (1989) study, henceforth referred to as P&W, argues that, based on permanent income hypothesis (PIH, due Friedman, 1957), the consumption of household i is based not on its current, but rather its permanent income:

$$\ln C_{ij} = Z_i \alpha_j + \beta_j \ln Y_i^P + \varepsilon_{ij}\,, \tag{1.1}$$

where: C_{ij} is the consumption of good j by household i, and Z_i is a vector of its preference shifting characteristics.

The permanent income cannot be observed directly, but P&W hypothesize (based on the PIH) that it is linked to the current income of the household by a factor of p_i:

$$Y_i = p_i Y_i^P, \tag{1.2}$$

However, surveys do not show the 'true' current income, only what the households choose to report (which may or may not be accurate). We can thus write:

$$Y_i = k_i Y_i^R,\ k_i \geq 1\,, \tag{1.3}$$

where the random variable k_i shows the degree of underreporting by household i. Combining Eqs.(1.2) and (1.3) and taking logarithms leads to the following relationship between permanent and reported incomes:

$$\ln Y_i^P = \ln Y_i^R - \ln p_i + \ln k_i. \tag{1.4}$$

Thus, the difference between reported and permanent income depends on two factors. First, the current life cycle stage of the household that determines the relationship between current and permanent incomes (p_i), and degree of underreporting that determines the relationship between 'true' current income and what the household reports (k_i). P&W assume that these factors are distributed in the population in the following way:

$$\ln p_i = \mu_p + u_i, \tag{1.5}$$

$$\ln k_i = \mu_k + v_i, \tag{1.6}$$

where μ_p and μ_k are average values of logarithms of these parameters and u_i and v_i are deviations from these means. These deviations are normally distributed with zero means and constant variances σ_u^2 and σ_v^2, respectively. Then by the log-normality of p_i the the mean of p_i (which is denoted as $\bar{p}$) can be expressed as:

$$\ln \overline{p} = \mu_p + \frac{1}{2}\sigma_u^2. \tag{1.7}$$

Now the difference in p between self-employed (SE) and employed (EE) becomes:

$$\ln \bar{p}_{SE} - \ln \bar{p}_{EE} = \mu_{pSE} - \mu_{pEE} = -\frac{1}{2}\left(\sigma_{uSE}^2 - \sigma_{uEE}^2\right). \tag{1.8}$$

The self-employed usually have a higher share of transitory income, i.e. they face more volatile shocks that will cause higher deviations of current income from permanent income. This implies that in general $\sigma_{uSE}^2 \geq \sigma_{uEE}^2$. By substitution of (1.4), (1.5) and (1.6) into (1.1) we obtain the relationship between consumption and reported income:

$$\ln C_{ij} = Z_i\alpha_j + \beta_j \ln Y_i^R - \beta_j\left(\mu_p - \mu_k\right) - \beta_j\left(u_i - v_i\right) + \varepsilon_{ij}. \tag{1.9}$$

Here, P&W make two crucial identifying assumptions. The first assumption is that p_i is the same for employees and the self-employed. This implies that any differences in $(\mu_p - \mu_k)$ across households will come from differences in μ_k, i.e. the degree of underreporting. The second crucial assumption is that $k_i = 1$ for employees (i.e. employees report their income truthfully). This allows them to interpret the difference in average k between self-employed and employed households as the extent of underreporting in the economy. Under these assumptions, the parameter γ in the following econometric model will estimate total degree of underreporting by self-employed households:

$$\ln food_i = Z_i\alpha + \beta \ln Y_i^R + \gamma SE_i + \eta_{ij}. \tag{1.10}$$

where SE_i is a dummy that takes 1 if the given household is self-employed and 0 otherwise. The definition of consumption is deliberately limited to food expenditures by P&W. They argue that food expenditures are most likely to be reported without systematic bias, and do not exhibit excessive variability. They show that under their assumptions lower (k_l) and upper (k_u) bounds of tax evasion are then computed as:

$$\ln k_l = \frac{\gamma}{\beta} - \frac{1}{2}\left(\sigma^2_{Y_{SE}} - \sigma^2_{Y_{EE}}\right), \tag{1.11}$$

$$\ln k_u = \frac{\gamma}{\beta} + \frac{1}{2}\left(\sigma^2_{Y_{SE}} - \sigma^2_{Y_{EE}}\right) + \mathrm{cov}(uv)_{SE}, \tag{1.12}$$

where: $\sigma^2_{Y_{SE}}$ and $\sigma^2_{Y_{EE}}$ are the residual variances from the first-stage regression of income on the instrumental variables for the self-employed and employed individuals, respectively and $\mathrm{cov}(uv)_{SE}$ is the covariance between u and v in (1.3) and (1.2) for self-employed people. This implies that upper bound will depend on the assumptions we make about the relationship between propensity to evade and volatility of income. We choose to assume $\mathrm{cov}\,(uv)_{SE} = 0$, because it gives the most conservative estimate of the upper bound and it is also preferred.

1.3 Data

We use household budget surveys of the Czech Republic, Russia, Slovakia, and Ukraine. All of these datasets track the characteristics of the sampled households, their income derived from various sources and expenditures on different kinds of goods and services. The definition of disposable income for our purposes is gross income net of taxes and other obligatory payments (such as health insurance) a household received during the year plus dissavings. Income is considered biased as in P&W and instrumented with the variables denoting ownership of various durables, the size and type of ownership of residence and interactions of the self-employed dummy with the included variables. The food expenditures are defined straightforwardly as the sum of food expenditures of the household during the year. The complete list of variable names and their meaning is given in Table 1.1. From each dataset, a sub-sample of households whose head is working was chosen. However, with the exception of Slovakia, there was no information whether the members of a household work full-time or part-time. Further, it is worth noting that there are doubts about the representativeness of the samples in some countries. In the Slovak data, the share of self-employed dropped significantly after 2004, resulting in around 3% of the working heads of households being self-employed. This is inconsistent with the labor force survey collected by the same statistical office (Statistical Office of the Slovak Republic) for the given year, which shows around 12% of the workforce being self-employed.

Table 1.1: List of variables

Variable name	Meaning
age	age of head
agesq	(age of head)^2
bc	=1 if hoh is blue collar
bcw	=1 if spouse is blue collar
car	number of cars
cell	number of cellphones
dish	number of dishwashers
ea	number of economically active members
hs	=1 if head has high school
hsw	=1 if spouse has high school
l_food	logarithm of food expenditures
l_income	logarithm of disposable income
nch1	number of children age<=5
nch2	number of children age 6-9
nch3	number of children age 10-14
nch4	number of children age >=15
nchsq	(number of children)^2
pc	number of computers
public	=1 if head works in public sector
publicw	=1 if spouse works in public sector
retired	number of retired members
room	number of rooms
sed	=1 if head describes self as self-employed
sed1	=1 if income coming from self-employment constitutes more than 25% of total income
sedw	=1 if spouse self-describes as self-employed
spouse	=1 if head is married
tv	number of television sets
uni	=1 if head has college or higher
uniw	=1 if spouse has college or higher
wcw	=1 if spouse is white collar

1.4 Results

The shadow economy estimates given by the P&W methodology are in Appendix 1.A, while the regression results appear in Appendix 1.B. The tax evasion estimates are relatively meager, in some cases the estimates are even negative. The regression results show that the coefficient on the self-employed dummy that should capture the differences between self-employed and employed households is relatively small and very often insignificant. There are two possible implications. Either there is very little income underreporting in the studied countries (especially compared to the UK, studied in P&W), or the identification based on this characteristic is not sufficient to distinguish evaders from non-evaders. The former implication is unrealistic, given the significantly higher non-compliance culture that is shown in the surveys.[7] The latter can also account for the sometimes negative estimates of the shadow economy. This insufficient separation of evaders from non-evaders may be caused by increased underreporting by employed individuals, which is a violation of one of the main identifying assumptions of not only the Pissarides and Weber study, but vast majority of more recent studies. Conceivable reasons for this failure of identification include partial under-the-table remuneration of employees that is understandably not admitted in the surveys, and by moonlighting employees, whose second income is unreported. As discussed in the Introduction, there are indications that under-the-table wages constitute a not insignificant share of employee compensation in transition countries (European Commission, 2007).

1.5 Conclusion

This chapter provides an overview of the most widely used methods of estimation of the size of the shadow economy. Using the seminal Pissarides and Weber (1989) study, I illustrate why the problematic ex ante separation of the sample into evaders and non-evaders (in this case self-employed and employed) can be problematic, especially in transition countries. The principal reason is the possibility of under-the-table remuneration of employees, which provides opportunity for tax evasion for salaried workers. This means that the statistical difference between employees and self-employed that should drive the identification disappears. Chapter 2 of this dissertation offers a solution to this problem

[7] As evidenced by the European Value Study data (EVS, 2011). Detailed discussion is provided in Chapter 4 of this dissertation.

by relaxing the ex ante assumption about who evades and who does not.

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1.A P&W shadow economy estimates

Table 1.2: Lower and Upper bounds of income tax evasion in the Czech Republic, 2000-2007

	2000	2001	2002	2003	2004	2005	2006	2007
k_l	1.05	1.16	1.16	1.13	1.15	1.12	1.16	1.17
Midpoint	1.05	1.16	1.16	1.14	1.15	1.12	1.16	1.17
k_u	1.06	1.16	1.16	1.14	1.15	1.13	1.16	1.17
% of hhs with share of income from SE>25%	19	19	19	20	20	20	22	22
Evasion (%GDP)	1%	3%	3%	3%	3%	3%	3%	4%

Table 1.3: Lower and Upper bounds of income tax evasion in Russia, 2003-2004

	2003	2004
k_l	1.09	0.98
Midpoint	1.11	1.03
k_u	1.13	1.07
% of hhs with share of income from SE>25%	4	4
Evasion (%GDP)	0.4%	0.1%

Table 1.4: Lower and upper bounds of income tax evasion in the Slovak Republic

	2000	2001	2002	2003†	2004	2005	2006	2007	2008
k_l	1.38	1.35	1.44	N/A†	1.00	.80	1.75	1.53	3.08
Midpoint	1.38	1.35	1.44	N/A†	1.01	.80	1.76	1.53	3.07
k_u	1.39	1.35	1.44	N/A†	1.02	.81	1.77	1.53	3.07
% of hhs having share of income from SE>25%	11	11	10	N/A†	10	7	5	4	3
Evasion (%GDP)	4.0	3.7	4.5	N/A†	0	-1.3	3.7	2.0	6.8

†The problems in data prevented us from computing tax evasion for this year

Table 1.5: Lower and Upper bounds of income tax evasion in Ukraine, 2000-2007

	2000	2001	2002	2003	2004	2005	2006
k_l	.096	.266	1.096	1.278	1.085	1.164	1.023
Midpoint	.096	.267	1.099	1.278	1.087	1.164	1.025
k_u	.097	.268	1.101	1.277	1.089	1.164	1.028
% of hhs with share of income from SE>25%	7.4	9.5	8.4	8.2	8.6	8.3	7.7
Evasion (%GDP)	-.067	-.064	0.8	2.3	0.8	1.4	0.2

1.B 2SLS results

Table 1.6: 2SLS results for Russia, 2003-2004

	2003		2004	
VARIABLES	lfood		lfood	
lncy	0.431***	(0.0211)	0.419***	(0.0213)
sed1	0.0445*	(0.0246)	0.0114	(0.0225)
bc	0.000285	(0.00741)	0.0121	(0.00757)
age	0.00237***	(0.000427)	0.00278***	(0.000414)
agesq	3.99e-05	(2.85e-05)	2.50e-06	(2.67e-05)
nch	0.0225	(0.0145)	0.0210	(0.0149)
nchsq	-0.0109***	(0.00401)	-0.00487	(0.00403)
lat	0.0215***	(0.00784)	0.0591***	(0.00808)
ren	-0.0327	(0.0244)	-0.0638***	(0.0232)
ch	0.201***	(0.0137)	0.176***	(0.0131)
wm	0.0728***	(0.0126)	0.0523***	(0.0120)
tv	0.0511	(0.0358)	-0.0212	(0.0434)
room	0.0365***	(0.00434)	0.0402***	(0.00417)
kids1	0.0629***	(0.0143)	0.0581***	(0.0138)
kids2	0.0581***	(0.0112)	0.0487***	(0.0115)
Constant	5.018***	(0.218)	5.319***	(0.226)
Observations	11,784		11,971	
R-squared	0.565		0.554	
σ^2_{YSE}	0.384		0.433	
σ^2_{YEE}	0.330		0.324	
Score overid test	48.03		51.56	
Prob>chi2	4.71e-05		1.29e-05	
Hausman test	181.8		186.4	
P>chi2	0		0	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.7: 2SLS results for the Czech Republic, 2000-2007

	2000	2001	2002	2003	2004	2005	2006	2007
VARIABLES	l_food	l_food	l_food	l_food	l_food	l_food	l_food	l_food
l_income	0.418***	0.426***	0.488***	0.453***	0.417***	0.444***	0.422***	0.483***
	(0.0448)	(0.0485)	(0.0490)	(0.0550)	(0.0450)	(0.0461)	(0.0514)	(0.0483)
sed1	0.0163	0.0532***	0.0464***	0.0608***	0.0589***	0.0561***	0.0630***	0.0749***
	(0.0162)	(0.0159)	(0.0158)	(0.0165)	(0.0154)	(0.0159)	(0.0151)	(0.0168)
bcw	-0.154***	-0.118***	-0.106***	-0.195***	-0.148***	-0.101***	-0.0705***	-0.0994***
	(0.0316)	(0.0299)	(0.0293)	(0.0341)	(0.0321)	(0.0310)	(0.0271)	(0.0318)
wcw	-0.113***	-0.0889***	-0.0804***	-0.129***	-0.0853***	-0.0706**	-0.0777***	-0.102***
	(0.0279)	(0.0264)	(0.0249)	(0.0298)	(0.0275)	(0.0280)	(0.0255)	(0.0307)
age	0.019***	0.0319***	0.0245***	0.0261***	0.0267***	0.0260***	0.0261***	0.0205***
	(0.00501)	(0.00540)	(0.00508)	(0.00525)	(0.00558)	(0.00544)	(0.00453)	(0.00510)
agesq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(5.86e-05)	(6.07e-05)	(5.81e-05)	(5.87e-05)	(6.26e-05)	(6.11e-05)	(5.04e-05)	(5.67e-05)
bc	0.00334	-0.00541	0.0145	0.0135	-0.0232	-0.0170	-0.0149	0.0212
	(0.0148)	(0.0155)	(0.0152)	(0.0156)	(0.0150)	(0.0158)	(0.0173)	(0.0164)
ea	0.161***	0.163***	0.138***	0.115***	0.161***	0.131***	0.126***	0.107***
	(0.0319)	(0.0266)	(0.0265)	(0.0285)	(0.0284)	(0.0293)	(0.0279)	(0.0285)
retired	0.133***	0.159***	0.119***	0.0376	0.100***	0.102***	0.116***	0.0693**
	(0.0268)	(0.0289)	(0.0292)	(0.0294)	(0.0289)	(0.0299)	(0.0301)	(0.0304)
nch1	0.120***	0.154***	0.144***	0.0195	0.135***	0.136***	0.121***	0.0830***
	(0.0212)	(0.0230)	(0.0209)	(0.0232)	(0.0217)	(0.0222)	(0.0192)	(0.0227)
nch2	0.158***	0.164***	0.152***	0.124***	0.148***	0.168***	0.134***	0.108***
	(0.0168)	(0.0187)	(0.0179)	(0.0182)	(0.0194)	(0.0213)	(0.0183)	(0.0205)
nch3	0.177***	0.192***	0.181***	0.191***	0.183***	0.193***	0.164***	0.168***
	(0.0161)	(0.0174)	(0.0147)	(0.0161)	(0.0176)	(0.0190)	(0.0177)	(0.0189)
nch4	0.209***	0.199***	0.186***	0.152***	0.209***	0.223***	0.187***	0.181***
	(0.0152)	(0.0170)	(0.0148)	(0.0153)	(0.0165)	(0.0175)	(0.0147)	(0.0165)
nchsq	-0.0158***	-0.0168***	-0.0127***	-0.00715**	-0.0167***	-0.0203***	-0.0141***	-0.0137***
	(0.00356)	(0.00396)	(0.00281)	(0.00304)	(0.00424)	(0.00505)	(0.00382)	(0.00490)
spouse	0.229***	0.187***	0.164***	0.255***	0.209***	0.210***	0.243***	0.254***
	(0.0264)	(0.0270)	(0.0279)	(0.0323)	(0.0284)	(0.0273)	(0.0273)	(0.0316)
Constant	4.759***	4.363***	3.807***	4.175***	4.598***	4.304***	4.616***	4.020***
	(0.504)	(0.530)	(0.559)	(0.626)	(0.519)	(0.533)	(0.603)	(0.566)
Observations	2,885	2,870	2,853	2,859	2,780	2,747	2,413	2,377
R-squared	0.645	0.653	0.661	0.632	0.646	0.625	0.647	0.670
σ^2_{YSE}	0.138	0.130	0.121	0.152	0.104	0.112	0.100	0.100
σ^2_{YEE}	0.109	0.121	0.115	0.126	0.105	0.0930	0.0954	0.124
Hausman test	37.38	30.08	14.42	28.80	25.38	8.099	6.442	4.528
P>chi2	0.000647	0.00745	0.419	0.0111	0.0310	0.884	0.954	0.991

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.8: 2SLS results for Slovakia, 2000-2008

	2000	2001	2002	2004	2005	2006	2007	2008
VARIABLES	l_food	l_food	l_food	l_food	l_food	l_food	l_food	l_food
l_income	0.0757	0.336***	0.271**	0.279***	0.331***	0.180*	0.341***	0.0951
	(0.136)	(0.128)	(0.130)	(0.104)	(0.121)	(0.0996)	(0.122)	(0.118)
sed1	0.0359	0.105**	0.122***	0.0116	-0.0796	0.0835	0.207***	0.272***
	(0.0501)	(0.0498)	(0.0377)	(0.0344)	(0.0525)	(0.0587)	(0.0780)	(0.0919)
nch1	0.177***	0.124***	0.135***	0.121***	0.134***	0.195***	0.239***	0.128***
	(0.0406)	(0.0343)	(0.0282)	(0.0389)	(0.0438)	(0.0405)	(0.0432)	(0.0438)
nch2	0.172***	0.124***	0.169***	0.0431***	0.00433	0.0574***	0.120***	0.118***
	(0.0366)	(0.0306)	(0.0282)	(0.0161)	(0.0214)	(0.0199)	(0.0274)	(0.0295)
nch3	0.199***	0.178***	0.201***	0.0473***	0.0362**	0.00714	-0.0392	-0.000989
	(0.0333)	(0.0276)	(0.0255)	(0.0138)	(0.0163)	(0.0186)	(0.0262)	(0.0258)
nch4	0.232***	0.179***	0.196***	0.0999***	0.0620***	0.0446***	0.0595***	0.0501***
	(0.0306)	(0.0283)	(0.0247)	(0.0156)	(0.0150)	(0.0157)	(0.0179)	(0.0185)
nchsq	-0.0169**	-0.0116**	-0.00966**	0.00178	0.00596	0.00776***	-0.000339	-0.00811*
	(0.00733)	(0.00465)	(0.00400)	(0.00313)	(0.00378)	(0.00249)	(0.00389)	(0.00414)
bcw	-0.0134	-0.00790	-0.0265	-0.0274	0.00951	-0.0124	-0.0873**	-0.132***
	(0.0499)	(0.0462)	(0.0443)	(0.0379)	(0.0343)	(0.0405)	(0.0440)	(0.0451)
wcw	0.0175	0.00616	-0.0632	-0.0605	0.0223	-0.0167	-0.112**	-0.153***
	(0.0513)	(0.0389)	(0.0395)	(0.0387)	(0.0384)	(0.0483)	(0.0447)	(0.0500)
age	0.0260**	0.0243**	0.00936	0.0304***	0.0369***	0.0320***	0.0263***	0.0251***
	(0.0115)	(0.0107)	(0.0100)	(0.00833)	(0.00835)	(0.00880)	(0.00827)	(0.00807)
agesq	-0.000212	-0.000207	-2.73e-05	-0.000283***	-0.000358***	-0.000311***	-0.000226**	-0.000197**
	(0.000134)	(0.000127)	(0.000117)	(9.44e-05)	(9.37e-05)	(9.76e-05)	(9.50e-05)	(9.20e-05)
bc	-0.0254	0.0256	0.0293	-0.0150	0.0565**	0.0287	0.0275	0.00826
	(0.0427)	(0.0330)	(0.0294)	(0.0265)	(0.0258)	(0.0238)	(0.0256)	(0.0254)
ptw	-0.105	-0.101	-0.115	0.123	0.0110	0.124	-0.199*	0.0263
	(0.0734)	(0.102)	(0.0774)	(0.118)	(0.123)	(0.0856)	(0.112)	(0.114)
ftw	-0.140***	-0.149***	-0.122***	0.0896**	-0.0552	0.00669	0.0303	0.0422
	(0.0478)	(0.0474)	(0.0407)	(0.0371)	(0.0355)	(0.0359)	(0.0425)	(0.0435)
pt	-0.0214	0.00181	-0.340**	-0.0930	0.0256	-0.0318	0.0631	-0.112
	(0.111)	(0.0978)	(0.149)	(0.106)	(0.111)	(0.0767)	(0.0920)	(0.0937)
spouse	0.296***	0.264***	0.296***	0.166***	0.193***	0.228***	0.153***	0.233***
	(0.0591)	(0.0638)	(0.0586)	(0.0339)	(0.0354)	(0.0305)	(0.0351)	(0.0346)
ea	0.234***	0.137**	0.209***	0.0428*	0.0422*	0.115***	0.108***	0.160***
	(0.0570)	(0.0612)	(0.0494)	(0.0227)	(0.0244)	(0.0278)	(0.0358)	(0.0334)
retired	0.353***	0.170***	0.228***	0.171***	0.117***	0.208***	0.131***	0.198***
	(0.0610)	(0.0626)	(0.0547)	(0.0327)	(0.0333)	(0.0377)	(0.0372)	(0.0368)
Constant	8.369***	5.422***	6.372***	4.604***	3.971***	5.434***	3.986***	6.425***
	(1.537)	(1.464)	(1.501)	(1.025)	(1.171)	(0.993)	(1.227)	(1.202)
Observations	1,368	1,352	1,403	2,560	2,551	2,613	2,509	2,571
R-squared	0.427	0.517	0.561	0.352	0.341	0.372	0.426	0.376
σ^2_{YSE}	0.169	0.138	0.139	0.174	0.146	0.153	0.0999	0.0873
σ^2_{YEE}	0.152	0.146	0.155	0.135	0.113	0.106	0.108	0.108
Hausman test	13.13	0.673	4.449	1.050	0.426	6.345	2.088	10.85
P>chi2	0.727	1	0.999	1	1	0.991	1.000	0.864

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.9: 2SLS results for Ukraine, 2000-2006

	2000	2001	2002	2003	2004	2005	2006
VARIABLES	l_food	l_food	l_food	l_food	l_food	l_food	l_food
l_income	0.448***	0.486***	0.542***	0.610***	0.672***	0.614***	0.578***
	(0.0794)	(0.0822)	(0.0703)	(0.0648)	(0.0582)	(0.0565)	(0.0502)
sed1	-1.048***	-0.642***	0.0511	0.150***	0.0559	0.0932**	0.0145
	(0.141)	(0.103)	(0.103)	(0.0452)	(0.0458)	(0.0434)	(0.0381)
age	0.0173**	0.00624	0.00380	0.0109**	0.00654	0.00864*	0.0153***
	(0.00718)	(0.00580)	(0.00532)	(0.00511)	(0.00429)	(0.00445)	(0.00412)
agesq	-0.000152**	-3.16e-05	1.18e-06	-5.12e-05	-1.94e-05	-4.58e-05	-0.000110**
	(7.76e-05)	(6.04e-05)	(5.69e-05)	(5.45e-05)	(4.59e-05)	(4.79e-05)	(4.36e-05)
nch	0.0616	0.0437	-0.0266	0.0314	0.0590**	0.0331	0.0582**
	(0.0381)	(0.0337)	(0.0344)	(0.0321)	(0.0259)	(0.0271)	(0.0251)
nchsq	-0.0202*	-0.000875	0.00849	-0.0137	-0.00490	-0.0194**	-0.0122**
	(0.0105)	(0.00879)	(0.00880)	(0.00881)	(0.00754)	(0.00755)	(0.00602)
lat	0.0736***	0.00739	-0.00123	0.0140	-0.00713	0.0105	-0.0146
	(0.0223)	(0.0220)	(0.0218)	(0.0204)	(0.0234)	(0.0216)	(0.0225)
ren	0.113	0.181***	-0.0541	0.0158	-0.0488	-0.114**	-0.0536
	(0.0836)	(0.0690)	(0.0668)	(0.0459)	(0.0506)	(0.0461)	(0.0447)
pc	0.0980	0.0255	0.0924**	0.0246	0.0125	0.0108	-0.0282
	(0.0675)	(0.0546)	(0.0421)	(0.0331)	(0.0284)	(0.0241)	(0.0212)
ch	0.0274	-0.0417	-0.0406*	-0.0443**	-0.0338*	0.00534	-0.0348*
	(0.0271)	(0.0272)	(0.0229)	(0.0194)	(0.0185)	(0.0183)	(0.0179)
wm	0.0784***	0.0987***	0.0824***	0.0465**	0.0699***	0.0516***	0.0658***
	(0.0256)	(0.0254)	(0.0249)	(0.0219)	(0.0188)	(0.0196)	(0.0186)
tv	0.179***	0.160***	0.116***	0.0815***	0.0370	0.0727***	0.0474**
	(0.0287)	(0.0300)	(0.0285)	(0.0243)	(0.0242)	(0.0219)	(0.0196)
room	0.000792	0.00967	0.00795	-0.0162*	-0.00344	-0.00974	-0.00159
	(0.0125)	(0.0111)	(0.0114)	(0.00972)	(0.00807)	(0.00808)	(0.00709)
kids1	-0.0349	-0.0427	-0.00308	0.0244	0.00589	0.0597**	0.00620
	(0.0368)	(0.0325)	(0.0316)	(0.0289)	(0.0248)	(0.0262)	(0.0244)
kids2	0.00822	-0.00346	0.00927	0.0139	0.0215	0.0583**	0.0227
	(0.0308)	(0.0273)	(0.0268)	(0.0260)	(0.0223)	(0.0236)	(0.0222)
town	0.249***	0.266***	0.355***	0.490***	0.282***	0.371***	0.321***
	(0.0418)	(0.0400)	(0.0324)	(0.0263)	(0.0223)	(0.0224)	(0.0197)
city	0.384***	0.419***	0.485***	0.574***	0.371***	0.469***	0.422***
	(0.0422)	(0.0404)	(0.0327)	(0.0271)	(0.0237)	(0.0236)	(0.0215)
married	0.0139	0.0445	0.0284	-0.0369	0.00622	0.00297	0.00663
	(0.0309)	(0.0288)	(0.0251)	(0.0237)	(0.0219)	(0.0197)	(0.0192)
h_size	0.0399**	0.0308	0.0286	0.0314*	-0.0121	0.00590	0.0172
	(0.0203)	(0.0205)	(0.0199)	(0.0173)	(0.0145)	(0.0151)	(0.0138)
Constant	3.108***	3.063***	2.599***	1.843***	1.696***	2.108***	2.340***
	(0.637)	(0.702)	(0.593)	(0.544)	(0.491)	(0.516)	(0.471)
Observations	4,214	4,062	3,291	4,119	4,369	4,664	4,739
R-squared	0.139	0.289	0.375	0.401	0.366	0.393	0.389
σ^2_{YSE}	0.172	0.194	0.171	0.141	0.125	0.133	0.151
σ^2_{YEE}	0.186	0.173	0.156	0.144	0.140	0.132	0.134
Hausman test	65.64	38.18	2.305	22.41	18.75	27.94	15.86
P>chi2	2.44e-07	0.00367	1.000	0.214	0.407	0.0629	0.602

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 2

Is Ceasar Getting All That He's Due? Using Household Data to Measure the Shadow Economy[1]

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Abstract

We develop an estimator of unreported income that relies on much more flexible identifying assumptions than those previously used. Assuming only that evading households have a higher consumption-income gap than non-evaders in surveys, an endogenous switching model with unknown sample separation enables the estimation of both the probability of hiding income and the expected amount of unreported income for each household. Using data from Czech and Slovak household budget surveys, we find the size of the shadow economy to be substantially larger than estimated using other techniques. These results are robust under a number of alternative specifications. Furthermore, we show that since the share of underreported income decreases with income level, true income inequality in these countries is lower than suggested by the reported income.

2.1 Introduction

Last chapter discussed most problematic aspects of contemporary methodologies of estimation of the size of the shadow economy. In this chapter, we relax some of the strictest assumptions in current methods to develop a more robust estimator of the shadow economy that can be used across countries. In contrast to heavily-used macroeconomic methods, we do not employ aggregate indicators and, therefore, do not suffer from the potential endogeneity problems associated with such measures. We employ broadly-collected household budget surveys that are available on a standardized basis across many countries. In contrast with current household-based measures, we avoid *a priori* assumptions about the division of the sample between evaders and non-evaders. Instead, we assume only that evading households have a higher consumption-income gap than non-evaders. Using an endogenous switching model with unknown sample separation enables us to estimate both the probability of hiding income and the expected amount of unreported income for each household. We demonstrate the proposed method by using data from Czech and Slovak household budget surveys and show that the size of the shadow economy is substantially larger than estimates derived using other techniques. Moreover, these results are robust to a number of alternative specifications and identification restrictions. Given that our methodology allows us to estimate the expected degree of underreporting for each household, we are also able compute the measure of inequality based on the estimated true income and compare it to the official statistics. Our results show that the true inequality might be lower than is suggested by the reported income.

The main difference between previous methodologies and ours is that we avoid the problem of arbitrary *a priori* assignment of individuals to evading and non-evading groups by using an endogenous switching regression with an unknown sample separation rule to estimate the probability of underreporting AND its potential extent. Such a technique has not previously been applied to the shadow economy,[2] although it has often been used in other contexts. In an early study, Dickens and Lang (1985) used such a model to test the theory of dual labor markets. Two more recent papers applied this methodology to family economics. Arunachalam and Logan (2006) analyzed two competing, unobservable incentives for offering a dowry (passing assets to the daughter and her family or acquiring

[2]DeCicca, Kenkel, and Liu (2013) use an endogenous switching regression to estimate the effect of state differences in cigarette excise taxes on the probability of cross-border cigarette purchases in the US. Their model, however, relies on an observable rather than unobservable separation rule since they know which purchases were made across a border.

a more desirable husband for their daughter) while Kopczuk and Lupton (2007) studied whether having a positive net worth at the time of death implies a bequest motive.

Other examples of the application of switching regressions with an unknown (or partially known) sample separation rule include the estimation of cartel stability by Lee and Porter (1984) and stochastic frontier models by Douglas, Conway, and Ferrier (1995), or Caudill (2003). These studies have established the feasibility of maximum likelihood and other estimation techniques in this situation.

2.2 Methodology

2.2.1 Consumption-income gap

Our analysis relies on the consumption-income gap as described by Gorodnichenko, Martinez-Vazquez, and Sabirianova Peter (2009) based on three assumptions arising from the permanent income hypothesis (Friedman, 1957):

$$Y_i^R = \Gamma_i Y_i^c, \text{ where: } \Gamma_i = \Gamma(\mathbf{S}_i) = \exp(-\mathbf{S}_i \boldsymbol{\gamma} + \text{error}), \quad (2.1)$$

$$Y_i^C = H_i Y_i^P, \text{ where: } H_i = H(\mathbf{L}_{1,i}) = \exp(\mathbf{L}_{1,i} \boldsymbol{\eta} + \text{error}), \quad (2.2)$$

$$C_i = \Theta_i Y_i^P, \text{ where: } \Theta_i = \Theta(\mathbf{L}_{2,i}) = \exp(\mathbf{L}_{2,i} \boldsymbol{\theta} + \text{error}), \quad (2.3)$$

where i denotes households. Equation (2.1) defines reported income as a fraction Γ of true income, where Γ is a function of household characteristics affecting underreporting ($\mathbf{S}_i$). In the estimates presented below this vector includes age (older people may have different attitudes due to such factors as differening risk aversion profiles), education, whether workers in the household are self-employed, working in a large or small firm (small firms may be more prone to save labor costs by paying a low "official" wage combined with a part of the wage paid "under the table"), or employed in the public or private sector (government is usually less likely to pay its employees "under the table," although on the other hand, public employees may be more prone to accepting bribes).

Equation (2.2) is based on the permanent income hypothesis, expressing true current income as a fraction H_i of the permanent lifelong income. H_i depends on the current stage of the life cycle of the head of the household and his or her spouse, including their ages, education and work experience (vector $\mathbf{L}_{1,i}$). Equation (2.3) defines consumption as a fraction Θ_i of the household's permanent income. The characteristics $\mathbf{L}_{2,i}$ affecting a household's consumption patterns (tastes) include the age of the head of the household and spouse, number and ages of children, number of other household members, marital status, and education among others. Taking logarithms of (2.1), (2.2) and (2.3) and substituting yields a definition of the consumption-income gap:

$$\log C_i - \log Y_i^R = \mathbf{S}_i\boldsymbol{\gamma} + \mathbf{L}_i\boldsymbol{\alpha} + \varepsilon_i \,, \tag{2.4}$$

where the vector α describes the combined effect of characteristics present in $L_{1,i}$ and $L_{2,i}$. What is critical is that if all other household characteristics are held equal, a higher consumption-income gap implies a higher degree of underreporting.

We focus on non-durables as our basic measure of consumption, because reporting of large purchases of durables may be less reliable than reporting of smaller, regular non-durable consumption. A household may be inclined to hide larger purchases of durables out of caution or fear, especially if it participates in the informal sector. Moreover, purchases of durable goods are more likely than other expenditures to actually be investment, especially if the household derives part of its income from self-employment. Limiting the measure of consumption to non-durables, however, requires us to make an assumption that preferences over non-durable and durable goods are homothetic, implying that the income elasticity of non-durable goods is unitary. This assumption has often been used in macroeconomic literature (see Eichenbaum & Hansen, 1990, Ogaki & Reinhart, 1998, or Gorodnichenko et al., 2009), although Pakoš (2011) contains a critique. Even Pakoš's estimate of the income elasticity of non-durable goods is, however, close to 1.0, lying in the interval [0.882, 0.954].

A second possible problem with basing estimates on non-durable consumption is that such consumption may include tax deductible purchases of items such as supplies or inputs for self-employed individuals. This is usually not the case with food, as used by Pissarides and Weber (1989). On the other hand, expenditures on food may not meet the homotheticity requirement. We will, therefore, report results based on both food and total non-durable consumption and find these to be gratifyingly consistent, suggesting that neither of these potential problems is critical.

2.2.2 From consumption-income gap to shadow economy

Without much loss of generality we can assume that there are two groups of individuals in every economy: those who evade and those who do not. These two groups of agents differ, all other characteristics held constant, by the average size of the gap between their income and consumption. For non-evaders, γ in Equation (2.4) is equal to 0 by definition. Since consumption is based on true rather than reported income, evading households will report consuming a greater share of their income. Under the assumption that, unlike income, consumption is measured more (and equally) accurately for both groups (for support of this assumption see Brzozowski & Crossley, 2011; Brewer & O'Dea, 2012; Meyer & Sullivan, 2013; Hurst, Li, & Pugsley, 2014; and Kreiner, Lassen, & Leth-Petersen, 2014), we can write:

$$\log C_i - \log Y_i^{R,e} = \mathbf{S}_i\boldsymbol{\gamma} + \mathbf{L}_i\boldsymbol{\alpha}_e + \varepsilon_{e,i} \quad \text{if } i \text{ is evading,} \tag{2.5}$$

$$\log C_i - \log Y_i^{R,ne} = \mathbf{L}_i\boldsymbol{\alpha}_{ne} + \varepsilon_{ne,i} \quad \text{if } i \text{ is not evading,} \tag{2.6}$$

where $Y_i^{R,e}$ and $Y_i^{R,ne}$ are the reported income if the household i evades and does not evade, respectively. It is reasonable to assume that agents evade if their expected gain from evasion exceeds a certain threshold f:

$$\left(\log C_i - \log Y_i^{R,e}\right) - \left(\log C_i - \log Y_i^{R,ne}\right) \geq f_i \, , \tag{2.7}$$

where f_i represents the costs of evasion including expected fines and costs associated with hiding income (including psychic costs such as risk or dishonesty aversion) for household i. One can think of Equation (2.7) as the reduced form of an underlying optimization problem. In this equation, agents compare the net benefits from the optimal level of underreporting with those from reporting incomes accurately.

If we assume that the cost of evasion is equal to a constant average cost k plus an error term $\varepsilon_{f,i}$ (the deviation of household i from this average)[3] we can write the probability of household i being in the evading regime as:

$$P = \Pr\left\{\mathbf{S}_i\boldsymbol{\gamma} + \mathbf{L}_i\left(\boldsymbol{\alpha}_e - \boldsymbol{\alpha}_{ne}\right) - k \geq \varepsilon_{f,i} + \varepsilon_{e,i} - \varepsilon_{ne,i}\right\} = \Pr\left\{\mathbf{Z}_i\delta \geq \varepsilon_{s,i}\right\} \, . \tag{2.8}$$

For estimating purposes, this system can be expressed as follows:

$$\left(\log C_i - \log Y_i^R\right)_e = \mathbf{X}_i\boldsymbol{\beta}_e + \varepsilon_{e,i} \, , \tag{2.9}$$

$$\left(\log C_i - \log Y_i^R\right)_{ne} = \mathbf{X}_i\boldsymbol{\beta}_{ne} + \varepsilon_{ne,i} \, , \tag{2.10}$$

[3] This deviation need not be random and, indeed, is treated in the estimation below as a function of household characteristics.

$$
\begin{aligned}
y_i^* &= \mathbf{Z}_i\boldsymbol{\delta} - \varepsilon_{s,i}\,, && (2.11)\\
\log C_i - \log Y_i^R &= \begin{cases} \left(\log C_i - \log Y_i^R\right)_e & \text{iff } y_i^* \geq 0\,,\\ \left(\log C_i - \log Y_i^R\right)_{ne} & \text{iff } y_i^* < 0\,, \end{cases} && (2.12)
\end{aligned}
$$

where $\mathbf{X}_i$ is the vector of explanatory variables that affect consumption and income and $\mathbf{Z}_i$ is the vector of variables that affect the tax evasion propensity.

The latent variable y_i^* can be interpreted as the propensity to evade. It cannot be observed, but if $y_i^* > 0$ (i.e. the household decides to evade), household i's gap is determined by Equation (2.9). If $y_i^* < 0$, the household does not want to evade and its consumption-income gap is determined by Equation (2.10).[4]

We can express the likelihood contribution of household i as:

$$
\begin{aligned}
L_i = {} & \Pr\left(\varepsilon_{s,i} \leq \mathbf{Z}_i\boldsymbol{\delta} \mid \mathbf{Z}_i, \mathbf{X}_i, \varepsilon_{e,i}\right) \cdot f\left(\varepsilon_{e,i}\right)\\
& + \Pr\left(\varepsilon_{s,i} > \mathbf{Z}_i\boldsymbol{\delta} \mid \mathbf{Z}_i, \mathbf{X}_i, \varepsilon_{ne,i}\right) \cdot f\left(\varepsilon_{ne,i}\right)\ .
\end{aligned} \tag{2.13}
$$

If we assume that $(\varepsilon_e, \varepsilon_{ne}, \varepsilon_s) \sim N(0, \Sigma)$,[5] where:

$$
\Sigma = \begin{pmatrix} \sigma_e^2 & & \\ \sigma_{e,ne} & \sigma_{ne}^2 & \\ \sigma_{e,s} & \sigma_{ne,s} & 1 \end{pmatrix}\,,
$$

the log-likelihood function (2.13) becomes:

$$
\begin{aligned}
\ln L\left(\boldsymbol{\beta}_e, \boldsymbol{\beta}_{ne}, \delta, \sigma_e, \sigma_{ne}, \sigma_{e,s}, \sigma_{ne,s}\right) = \sum_{i=1}^{N} \ln \Bigg\{ & \frac{1}{\sigma_e}\Phi\left(\frac{\mathbf{Z}_i\boldsymbol{\delta} - \frac{\sigma_{e,s}}{\sigma_e^2}\varepsilon_{e,i}}{\left(1 - \frac{\sigma_{e,s}^2}{\sigma_e^2}\right)^{.5}}\right) \cdot \phi\left(\frac{\varepsilon_{e,i}}{\sigma_e}\right)\\
& + \frac{1}{\sigma_{ne}}\left[1 - \Phi\left(\frac{\mathbf{Z}_i\boldsymbol{\delta} - \frac{\sigma_{ne,s}}{\sigma_{ne}^2}\varepsilon_{ne,i}}{\left(1 - \frac{\sigma_{ne,s}^2}{\sigma_{ne}^2}\right)^{.5}}\right)\right] \cdot \phi\left(\frac{\varepsilon_{ne,i}}{\sigma_{ne}}\right)\Bigg\}\,,
\end{aligned} \tag{2.14}
$$

[4] This idea is, of course, well known in many areas of applied economics. For example, recall the propensity to work in estimation of labor supply. Hours worked, just as hidden income in our case, are non-zero if and only if $y^* > 0$, leading to a distribution censored at 0.

[5] This assumption is reasonable if the distributions of income and consumption are both log-normal (see Equations (2.1)-(2.3)). Evidence from various countries shows that a log-normal distribution is a good approximation of empirical distribution of income (especially up to the 98th percentile – see e.g. Clementi & Gallegati, 2005) This holds for our data as well.

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal density and the cumulative distribution functions respectively, and:

$$\begin{aligned} \varepsilon_{e,i} &= (\ln C_i - \ln Y_i) - \mathbf{X}_i \boldsymbol{\beta}_e\,, && (2.15) \\ \varepsilon_{ne,i} &= (\ln C_i - \ln Y_i) - \mathbf{X}_i \boldsymbol{\beta}_{ne}\,. && (2.16) \end{aligned}$$

Note that, as usual in this type of estimation, $\sigma_{e,ne}$ is unidentified, as the two regimes never occur at the same time (see Maddala, 1983). Technical details of the maximization of Equation (2.14) are given in the Appendix. For robustness purposes we employ several different identification strategies. It is generally desirable to find exclusion restrictions such that $\mathbf{Z}_i \neq \mathbf{X}_i$, thereby ensuring that all other parameters (except σ_s, which is normalized to 1) are identifiable. We use two sets of such restrictions, one that excludes self-employment and public sector employment from $\mathbf{Z}_i$ and a second that adds employment in a blue-collar occupation (and a white collar occupation for the spouse of the household head) to the excluded variables. Finally, given that the model is nonlinear, as an additional robustness check, we also estimate it identified by functional form only.

2.2.3 Measure of the shadow economy

Under the initial assumption of correct consumption reporting, the expected value of the difference in the gaps for both regimes of household i is equal to:

$$\mathbb{E}\left[(\log C_i \widehat{- \log} Y_i^R)_e - (\log C_i \widehat{- \log} Y_i^R)_{ne}\right] = \mathbb{E}\left[\left(\log Y_{i,ne}^R \widehat{- \log} Y_{i,e}^R\right)\right], \qquad (2.17)$$

which is household i's estimated degree of income underreporting as a fraction of its reported income. Recalling Equations (9) and (10), the overall size of the shadow economy is measured by the expected value of this difference in gaps, i.e., the sum of the differences between the income-consumption gaps for the respective regimes weighted by the probability of each household being in the shadow sector:

$$\widehat{Evasion} = \frac{1}{N}\sum_{i=1}^{N}\left(\mathbf{X}_i\hat{\boldsymbol{\beta}}_e - \mathbf{X}_i\hat{\boldsymbol{\beta}}_{ne}\right)\cdot \hat{P}_{e,i}\,. \qquad (2.18)$$

The probability of being in the shadow sector $\hat{P}_{e,i}$ can be computed by Bayes' theorem as:

$$\hat{P}_{e,i} = \frac{\frac{1}{\hat{\sigma}_e}\Phi\left(\frac{\mathbf{Z}_i\hat{\boldsymbol{\delta}} - \frac{\hat{\sigma}_{e,s}}{\hat{\sigma}_e^2}e_{e,i}}{\left(1-\frac{\hat{\sigma}_{e,s}^2}{\hat{\sigma}_e^2}\right)^{.5}}\right)\phi\left(\frac{e_{e,i}}{\hat{\sigma}_e}\right)}{\frac{1}{\hat{\sigma}_e}\Phi\left(\frac{\mathbf{Z}_i\hat{\boldsymbol{\delta}} - \frac{\hat{\sigma}_{e,s}}{\hat{\sigma}_e^2}e_{e,i}}{\left(1-\frac{\hat{\sigma}_{e,s}^2}{\hat{\sigma}_e^2}\right)^{.5}}\right)\phi\left(\frac{e_{e,i}}{\hat{\sigma}_e}\right) + \frac{1}{\hat{\sigma}_{ne}}\left[1-\Phi\left(\frac{\mathbf{Z}_i\hat{\boldsymbol{\delta}} - \frac{\hat{\sigma}_{ne,s}}{\sigma_{ne}^2}e_{ne,i}}{\left(1-\frac{\hat{\sigma}_{ne,s}^2}{\hat{\sigma}_{ne}^2}\right)^{.5}}\right)\right]\cdot\phi\left(\frac{e_{ne,i}}{\hat{\sigma}_{ne}}\right)}, \tag{2.19}$$

where:

$$e_{e,i} = (\ln C_i - \ln Y_i) - \mathbf{X}_i\hat{\boldsymbol{\beta}}_e\,, \tag{2.20}$$

$$e_{ne,i} = (\ln C_i - \ln Y_i) - \mathbf{X}_i\hat{\boldsymbol{\beta}}_{ne}\,. \tag{2.21}$$

Equation (2.18) will thus give the size of the shadow economy as a fraction of an economy's officially reported income.

To increase robustness to the choice of initial values and the presence of outliers, Monte Carlo simulations were used to compute both means and standard errors of the estimators. For each country, random samples with replacement were drawn from the data, with the estimation of Equation (2.14) and computation of the shadow economy from Equations (2.18) and (2.19) made for each sample.[6] We continued until 250 samples converged, resulting in a set of estimates from which the mean estimates are computed. Standard errors are then the standard errors of these estimated means.

2.3 Data

We illustrate the use of our estimator by applying it to recent data from the Czech and Slovak Republics. The choice of these countries is not arbitrary. Rather, they represent modern, EU member economies with the required data collected by Eurostat standards, where the assumption that only self-employed households hide income (as assumed by Pissarides & Weber, 1989) and numerous others seems particularly questionable. In both countries we use the Household Budget Survey from 2008.

[6]See Appendix 2.5 for details. Sample draws that failed to converge were dropped from the data (see note 11 below).

2.3.1 Czech Republic

The data from the 2008 Czech household budget survey contain information about income from various sources and expenditures on different categories of goods and services for 3,271 Czech households. We restrict our analysis to a subsample of 2138 households with working heads.[7] Summary statistics (weighted means) for this subsample are given in Table 2.1. The definition of disposable income is the monthly average of the total gross income of the household from all sources minus all taxes and obligatory payments (such as health insurance, which is technically a tax in the Czech Republic). To account for possible consumption smoothing and precautionary saving (which may be greater for certain types of households), net dissavings were included in income. We define consumption as the sum of expenditures on non-durable goods, more specifically, expenditure on food both at home and away from home, alcohol and tobacco,[8] clothing and footwear, rents, utilities and other services. As discussed above, controls include dummies for public sector or self-employment status of the head of household or spouse, blue-collar employment of the head or spouse,[9] white collar employment of the spouse, age of the household head, square of age (previous research shows that risk aversion increases with age but perhaps at a declining rate (see Guiso, Sapienza, & Zingales, 2013) and education of the household head.

2.3.2 Slovak Republic

As in the Czech case, the Slovak household budget survey for 2008 was used. Overall, the sample contains 4,718 households. Estimation was done on a subsample of 2,991 households whose head was working (either employed or self-employed) during 2008. Summary statistics for Slovak households included in the subsample can be seen in Table 2.2. The definitions of variables are almost an exact copy of those of their Czech counterparts, except for marital status, which is explicitly observed in the Slovak data.

[7]The reduction in sample size is primarily due to the presence of households headed by retirees.

[8]We recognize that consumption of alcohol and tobacco is likely to be underreported (Stockwell et al., 2004) but have no reason to believe that this underreporting is correlated with underreporting of income.

[9]Although we use the term "spouse" throughout, explicit marital status cannot be determined from the Czech data, which only reports whether the household head has a life partner, not the exact legal status of the relationship.

Table 2.1: Summary statistics of the subsample in the Czech HBS, 2008

Variable	**Mean**	**Std. Dev.**
Total no. of households	2,138	N/A
Household members	2.606	1.192
Economically active	1.49	0.585
Not economically active excl. children	0.299	0.474
Children	0.817	0.943
Heads with a spouse or a partner	1,486	N/A
Heads with 'maturita'*	814	N/A
Heads with bachelor's degree and higher	264	N/A
Spouses with 'maturita'*	854	N/A
Spouses with bachelor's degree and higher	174	N/A
Age of head	45.306	11.073
Female heads	523	N/A
Blue collar heads	1,170	N/A
Self-employed heads	456	N/A
Heads in public sector	610	N/A
Blue collar spouses	294	N/A
White collar spouses	737	N/A
Self-employed spouses	70	N/A
Spouses in public sector	522	N/A
Monthly expenses on food (CZK**)	6316.622	56.66
Monthly expenses on non-durables (CZK)	18,710.787	7,094.331
Monthly disposable income (CZK)	31,750.111	16,346.241

* 'Maturita' is the high school exit exam taken by students in academic high schools and selected vocational schools. It can be compared to A-level exams in the UK.
** The average exchange rate of the Czech crown to the USD in 2008 was approximately 19.35 CZK/USD.

Table 2.2: Summary statistics of the subsample in the Slovak HBS, 2008

Variable	**Mean**	**Std. Dev.**
Total number of households in the subsample	2,885	N/A
Household members	3.275	1.307
Economically active	1.749	0.721
Not economically active excl. children	0.478	0.627
Children	1.048	1.053
Married heads	2,048	N/A
Heads with 'maturita'*	1,425	N/A
Heads with bachelor's degree and higher	457	N/A
Spouses with 'maturita'*	1,259	N/A
Spouses with bachelor's degree and higher	295	N/A
Age of head	44.096	9.829
Female heads	702	N/A
Blue collar heads	1,192	N/A
Self-employed heads	483	N/A
Heads in public sector	761	N/A
Blue collar spouses	313	N/A
White collar spouses	2,158	N/A
Self-employed spouses	116	N/A
Spouses in public sector	671	N/A
Monthly expenses on food (SKK**)	6462.602	50.139
Monthly expenses on non-durables (SKK**)	23,925.25	10,110.226
Monthly disposable income (SKK**)	33,365.971	12,972.335

*'Maturita' is the high school exit exam taken by students in academic high schools and selected vocational schools. It can be compared to A-level exams in the UK.
** The average exchange rate of the Slovak crown to the USD in 2008 was approximately 21.573 SKK/USD.

2.4 Results

2.4.1 Size of the shadow economy

As discussed above, the system of Equations (2.9) – (2.12) was estimated using Monte Carlo methods. Structural results using total non-durable consumption and the full set of exclusion restrictions are reported in Tables 2.6 and 2.8, respectively. Those for other specifications of consumption and exclusion restrictions are available from the authors on request. In all cases the likelihood ratio test rejects the null hypothesis of joint statistical insignificance of estimates at the 1 percent level.[10] Plugging the estimated structural coefficients into Equation (2.18) yields the estimates of the shadow economy in Tables 2.3 and 2.4.

The robustness of our results to alternative definitions of consumption (non-durables, food, non-durables minus rents) and different sets of exclusion restrictions including with identification based solely on the functional form is striking. This would imply that slight violations of the homotheticity assumption are not critical for the empirical results. With respect to identification assumptions, although the sizes of the shadow economy estimated with and without the exclusion restrictions are remarkably close, it is, not surprisingly, much more difficult to reach convergence without them. Identification becomes much easier as more exclusion restrictions are added.[11]

The key finding is that under all alternative specifications, the shadow economy in the Czech Republic is tightly estimated to be between 20 and 22 percent of reported income in 2008, while in Slovakia this fraction is between 25 and 35 percent. Thus, to arrive at true income in these economies, we have to multiply the officially reported income by approximately 1.2 and 1.3 respectively. As can be seen in Table 2.5 these estimates exceed others in the literature, often by a substantial amount.[12] From these results it is obvious

[10]The likelihood ratio test is a natural choice to test the assumption that divided households into two groups based on their consumption-income gaps. Given that a model consisting of a single gap function is nested in the endogenous switching model, such a test can be used to compare the two models, with the null hypothesis being that both models explain data equally well. Following Dickens and Lang (1985), the degrees of freedom are equal to the number of constraints plus the number of unidentified parameters (found only in the switching equation). As argued by Goldfeld and Quandt (1976), this leads to a conservative critical value.

[11]Without any exclusion restrictions, we need to draw more than 50,000 bootstrap samples to gain convergence in 250 cases. With only self-employed and public sector employment dummies for household heads and spouses (if any), the number of samples needed drops to around 1,000. When we add also a blue-collar dummy for heads and spouses and a white-collar dummy for spouses, this number is further decreased to around 400.

[12]With the notable exception of Alm and Embaye (2013), whose estimates are uniformly higher than

Table 2.3: Shadow economy estimates – Czech Republic (2008)

Consumption measure	Exclusion restrictions	Shadow economy as % of reported income (bootstrapped S.E.)	Shadow economy as % of total income (bootstrapped S.E.)
Nondurables	Self-Employed, Public Sector, Blue Collar, White Collar	21.99% (0.99%)	17.16% (0.36%)
Nondurables	Self-Employed, Public Sector	21.68% (1.08%)	16.93% (0.65%)
Nondurables	None (Identification by Functional Form)	22.41% (4.97%)	16.54% (2.74%)
Nondurables (excluding rents)	Self-Employed, Public Sector, Blue Collar, White Collar	19.36% (1.72%)	15.07% (1.07%)
Food only	Self-Employed, Public Sector, Blue Collar, White Collar	26.32% (1.24%)	19.67% (0.76%)

Table 2.4: Shadow economy estimates – Slovak Republic (2008)

Consumption measure	Exclusion restrictions	Shadow economy as % of reported income (bootstrapped S.E.)	Shadow economy as % of total income (bootstrapped S.E.)
Nondurables	Self-Employed, Public Sector, Blue Collar, White Collar	30.44% (1.12%)	22.29% (0.29%)
Nondurables	Self-Employed, Public Sector	31.71% (1.08%)	23.01% (0.66%)
Nondurables	None (Identification by Functional Form)	36.28% (1.89%)	25.29% (1.16%)
Nondurables (excluding rents)	Self-Employed, Public Sector, Blue Collar, White Collar	25% (0.99%)	18.90% (0.67%)
Food only	Self-Employed, Public Sector, Blue Collar, White Collar	23.92% (1.26%)	17.52% (0.83%)

that in post-communist countries at least, underreporting of income extends to wage and salary workers as well as the self-employed.

Table 2.5: Alternative Estimates of the Shadow Economy as Percent of GDP*

Estimation Method	Source	Year	Czech Rep.	Slovak Rep.
Consumption-income Gap (switching regression)	This Chapter	2008	17.6%	22.9%
Food Engel Curves (self-employed exclusion)	Chapter 1	2008	4.0%	6.8%
Currency Deposit Ratio	Embaye (2007)	2000-2005	8.0%	12.6%
Currency Deposit Ratio (panel GMM difference)	Alm and Embaye (2013)	2006	23.2%	25.1%
MIMIC	Buehn and Schneider (2013)	2008	15.2%	16.0%
Dynamic General Equilibrium	Elgin and Oztunali (2012)	2008	16.8%	16.6%
Structural Model (calibrated to M1)	Ruge (2010)	2001	8.2%	8.1%
Structural Model (calibrated to M2)	Ruge (2010)	2001	3.3%	3.3%
Statistical Office	Calculated from Quintano and Mazzocchi (2010)	2008	5.4%	13.6%

*Not all sources make it clear whether the estimate of the shadow economy is expressed as a percentage of reported GDP or Total GDP (reported plus unreported). Where unclear we have assumed the latter. If estimates are of the former, it would make the difference between our numbers and those from other studies even greater.

Equation (2.19) enables calculation of the predicted probability of hiding income defined on the interval $[0, 1]$ for every household in the sample. As might be expected from Tables 2.3 and 2.4, the mean of this estimated probability is substantially higher in Slovakia, where the average household has an estimated 54 percent probability of hiding at least some income, than it is in the Czech Republic, where the corresponding estimated probability is 34 percent.

2.4.2 Determinants of underrepoting

The impact of various factors on the probability of a household underreporting income (computed for each observation and then averaged) corresponds with intuition, as can be seen in Tables (2.7) and (2.9), which report the extensive margin of shadow economy participation. Households headed by women are substantially less likely to underreport income (by 12 percentage points in each country). This result is consistent with previous studies of gender differences in tax evasion (see Baldry, 1987; McGee, 2012). Possible

those found elsewhere.

explanations for this finding include gender differences in risk aversion or honesty[13] and the higher frequency with which primarily male household heads are charged with calculating tax reporting forms. The same results are found for married households in Slovakia where households headed by single males are the most likely to underreport. However, a care has to be taken with the interpretation of the female dummy coefficient due to the structure of the data. In the Czech Republic, heads of households constituted by nuclear families (where both spouses are present) are always male. In theory, this does not hold for Slovakia, where the head is arbitrarily chosen by the household itself in the 2008 data. In practice, however, the self-reported heads of nuclear families are predominantly male (in 94% of households with working heads). Therefore, the coefficient on the female dummy could partially capture the effect of incomplete family, as well.[14]

To show the marginal effects graphically, Figures 2.1-2.4 compare the distribution of expected underreporting (i.e. combined effect of both intensive and extensive margins) of households containing at least one self-employed spouse with those where both spouses are formally employed, and the same comparison of households with female and male heads, respectively. We can see that for households with at least one self-employed spouse, the distribution of underreporting is more left-skewed than that of the households with both spouses employed, which results from the higher average underreporting among households with self-employed members. The differences between men and women are slightly less pronounced but still suggest that male-headed households are more likely to underreport income.

Job characteristics (blue collar employment, self-employment and working in the public sector) of household heads are uniformly more predictive than that of their spouses, again probably due to greater variation in males' behavior with respect to underreporting. In both countries households working in the public sector are less likely to hide income,

[13]Previous studies often find that women are more risk averse than men. See, for example Halek and Eisenhauer (2001) and Eckel and Grossman (2008).

[14]We thank Kamila Fialová for this comment.

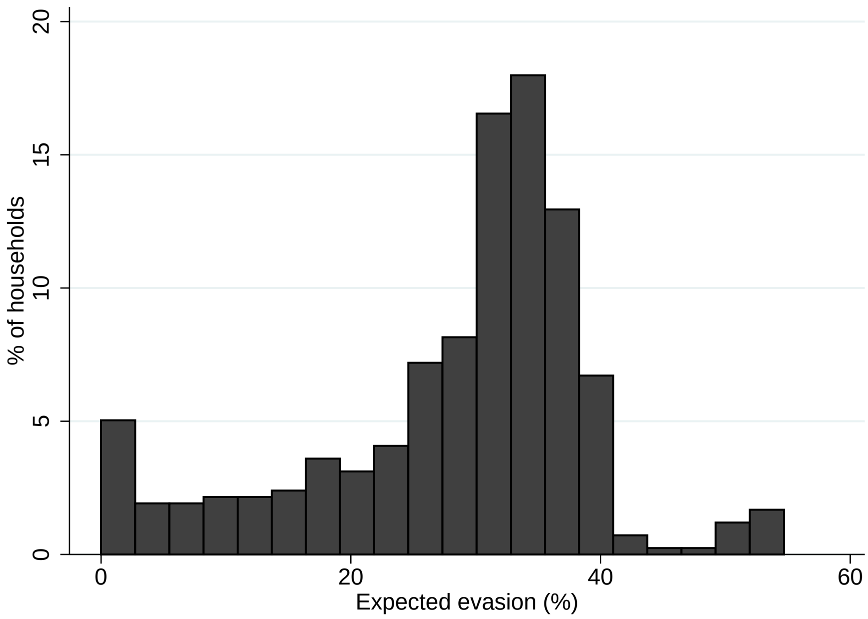
Table 2.6: Structural model coefficients – Czech Republic (2008)

VARIABLES	Shadow sector $\ln C - \ln Y$		Official sector $\ln C - \ln Y$		Switching equation Latent variable	
constant	-0.452***	(0.012)	0.264***	(0.637)	3.061***	(0.459)
# of children	-0.000	(0.001)	0.007	(0.007)		
# of employed	0.000	(0.002)	-0.034***	(0.012)		
# of unemployed	0.004**	(0.002)	-0.054***	(0.015)		
is married	0.003	(0.004)	0.097	(0.608)	-1.045**	(0.434)
high school degree	-0.000	(0.003)	-0.018	(0.017)	-0.010	(0.029)
bachelor's degree or higher	-0.007***	(0.002)	-0.047*	(0.027)	0.108***	(0.039)
high school degree (spouse)	0.003	(0.003)	0.046	(0.029)	-0.071*	(0.041)
bachelor's degree or higher (spouse)	1.242	(1.419)	-0.080	(0.151)	0.867	(1.044)
age	0.001	(0.000)	0.010*	(0.005)	-0.029***	(0.007)
age^2	-0.000	(0.000)	-0.001*	(0.001)	-0.000***	(0.000)
hoh is female	0.001	(0.004)	0.072	(0.610)	-1.021**	(0.432)
has children					-0.000	(0.022)
blue collar					-0.012	(0.016)
works in public sector					0.028	(0.017)
self-employed					0.026	(0.018)
spouse in public sector					0.010	(0.022)
white collar spouse					0.043	(0.028)
blue collar spouse					0.040	(0.034)
self-employed spouse					0.945	(0.675)
σ_1	0.286***	(0.001)				
σ_2			0.847***	(0.017)		
σ_{13}					0.254***	(0.004)
σ_{23}					-0.721***	(0.030)
Observations			2,138			
Log likelihood			-342320			
LR test			59814			
Prob>$\chi^2(40)$			0.0000			

Bootstrapped standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The structural coefficients for consumption-income gap equations express also the marginal effects given variables have on consumption-income gap. The structural coefficients for switching equation do not have a straightforward interpretation. The marginal effects on probability are shown in Table 2.7.

Figure 2.1: Expected underreporting (CR): self-employed vs employed

(a) At least one spouse self-employed



(b) Both spouses employed

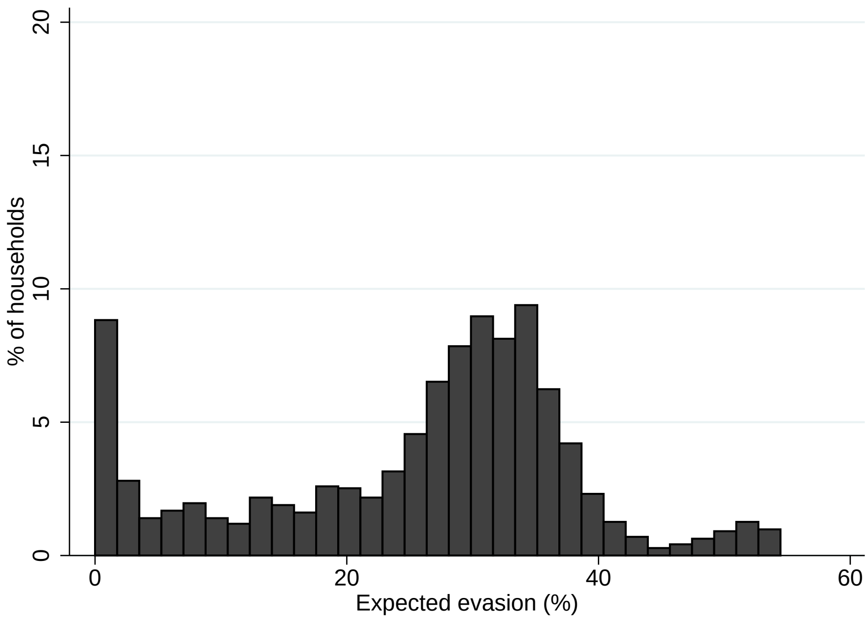
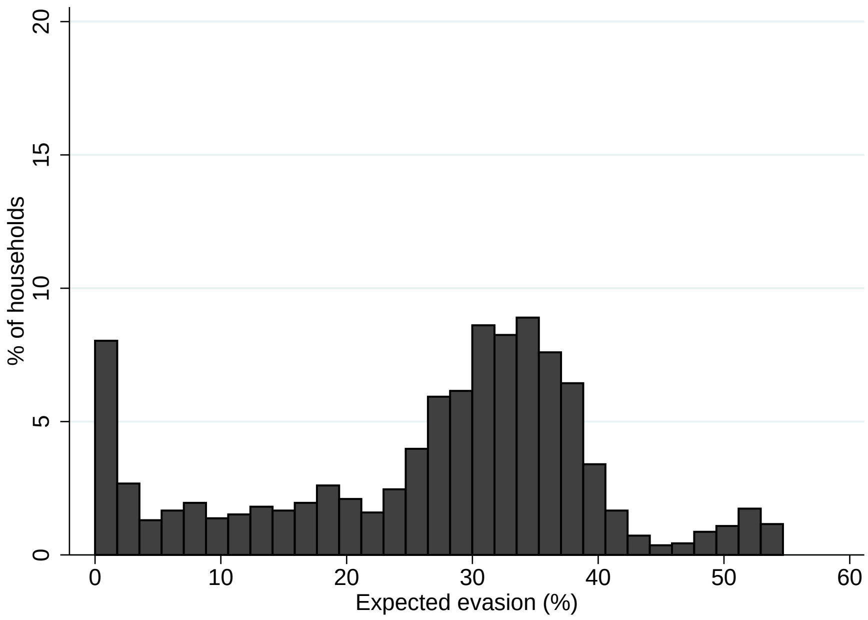


Figure 2.2: Expected underreporting (CR): male vs female heads of household

(a) Male head



(b) Female head

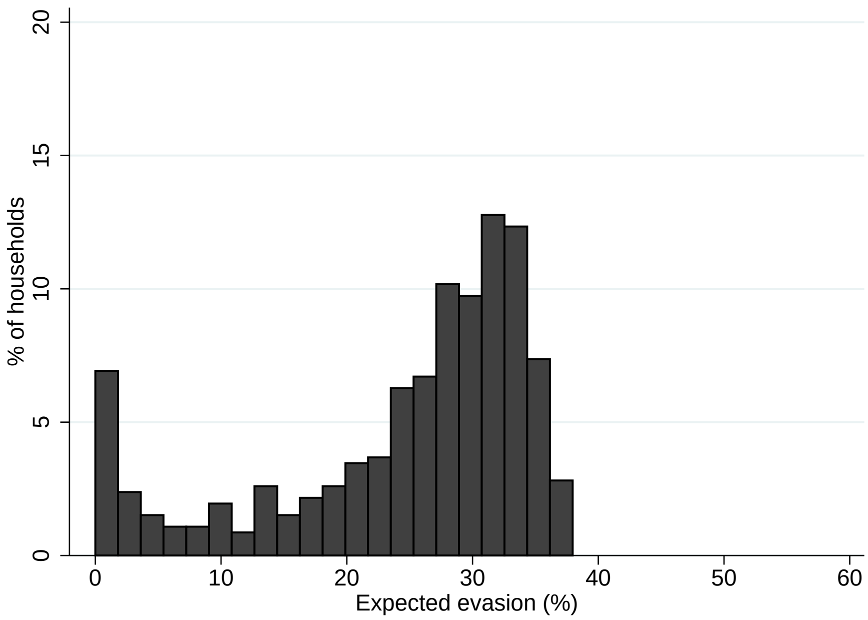
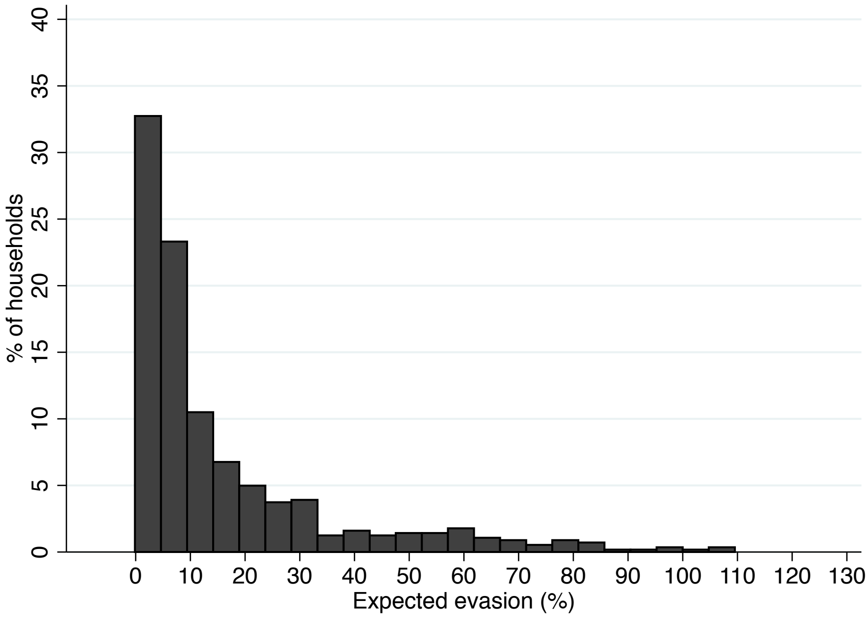


Figure 2.3: Expected underreporting (Slovakia) – self-employed vs employed

(a) At least one spouse self-employed



(b) Both spouses employed

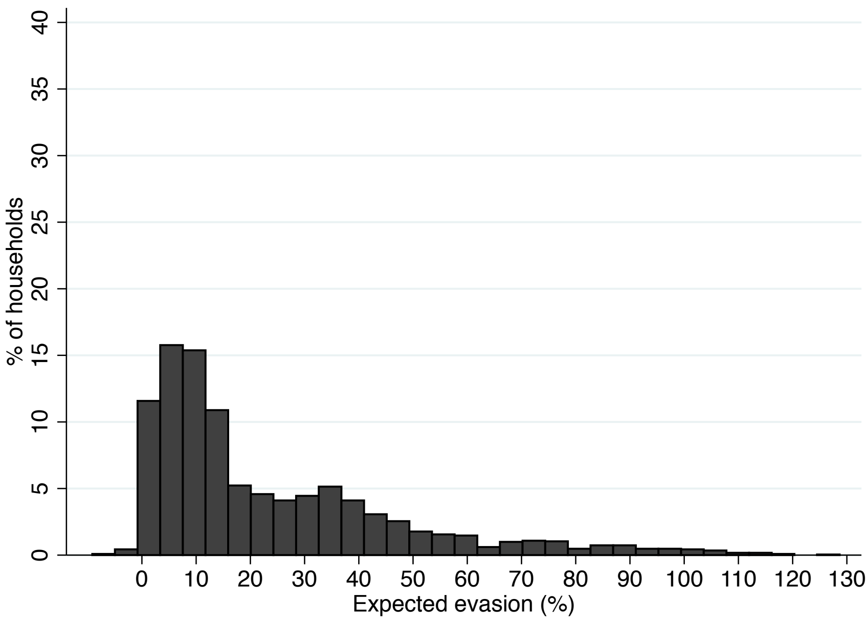
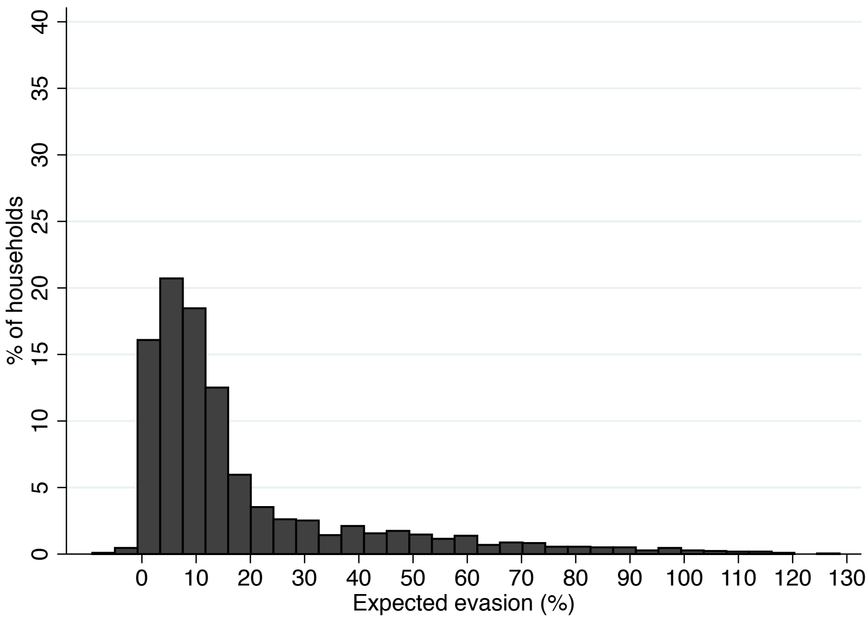


Figure 2.4: Expected underreporting (Slovakia): male vs female heads of household

(a) Male head



(b) Female head

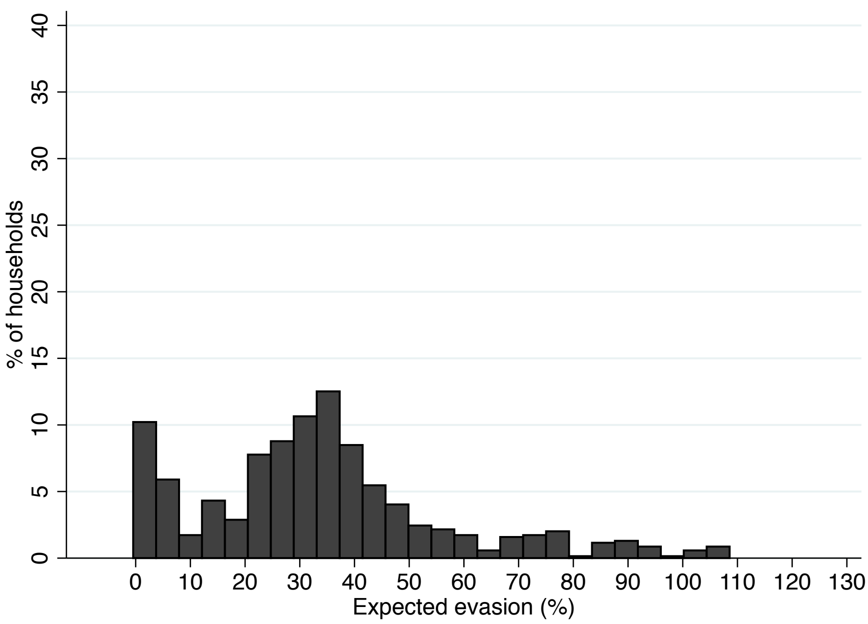


Table 2.7: Marginal effects - Czech Republic

VARIABLES	Probability of being in the shadow sector
is married	0.009
age	0.039
age^2	-0.000
female	-0.124
has children	0.045
high school degree	-0.081
bachelor's degree or higher	-0.047
high school degree (spouse)	0.032
bachelor's degree or higher (spouse)	0.061
blue collar	-0.009
self-employed	-0.059
works in public sector	-0.015
blue collar spouse	-0.004
white collar spouse	0.058
self-employed spouse	-0.006
spouse in public sector	-0.006

The average marginal effects were computed as the average of marginal effects predicted for every observation in the subsample.

although the effect is higher when the head is so employed rather than the spouse. Results with respect to self-employment are somewhat puzzling. Such status, as expected, has a substantial effect for both household heads and their spouses in Slovakia while in the Czech Republic both effects are actually negative, posing an obvious question for further research and reinforcing the danger of relying on *a priori* identifying assumptions. In both countries households headed by blue-collar workers (or containing spouses with blue-collar jobs) are less likely to underreport. Workers with high school degrees are less likely to underreport than those with either more or less education.

These results suggest that, in addition to being greater in overall magnitude, the propensity to underreport income is more generalized in Slovakia than in the Czech Republic. On average every second Slovak household underreports its income, while in the Czech Republic every third household hides at least a portion of its income. The findings with respect to both extent and composition of underreporting are consistent with the overall level of economic development in Slovakia. In 2008, when our data was collected, GDP per capita was 75 percent greater in the Czech Republic than in Slovakia ($23,833 as opposed to $13,603). Schneider (2012) reports that, among OECD countries, lower GDP per capita is associated with a higher propensity to work in the shadow economy.

Table 2.8: Structural model coefficients - Slovak Republic (2008)

VARIABLES	Evading regime $\ln C - \ln Y$		Non-evading regime $\ln C - \ln Y$		Switching equation N/A (latent)	
constant	-0.167***	(0.069)	-0.132	(0.139)	-2.751***	(0.828)
# of children	-0.008***	(0.002)	-0.019***	(0.001)		
# of employed	-0.113***	(0.002)	-0.080***	(0.002)		
# of unemployed	-0.038***	(0.002)	-0.046***	(0.002)		
is married	0.025***	(0.0048)	-0.050***	(0.0120)	0.021***	-0.004
high school degree	0.038***	(0.013)	0.042***	(0.005)	-0.180***	(0.037)
bachelor's degree or higher	0.012	(0.013)	-0.050***	(0.011)	-0.209***	(0.039)
high school degree (spouse)	-0.007	(0.010)	-0.041	(0.126)	0.058	(0.125)
bachelor's degree or higher (spouse)	-0.116***	(0.017)	-0.016	(1.355)	-0.007	(0.933)
age	0.005*	(0.003)	-0.021***	(0.002)	0.128***	(0.011)
age^2	0.000	(0.000)	0.000	(0.000)	-0.001***	(0.000)
female	0.001	(0.011)	0.050***	(0.007)	0.037	(0.743)
has children					0.165***	(0.017)
blue collar					-0.035***	(0.013)
works in public sector					-0.056***	(0.010)
self-employed					-0.218***	(0.026)
blue collar spouse					-0.013	(0.760)
white collar spouse					0.212	(1.229)
spouse in public sector					-0.021	(0.019)
self-employed spouse					-0.021	(0.932)
σ_1	0.250***	(0.001)				
σ_2			0.547***	(0.009)		
σ_{13}					0.184***	(0.022)
σ_{23}					0.487***	(0.023)
Observations			2,885			
Log likelihood			-510636			
LR test			434086			
Prob>$\chi^2(40)$			0.0000			

Bootstrapped standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The structural coefficients for consumption-income gap equations express also the marginal effects given variables have on consumption-income gap. The structural coefficients for switching equation do not have a straightforward interpretation. The marginal effects on probability are shown in Table 2.9.

Table 2.9: Marginal effects - Slovak Republic (2008)

VARIABLES	Probability of being in the shadow sector
is married	-0.125
age	0.044
age^2	-0.000
female	-0.124
has children	-0.017
high school degree	-0.073
bachelor's degree or higher	-0.015
high school degree (spouse)	0.050
bachelor's degree or higher (spouse)	0.089
blue collar	-0.075
self-employed	0.152
works in public sector	-0.050
blue collar spouse	-0.018
white collar spouse	-0.010
self-employed spouse	0.087
spouse in public sector	-0.008

The average marginal effects were computed as the average of marginal effects predicted for every observation in the subsample.

Similarly, Williams (2013) reports that undeclared envelope wages are more common in poorer nations.[15]

2.4.3 Effect on income inequality

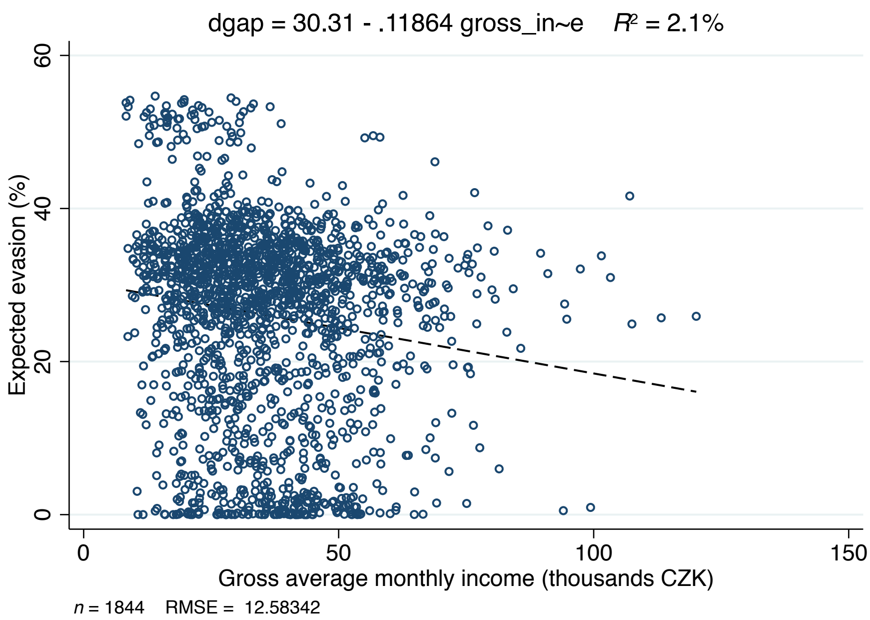
One of the ambiguous predictions of theoretical models of tax evasion is the relationship between income level and income underreporting. Models of tax evasion that treat it as a gamble (beginning with Allingham & Sandmo, 1972) often argue that results depend on whether the relative risk aversion is decreasing or increasing with income. In the first case the share of underreported income will increase with the level of income, in the latter it will decrease. Although these models are criticized on the grounds that they fail to explain many empirical observations, most behavioral models offer reasons why income level and the share underreported might be connected including the correlation of income with characteristics like attitude towards the tax system, satisfaction with the government,

[15] An alternative explanation might be that in 2008 cash register receipts were required for all transactions in the Czech Republic (introduced in 2007) while a similar reform was not introduced in Slovakia until 2011. Both countries had moved from a progressive to a flat tax before 2008.

or inequality aversion. It is also possible that higher income households under-report less because they are more able to make use of technically legal methods of tax avoidance.

Our results (Figs 2.5 and 2.6) suggest that expected evasion is a slightly decreasing function of income. This can have important implications for the analysis of income inequality computed based on reported data. If lower income households underreport a higher share of their income, as is our case, measures of income inequality (such as the Gini coefficient) based on reported income will overestimate true inequality. The link between income level and underreporting is shown in Table 2.10. The difference is modest, although it is important to note that the countries in question are among the most equal in the world to begin with.[16] The effect can be even more pronounced in other countries with higher income inequality. This result also shows that tax evasion can have important and complex normative implications for policy about redistribution and fairness. In this case, the existence of tax evasion decreases progressivity (or increases regressivity) of tax systems.

Figure 2.5: Expected underreporting and gross income (CR)



[16]According to the latest World Bank estimates for Czech and Slovak Republics (World Bank, 2012), these countries are tied for 5th and 6th place with the same reported Gini coefficient of 26.1.

Figure 2.6: Expected underreporting and gross income (Slovakia)

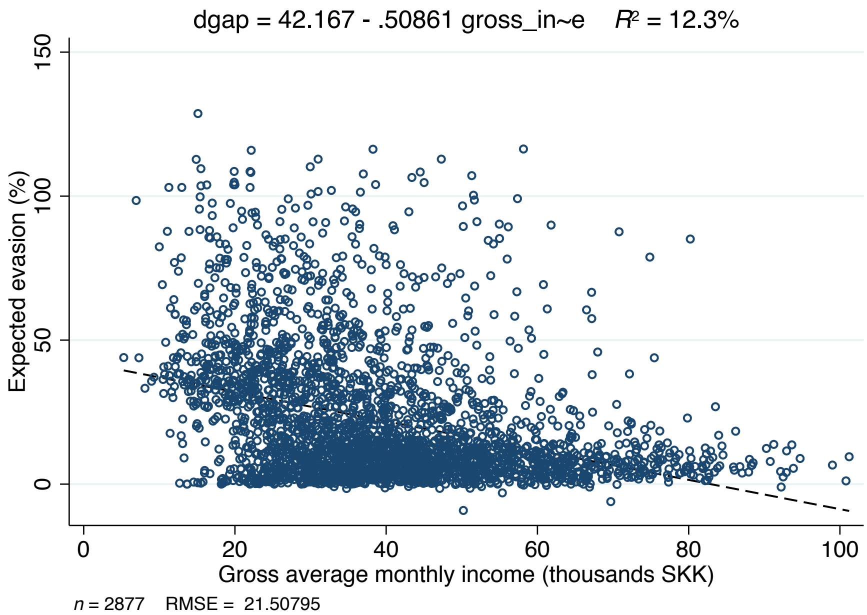


Table 2.10: Gini coefficients based of reported and actual income

Country	Gini coefficient reported income	Gini coefficient true income (estimated)
Czech Republic	0.214	0.205
Slovak Republic	0.217	0.209

2.5 Conclusion

The size of the shadow economy was estimated based on microeconomic data without imposing the unrealistic assumptions that have hampered previous estimators and are likely to have led to under-estimating the size of the shadow economy by excluding underreporting among those who unjustifiably assumed to fully report their income. The application of this methodology to Czech and Slovak data yields estimates of the size of the shadow economy that are substantially larger than those obtained from other methodologies (both macroeconomic techniques and microeconomic ones using standard techniques). The logical explanation is that employees being paid under the table or having a secondary, undeclared, source of income while not being officially classified as "self-employed" constitute a major source of unreported income. Excluding the possibility of such hidden income can result in serious under-estimation of the size of the shadow economy and distortions in observed income distributions with important policy implications.

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Technical Appendix

The estimation was done in TSP 5.1 (64-bit) via the command 'ml'. This command maximizes the log-likelihood function numerically[17] and, therefore, choosing appropriate initial values is essential for convergence. The initial values were set by a procedure described in Dutoit (2007). We initially separate the sample through a dummy $I_i = 1$ if the household i's gap is above a certain threshold (creating an initial group presumed to be evading) or $I_i = 0$ if it is below that threshold (initially assumed non-evading group). To obtain initial values of $\boldsymbol{\delta}$, a probit regression of I_i on $\mathbf{Z}_i$ is run. After that we use these estimated values $\left(\hat{\delta}\right)$ to obtain initial values of the $\boldsymbol{\beta}$'s by running the following OLS regressions:

$$\ln C_i - \ln Y_i = \mathbf{X}_i \boldsymbol{\beta}_e - \sigma_{e,s} \frac{\phi\left(\mathbf{Z}_i \hat{\boldsymbol{\delta}}\right)}{\Phi\left(\mathbf{Z}_i \hat{\boldsymbol{\delta}}\right)} + \varepsilon_{i,e} \text{ if } I_i = 1 \,, \tag{2.22}$$

and

$$\ln C_i - \ln Y_i = \mathbf{X}_i \boldsymbol{\beta}_{ne} + \sigma_{ne,s} \frac{\phi\left(\mathbf{Z}_i \hat{\boldsymbol{\delta}}\right)}{1 - \Phi\left(\mathbf{Z}_i \hat{\boldsymbol{\delta}}\right)} + \varepsilon_{i,ne} \text{ if } I_i = 0 \,. \tag{2.23}$$

Then we get initial values of σ_e and $\sigma_{e,s}$ by running the following OLS estimation:

$$\hat{u}_{e,i}^2 = \sigma_e^2 - \sigma_{e,s} \frac{\phi\left(\mathbf{Z}_i \hat{\boldsymbol{\delta}}\right)}{\Phi\left(\mathbf{Z}_i \hat{\boldsymbol{\delta}}\right)} \,,$$

where $\hat{u}_{e,i} = (\ln C_i - \ln Y_i) - X_i \hat{\beta}_e$, where $\hat{\beta}_e$ is the estimate of β_e coming from Equation (2.22). The initial values of σ_{ne} and $\sigma_{ne,s}$ are obtained analogously by running:

$$\hat{u}_{ne,i}^2 = \sigma_{ne}^2 - \sigma_{ne,s} \frac{\phi\left(\mathbf{Z}_i \hat{\boldsymbol{\delta}}\right)}{1 - \Phi\left(\mathbf{Z}_i \hat{\boldsymbol{\delta}}\right)} \,.$$

These initial values of δ, $\boldsymbol{\beta}$'s and σ's are used as starting values for the numerical optimization procedure.

To make the results robust, for each random sample within the Monte Carlo simulation the initial sample separation is in turn set to the first, second and third quartiles, and the

[17] For more detailed information on this command including stopping rules, see the TSP manual at http://www.tspintl.com/products/manuals.htm.

mean of the consumption-income gap of the given Monte Carlo sample. After applying the above procedure to each of these initial splits, we choose the results of the one that yields the highest log-likelihood as the final results for the given sample. This process results in the data series from which statistics such as the estimated size of shadow economy and its standard error are computed.

Chapter 3

'Flattening' the Tax Evasion: Evidence from the Post-Communist Natural Experiment[1]

[1]This chapter will published as Filer, R.K., Hanousek, J., Lichard, T., and Torosyan, K. (forthcoming). 'Flattening' the Tax Evasion: Evidence from the Post-Communist Natural Experiment, CEPR Working Paper.

Abstract

We analyze the tax evasion response to the introduction of a flat tax in several transition economies. Using a novel estimator based on household level data, we show that in the majority of studied countries, there was no discernible effect of flat tax reform. This may imply that decreases in the marginal tax rate in themselves are not the main driver in determination of the size of the shadow economy, but that there is an important synergy between changes in marginal tax rates and changes in satisfaction with government services, as the only countries that show a response to the flat tax reform are those countries where satisfaction with government services increased. Additionally, our results show a procyclicality of the size of the shadow economy that is in line with previous research.

3.1 Introduction

This paper analyzes a unique natural experiment involving substantial changes in tax systems in post-communist countries in Central and Eastern Europe. In several sets of structurally and culturally closely-related economies, at least one country adopted a variant of a flat tax reform, while one or more otherwise highly similar neighboring countries retained a complex, progressive tax code. This pattern of reform enables difference-in-difference estimates of the impact of major tax system simplification and lower tax rates on tax evasion decisions.

In recent decades economists and policy makers have paid increasing attention to the hidden economy. Although several researchers have introduced subtle distinctions (see Bloem & Shrestha, 2000), we will not attempt to differentiate among what others have called the hidden economy, shadow economy, underground economy, unreported economy, unofficial economy, and grey economy. For our purposes, the hidden economy refers to all productive activities that are not recorded in formal statistical collection by government agencies. We do not distinguish between economic activity that is hidden from the authorities because it is illegal in and of itself, and economic activity that is illegal only because it is unreported to tax authorities. In the words of Feige to a session of the American Economic Association in 1980 (cited in Feige & Urban, 2003, p. 4):

> The observed sector of the economy consists of those economic activities that are regularly caught in the net of our official statistical accounting mechanism. It is this observed sector that furnishes us with our perceptions of the fundamental facts of economic life. Not only does it function as the basis for generating the questions that the economics profession seeks to answer, it also provides the fodder for our forecasting industry, our empirical tests, and our policy prescriptions. Thus, any major systematic discrepancy between our observations of macroeconomic life and actual macroeconomic activity serves to generate misguided questions, to produce erroneous answers, and perhaps most damagingly, to disseminate systematically false information among citizens and policy makers alike.... The unobserved sector, being the complement of the observed sector, consists of those activities (legal or illegal, market or non-market, monetary or barter) that escape the purview of our current societal measurement apparatus.

Recently, recognizing that the lack of precise estimates of GDP results in severe shortcomings both for users and for producers of national accounts, official statistical agencies have devoted considerable attention to measuring various parts of the hidden economy (OECD, 2002), while scholars and policy makers alike have investigated the factors that lead individuals and firms to hide economic activity. These factors are obviously complex and varied. Illegal activity is likely to be hidden from statistical agencies in the belief that information may be shared with law enforcement authorities. Participation in the hidden economy is also a way of escaping regulatory burdens in labor or product markets, including restrictions on various production technologies for e.g. environmental reasons (Johnson, Kaufmann, & Zoido-Lobaton, 1998;Friedman, Johnson, Kaufmann, & Zoido-Lobaton, 2000). For post-communist countries, there is also evidence that a lack of political stability and the existence of corruption promote unrecorded economic activity (May, Pyle, & Sommers, 2002).

Most work on the hidden economy assumes that tax evasion is a primary reason for unrecorded economic activity. Economists as early as Kaldor (1956) focused on tax evasion as a motivator for participation in the shadow economy. Past theoretical work has produced ambiguous conclusions regarding the impact of tax rates and structures on incentives to hide economic activity. Allingham and Sandmo (1972), and Yitzhaki (1974) assert that reduction in tax rates may alter penalties for noncompliance and, therefore, cost/benefit calculations, such that workers conceal a greater share of their income. Similar results have been found for tax rates by Pencavel (1979) and tax progressivity by Koskela (1983). Adding decreasing absolute and non-increasing relative risk aversion to such a model, however, implies that increases in either tax rates or progressivity will cause a growth in the underground economy (Trandel & Snow, 1999). Other works showing a positive theoretical relationship between taxes and hidden economic activity include Kesselman (1989), Cowell (1985) and Watson (1985). A summary of this literature is provided by Sandmo (2005), and Slemrod (2007). The results of empirical work on the link between taxes and the size of the hidden economy are also mixed. While some studies (Friedman et al., 2000 for example) find no, or even a negative, relationship between taxes and the size of the hidden economy, the vast majority of studies find that higher average and/or marginal tax rates as well as greater complexity of the tax system are associated with an increase in the size of the hidden economy. Examples include Schneider (1986), Lacroix and Fortin (1992), Hill and Kabir (1996), Cebula (1997), Giles and Johnson (2002), and Thießen (2003).

As evidenced above, researchers and policy makers initially explained participation in the shadow economy by a simple, rational cost-benefit analysis – people evade taxes when the income gain from tax evasion (i.e. taxes not paid) is higher than the penalty weighted by the probability of getting caught (Allingham & Sandmo, 1972). However, this view is challenged by recent literature that argues that the observed extent of compliance cannot be explained solely by the level of enforcement. This strand of literature (the so called 'tax morale' literature) stresses the importance of factors like satisfaction with the government, patriotism (Konrad & Qari, 2012), perceived prevalence of cheating, or ethics (Torgler, 2002; Alm & Torgler, 2011). As our results suggest, the tax morale can potentially account not only for some cross-section differences across countries, but for within-country tax evasion dynamics as well. To put it simply, one should consider changes in tax evasion are not only a result of taxpayers' simple lottery calculus, but entertain a possibility that they are influenced by, among other factors, changes in citizens' satisfaction with government policies and with the quality of public services.[2]

3.2 The Natural Experiment of "Flat-Tax" Reform in Post-Communist Europe

One of the most commonly suggested remedies for the income tax evasion is a move to a flat (uniform rate) tax. The rationale is that, under progressive taxation, some individuals have a significantly greater incentive to underreport than others, as shares of their income above certain thresholds are taxed at higher marginal tax rates. The gains from tax evasion are thus not increasing linearly with income, but experience discontinuous shifts upwards at points where tax brackets change. In other words, a progressive tax regime creates discontinuities, where an individual whose income is slightly above a certain threshold has a disproportionally greater incentive to hide a part of their income than an individual whose income falls just under the same threshold. Therefore, a move to a uniform marginal tax rate should lower the incentives for the former hypothetical taxpayer in our example, potentially leading to a decrease in the income tax evasion.

Post-communist Central and Eastern European countries provide an unprecedented opportunity to test the ability of flat tax reforms to reduce the extent of the hidden economy. The countries of the region began the transition with progressive and, typically, high rates of personal income tax as well as traditionally large hidden economies. Since the

[2]For the evidence of this link from the Czech and Slovak Republics, Hungary, and Poland, see Hanousek and Palda (2004).

start of transition, most of these tax regimes have also become increasingly complex.[3] In recent years, however, some of these countries have adopted simplified, flat-tax regimes.[4] Even more fortuitously, several of these flat-tax adopters are closely linked to other structurally and economically highly similar countries that have not adopted such reforms. This linkage occurs because of the unique experience of country formation in the years following the collapse of communism. During the 1990s all three federated states in the region (Czechoslovakia, the Union of Soviet Socialist Republics and Yugoslavia) split into multiple successor states. In each of these groupings, some countries moved to a flat tax system while others did not (or did so at a significantly later time). This situation provides a ready set of difference-in-differences comparisons among countries that share similar backgrounds, legal structures, institutions and economic situations. In Table 3.1 we summarize the personal income tax systems and flat tax reforms in the sets of countries we analyze.[5] Several important facts are evident from Table 3.1. Although the best previous estimates of the hidden economies' share of national income are likely to be inaccurate (Hanousek & Palda, 2006), it is informative that they are highly similar within each country group but vary widely across groups. Where implemented, flat tax rates are similar across countries and typically are substantially below top rates either prior to reform or compared to other countries within each group that did not implement a flat-tax reform. There is, however, substantial variation in the top marginal rate prior to reform across the four country groups, ranging from 20 percent in Serbia to 40 percent in Ukraine.

Although all of the post-communist reforms differed in important ways from a pure Hall and Rabushka (1995) flat tax, each involved substantial simplification of the tax system combined with significant reductions in marginal and, generally, average tax rates.[6]

[3] In the Czech Republic, for example, the length of the tax code increased from under 14,000 words in 1993 to over 81,000 in 2005. During this period there were more than 50 revisions of the tax code. Similarly, the original income tax law contained the phrase "with the exception of" 50 times while the 2005 law used this phrase 254 times (Dušek & Žigić, 2005, p. 41)

[4] See Grabowski (2005) and Keen, Kim, and Varsano (2006) for discussion of these reforms.

[5] Lithuania, Latvia and Estonia were leaders in flat tax reforms, but they were early and simultaneous adopters, making comparative analysis impossible. Romania also adopted a flat tax reform in 2005 but was not part of a formerly federated state.

[6] It is important to recognize that income taxes generate only a fraction of revenue in the counties examined. The degree to which other taxes, including Value Added Taxes (VAT), payroll taxes and corporate profit taxes, were reformed along with income taxes varies across countries and are an important consideration, as are the changes in the tax base for income taxes on items such as investment income that were typically included in the reforms. Georgia, interestingly, is the only flat tax adopter to remove all elements of progressivity by eliminating all exclusions from income, even basic allowances for very low levels of earned income.

Table 3.1: Chronology of flat tax reforms in selected countries

Country	Period	Personal Income Tax Rate*	Est.Hidden Economy 1999-2000** (% GDP)
Czech Republic	Prior to 1/1/2008	Progressive 12% - 32%	19.1%
Czech Republic	After 1/1/2008	FLAT 15%***	
Slovakia	Prior to 1/1/2004	Progressive 10% - 38%	18.9%
Slovakia	After 1/1/2004	FLAT 19%	
Croatia	Entire Period	Progressive 15% - 45%	33.4%
Montenegro	Entire Period	Progressive 0% - 23%	36.4%†
Serbia	Prior to 1/1/2003	Progressive 10% - 20%	36.4%†
Serbia	After 1/1/2003	FLAT 14%	
Ukraine	Prior to 1/1/2004	Progressive 10% - 40%	52.2%
Ukraine	After 1/1/2004	FLAT 13%	
Russia	Prior to 1/1/2001	Progressive 12% - 30%	46.1%
Russia	After 1/1/2001	FLAT 13%	
Armenia	Entire Period	Progressive 10% - 20%	46.3%
Georgia	Prior to 1/1/2005	Progressive 10% - 20%	67.3%
Georgia	After 1/1/2005	FLAT 12%	

*Tax rates are for the current year or at the time of flat tax implementation. There may have been either increases or decreases in rates at various points during the period examined.
**Figures are estimates using the multiple-indicator/multiple-cause estimates in Schneider (2004).
***Taxation of wage workers and salaried workers in the Czech Republic is based on the so-called 'super-gross salary'—individual salary plus health and social insurance contributions paid by employers.
†Figures are not available independently for Serbia and Montenegro.

Proponents of flat-tax reforms have endorsed each enthusiastically, claiming major success in reducing the size of the hidden economy. According to Rabushka (2005):

> Russia is the big story. It took the tax reform world by storm in 2000 with a 13 percent flat tax, replacing its previous three-bracket system that topped out at 30 percent. The results have been spectacular. The economy has enjoyed four years of sustained growth. Real (inflation-adjusted) ruble revenue from the personal income tax rose 25.2 percent in 2001, 24.6 percent in 2002, 15.2 percent in 2003, and 16 percent in the first half of 2004. By year end, total receipts will have more than doubled; the share of consolidated budget revenue received from the personal income tax increased from 12.1 percent in 2000 to 17 percent at the end of 2003.

Proponents assert a causal relationship between flat-tax reform and reduction in the size of the hidden economy, claiming that the constant expansion of the government tax revenue [in Russia] is the result of less tax evasion and increased incentives to work, save, and invest (Grecu, 2004). There have been few rigorous economic analyses that could justify the claims of advocates. Ivanova, Keen, and Klemm (2005) use household data from the

Russian Longitudinal Monitoring Survey and find that there is no evidence of a strong supply side effect of the reform. Compliance, however, does appear to have improved quite substantially according to their study – by about one third. This increase in compliance seemed concentrated among households in the top two tax brackets before the introduction of the flat tax. Gorodnichenko, Martinez-Vazquez, and Sabirianova Peter (2009) estimated a lower effect – they computed that tax evasion decreased by 9-12 percent. Moreover, they found that the reform's effect on productivity was fairly small. Gaddy and Gale (2005), on the other hand, speculate that the increase in compliance is more likely attributable to changes in the administration and enforcement of tax laws and to other structural changes than it is to lower rates (p. 983). Chua (2003) reaches a similar conclusion. The flat tax reform in Georgia was studied by Torosyan and Filer (2014), who found that its effects on income underreporting were minimal, and that even those are attributable more to an increase in enforcement effort than to changes in marginal tax rates. Most recently, flat tax was introduced in Hungary between 2010 and 2013. This reform was studied by Tóth and Virovácz (2013) in a static microsimulation model; however, the authors only examined the effect on tax revenues, which were estimated to have decreased as a result of the flat tax. But to our knowledge there has been no scientific study of the impact of the tax reforms in the Czech Republic, Slovakia, or Serbia on compliance.

With the goal of adding to the (not only) geographically limited evidence on the effects of flat tax reform on tax evasion, this paper estimates the extent of income underreporting for eight countries in the CEE region. More precisely, we analyze tax evasion patterns in four pairs of structurally and institutionally linked countries (as discussed above), where one of them adopted the flat tax reform and the other did not, or, if both introduced the reform, one of them did it significantly later. This allows us to use the shadow economy estimates for nonadopters to control for aggregate underreporting trends in the region when computing the conditional change in tax evasion in the adopting countries after the flat tax reform. Our results show a significant negative effect of the reform on income underreporting in two countries only: Russia and Serbia. As a possible explanation, we show that these results can be linked to changes in factors linked to overall tax morale, such as satisfaction with the government. These results can provide important policy guidance not just in the post-communist transition economies, but throughout the world.

3.3 Methodology

To estimate the shadow economies in the selected countries, we use the endogenous switching regression methodology developed in Lichard, Hanousek, and Filer (2013). This methodology allows us to relax the assumption that wage and salary workers do not evade, which is still crucial in most recent tax evasion studies based on microeconomic data.[7] This identifying assumption is arguably untrue, especially for countries in our sample.[8] Although the difference-in-differences methodology used by Gorodnichenko et al. (2009) does not need this assumption either and is a natural choice for policy evaluation when having the advantage of panel data, the structure of the data in the majority of countries in this study precludes us from using this diff-in-diff method.[9] Moreover, unlike the aforementioned study, our methodology estimates the overall size of the shadow economy (as opposed to a change only), which may be of interest in itself. Below we briefly summarize this methodology.[10]

The most important identifying assumptions we use are that: 1.) evaders underreport their income both on tax returns and in household budget surveys, and 2.) nondurable consumption is measured without systematic error. Both of these assumptions are not only common in the literature cited above, but are supported by empirical evidence as well (see e.g. Brewer & O'Dea, 2012; Kreiner, Lassen, & Leth-Petersen, 2013; and Hurst et al., 2014). Under these assumptions we argue, as do Gorodnichenko et al. (2009), that evaders have higher consumption-income gap (the difference between log-consumption and log-income) than non-evaders. Thus, the econometric system consists of three equations: two equations describing the consumption-income gap for evading and non-evading groups, respectively, and a switching equation that describes the decision to evade. More precisely:

$$\left(\log C_i - \log Y_i^R\right)_e = \mathbf{X}_i\boldsymbol{\beta}_e + \varepsilon_{e,i}\,, \tag{3.1}$$

$$\left(\log C_i - \log Y_i^R\right)_{ne} = \mathbf{X}_i\boldsymbol{\beta}_{ne} + \varepsilon_{ne,i}\,, \tag{3.2}$$

[7] The seminal study whose identification strategy hinges on this assumption is Pissarides and Weber (1989). Other examples of the use of this identification include Lyssiotou, Pashardes, and Stengos (2004), Engström and Holmlund (2009), Tedds (2010), Ekici and Besim (2014), Hurst, Li, and Pugsley (2014), and Kukk and Staehr (2014)

[8] For evidence about the extent of the 'envelope' or 'under the table' wages problem in the EU, see European Commission (2007).

[9] The household budget surveys from the countries in our sample—with the sole exception of Russia—are either not in panel data form, or their panel structure does not cover sufficiently long period before and after the respective reform

[10] For a detailed discussion and an explicit derivation of the following equations see Lichard et al. (2013).

$$
\begin{aligned}
y_i^* &= \mathbf{Z}_i\boldsymbol{\delta} - \varepsilon_{s,i}\,, && (3.3)\\
\log C_i - \log Y_i^R &= \begin{cases} \left(\log C_i - \log Y_i^R\right)_e & \text{iff } y_i^* \geq 0\,, \\ \left(\log C_i - \log Y_i^R\right)_{ne} & \text{iff } y_i^* < 0\,, \end{cases} && (3.4)
\end{aligned}
$$

where $\mathbf{X}_i$ is the matrix of household attributes determining the consumption income gap (with small variation between countries, these contain preference shifters such as age of head and spouse (if any) and their squares, number of children, number of elderly, and education of head and spouse. Variable y^* is a latent (unobserved) variable that can be thought of as a propensity to evade. The households will evade if the returns from evasion are higher than the costs (including psychic costs, such as disutility coming from risk aversion or dishonesty). Both costs and returns can be heterogeneous in the population. Matrix $\mathbf{Z}_i$ contains household characteristics that affect a household's decision to evade (proxy variables for the cost of evasion), especially job characteristics. To aid the identification, we mantain exclusion restrictions – as discussed in Section 3.4 – $\mathbf{Z}_i$ contains a sub-set of variables that $\mathbf{X}_i$ does not.

Under some assumptions about the error term, in particular normality,[11] we can estimate the coefficients in Equations (3.1)-(3.4) by the maximum likelihood technique, with the following log-likelihood function:

$$
\begin{aligned}
\ln L\left(\boldsymbol{\beta}_e, \boldsymbol{\beta}_{ne}, \delta, \sigma_e, \sigma_{ne}, \sigma_{e,s}, \sigma_{ne,s}\right) = \sum_{i=1}^{N} \ln \Bigg\{ & \frac{1}{\sigma_e}\Phi\left(\frac{\mathbf{Z}_i\boldsymbol{\delta} - \frac{\sigma_{e,s}}{\sigma_e^2}\varepsilon_{e,i}}{\left(1-\frac{\sigma_{e,s}^2}{\sigma_e^2}\right)^{.5}}\right) \cdot \phi\left(\frac{\varepsilon_{e,i}}{\sigma_e}\right) \\
& + \frac{1}{\sigma_{ne}}\left[1 - \Phi\left(\frac{\mathbf{Z}_i\boldsymbol{\delta} - \frac{\sigma_{ne,s}}{\sigma_{ne}^2}\varepsilon_{ne,i}}{\left(1-\frac{\sigma_{ne,s}^2}{\sigma_{ne}^2}\right)^{.5}}\right)\right] \cdot \phi\left(\frac{\varepsilon_{ne,i}}{\sigma_{ne}}\right)\Bigg\}\,.
\end{aligned}
\tag{3.5}
$$

Once the coefficients are estimated, the size of the income underreporting can be computed as an average difference between the consumption-income gap of evaders and non-evaders

[11] As we argue in Lichard et al. (2013), this assumption is reasonable if income follows log-normal distribution. It has been shown this is a good approximation of the empirical distribution.

weighted by the estimated probability of being in the evading regime:[12]

$$\widehat{Evasion} = \frac{1}{N}\sum_{i=1}^{N}\left(\mathbf{X}_i\hat{\boldsymbol{\beta}}_e - \mathbf{X}_i\hat{\boldsymbol{\beta}}_{ne}\right)\cdot \hat{P}_{e,i}\,. \tag{3.6}$$

This probability can be computed by Bayes' rule as:

$$\hat{P}_{e,i} = \frac{\frac{1}{\hat{\sigma}_e}\Phi\left(\frac{\mathbf{Z}_i\hat{\boldsymbol{\delta}} - \frac{\hat{\sigma}_{e,s}}{\hat{\sigma}_e^2}e_{e,i}}{\left(1-\frac{\hat{\sigma}_{e,s}^2}{\hat{\sigma}_e^2}\right)^{.5}}\right)\phi\left(\frac{e_{e,i}}{\hat{\sigma}_e}\right)}{\frac{1}{\hat{\sigma}_e}\Phi\left(\frac{\mathbf{Z}_i\hat{\boldsymbol{\delta}} - \frac{\hat{\sigma}_{e,s}}{\hat{\sigma}_e^2}e_{e,i}}{\left(1-\frac{\hat{\sigma}_{e,s}^2}{\hat{\sigma}_e^2}\right)^{.5}}\right)\phi\left(\frac{e_{e,i}}{\hat{\sigma}_e}\right) + \frac{1}{\hat{\sigma}_{ne}}\left[1-\Phi\left(\frac{\mathbf{Z}_i\hat{\boldsymbol{\delta}} - \frac{\hat{\sigma}_{ne,s}}{\sigma_{ne}^2}e_{ne,i}}{\left(1-\frac{\hat{\sigma}_{ne,s}^2}{\hat{\sigma}_{ne}^2}\right)^{.5}}\right)\right]\cdot\phi\left(\frac{e_{ne,i}}{\hat{\sigma}_{ne}}\right)}\,.$$

In order to make our results robust to outliers and initial conditions, we employ the following Monte Carlo technique. First, we form a bootstrap sample by drawing N households with replacement from the original sample (N is set to be equal to the original sample size). Then we choose the initial guess for the value of consumption-income gap that splits the sample between evaders and non-evaders. Afterwards the dummy indicator of this split is regressed on $\mathbf{Z}_i$ in a probit model to obtain initial values of δ. To get initial values of βs, we estimate Equations (3.1) and (3.2) through OLS separately for each group split by this initial guess. These estimates are used as initial values for the maximization of maximum likelihood equation (3.5). We set the initial split by dividing the sample in turn along the sample mean and first, second, and third sample quartiles of the consumption-income gap. Then we choose the results with the highest log-likelihood as final. The procedure is repeated 250 times to obtain 250 estimates of the shadow economy for each country and year. Finally, we compute mean and standard errors of these estimates, which represent the final estimate of the size of the shadow economy for the given country-year pair and its confidence interval. Our methodology leads to a time series of shadow economy estimates for every country. To estimate the effect of the flat tax reforms on the size of the shadow economy we take advantage of the fact that these reforms took place at a different point in time in each country and use the pairs of countries that are economically, culturally, and historically close (Czech Republic and Slovakia, Russia and Ukraine, Georgia and Armenia, and Serbia and Croatia) to form

[12]Under the initial assumption of correct consumption reporting, the expected value of the difference in the gaps for both regimes of household i is equal to: $\mathbb{E}\left[\left(\widehat{\log C_i - \log Y_i^R}\right)_e - \left(\widehat{\log C_i - \log Y_i^R}\right)_{ne}\right] = \mathbb{E}\left[\left(\widehat{\log Y_{i,ne}^R} - \widehat{\log Y_{i,e}^R}\right)\right]$.

treatment and control groups to estimate the effect of the respective flat tax reforms.

3.4 Data

The size of the shadow economy is estimated using household budget surveys collected by statistical offices of respective countries, with exception of Russia. The Russian estimate is obtained using Russia Longitudinal Monitoring survey, RLMS-HSE, conducted by the Higher School of Economics and ZAO "Demoscope" together with the Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS.[13] Unfortunately, data for some years were not available for certain countries. The summary of the data for each country can be seen in Table 3.2.

Table 3.2: Summary of the Household Budget Surveys of respective countries

Country	Sample size (Households with working heads)	Years used in this study
Czech Republic	2,138-2,572	2000-2010
Slovakia	1,345-2,991	2000-2002; 2004-2010
Croatia	406-1,222	2000-2005; 2007
Serbia	988-2,494	2002; 2003; 2007
Ukraine	3,958-4,739	1999-2007
Russia	2,108-3,498	1998; 2000-2007
Armenia	4,527-5906	2004; 2007
Georgia	3,388-3,833	2003-2007

When choosing variables into $\mathbf{X}_i$ and $\mathbf{Z}_i$, our goal was to include similar characteristics for all countries (as the information set differs between the dataset). Thus, following our earlier work (Lichard et al., 2013), $\mathbf{X}_i$ contains information on preference shifters such as age of household head and spouse/partner (if any) and its square, number of adults of working age, retirees and children, education of head and spouse/partner and whether the head of household is female. Matrix $\mathbf{Z}_i$ includes information from $\mathbf{X}_i$ plus job characteristics for head and spouse: whether they are public/private employees or self-employed, whether they are blue or white collar workers, and the size of the company where they are employed and if it is foreign or domestic (this information is available only for Russia). We define disposable income Y_i^R as the total gross income of the household from all sources minus all taxes and obligatory payments (such as health insurance, which is technically a tax in most countries under study). To account for possible

[13]RLMS-HSE sites: http://www.cpc.unc.edu/projects/rlms-hse; http://www.hse.ru/org/hse/rlms

consumption smoothing and precautionary saving (which may be greater for certain types of households), net dissavings were included in income. We define consumption C_i as the sum of expenditures on non-durable goods, including expenditure on food both at home and away from home, alcohol and tobacco,[14] clothing and footwear, rents, utilities and other services. Thus, the implicit assumption in Equations (3.1)-(3.4) is that preferences over nondurables and durables are homothetic. This assumption is often used in the literature (see Eichenbaum & Hansen, 1990; Ogaki & Reinhart, 1998; and Gorodnichenko et al., 2009). Moreover, in our previous work (Lichard et al., 2013) we studied the sensitivity of our methodology to different measures of consumption (such as food only, nondurables excluding rent etc.) and to different exclusion restrictions – even estimating without any exclusion restrictions based on the functional form. The estimates of the shadow economy were robust to these modifications of assumptions.

3.5 Results

The evolution of the shadow economy over time in the pairs of countries can be seen in Figures 3.1-3.4.[15] These figures show the evolution of the shadow economy over time as a share of income reported in the survey and as a share of estimated true income, respectively. The results of t-tests of difference in differences estimators (Table 3.3) do not seem to support the claims of flat tax proponents about its effect on the tax evasion. With the exception of Russia (7 percentage points decrease) and Serbia (14.8 percentage point decrease), the shadow economy either remained the same or even slightly increased, as in the case of Slovakia (by 4.2 percentage points). It is important to note is that our estimate for the effect of Russian flat tax reform (7%-11% decrease with standard errors of 1.7%) is not significantly different from the result obtained by Gorodnichenko et al. (2009), who found around 9-12 percentage point decrease (depending on specification) with standard errors of approximately three percent.

Thus, our estimates do not show a significant decrease in tax evasion after the flat tax reform in most countries. This result is difficult to explain by differences between pre-reform marginal tax rates and the adopted flat tax rate, as Russia and Serbia did not experience significantly higher drops in marginal tax rates than other countries under

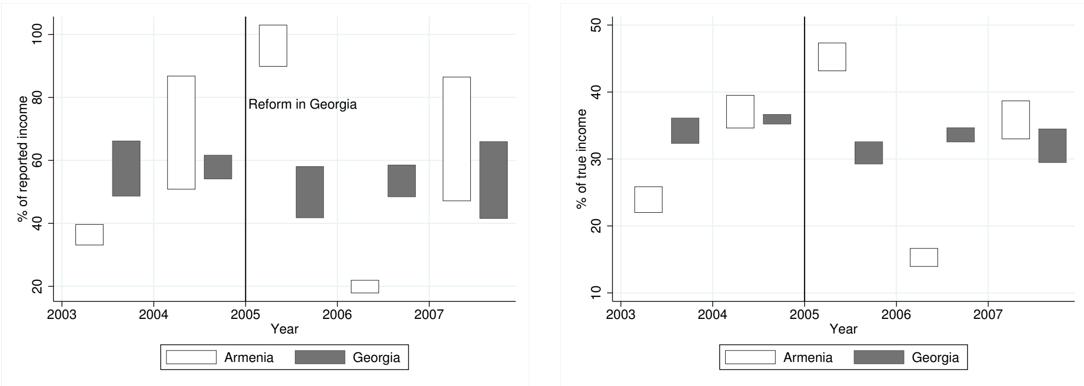
[14]We recognize that consumption of alcohol and tobacco is likely to be under-reported (Stockwell et al., 2004) but have no reason to believe that this underreporting is correlated with underreporting of income.

[15]Detailed results of the maximum likelihood estimations for all countries are available upon request.

study (see Table 3.1).

Figure 3.1: Shadow economy in Armenia and Georgia

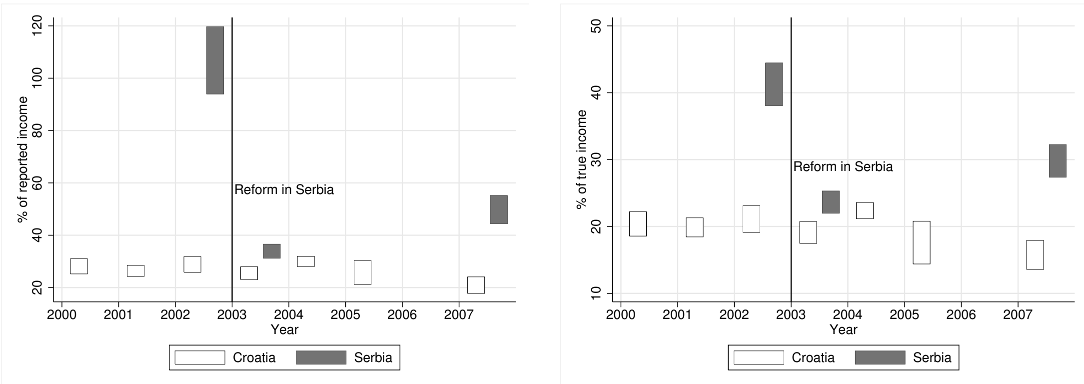
(a) As a percentage of reported income **(b)** As a percentage of total income



Bars represent 95% confidence intervals

Figure 3.2: Shadow economy in Croatia and Serbia

(a) As a percentage of reported income **(b)** As a percentage of total income



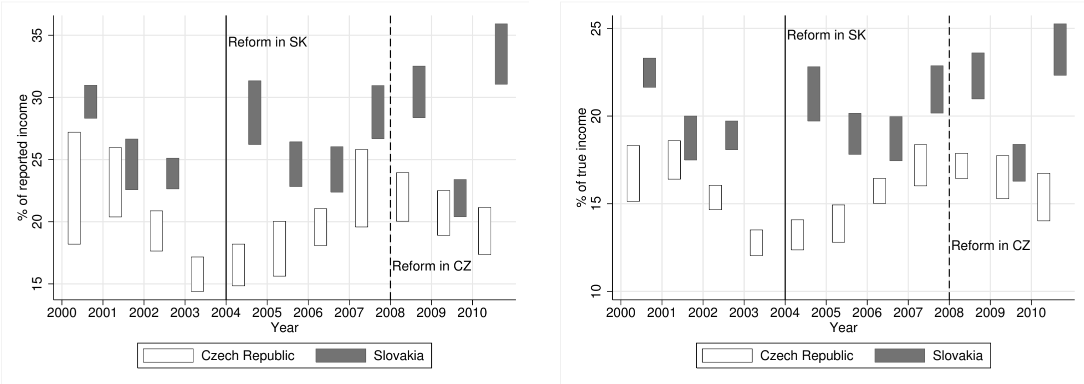
Bars represent 95% confidence intervals

Table 3.3: Estimates of the changes in the size of the shadow economy

	Year of the reform included			Year of the reform excluded		
	Diff-in-diff	SE	p-value	Diff-in-diff	SE	p-value
Czech Rep	0.675	0.806	0.402	-0.965	0.823	0.241
Slovakia	4.180	0.781	0.000	1.649	0.747	0.027
Russia	-7.039	1.674	0.000	-11.150	1.667	0.000
Ukraine	2.573	1.661	0.121	-1.815	1.525	0.234
Georgia	-3.271	14.015	0.815	-2.032	14.015	0.885
Serbia	-14.791	2.461	0.000	-9.525	2.494	0.000

Figure 3.3: Shadow economy in the Czech Republic and Slovakia

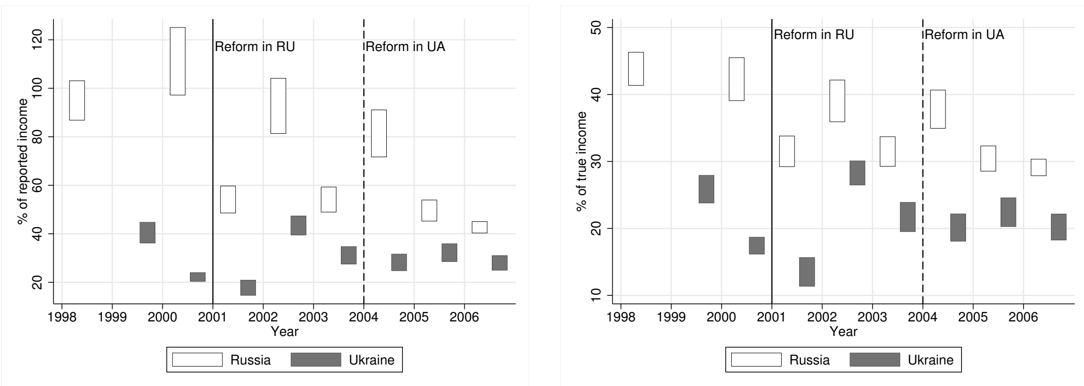
(a) As a percentage of reported income **(b)** As a percentage of total income



Bars represent 95% confidence intervals

Figure 3.4: Shadow economy in Russia and Ukraine

(a) As a percentage of reported income **(b)** As a percentage of total income



Bars represent 95% confidence intervals

More likely, our results may suggest that the marginal tax rate alone may not be the most important driver of the size of the shadow economy. As Hanousek and Palda (2004) argue, tax evasion is highly correlated with the satisfaction of taxpayers with the government. To see if there is some support for this hypothesis, we can turn to a widely used survey of values, the European Value Survey (EVS, 2011). EVS is a longitudinal survey that tracks preferences, attitudes, values, and opinions about various aspects of respondents' lives across a multitude of countries. Unfortunately, two out of five countries that adopted the flat tax reform are not present in the third wave of the EVS (1999), making any rigorous statistical analysis almost impossible.[16] Thus, we make the following points with caution.

Table 3.4 compares the changes in respondents' answers to questions about attitudes towards government, civil service, accepting a bribe, cheating on taxes and paying cash to avoid taxes between 1999 and 2008.[17] We conducted two tests. The first test is a classical difference in mean test (and the sign of this test indicates the direction of the change) conducted using Kendall's tau-b statistic. It is presented in the first row for each country. The second test is a (non-parametric) Pearson chi-square test, with p-values in the second row. Let us note that first three columns correspond to different measures of satisfaction with government services. Because in both cases we test the difference between the fourth and third wave, Table 3.4 clearly indicates improvement in satisfaction if (a) and (c) columns are negative and (b) column is positive. Positive values in the remaining three columns (justification of accepting a bribe, cheating on taxes and paying cash to avoid taxes) imply deterioration, while negative values indicate improvement.

It is clear that countries that do not show a significant change in tax evasion experienced a deterioration (or at least no change) in several of these dimensions. While the Czech Republic saw a slight improvement in attitudes towards unjustified claim of benefits, tax evasion and corruption, the change in other dimensions being insignificant, in Slovakia the attitudes in all dimensions except unjustified claiming of benefits worsened significantly. In Ukraine, only confidence in civil service and satisfaction with democracy went up. All other dimensions worsened. This result is in stark contrast to Russia, where all measures directly connected to the perception of governance quality (confidence in civil service,

[16] Overall, three out of eight countries in our sample were not included in the third round of the EVS: Armenia, Georgia and Serbia.

[17] Detailed structure of answers can be found in the Appendix.

Table 3.4: Pearson test of change in attitudes concerning satisfaction with government, cheating, evasion, and corruption (Wave 4 and 3 of the EVS).

	(a)	(b)	(c)	(d)	(e)	(f)
Armenia†	.	.	.	.	.	.
Croatia	0.061	0.665***	-0.174***	0.029	-0.095	0.398***
	0.304	0.000	0.000	0.243	0.338	0.006
Czech Rep	-0.131***	0.474***	-0.008	0.444***	0.578***	1.006***
	0.008	0.000	0.070	0.000	0.000	0.000
Georgia†	.	.	.	.	.	.
Russia	-0.307***	2.714***	-0.731***	0.504***	0.280**	0.314**
	0.000	0.000	0.000	0.000	0.014	0.030
Serbia†	.	.	.	.	.	.
Slovakia	-0.276***	1.674***	-0.392***	-0.322***	0.307***	-0.299**
	0.000	0.000	0.000	0.614	0.000	0.684
Ukraine	0.156***	-0.375***	0.051	-0.340***	-0.973***	-0.856***
	0.000	0.023	0.075	0.000	0.000	0.000

The columns correspond to the following survey questions:
(a) How much confidence in: civil service (1-most – 4-none)
(b) View of government (1-very bad – 10-very good)
(c) Are you satisfied with democracy (1-most satisfied – 4-least satisfied)
(d) Do you justify: accepting a bribe (1-never – 10-always)
(e) Do you justify: cheating on tax (1-never – 10-always)
(f) Do you justify: paying cash to avoid taxes (1-never – 10-always)
†Armenia, Georgia and Serbia were not included in the third wave.
Note: The first row contains the results of the standard test of mean differences in responses between two consecutive European Value Surveys (Waves 3 and 4), where *** implies $p<0.01$, and ** signifies $p<0.05$. The econd row contains p-values of the Pearson chi-square non-parametric test of the same null hypothesis, i.e., that there was no change in responses between two consecutive European Value Surveys (Waves 3 and 4).

satisfaction with democracy, and view of government) went up more than in any other country. The results presented in Table 3.4 thus indicate that there may be a synergistic effect of satisfaction with public services and marginal tax rate decreases when it comes to the shadow economy, where countries with higher satisfaction with public policies benefit more from flat tax reforms (Russia) than countries where the satisfaction has a downward trend (Slovakia).[18] This idea is corroborated by Table 3.5, which summarizes Transparency International's Corruption Perception Index and our estimates of the size of the shadow economy for 2007. Spearman's correlation coefficient between these two measures is -0.55,[19] which implies that countries with higher CPI (i.e. with less perceived corruption) tend to have smaller shadow economies. This is an intuitive result that fits into the narrative of the overall effect of tax morale. All the above results suggest that there can be a nontrivial interaction between satisfaction with public services and changes in marginal tax rates influencing the size of the shadow economy. Moreover, these results support tax morale as an important determinant of hidden economic activity.

Table 3.5: Shadow economy estimates and CPI in 2007

Country	% of reported income	CPI
Armenia	67%	3
Croatia	21%	4.1
Czech Republic	23%	5.2
Georgia	54%	3.4
Russia	43% (2006)	2.3
Serbia	50%	3.4
Slovakia	29%	4.9
Ukraine	35%	2.7

3.5.1 Cyclicality of the shadow economy

Another interesting feature of our results is an apparent cyclical pattern, which could suggest a connection to business cycles as measured by the official income statistics. Many theoretical models imply that the share of declared income is a function of actual income, although these models often find the relationship ambiguous[20]. Empirically, however, there

[18] One can of course argue that satisfaction with public services is endogenous to tax system features, but it is not the most important determinant by far, as flat tax reform is a feature common to all countries in question.

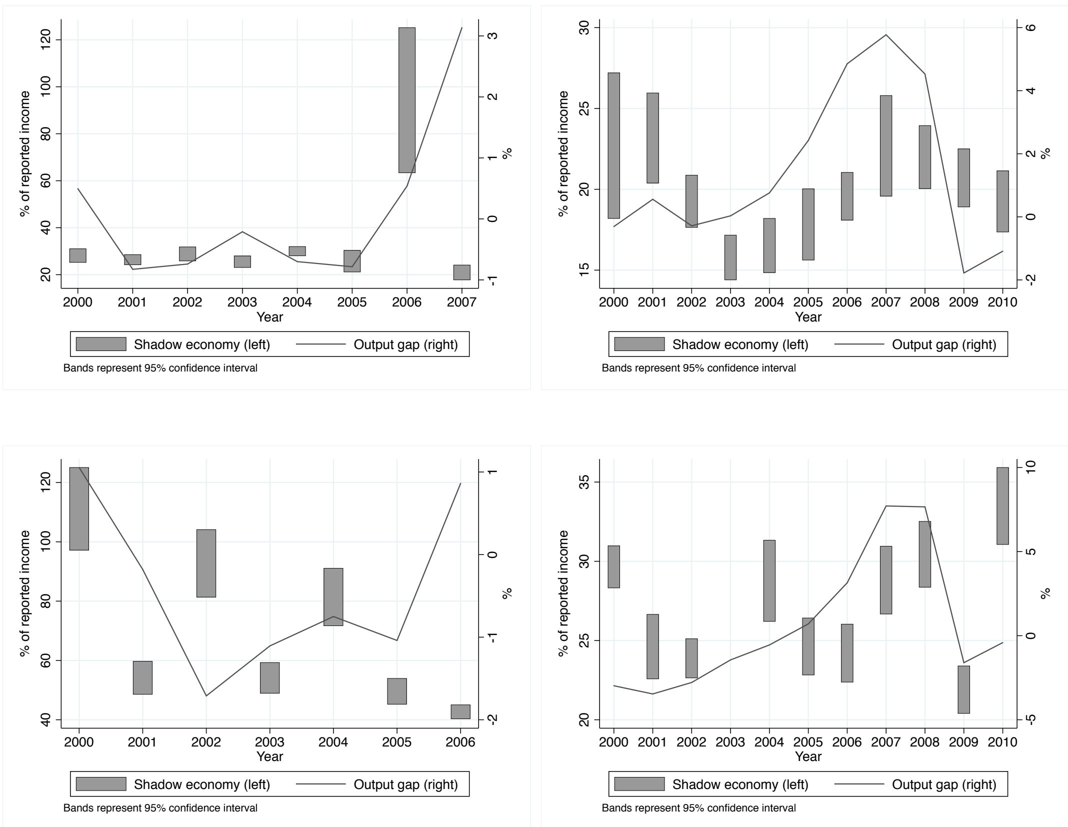
[19] Although due to the low number of observations, the estimate's p-value is slightly above 10%, so any conclusion here is made with caution.

[20] For example, in the seminal Allingham and Sandmo (1972) model, the sign of the effect depends on whether the relative risk aversion is constant, decreasing, or increasing.

is a strong previous evidence that cyclical components of hidden and official economies are not only positively correlated, but several studies found have found Granger causality going from measured to hidden GDP (Giles, 1997b; Bajada, 2003; Giles, 1997a; Giles, Tedds, & Werkneh, 2002). Our results exhibit a similar positive association, as can be seen in Figure 3.5, which shows plotted the cyclical component of GDP estimated through a Hodrick-Prescott filter and our estimates of the shadow economy for countries for which we had at least six years of data. However, because not even these countries have a sufficient number of observations to implement more sophisticated Granger causality tests as in the above studies, we did a simple correlation between the cyclical component and our estimates instead. Table 3.6 shows that most countries exhibit positive correlations, which is in line with the previous research. The only country exhibiting negative association is Russia, which is probably due to the decrease in tax evasion caused by the introduction of the flat tax reform.

Figure 3.5: Cyclicality of official and hidden GDP

(a) Croatia **(b)** Czech Republic



(c) Russia **(d)** Slovakia

Table 3.6: Correlation between the cyclical component of GDP and the hidden economy

Country	Correlation
Croatia	0.246
Ukraine	0.419
Russia	-0.663
Czech Rep	0.324
Slovakia	0.299

3.6 Conclusion

This paper estimates the tax evasion effect of flat tax reforms in selected transition countries. Our results do not show much empirical support for an often proposed advantage of the flat tax reform – a decrease in tax evasion. We find indications that there are more important factors that determine the size of the shadow economy. More precisely, satisfaction with government and quality of public services seems to be driving some of the changes in income underreporting in the countries under study, which is consistent with previous literature on tax morale. The main insight for policy is that flat tax reforms are not a surefire way to decrease the size of the shadow economy, as there seems to be an interaction between the satisfaction of individuals with public policies and moderate decreases of the marginal tax rate. In countries, where satisfaction decreased and corruption increased, flat tax reform does not seem to have a large effect. This suggests that a fight against shadow economy is ineffective without efforts to increase the perceived efficiency and quality of public services, and to decrease perceived corruption. Moreover, in line with previous research, we show that our estimates of the shadow economy size exhibit procyclicality. However, we admit the limited scope of our evidence and thus further research into the interaction is needed to confirm the phenomenon.

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Table 3.7: Czech Republic

good/bad: more respect for authority

EVS-wave	good		don't mind		bad		Total
	No.	%	No.	%	No.	%	No.
1999-2001	441.0	46.8	259.0	27.5	242.0	25.7	942.0
2008-2010	433.0	52.1	231.0	27.8	167.0	20.1	831.0
Total	874.0	49.3	490.0	27.6	409.0	23.1	1,773.0
Pearson chi2(2) =	8.5104	Pr =	0.014				

how much confidence in: civil service

EVS-wave	a great deal		quite a lot		not very much		none at all		Total
	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	15.0	1.5	186.0	18.2	676.0	66.3	143.0	14.0	1,020.0
2008-2010	40.0	4.4	275.0	30.0	432.0	47.2	169.0	18.4	916.0
Total	55.0	2.8	461.0	23.8	1,108.0	57.2	312.0	16.1	1,936.0
Pearson chi2(3) =	79.0868	Pr =	0.000						

are you satisfied with democracy

EVS-wave	very satisfied		rather satisfied		not very satisfied		not at all satisfied		Total
	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	10.0	1.0	389.0	38.3	510.0	50.2	106.0	10.4	1,015.0
2008-2010	17.0	1.9	363.0	40.0	409.0	45.0	119.0	13.1	908.0
Total	27.0	1.4	752.0	39.1	919.0	47.8	225.0	11.7	1,923.0
Pearson chi2(3) =	8.6380	Pr =	0.035						

view government: very bad-very good

EVS-wave	bad																		very good		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	68.0	6.7	83.0	8.1	209.0	20.5	214.0	21.0	202.0	19.8	125.0	12.3	83.0	8.1	32.0	3.1	3.0	0.3	0.0	0.0	1,019.0
2008-2010	72.0	7.7	68.0	7.3	130.0	13.9	142.0	15.2	182.0	19.5	137.0	14.7	124.0	13.3	64.0	6.8	12.0	1.3	4.0	0.4	935.0
Total	140.0	7.2	151.0	7.7	339.0	17.3	356.0	18.2	384.0	19.7	262.0	13.4	207.0	10.6	96.0	4.9	15.0	0.8	4.0	0.2	1,954.0
Pearson chi2(9) =	60.8563	Pr =	0.000																		

Table 3.8: Czech Republic

do you justify: claiming state benefits

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	660.0	64.6	170.0	16.6	82.0	8.0	37.0	3.6	35.0	3.4	15.0	1.5	13.0	1.3	4.0	0.4	3.0	0.3	3.0	0.3	1,022.0
2008-2010	450.0	48.0	152.0	16.2	109.0	11.6	52.0	5.5	71.0	7.6	36.0	3.8	22.0	2.3	22.0	2.3	14.0	1.5	9.0	1.0	937.0
Total	1,110.0	56.7	322.0	16.4	191.0	9.7	89.0	4.5	106.0	5.4	51.0	2.6	35.0	1.8	26.0	1.3	17.0	0.9	12.0	0.6	1,959.0
Pearson chi2(9) =	89.3278	Pr =	0.000																		

do you justify: cheating on tax

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	552.0	54.0	187.0	18.3	113.0	11.1	49.0	4.8	58.0	5.7	23.0	2.3	18.0	1.8	12.0	1.2	2.0	0.2	8.0	0.8	1,022.0
2008-2010	414.0	44.1	151.0	16.1	124.0	13.2	60.0	6.4	66.0	7.0	39.0	4.2	33.0	3.5	24.0	2.6	15.0	1.6	12.0	1.3	938.0
Total	966.0	49.3	338.0	17.2	237.0	12.1	109.0	5.6	124.0	6.3	62.0	3.2	51.0	2.6	36.0	1.8	17.0	0.9	20.0	1.0	1,960.0
Pearson chi2(9) =	45.4508	Pr =	0.000																		

do you justify: accepting a bribe

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	488.0	47.7	230.0	22.5	117.0	11.4	54.0	5.3	61.0	6.0	24.0	2.3	20.0	2.0	14.0	1.4	5.0	0.5	9.0	0.9	1,022.0
2008-2010	391.0	42.0	166.0	17.8	119.0	12.8	71.0	7.6	69.0	7.4	43.0	4.6	27.0	2.9	22.0	2.4	14.0	1.5	10.0	1.1	932.0
Total	879.0	45.0	396.0	20.3	236.0	12.1	125.0	6.4	130.0	6.7	67.0	3.4	47.0	2.4	36.0	1.8	19.0	1.0	19.0	1.0	1,954.0
Pearson chi2(9) =	32.3163	Pr =	0.000																		

do you justify: paying cash to avoid taxes

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	406.0	40.1	213.0	21.0	163.0	16.1	81.0	8.0	79.0	7.8	35.0	3.5	15.0	1.5	10.0	1.0	4.0	0.4	7.0	0.7	1,013.0
2008-2010	271.0	29.4	105.0	11.4	149.0	16.2	98.0	10.6	119.0	12.9	62.0	6.7	46.0	5.0	34.0	3.7	21.0	2.3	17.0	1.8	922.0
Total	677.0	35.0	318.0	16.4	312.0	16.1	179.0	9.3	198.0	10.2	97.0	5.0	61.0	3.2	44.0	2.3	25.0	1.3	24.0	1.2	1,935.0
Pearson chi2(9) =	122.0004	Pr =	0.000																		

Table 3.9: Russia

good/bad: more respect for authority

EVS-wave	good		don't mind		bad		Total
	No.	%	No.	%	No.	%	No.
1999-2001	669.0	56.9	423.0	36.0	84.0	7.1	1,176.0
2008-2010	422.0	56.6	257.0	34.5	67.0	9.0	746.0
Total	1,091.0	56.8	680.0	35.4	151.0	7.9	1,922.0
Pearson chi2(2) =	2.2694	Pr =	0.322				

how much confidence in: civil service

EVS-wave	a great deal		quite a lot		not very much		none at all		Total
	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	41.0	3.3	420.0	34.2	504.0	41.0	263.0	21.4	1,228.0
2008-2010	81.0	9.7	359.0	43.0	293.0	35.1	102.0	12.2	835.0
Total	122.0	5.9	779.0	37.8	797.0	38.6	365.0	17.7	2,063.0
Pearson chi2(3) =	72.5346	Pr =	0.000						

are you satisfied with democracy

EVS-wave	very satisfied		rather satisfied		not very satisfied		not at all satisfied		Total
	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	6.0	0.5	92.0	7.4	544.0	43.6	605.0	48.5	1,247.0
2008-2010	31.0	4.0	289.0	37.1	363.0	46.7	95.0	12.2	778.0
Total	37.0	1.8	381.0	18.8	907.0	44.8	700.0	34.6	2,025.0
Pearson chi2(3) =	441.5043	Pr =	0.000						

view government: very bad-very good

EVS-wave	bad																		very good		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	472.0	36.4	192.0	14.8	285.0	22.0	132.0	10.2	149.0	11.5	33.0	2.5	21.0	1.6	12.0	0.9	2.0	0.2	0.0	0.0	1,298.0
2008-2010	46.0	5.6	40.0	4.9	65.0	7.9	85.0	10.3	189.0	22.9	156.0	18.9	127.0	15.4	76.0	9.2	17.0	2.1	23.0	2.8	824.0
Total	518.0	24.4	232.0	10.9	350.0	16.5	217.0	10.2	338.0	15.9	189.0	8.9	148.0	7.0	88.0	4.1	19.0	0.9	23.0	1.1	2,122.0
Pearson chi2(9) =	773.1784	Pr =	0.000																		

Table 3.10: Russia

do you justify: claiming state benefits

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	735.0	57.8	156.0	12.3	114.0	9.0	63.0	5.0	101.0	7.9	29.0	2.3	20.0	1.6	23.0	1.8	11.0	0.9	20.0	1.6	1,272.0
2008-2010	371.0	44.3	75.0	9.0	87.0	10.4	65.0	7.8	106.0	12.7	50.0	6.0	33.0	3.9	18.0	2.2	6.0	0.7	26.0	3.1	837.0
Total	1,106.0	52.4	231.0	11.0	201.0	9.5	128.0	6.1	207.0	9.8	79.0	3.7	53.0	2.5	41.0	1.9	17.0	0.8	46.0	2.2	2,109.0
Pearson chi2(9) =	77.1734	Pr =	0.000																		

do you justify: cheating on tax

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	568.0	44.3	128.0	10.0	123.0	9.6	81.0	6.3	156.0	12.2	44.0	3.4	54.0	4.2	56.0	4.4	18.0	1.4	54.0	4.2	1,282.0
2008-2010	345.0	40.2	75.0	8.7	83.0	9.7	58.0	6.8	110.0	12.8	50.0	5.8	50.0	5.8	30.0	3.5	16.0	1.9	42.0	4.9	859.0
Total	913.0	42.6	203.0	9.5	206.0	9.6	139.0	6.5	266.0	12.4	94.0	4.4	104.0	4.9	86.0	4.0	34.0	1.6	96.0	4.5	2,141.0
Pearson chi2(9) =	14.8549	Pr =	0.095																		

do you justify: accepting a bribe

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	896.0	68.3	134.0	10.2	102.0	7.8	49.0	3.7	67.0	5.1	18.0	1.4	12.0	0.9	12.0	0.9	8.0	0.6	13.0	1.0	1,311.0
2008-2010	497.0	58.0	104.0	12.1	58.0	6.8	47.0	5.5	57.0	6.7	31.0	3.6	19.0	2.2	19.0	2.2	13.0	1.5	12.0	1.4	857.0
Total	1,393.0	64.3	238.0	11.0	160.0	7.4	96.0	4.4	124.0	5.7	49.0	2.3	31.0	1.4	31.0	1.4	21.0	1.0	25.0	1.2	2,168.0
Pearson chi2(9) =	45.7930	Pr =	0.000																		

do you justify: paying cash to avoid taxes

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	451.0	36.7	135.0	11.0	140.0	11.4	97.0	7.9	175.0	14.3	50.0	4.1	40.0	3.3	55.0	4.5	26.0	2.1	59.0	4.8	1,228.0
2008-2010	304.0	37.1	62.0	7.6	79.0	9.6	55.0	6.7	109.0	13.3	43.0	5.2	54.0	6.6	44.0	5.4	24.0	2.9	46.0	5.6	820.0
Total	755.0	36.9	197.0	9.6	219.0	10.7	152.0	7.4	284.0	13.9	93.0	4.5	94.0	4.6	99.0	4.8	50.0	2.4	105.0	5.1	2,048.0
Pearson chi2(9) =	24.8342	Pr =	0.003																		

Table 3.11: Slovakia

good/bad: more respect for authority

EVS-wave	good		don't mind		bad		Total
	No.	%	No.	%	No.	%	No.
1999-2001	479.0	67.2	152.0	21.3	82.0	11.5	713.0
2008-2010	380.0	66.7	160.0	28.1	30.0	5.3	570.0
Total	859.0	67.0	312.0	24.3	112.0	8.7	1,283.0
Pearson chi2(2) =	20.0686	Pr =	0.000				

how much confidence in: civil service

EVS-wave	a great deal		quite a lot		not very much		none at all		Total
	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	13.0	1.8	270.0	36.8	346.0	47.1	105.0	14.3	734.0
2008-2010	35.0	5.1	341.0	49.6	270.0	39.2	42.0	6.1	688.0
Total	48.0	3.4	611.0	43.0	616.0	43.3	147.0	10.3	1,422.0
Pearson chi2(3) =	53.2781	Pr =	0.000						

are you satisfied with democracy

EVS-wave	very satisfied		rather satisfied		not very satisfied		not at all satisfied		Total
	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	4.0	0.5	186.0	24.4	401.0	52.6	171.0	22.4	762.0
2008-2010	13.0	1.9	318.0	46.8	291.0	42.9	57.0	8.4	679.0
Total	17.0	1.2	504.0	35.0	692.0	48.0	228.0	15.8	1,441.0
Pearson chi2(3) =	109.4039	Pr =	0.000						

view government: very bad-very good

EVS-wave	bad																		very good		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	91.0	11.9	98.0	12.8	150.0	19.6	139.0	18.2	149.0	19.5	81.0	10.6	42.0	5.5	10.0	1.3	2.0	0.3	3.0	0.4	765.0
2008-2010	16.0	2.4	25.0	3.8	57.0	8.6	57.0	8.6	175.0	26.5	132.0	20.0	110.0	16.6	60.0	9.1	20.0	3.0	9.0	1.4	661.0
Total	107.0	7.5	123.0	8.6	207.0	14.5	196.0	13.7	324.0	22.7	213.0	14.9	152.0	10.7	70.0	4.9	22.0	1.5	12.0	0.8	1,426.0
Pearson chi2(9) =	263.9635	Pr =	0.000																		

Table 3.12: Slovakia

do you justify: claiming state benefits

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	303.0	39.2	159.0	20.6	86.0	11.1	59.0	7.6	63.0	8.2	36.0	4.7	21.0	2.7	21.0	2.7	11.0	1.4	14.0	1.8	773.0
2008-2010	262.0	37.9	102.0	14.7	77.0	11.1	85.0	12.3	94.0	13.6	34.0	4.9	15.0	2.2	5.0	0.7	6.0	0.9	12.0	1.7	692.0
Total	565.0	38.6	261.0	17.8	163.0	11.1	144.0	9.8	157.0	10.7	70.0	4.8	36.0	2.5	26.0	1.8	17.0	1.2	26.0	1.8	1,465.0
Pearson chi2(9) =	34.8918	Pr =	0.000																		

do you justify: cheating on tax

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	467.0	60.2	127.0	16.4	51.0	6.6	29.0	3.7	42.0	5.4	17.0	2.2	15.0	1.9	10.0	1.3	5.0	0.6	13.0	1.7	776.0
2008-2010	339.0	48.5	105.0	15.0	59.0	8.4	76.0	10.9	83.0	11.9	17.0	2.4	6.0	0.9	7.0	1.0	3.0	0.4	4.0	0.6	699.0
Total	806.0	54.6	232.0	15.7	110.0	7.5	105.0	7.1	125.0	8.5	34.0	2.3	21.0	1.4	17.0	1.2	8.0	0.5	17.0	1.2	1,475.0
Pearson chi2(9) =	63.2857	Pr =	0.000																		

do you justify: accepting a bribe

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	300.0	38.7	145.0	18.7	87.0	11.2	48.0	6.2	75.0	9.7	47.0	6.1	27.0	3.5	16.0	2.1	11.0	1.4	20.0	2.6	776.0
2008-2010	291.0	41.4	103.0	14.7	92.0	13.1	70.0	10.0	105.0	14.9	20.0	2.8	12.0	1.7	3.0	0.4	4.0	0.6	3.0	0.4	703.0
Total	591.0	40.0	248.0	16.8	179.0	12.1	118.0	8.0	180.0	12.2	67.0	4.5	39.0	2.6	19.0	1.3	15.0	1.0	23.0	1.6	1,479.0
Pearson chi2(9) =	54.3972	Pr =	0.000																		

do you justify: paying cash to avoid taxes

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	171.0	22.2	124.0	16.1	119.0	15.5	67.0	8.7	119.0	15.5	45.0	5.9	42.0	5.5	39.0	5.1	19.0	2.5	24.0	3.1	769.0
2008-2010	185.0	26.7	97.0	14.0	99.0	14.3	70.0	10.1	134.0	19.3	44.0	6.3	25.0	3.6	12.0	1.7	8.0	1.2	20.0	2.9	694.0
Total	356.0	24.3	221.0	15.1	218.0	14.9	137.0	9.4	253.0	17.3	89.0	6.1	67.0	4.6	51.0	3.5	27.0	1.8	44.0	3.0	1,463.0
Pearson chi2(9) =	26.3273	Pr =	0.002																		

Table 3.13: Ukraine

good/bad: more respect for authority

EVS-wave	good		don't mind		bad		Total
	No.	%	No.	%	No.	%	No.
1999-2001	338.0	66.5	137.0	27.0	33.0	6.5	508.0
2008-2010	353.0	59.7	176.0	29.8	62.0	10.5	591.0
Total	691.0	62.9	313.0	28.5	95.0	8.6	1,099.0
Pearson chi2(2) =	7.8138	Pr =	0.020				

how much confidence in: civil service

EVS-wave	a great deal		quite a lot		not very much		none at all		Total
	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	26.0	4.6	207.0	36.8	228.0	40.5	102.0	18.1	563.0
2008-2010	13.0	1.9	238.0	35.2	245.0	36.2	181.0	26.7	677.0
Total	39.0	3.1	445.0	35.9	473.0	38.1	283.0	22.8	1,240.0
Pearson chi2(3) =	18.8354	Pr =	0.000						

are you satisfied with democracy

EVS-wave	very satisfied		rather satisfied		not very satisfied		not at all satisfied		Total
	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	9.0	1.5	92.0	15.6	307.0	52.1	181.0	30.7	589.0
2008-2010	18.0	2.7	88.0	13.0	331.0	48.9	240.0	35.5	677.0
Total	27.0	2.1	180.0	14.2	638.0	50.4	421.0	33.3	1,266.0
Pearson chi2(3) =	6.1730	Pr =	0.103						

view government: very bad-very good

EVS-wave	bad																		very good		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	104.0	17.7	85.0	14.4	131.0	22.2	74.0	12.6	118.0	20.0	30.0	5.1	26.0	4.4	13.0	2.2	6.0	1.0	2.0	0.3	589.0
2008-2010	209.0	29.8	88.0	12.6	128.0	18.3	95.0	13.6	89.0	12.7	45.0	6.4	23.0	3.3	16.0	2.3	5.0	0.7	3.0	0.4	701.0
Total	313.0	24.3	173.0	13.4	259.0	20.1	169.0	13.1	207.0	16.0	75.0	5.8	49.0	3.8	29.0	2.2	11.0	0.9	5.0	0.4	1,290.0
Pearson chi2(9) =	36.3173	Pr =	0.000																		

Table 3.14: Ukraine

do you justify: claiming state benefits

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	273.0	47.2	72.0	12.5	46.0	8.0	47.0	8.1	52.0	9.0	21.0	3.6	23.0	4.0	16.0	2.8	9.0	1.6	19.0	3.3	578.0
2008-2010	457.0	65.9	50.0	7.2	39.0	5.6	36.0	5.2	52.0	7.5	18.0	2.6	17.0	2.5	12.0	1.7	3.0	0.4	9.0	1.3	693.0
Total	730.0	57.4	122.0	9.6	85.0	6.7	83.0	6.5	104.0	8.2	39.0	3.1	40.0	3.1	28.0	2.2	12.0	0.9	28.0	2.2	1,271.0
Pearson chi2(9) =	50.6628	Pr =	0.000																		

do you justify: cheating on tax

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	228.0	38.8	57.0	9.7	57.0	9.7	38.0	6.5	68.0	11.6	28.0	4.8	28.0	4.8	34.0	5.8	21.0	3.6	29.0	4.9	588.0
2008-2010	399.0	57.6	59.0	8.5	39.0	5.6	29.0	4.2	77.0	11.1	28.0	4.0	19.0	2.7	18.0	2.6	6.0	0.9	19.0	2.7	693.0
Total	627.0	48.9	116.0	9.1	96.0	7.5	67.0	5.2	145.0	11.3	56.0	4.4	47.0	3.7	52.0	4.1	27.0	2.1	48.0	3.7	1,281.0
Pearson chi2(9) =	60.6777	Pr =	0.000																		

do you justify: accepting a bribe

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	379.0	62.6	78.0	12.9	37.0	6.1	35.0	5.8	45.0	7.4	6.0	1.0	11.0	1.8	6.0	1.0	1.0	0.2	7.0	1.2	605.0
2008-2010	555.0	77.5	35.0	4.9	32.0	4.5	25.0	3.5	39.0	5.4	13.0	1.8	5.0	0.7	4.0	0.6	4.0	0.6	4.0	0.6	716.0
Total	934.0	70.7	113.0	8.6	69.0	5.2	60.0	4.5	84.0	6.4	19.0	1.4	16.0	1.2	10.0	0.8	5.0	0.4	11.0	0.8	1,321.0
Pearson chi2(9) =	50.8645	Pr =	0.000																		

do you justify: paying cash to avoid taxes

EVS-wave	never		2		3		4		5		6		7		8		9		always		Total
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.
1999-2001	212.0	38.8	39.0	7.1	50.0	9.2	36.0	6.6	76.0	13.9	39.0	7.1	24.0	4.4	25.0	4.6	11.0	2.0	34.0	6.2	546.0
2008-2010	354.0	54.7	42.0	6.5	43.0	6.6	34.0	5.3	83.0	12.8	33.0	5.1	14.0	2.2	13.0	2.0	6.0	0.9	25.0	3.9	647.0
Total	566.0	47.4	81.0	6.8	93.0	7.8	70.0	5.9	159.0	13.3	72.0	6.0	38.0	3.2	38.0	3.2	17.0	1.4	59.0	4.9	1,193.0
Pearson chi2(9) =	38.1158	Pr =	0.000																		

Chapter 4

Sand in the Wheels or Wheels in the Sand? Tobin Taxes and Market Crashes[1]

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Abstract

The recent economic crisis revived interest in financial transaction taxes (FTTs) as a means to offset negative risk externalities. However, up-to-date academic research does not provide sufficient insights into the effects of transaction taxes on financial markets as the literature has here-to-fore been focused too narrowly on Gaussian variance as a measure of volatility. In this paper, we argue that it is imperative to understand the relationship between price jumps, Gaussian variance, and FTTs. While Gaussian variance is not necessarily a problem in itself, the non-normality of return distribution caused by price jumps affects not only the performance of many risk-hedging algorithms but directly influences the frequency of catastrophic market events. To study the aforementioned relationship, we use an agent-based model of financial markets. Its results show that the relationship between FTTs and price jumps is intricate. This result implies that regulators may face a trade-off between overall variance and price jumps when designing optimal tax.

4.1 Introduction

James Tobin first proposed a tax on spot conversions of one currency into another (Tobin, 1978) in the aftermath of the Bretton-Woods system break-up, as a way to mitigate short-term financial round-trip excursions into another currency. His intention was "to throw some sand in the wheels of our excessively efficient international money markets" (p.154). He and his co-authors offered more arguments in favor of the tax in Eichengreen, Tobin, and Wyplosz (1995). But Tobin's idea was just a specific application of Keynes's idea of a tax on transactions mitigating the effect of speculation on financial markets (Keynes, 2006). However, the name 'Tobin tax' is today often used to denote not only foreign exchange transaction taxes, but financial transaction taxes (FTTs) in general. Therefore, the following text uses these terms interchangeably.

The debate on the merits of Tobin-like taxes has not so far reached a definite conclusion. Proponents of the tax claim that an increased transaction cost affects short-term high volume trading (speculation) more than long-term positions, decreasing market volatility and thus potential for crashes. In this regard, the tax can be thought of as a Pigovian tax on a negative risk externality, as increased volatility can decrease welfare and efficiency. Opponents of the Tobin tax generally claim that it can, in fact, increase volatility by decreasing market liquidity, or that speculative trading serves to stabilize prices around the long-run equilibrium. Although recently the debate has been gaining new traction in political circles, it is often driven more by ideology and politics rather than rigorous academic research. The academic debate has been historically driven mostly by theoretical models, although more recently, simulation and empirical studies have been gaining some ground. However, both theoretical predictions and empirical evidence are so far mixed.[2]

The principal contribution of this paper is to study the relationship between price jumps and variance, and how transaction taxes affect them – a point that has been so far rather ignored in the literature. We will show that the relationship of Gaussian variance, price jumps, and liquidity is not straightforward. More precisely, we show that while volatility (as measured by standard deviation of prices) can go down with changes in the tax rate, while the number of price jumps can go up. Given that price jumps are non-linear phenomena, they are connected to black swan events, such as market crashes. Thus, they should be a focus of any research that aims to study market stability.

The rest of the paper is organized as follows. We discuss how our work relates to the

[2]See McCulloch and Pacillo (2011) and Matheson (2012) for a discussion of previous research.

current literature in Section 4.2. We describe the agent-based model for a simulation of the artificial financial markets in Section 4.3. Furthermore, in Subsection 4.3.3, we model the impact of the FTT on the price process and provide estimators to quantify this effect. Sections 4.4–4.6 review the results of our analysis. We discuss the importance of the results and avenues for further research in Section 4.7.

4.2 Literature review

The arguments against the tax are often based on the efficient market hypothesis (EMH from now on; see Fama, 1965), which implies speculators cannot destabilize a market, as rational arbitrageurs would trade against them and drive prices towards their fundamental level. However, as De Long, Shleifer, Summers, and Waldmann (1990) showed in an early study, this result is not robust to the choice of arbitrageurs' risk aversion and length of their trading horizon, as more risk averse rational traders may not be willing to trade against noise traders. Another argument against FTTs claims that speculative trading provides liquidity and helps to incorporate new information into the prices. Opposing views argue that externalities, imperfect information, and other frictions may cause inefficiencies, and that in these cases, FTTs can help the economy reach the second best outcome. Furthermore, Farmer (2002) pointed out the dangers of applying rational expectations equilibrium models to financial markets, arguing that these models have trouble explaining the stylized facts of financial markets such as excess and clustered volatility, and speculative trading.This argument was one of the reasons for the development of literature focused on the microeconomic behavior of the financial market agents. Earlier examples of heterogeneous agent models include Palley (1999), who combined noise traders (which were shown in prior literature to increase volatility, see e.g. De Long et al., 1990) with the literature analyzing the Tobin tax. He identified conditions under which such a tax drives out noise traders, thus benefiting fundamental traders, lowering volatility, and leading to higher efficiency. Also, he concluded that there is a trade-off between costs and benefits because Tobin tax may discourage fundamental traders, as well. Westerhoff (2003) used a model with fundamentalist and chartist traders in foreign exchange markets. In this model, a low tax rate first crowds out chartism, but higher rates lead to misalignment due to a decreasing number of fundamentalists. Using a different approach, Mathevet and Steiner (2012) show in a dynamic global game that in an imperfect information setting transaction taxes may stop sudden investment reversals under certain conditions, thus increasing welfare.

The empirical evidence on this issue is scant (one of the reasons is that the tax has never been adopted in its true form as a global tax) and, as we will argue, methodologically problematic. The few papers that have attempted tried to estimate the effect empirically (estimating the effect of transaction taxes either on local foreign exchange or financial markets) offer support for all possible sides of the debate. Researchers who have found evidence against the transaction tax includes Umlauf (1993) who, based on time series data on equity returns in Sweden, found that by introducing transaction tax, the volatility measured by the conditional variance went up and trading volumes down. Moreover, the author argued that a significant amount of trading activity moved to London. However, it must be noted that the Swedish transaction tax of one percent (later increased to two percent) was higher[3] than what Tobin proposed originally (0.5 percent), and the author himself notes that "appropriate theoretical foundations are lacking" making the estimation imprecise, and he warns against "generalizing from a single data point" (*ibid.* p. 239). Aliber, Chowdhry, and Yan (2003) examined the effect of transaction costs in general on volatility (defined as the standard deviation of prices) in foreign exchange rates for four different currencies, and found a positive relationship as well. The opposite result, in support of proponents of the Tobin tax, can be found in Liu and Zhu (2009), who found that lowering transaction costs in Japan led to higher volatility, implying a negative correlation between transaction costs and volatility. Finally, a third set of literature has not found any significant effect—see e.g. Hu (1998), who studied the effects of stock transaction tax on market volatility and turnover taking advantage of 14 tax changes that occurred in the stock markets of Hong Kong, Japan, South Korea, and Taiwan during the period 1975-1994.

We see two major issues that are left rather unexplored. First, a scale effect arguably plays a major role (Tobin tax was meant to be a global tax). Small markets like Sweden do not have a significant impact on the world economy, so if speculative trading moves abroad, it does not alter the volatility on these foreign markets, but may very much hurt trade volumes domestically. However, if the market is large enough, there will be an impact on foreign markets as well. Second, perhaps more importantly, we argue that studies have ignored a significant source of information by focusing on conditional

[3]Note although the tax rate was initially 0.5 percent and later increased to one percent, this tax was nominally borne by both sides of the transaction, implying an overall tax rate of one and two percent, respectively.

variance as a single measure of volatility. Concerning the first point, some work has already been done. Westerhoff and Dieci (2006) studied the phenomenon in a model with heterogeneous agents, who can trade in different markets and can choose a trading strategy (e.g. a fundamentalist vs. chartist). The importance of strategies evolve over time according to their fitness. They find that the tax decreases volatility in the market where it was imposed, while increasing it in the other. The opposite effect of transaction tax on volatility in a two-market framework was obtained by Mannaro, Marchesi, and Setzu (2008), who used the methodology of agent-based models (ABMs). They used four types of traders with different strategies, who can trade in a maximum of two markets. However, the relative share of strategies is kept fixed exogenously, but agents may choose where to trade and whether to trade at all. On the other hand, one of the few more recent studies, Bianconi, Galla, Marsili, and Pin (2009), concluded that a transaction tax decreases volatility. Their ABM based on Minority Game framework used again fixed strategies that were randomly distributed across agents at the beginning of the simulation.

Our second—more important and thus far unexplored—point is that all of these studies focused on conditional Gaussian variance as a measure of volatility. They ignore an additional source of volatility—price jumps. The literature suggests (such as Merton, 1976, and Giot, Laurent, & Petitjean, 2010) that the volatility of most financial instruments can be decomposed into two parts: a regular Gaussian component and a price jump component. Many models that aim to estimate conditional variance, such as various GARCH models[4], ignore the price jump component while allowing the realized variance to deviate from the Gaussian distribution. However, as we show in this paper, the link between price jumps and conditional variance is not that straightforward—the measure of one may rise while the measure of the other decreases. A higher conditional variance is not necessarily a problem *per se* because it does not automatically lead to a leptokurtic return distribution. Fat tails, which have become a stylized fact of financial markets, are better explained by price jumps, so even if the transaction tax increases conditional variance, its effect on price jump frequency may be the opposite, thus making the distribution less fat-tailed. If this is the case, the tax would not only improve the prediction power of standard asset pricing models that use normal distribution but, given that catastrophic events are not Gaussian in nature, it would lead to a higher stability of financial markets. However, the relationship between transaction taxes and price jumps has heretofore been rather ignored in the literature.

[4] For an overview see Hamilton (1994).

This paper argues that it is crucial to understand the effect of the Tobin tax on price jumps. As Andersen, Benzoni, and Lund (2002) and Andersen, Bollerslev, and Diebold (2007) show, price jumps are present in the majority of price time series; therefore, their presence should be the subject of research. Price jumps can have a serious adverse impact on the predictive power of pricing formulae and on calculation of the estimates of the financial variables. Moreover, price jumps are a source of non-normality and may cause black-swan events on financial markets.[5]

While the presence of price jumps in the data is well established, the literature disagrees on their origin. One branch of literature (Merton, 1976; Lee & Mykland, 2008; Lahaye, Laurent, & Neely, 2011) considers new information a primary source of price jumps, while other authors, like Joulin, Lefevre, Grunberg, and Bouchaud (2008) and Bouchaud, Kockelkoren, and Potters (2006), conclude that price jumps are mainly caused by a local lack of liquidity with news announcements having a negligible effect. The third branch—behavioral finance literature (e.g. Shiller, 2005)—suggests that price jumps are caused by the behavior of market participants themselves. In order to analyze the two latter views, the ABM methodology is especially appropriate since it allows for the explicit modeling of interactions among market participants.

4.3 Modeling financial markets with transaction tax

This section introduces the framework used to model the financial transaction tax in financial markets and its impact on the distribution of log-returns with a special focus on extreme price movements. We use the agent-based computational model by Raberto, Cincotti, Focardi, and Marchesi (2003) and Mannaro et al. (2008). Their modeling framework replicates the stylized facts of financial returns and therefore, in the subsequent part, we implement recent understanding from financial econometrics to properly assess the response of the extreme price movements to the FTT.

4.3.1 The agent-based model

We study the relationship between the price process and the FTT using an agent-based model (ABM). ABMs are especially appropriate for studying the impact of FTTs on

[5]For illustrations of changes in the pricing formulae caused by price jumps see Pan (2002) or Broadie and Jain (2008). Brooks, Černý, and Miffre (2011) discuss the effect of higher moments on optimal allocations within a utility-based framework.

financial markets because:

1. They allow for the explicit modeling of said transactions (interactions);
2. They allow for the modeling of each agent independently.

Thus explicitly modeled micro interactions lead to the emergence of macro properties (a bottom-up approach). Our basic model is based on the methodology of Raberto et al. (2003) and Mannaro et al. (2008), who present an agent-based model of artificial ex ante heterogeneous traders, which leads to the price dynamics of financial assets satisfying the well-known stylized facts of clustering volatility, non-zero skewness, and higher kurtosis, or price jumps. In particular, we consider four types of agents based on their behavior: random traders, fundamentalist traders, momentum traders, and contrarian traders. We use the parameters calibrated by Raberto et al. (2003) and Mannaro et al. (2008) so that the price series generated match the usual stylized facts of financial markets. It is worth pointing out out that the four types of trading agents can be related to various types of institutional traders in the market ranging from noise retail traders to sophisticated hedge funds. To illustrate, the momentum traders can represent the real-world marginal retail investors following the moving averages, as well as the large algo funds, who employ advanced algorithms to capture the emergence of trend channels.

The agent-based modeling procedure itself is performed as follows (analogously to Lavička, Lin, & Novotný, 2010): We set initial conditions of the model including the number of interacting agents and various model-specific parameters described below. Then, we let the economy evolve step by step until a pre-determined number of steps (or trading days) is reached. At every step, we record the closing price, the overall traded amount of assets, the amount of assets sold and bought by each trader group, total demand and total supply by each trader group, wealth in each trader group, and the tax revenue.

In our specification, we assume that every agent acting in the markets is working in the same time scale. This means that every agent has the same computational and trading ability to react to the price movements. We stress this fact by denoting every such moment as a trading day. However, it is important to keep in mind that this is for presentation purposes only and every such step could be called a trading millisecond, which would seemingly mimic the "continuous-time" operations of current financial markets.

Finally, we assume fixed strategies for all the agents throughout the paper. This means that an agent cannot change the strategy as time passes based on the performance of such strategy. The reasons for this assumptions are three-fold. First, we want to observe the effect of the introduction of the FTT on the immediate markets. Keeping the same proportion of traders with different trading strategies allows us to understand the different pressure caused by the FTT on different trading strategies. Second, trading agents usually stick to one strategy and do not switch often. For instance, the macro hedge fund is not very likely to switch its trading strategy to high-frequency algorithmic trading as it would be too costly, and would send a misleading signal to potential investors. This does not mean that such a fund will not evolve; however, the development will rather be in the form of improvements to macro research and in experimentation with different macro models. Finally, the different agents with different strategies may represent the different parts of one legal entity. The professional trader will usually try a set of strategies and keep an independent track of them as it would be convenient for back-testing and risk management. Similarly, a large investment bank will have as its subsidiaries different hedge funds that will explore different strategies. These hedge funds will have independent accounting and will very likely be independent legal entities. As the agents differ in their wealth and all the trading strategies are proportional to the trading wealth, our model covers all of the above cases.

4.3.2 Trader types

Our artificial market consists of traders distributed into four groups based on their decision rules (random, fundamentalist, momentarian, and contrarian). At any given time t, an agent i is characterized by her cash holdings ($c_i(t)$) and asset holdings ($a_i(t)$), in addition to the strategy she follows.

Random traders Random traders (denoted as R) do not follow any particular strategy—with equal probability they issue a buy or a sell order. They are a proxy for traders that trade for their private reasons independent of the market situation, or who follow noisy information. Such a trader may include those who need to hedge their positions, institutional investors, or long-term traders who aim to trade over a horizon exceeding any of those considered in this study.

If random traders buy (sell), the limit price of their buy (sell) order is determined as:

$$l_i^b = p(t) \cdot X , \tag{4.1}$$

$$l_i^s = \frac{p(t)}{X}, \tag{4.2}$$

where $X \sim N(\mu, s_i)$ and $p(t)$ is the last market closing price. The standard deviation s_i of this Gaussian distribution is determined as:

$$s_i = k \cdot \sigma_i(\omega_i) , \tag{4.3}$$

where $\sigma_i(\omega_i)$ is the standard deviation of the log-returns computed based on window length following uniform distribution $\omega_i \sim U[2,5]$. Parameter k is the sensitivity of market traders to market volatility and is set to 1.9. As Mannaro et al. (2008) argue, the dependence on past variance simulates a GARCH-type memory. The problem may arise when s_i becomes so large that the realization of $N(\mu, s_i)$ becomes negative. We solve this problem by setting the sell or buy order to zero in these cases.

The traded amount is random and determined as follows:

$$q_i^b = U_N\left(0, \lfloor c_i(t)/l_i^b \rfloor\right) , \tag{4.4}$$

$$q_i^s = U(0, a_i(t)) , \tag{4.5}$$

where $\lfloor c_i(t)/l_i^b \rfloor$ is an integer-valued quantity denoting the maximum amount of stocks the trader is able to buy for the price l_i^b with $\lfloor X \rfloor$ denoting the highest integer smaller than X and $U_N(i,j)$ being an integer-valued uniform distribution, which draws integers between i and j, inclusively.

Fundamentalist traders Fundamentalist traders (F) base their decisions on their beliefs about the fundamental price of assets. Such traders are assumed to be endowed with enough faculty to process all available information ranging from macro-economic fundamentals to accounting variables. As a consequence, they have perfect knowledge of the fundamental price and try to arbitrage the difference between the current price and the fundamental price, as they know the system is mean reverting towards the fundamental price. Such traders include macro hedge funds or traders who closely follow particular companies/sectors.

If a fundamentalist trader i decides to buy or sell, he buys/sells the following amount of assets

$$q_i^b = \min\left(\left\lfloor\frac{c_i(t)}{p_f}\right\rfloor, \left\lfloor k\cdot\frac{|p(t)-p_f|}{p_f}\cdot\frac{c_i(t)}{p_f}\right\rfloor\right), \tag{4.6}$$

$$q_i^s = \min\left(a_i(t), \left\lfloor k\cdot\frac{|p(t)-p_f|}{p_f}\cdot a_i(t)\right\rfloor\right), \tag{4.7}$$

which depends on the current $(p(t))$ and the fundamental (p_f) price of the asset, with parameter k being the same as in the random traders' case. In effect, these traders are arbitrageurs who try to take advantage of the differences between market and fundamental price of assets.

Momentum traders Momentum traders—denoted as T—follow trends. They buy when the price goes up and sell when it goes down. Momentum trading strategies are still popular among investors, and this type of trader, thus, represents algorithmic hedge funds, whose algorithms predict the continuation of the trend, or, for instance, retail traders who bet on the combination of the signals involving moving averages and thus fully rely on technical analysis. Momentum traders can also contribute to the building up of bubbles, as their behavior is inherently based on herding and involves a positive feedback.

Each momentum trader is assumed to look back at the history based on an idiosyncratic time window ω_i, which is randomly drawn from a normal distribution as $\omega_i \sim U[3, 20]$ at the beginning of the simulation. This setup mimics the wide variety of trading strategies. If a momentum trader i decides to issue an order, the limit price l_i is computed as:

$$l_i = p(t)\cdot\left[1 + k\cdot\frac{p(t)-p(t-\omega_i)}{\omega_i p(t-\omega_i)}\right], \tag{4.8}$$

where k is the same parameter as in previous cases. Conditional on the decision to sell (if $l_i < p(t)$) or to buy (if $l_i > p(t)$), the exact quantities are computed as follows:

$$q_i^b = \min\left(\left\lfloor\frac{c_i(t)}{l_i}\right\rfloor, \left\lfloor\frac{c_i(t)}{l_i}\cdot u\cdot\left[1 + k\cdot\frac{|p(t)-p(t-\omega_i)|}{\omega_i p(t-\omega_i)}\right]\right\rfloor\right), \tag{4.9}$$

$$q_i^s = \min\left(a_i(t), \left\lfloor a_i(t)\cdot u\cdot\left[1 + k\cdot\frac{|p(t)-p(t-\omega_i)|}{\omega_i p(t-\omega_i)}\right]\right\rfloor\right), \tag{4.10}$$

where $u \sim U(0, 1)$.

Contrarian traders Similarly to momentum traders, contrarian traders (C) follow technical analysis of trends; however, they expect that if the price is rising, it is going to fall soon, so they try to sell near the maximum and vice versa. These traders benefit from the herding behavior of momentum traders. Thus, by introducing negative feedback into the market, they inadvertently lean against forming bubbles.

This implies that their behavioral rules are the same as those of momentum traders, only in the opposite direction. In particular, the decision to sell (buy) occurs if the $l_i > p(t)$ ($l_i < p(t)$), with all other variables remaining the same.

Price clearing mechanism

The market clearing price p^* is determined as the intersection of the demand and supply curves. More specifically, the orders are sorted by price: sell orders whose price satisfies $s_v \leq p^*$ from the lowest to highest, and buy orders whose price satisfies $b_u \geq p^*$ from the highest to lowest. These buy and sell orders are then matched from the bottom of the list while there is at least one pair to be matched. In case the last buy or sell order is satisfied only partially, p^* is determined as a weighted average of the bid and the ask price. Based on this matching, variables a_i and c_i are updated accordingly for each trader who made an exchange.

The provided model thus generates for every trading day a market price along with the volume and other market characteristics describing the profile of each of the four trading groups. In the following, we focus on the price-generating process, which by construction satisfies the standard stylized facts known in the market; see Raberto et al. (2003) and Mannaro et al. (2008).

Tax collection

The main goal of this paper is to analyze the impact of introducing FTT on the properties—in particular, higher moments—of the price generating process. In this framework, the tax rate is imposed on both sides of the transaction. More precisely, it is added on top of the buy price for buyers, and subtracted from the sell price for sellers. Thus, the effective tax rate is twice the nominal tax rate in our model.

Every trade thus causes a decrease of money supply available for traders in the market, as a fraction of the turnover is collected. In order to prevent the ever-decreasing money supply, every 60 days we return tax revenues into the system as a lump sum divided among traders, while maintaining the existing distribution of the cash. Such a lump sum return represents both the returns on the money flows and can be also interpreted as the dividend payouts; however, the preserved money distribution constraint does not support the latter interpretation.

The price-generating process

This set of strategies offers a diverse combination of micro-based strategies, which leads to an emergence of a a wide distribution of demanded and supplied assets on both sides of the trading book. The price clearing mechanism based on the law of supply and demand, then, implies the price-generating process, which satisfies the basic stylized facts as shown by Raberto et al. (2003) and Mannaro et al. (2008). The provided framework thus represents a natural laboratory to study the impact of financial frictions on markets and their particular impact on price dynamics.

4.3.3 Model of price process

The ABM introduced in the previous section mimics the real price formation and discovery process which can be found in real financial markets. Our main objective is to understand the impact of the imposed FTT on the price dynamics. We focus on the dependence between price jumps of a realized price path and the FTT. For that purpose, we employ the standard approach from the finance and econometrics literature to consider the price process to be modeled by the discontinuous semi-martingale. It follows the pioneering work of Merton (1976), who employed the discontinuous price process for option pricing, and more recent works of Barndorff-Nielsen and Shephard (2006), Lee and Mykland (2008), Aït-Sahalia and Jacod (2012), and González-Urteaga, Muga, and Santamaria (2015), among others, who model returns using the same approach. Such an approach allows us to explicitly distinguish the continuous part of the volatility, usually ascribed to the Brownian motion, and the discontinuous part, which can be attributed to price jumps.

We consider the dynamics of the log-price of an asset to take the form of the Ito semi-martingale described by the following stochastic differential equation:

$$dX_t = \eta_t dt + \sigma_t dB_t + \int_{\Re} x \cdot \mu\left(dt, dx\right) \,, \tag{4.11}$$

where $B\left(t\right)$ is a standard Brownian motion,the spot volatility σ_t is a càdlàg process bounded away from zero almost surely, the drift η_t is, in our case, identically equal to zero,[6] and the variable $\mu(dt, dx)$ is an integer-valued random measure that captures a jump in X_t over a time interval $[t, t+dt)$ meaning that a price jump arrives on the market whenever $\Delta X_t \equiv X_t - X_{t-} \neq 0$. Let us further define a jump intensity $dt \otimes \nu_t(dx)$, where $\nu_t(dx)$ is some non-negative measure with a constraint $\int_{\Re} (x^2 \wedge 1)\, \nu_t(dx) < \infty$. More precisely, we assume large price jumps with finite activity. As a result, for any fixed interval $[0, T]$, there is a finite number of time moments t such that $\Delta X_t \neq 0$. For mathematical details, see Jacod and Shiryaev (1987).

For a certain fixed interval $[0, T]$ the jump term with a corresponding jump intensity ν_t gives rise to a finite number of price jumps. More precisely, a finite number of $t_i \in [0, T]$ exists such that $U_i \equiv \Delta X_{t_i} > 0$ in the limit, with $i = 1, \ldots, N_T$. In such a case, we observe exactly N_T price jumps. The term ν_t thus affects both the U_i and the grid $\mathcal{T}_T = \{t_1, \ldots, t_{N_T}\}$, including its cardinality.

Financial transaction tax

The Tobin tax in the model affects the trading habits of the agents in the economy and thus the random processes in Equation (4.11). In particular, the process driving the Gaussian volatility and the jump measure depends on the tax rate τ:

$$\begin{array}{rl} \sigma_t \rightarrow & \sigma_t(\tau) \\ \nu_t \rightarrow & \nu_t(\tau) \end{array} . \tag{4.12}$$

Estimating the functional dependence between the spot processes in Equation (4.12) and the FTT is not a straightforward task, as the randomness in the spot processes would be a confounding factor.[7] Any test would therefore require a comparison of the random processes that depend on the current state of the world. A possible solution would be to use filtering techniques to extract the latent processes $\sigma_t(\tau)$ and $\nu_t(\tau)$. The more intuitive solution employed in this paper uses the integrated variables to measure the impact of the FTT over a certain time horizon on the integrated quantities. In particular, we focus on the first four moments, and estimate the distributional properties of the log-returns r_t as a function of the FTT. In addition, as per $\nu_t(\tau)$ measure, we estimate the number of price jumps per given sample path and analyze the impact of the FTT on the frequency

[6] The fundamental price in our model is fixed, which is equivalent to a world with zero deterministic interest rates. An alternative and equivalent explanation is that our model describes de-trended data. The provided framework is valid even in the case of a general CAR process with a locally persistent price process at a given sampling frequency.

[7] Recall that σ_t itself is a random process with a structure similar to the log-price equation.

of price jumps.

Estimating the number of price jumps

Estimating the price jump contribution to the overall quadratic variance is one way to assess the role of price jumps in the price process. Alternatively, we may directly identify the overall number of price jumps. For a given sampling frequency, we thus assess the cardinality of the set of returns which contain at least one price jump.

To test for the presence of a price jump in a particular return, we employ a test developed by Lee and Mykland (2008). As Hanousek, Kočenda, and Novotný (2012) argue, this test is optimal with respect to Type-II errors. It is based on the bipower variance suggested by Barndorff-Nielsen and Shephard (2004) for underlying processes following Equation (4.11). The test statistic is based on the results of the extreme value theory. More precisely, the key quantity is the distribution of maximum returns normalized by the spot integrated variance. The spot quadratic variance is estimated using the bipower variance over a moving window capturing the immediate past movements of the price process. Namely, the test statistic developed by Lee and Mykland (2008) is defined as:

$$\frac{\max_{t \in A_n} |\mathcal{L}_t| - C_n}{S_n} \to \xi \,, \tag{4.13}$$

where A_n is the tested region with n observations, and $\mathcal{L}_t = r_t/\hat{\hat{\sigma}}_t$, $C_n = \frac{(2\ln n)^{1/2}}{\mu_1} - \frac{\ln \pi + \ln(\ln n)}{2\mu_1(2\ln n)^{1/2}}$, $S_n = \frac{1}{\mu_1(2\ln n)^{1/2}}$, $\mu_1 = E(|z|)$ with $z \sim N(0,1)$, and where $\hat{\hat{\sigma}}_t$ stands for the spot bipower variance defined as:

$$\hat{\hat{\sigma}}_t^2 = \frac{1}{T-1} \sum_{u=t-T+1}^{t-1} |r_u| \, |r_{u-1}| \,. \tag{4.14}$$

Note that the term μ_1^{-2} is included in coefficients C_n and S_n.

Lee and Mykland (2008) show that under the null hypothesis of no price jump, the random variable ξ follows the standard Gumbel distribution function $P(\xi \leq x) = \exp(e^{-x})$. The number of price jumps detected in this way is then counted for a given window, in our case 120 days.

4.3.4 Simulation procedure

The artificial financial market described above is used for extensive Monte Carlo simulations in a modified Zarja C++ environment for agent-based modeling.[8]. To evaluate the robustness of the results to initial conditions, we run different specifications varying the total set of agents in the economy, the relative share of different traders, and the probability of trading p described in Section 4.3.2. The most significant robustness check is an increase of number of agents to 10,000.

For all of the specifications above, the initial wealth of agent i both in cash and stocks is set as follows. First, the overall cash is divided proportionally among the trader groups. Within the trader groups, the cash is divided following the Zipf law. After fixing the tax rate, which remains the same for a given specification, agents begin to interact according to their respective decision rules. Every simulation run is composed of 3,600 trading sessions, or trading days, which corresponds to 15 years. The first five years of market operations are then considered as the initialization period, and those data are not taken into account. Every simulation run is then repeated 200 times for each tax rate. The tax rate is varied from zero to three percent in 0.05 percentage point increments.

At the end of every trading day of each simulation, we collect the following data: the market price of the traded asset, the daily traded volumes, and the behavior and wealth (both in terms of assets and cash) of the different trader types. As a result, for every level of the Tobin tax, we obtain 200 samples of 10 trading years worth of daily data. This sample is large enough for robust statistical inferences.

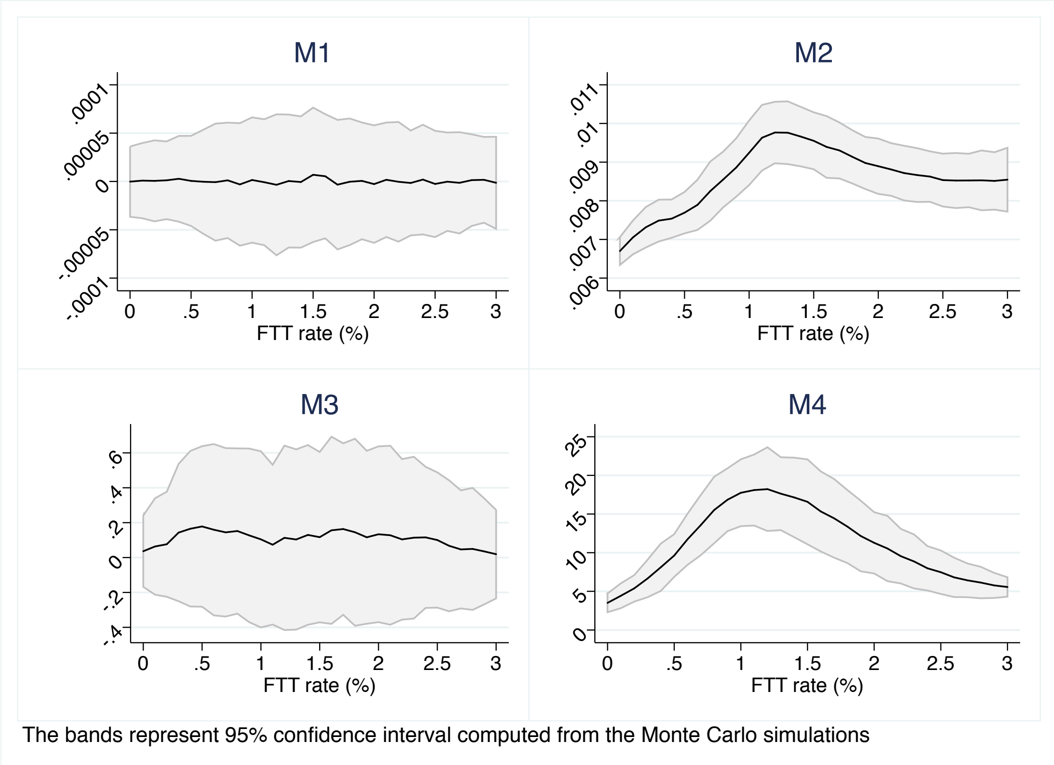
4.4 Results

This section reports the results of a baseline model with 400 traders. The baseline corresponds to the specifications used in previous studies and thus directly extends the existing literature. Moreover, we have run robustness checks, the most significant being an increase of number of agents to 10,000. This particular robustness check allows us to determine if there is any nonlinear scale effect that would interact with the effect of the Tobin tax. Its results are available upon request.

In this section, we report the results of a simulation with 400 traders, distributed into the four trader groups described in Section 4.3.2. More precisely, our baseline market

[8] Downloadable from `http://sourceforge.net/projects/politeconomy`.

Figure 4.1: The first four moments of the log-return distribution for $N = 400$



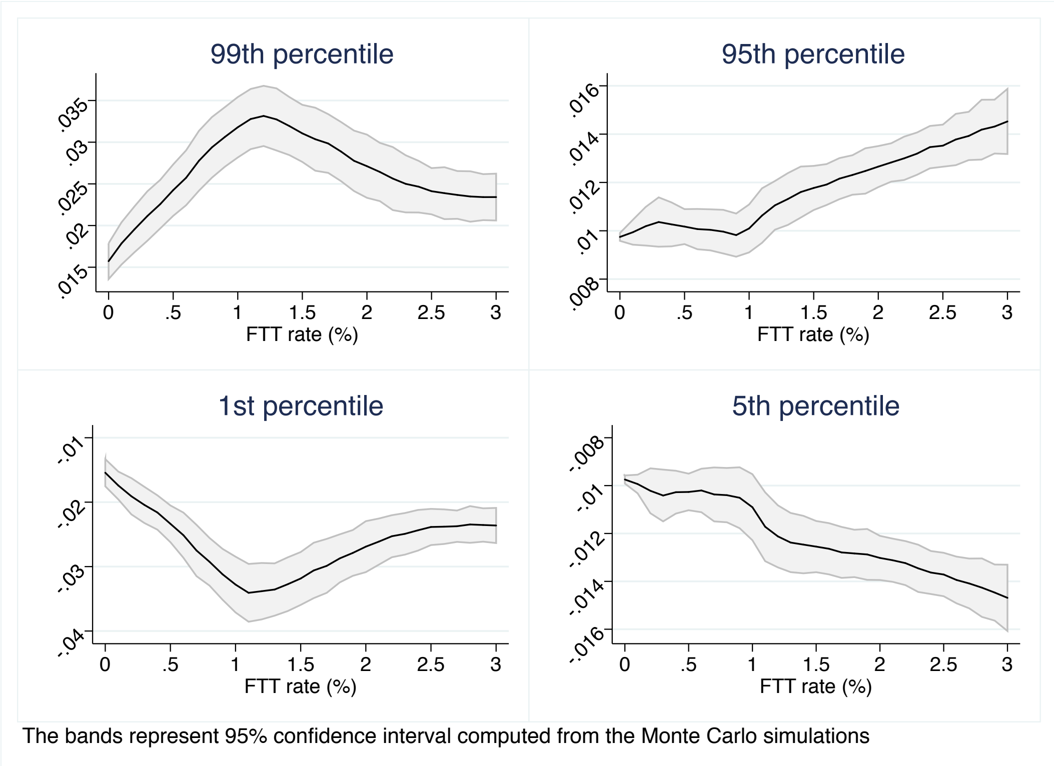
consists of 40 percent of random traders, 30 percent of fundamentalist traders, and 30 percent of chartists (divided evenly between trend followers and contrarians).

4.4.1 Price Behavior

Figure 4.1 shows the first four moments of the distribution of log-returns with 95 percent confidence bands. It is evident from the figures that the tax has an insignificant effect on the mean and skewness of the distribution. A comparison of variance and kurtosis shows that, at low levels, a rise in the tax is causing the increase in both variance and kurtosis. The distribution is thus more volatile with fatter tails. From approximately a 1 percent tax, the trend is reversed—both variance and kurtosis start to decrease.Near the highest value of the Tobin tax considered in this paper, the kurtosis gets back to the no-tax values while variance stays at increased values, resembling plateau-like behavior.

Figure 4.2 depicts the 1st, 5th, 95th, and 99th percentiles of the return distribution. Clearly, the distribution of returns, as seen from the first and 99th percentiles, widens up to the tax rate of around 1 percent and then narrows, corroborating the second and fourth moments. The 5th and 95th percentiles, however, show a different picture. Up to a

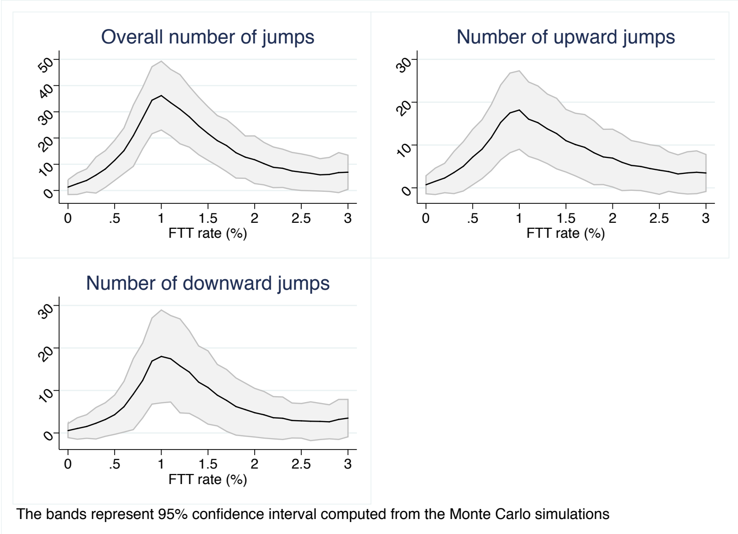
Figure 4.2: Percentiles for $N = 400$



rate of one percent, the value remains flat, where beyond that point the distribution tends to widen. This suggests a qualitative change in the distribution as the two percentiles do not move together. This observation emphasizes an important fact – using a different values of value-at-risk (VaR) can yield qualitatively different results.

In conclusion, a plain comparison of the first four moments supports the well-accepted belief of market practitioners that the FTT will increase the market volatility. Given that it is often caused by markets losing their depth, this is usually interpreted as a bad signal. However, our figures also show that the fourth moment—the proxy for fat tails—moves in line with the variance. After reaching certain critical value (around the tax rate of 1 percent) the trend is reversed, as the fourth moment is decreasing at a higher pace than variance. Moreover, different percentiles suggest a qualitative change in the distribution of returns and show that the risk-measures may show a different story based on the considered parameters. This may suggest that the relationship between the volatility and the FTT is more intricate. Such a pattern also shows that FTT does not have a simple linear impact on the distribution of returns. In the following sections, we focus more in detail on extreme events and answer the question whether the decrease in black-swan events caused by the Tobin tax really offsets the cost of higher Gaussian volatility.

Figure 4.3: Number of jumps for $N = 400$



4.4.2 Jump statistics

In the following text, we explore the rate of price jump arrivals in greater detail, as neither the momentum-based tools nor the percentile analysis can properly assess the role of extreme returns. We employ the test statistics in Equation (4.13) with a 95 percent confidence interval and identify price jumps in the entire sample for each tax rate. In addition to overall price jumps, we also study upward and downward jumps separately.

Figure 4.3 depicts the number of identified price jumps as a function of the tax rate. The rate of arrival of overall, upward, and downward price jumps increases with an increasing tax rate at first, and reaches its maximum at around 1 percent tax. Above this value the number of jumps starts to decrease, reaching tax-less values when nearing the highest tax rates considered in this paper. In conclusion, certain values of the FTT can significantly increase the rate of price jumps and thus make the markets riskier. However, our analysis suggests that certain rates of the FTT do not change the number of price jumps.. This intuition is in line with the pattern exhibited by variance and kurtosis in Figure 4.1.

4.4.3 Aggregate market data

In this section, we focus on additional aggregate market data. Precisely, we analyze traded volumes as a function of the Tobin tax as the decrease in liquidity is allegedly one of the main costs of FTTs.

Figure 4.4: Average trading volume for $N = 400$

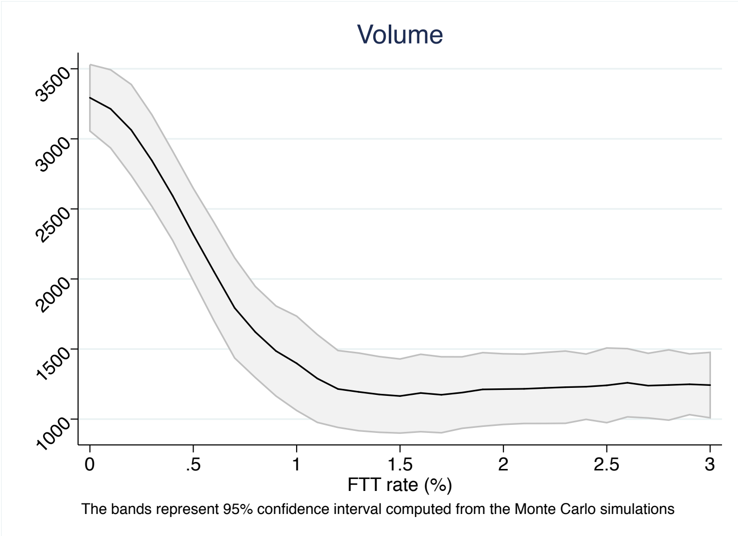


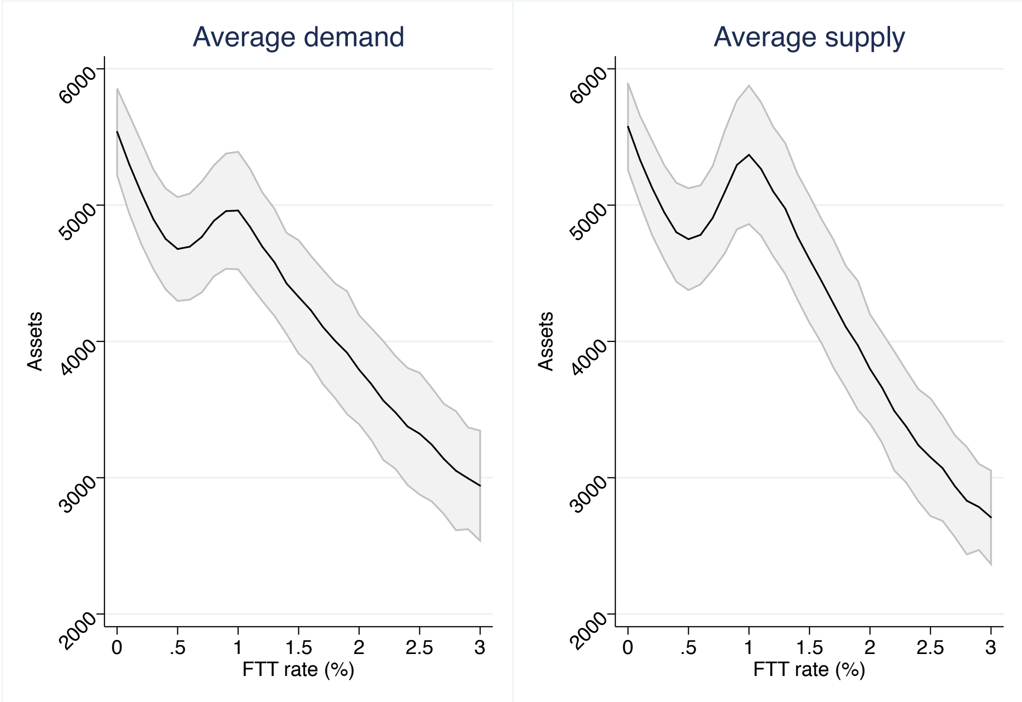
Figure 4.4 depicts the relationship between traded volumes and the tax rate. The results clearly show that the traded volume is negatively affected by the FTT. The traded volume is dramatically decreasing up to the tax rate of one percent. After that value, the volumes remain intact and there is no further response of the traded volumes to the increasing FTT. Thus, our analysis confirms the intuition that the FTT is negatively affecting market liquidity and suppressing market activity. However, our analysis further shows that traded volumes are directly linked to the distribution of returns.

Let us now turn our attention to Figure 4.5, where we analyze the response of supply and demand to the imposed tax rate. Both demand and supply show non-linear behavior. In particular, they are initially decreasing up to the tax rate of 0.5 percent, when they reach a local minimum. Afterwards, there is a slightly increasing trend that continues up to the tax rate of one percent. Beyond this point, the trend reverses and the volumes steadily decrease without any significant slowdown. The existence of local minima is not what one would expect given that the variance and kurtosis were maximized around the tax rate of one percent. Thus, the wideness of the return distribution is not caused simply by the lack of the supply and demand.

4.4.4 Market microstructure

To determine what exactly drives these results, we now turn our attention to the microstructure of our artificial market. More precisely, we focus on changes in the aggregate behavior of the four trading groups caused by the variation in the tax rate. Figure 4.6

Figure 4.5: The average supplied and demanded volumes for $N = 400$



The bands represent 95% confidence interval computed from the Monte Carlo simulations

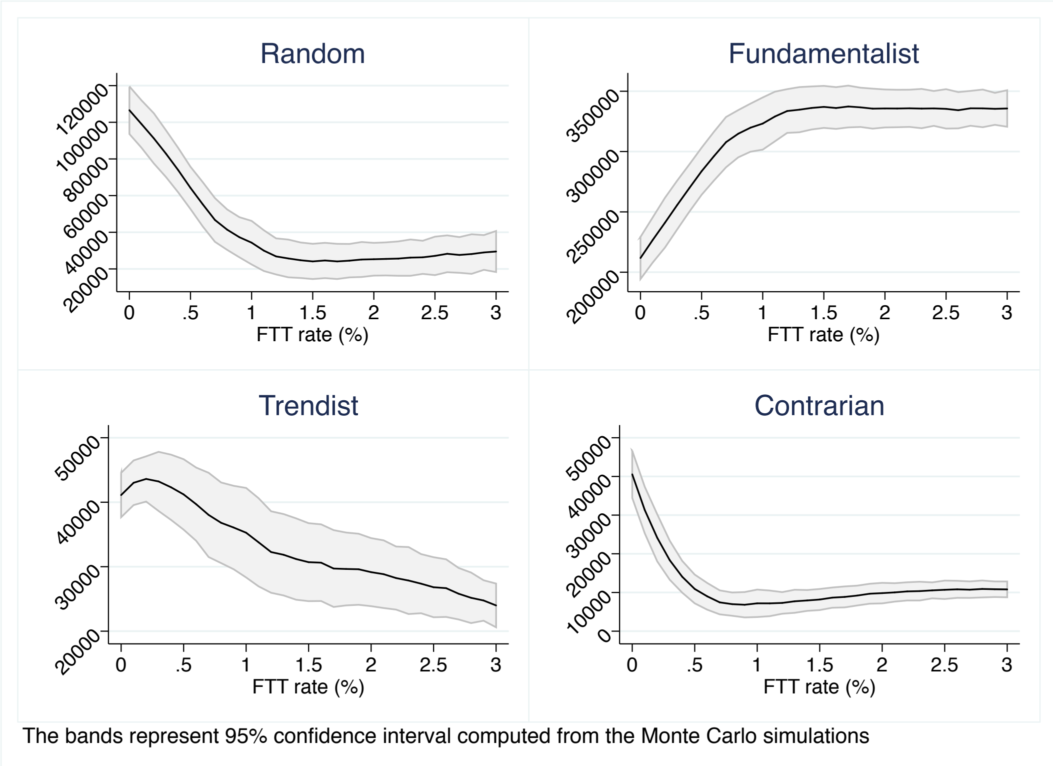
reports the average daily inventories—assets and cash—for the four groups as a function of the Tobin tax.

For random and contrarian traders, an increase in the tax rate has a negative effect on both asset and money stocks. The pattern resembles the overall situation for aggregate volumes. Trendists' wealth and inventories exhibit a local maximum at the tax rate of around 0.25. Beyond that point the amount of assets tend to decrease without any visible saturation up until the maximum tax rate considered in this study. Finally, fundamentalist traders clearly benefit from the growing Tobin tax. The amount of money and assets they hold are positively affected by the tax rate. As fundamentalists are the only traders whose trading pushes the price towards the fundamental value of the asset, the effect of the Tobin tax on the price discovery process can be interpreted as positive. The saturation occurs around one percent, in line with the saturation point discussed in the previous paragraph. This evidence suggests that the Tobin tax affects fundamentalists' and other traders' asset stocks in the opposite way.

The effects of the tax on the price process and the rate of price jumps are directly connected to the liquidity of the market. Figure 4.7 reports the daily averages of supply and demand of the assets by the respective trader groups. Both demand and supply

Figure 4.6: Inventories by traders for $N = 400$

(a) Assets



(b) Cash

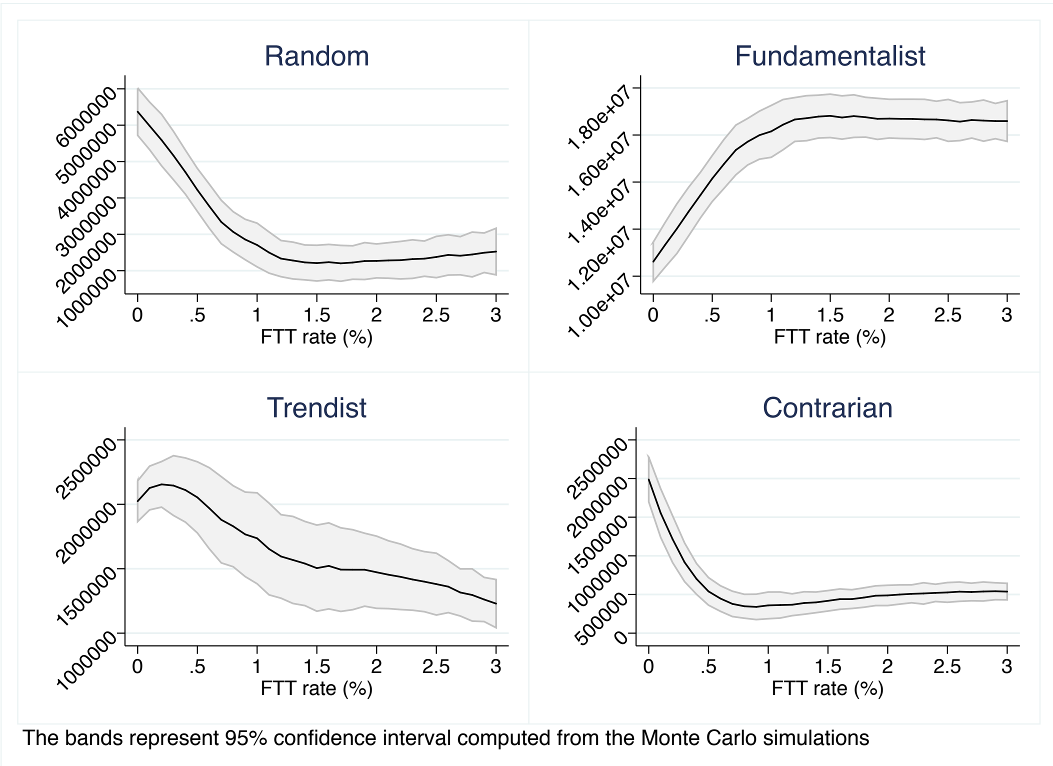


exhibit similar patterns.

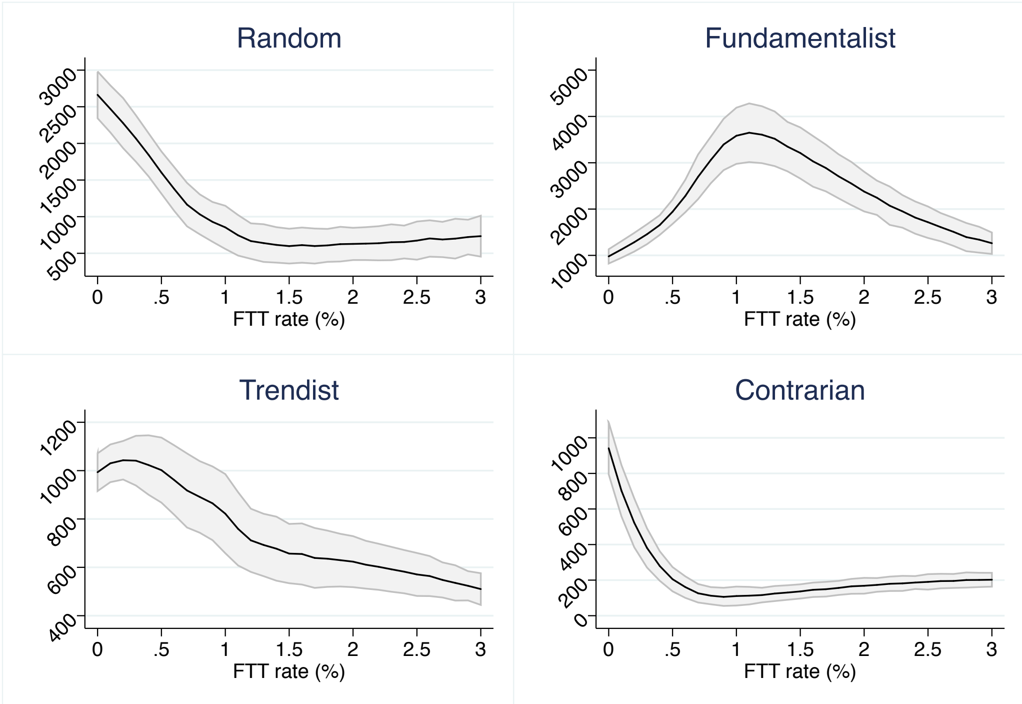
Random and contrarian traders' quantities go in line with the aggregate traded volumes as they rapidly decrease with increasing tax rate up to a tax rate of around one percent where the trend stops and slightly reverts. The trendists' supply is in line with the assets and cash holdings. Its value reaches a maximum at around 0.25 percent and then starts decreasing. The fundamentalist traders' supply and demand exhibits a different pattern than their asset and cash holdings. The quantity reaches its maximum around one percent and then tends to decrease without any apparent saturation. That suggests an increase of the Tobin tax beyond one percent causes an accumulation of holdings by fundamentalists, while damping their market activity. Thus, the FTT tends to decrease overall volume by repelling mainly the non-fundamentalist traders.

Figure 4.8 shows the results of the interaction between supply and demand. It reports the average amount of assets sold and purchased by individual traders. The pattern of response to the imposed Tobin tax goes against the results we have analyzed so far. The one exception is the activity of random traders, whose pattern is similar to that of their supply and demand. For the fundamentalist traders, the market activity reaches its maximum at around 0.5 percent, where it starts to decrease. Furthermore, at the tax rate of around one percent, the speed of the decline slows down, confirming the qualitative transition of the overall behavior at approximately one percent tax rate. Trendist traders' market activity resembles their supply and demand patterns except for the fact that the decline of the traded volumes stops when the tax rate reaches one percent. Contrarians exhibit the most counter-intuitive pattern. At the tax rate of around 0.25 percent their market activity reaches a maximum and then starts decreasing until the tax rate hits a value of one percent. There the trading volume reaches a minimum and starts increasing again, showing highly non-linear behavior.

This result is corroborated by Figure 4.9, which depicts the amount of assets per trader held by every type of trading strategy in the model as a function of the tax rate. The intensity of the line color denotes the level of the tax rate, with black being the zero rate and lighter shades of gray signifying higher tax rates. While traders in our model cannot choose their strategy, the relative amount of assets held by different trader groups can still be perceived as the fitness of the given strategy. The figure clearly shows that growing tax rates would make the fundamentalist strategy more attractive if the traders could choose it. The other strategies tend to decrease in fitness as the Tobin tax rises, although the trend is not strictly monotonous. One example is the fitness of the momentarian strategy

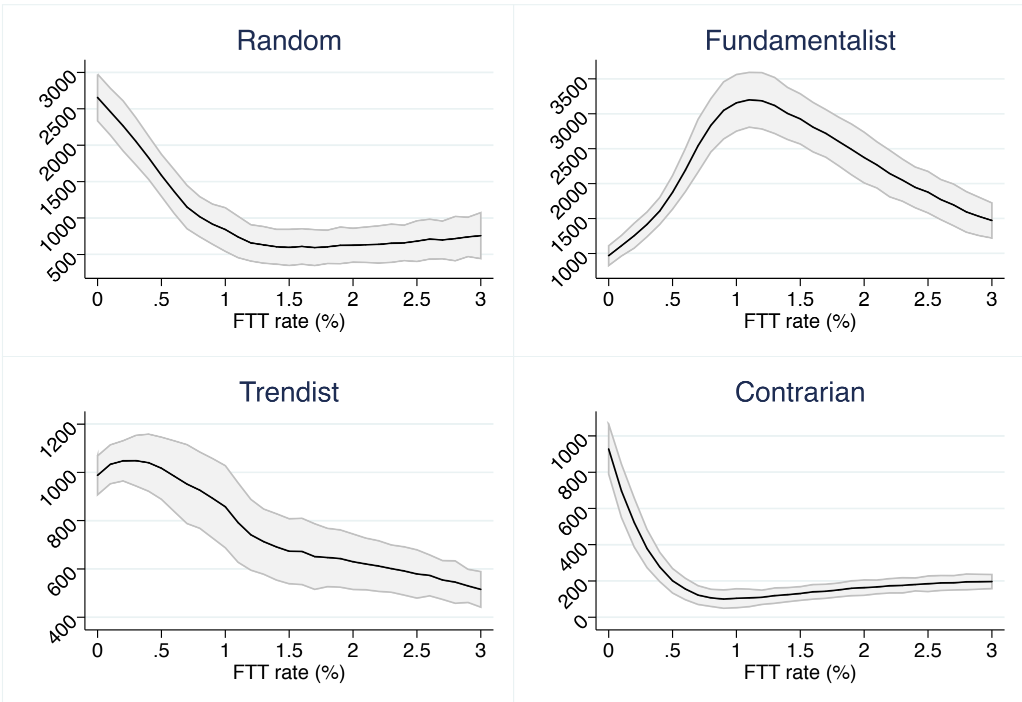
Figure 4.7: Market order book by traders for $N = 400$

(a) Supply



The bands represent 95% confidence interval computed from the Monte Carlo simulations

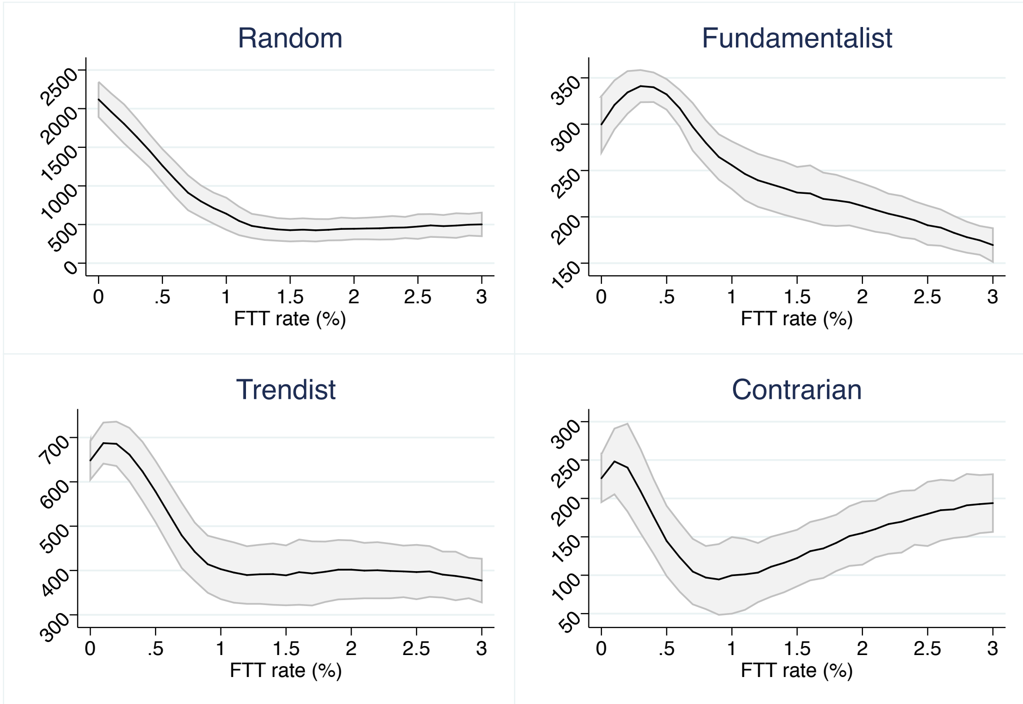
(b) Demand



The bands represent 95% confidence interval computed from the Monte Carlo simulations

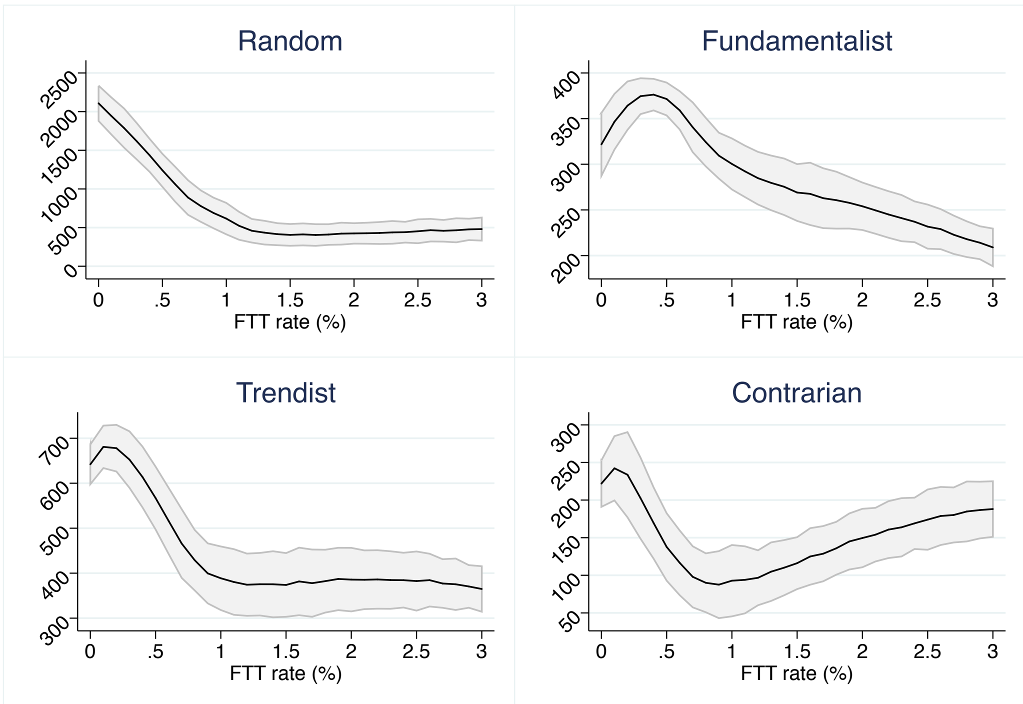
Figure 4.8: Market activity by traders for $N = 400$

(a) Sold assets



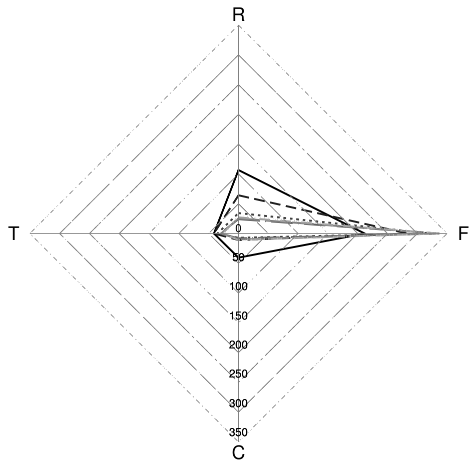
The bands represent 95% confidence interval computed from the Monte Carlo simulations

(b) Purchased assets



The bands represent 95% confidence interval computed from the Monte Carlo simulations

Figure 4.9: Assets by trader types for $N = 400$.



Note: The intensity of color is a decreasing function of the tax rate (black=0%). The values are in thousands of assets.

at the tax rate of one percent. However, the momentarian strategy is suppressed as the tax rate rises. Moreover, we see that the momentarian strategy exhibits the least amount of held assets at zero tax rate. This suggests that the share of traders with this strategy would be decreasing in a endogenous strategy setting.

4.5 FTT and the different traders

So far, we have analyzed the impact of the FTT on the market as a whole. We have shown that there is a non-linear relationship between the FTT and market volatility, defined both with and without price jumps. In this section, we aim to provide this missing piece and demonstrate how different types of traders contribute to the link between FTT and volatility. We do this by imposing the FTT on each group separately and studying the response of the market. This approach allows us to determine whether the response of respective groups to the tax differs.

We perform a Monte Carlo exercise with the same parameters as in the baseline scenario. In particular, we are interested in the quadratic and integrated variations and their response to the FTT imposed on a given type of traders.

Figure 4.10 depicts the quadratic and integrated variations as a function of the FTT imposed on different types of traders.[9] Based on their responses, we can divide traders

[9]The rigorous statistical analysis can be found in Table 4.1 in the Appendix.

into two subgroups. The first subgroup, composed of fundamentalists, momentarians, and random traders exhibits a decrease in both types of variations as the tax rate increases. As the error bars represent the 95% confidence interval, the members of this subgroup do not respond to the tax in a significantly different manner. Contrarians seem to form a separate group on their own. They exhibit highly non-linear response to the FTT. In their case, FTT causes an initial increase in both types of variation. As the tax rate increases further, the trend is reversed until it hits a minimum at around 1% FTT. Beyond this point it starts another monotonous increase. The error bars suggest a significantly different effect of contrarian strategy compared to other strategies. These findings therefore suggest that contrarians are the source of the nonlinearity in the relationship between FTT and the market volatility we observed before.

Figure 4.11 depicts the JS ratio, defined as the difference between the quadratic and integrated variations normalized by the quadratic variation. As the quadratic variation captures the presence of price jumps, while the integrated variation ignores it, higher value of the JS ratio implies higher frequency of price jumps. The figure accentuates the difference between the groups. The imposition of the tax on the members of the first subgroup does not cause a significant response in the price jump frequency for moderate tax rates. When the FTT is imposed on contrarians, on the other hand, the amount of the jump variation decreases moderately at first, only to start radically increasing at around 0.5 percent. This increasing trend becomes more moderate at approximately 1 percent. Therefore, we may conclude that imposing the FTT on the contrarians makes the markets more volatile, where the structure of the volatility changes with the increasing proportion of the "bad"—non-Gaussian—volatility originating in price jumps. This also confirms the special characteristics of the 0.5 and one percent tax rates exhibit in previous figures.

4.6 Comparative statics

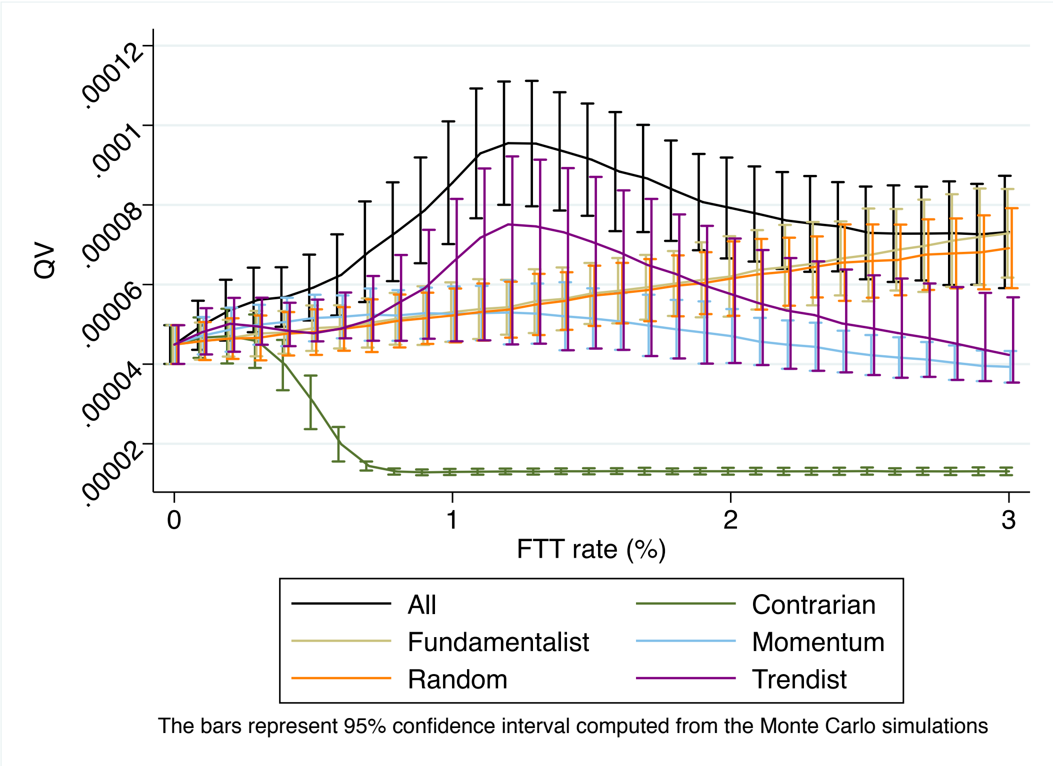
The analysis in the previous sections was focused on the long-term effects of the FTT. However, a comparative statics analysis may be of equal interest.[10] Therefore, the point of this section is to analyze how the market responds to changes in tax rates. More precisely, we will study how the market adapts in two scenarios:

1. the response of the system to an introduction of a positive tax rate in a market with

[10]We thank an anonymous referee for this suggestion.

Figure 4.10: Quadratic and Integrated Variation by types of traders.

(a) Quadratic Variation



(b) Integrated Variation

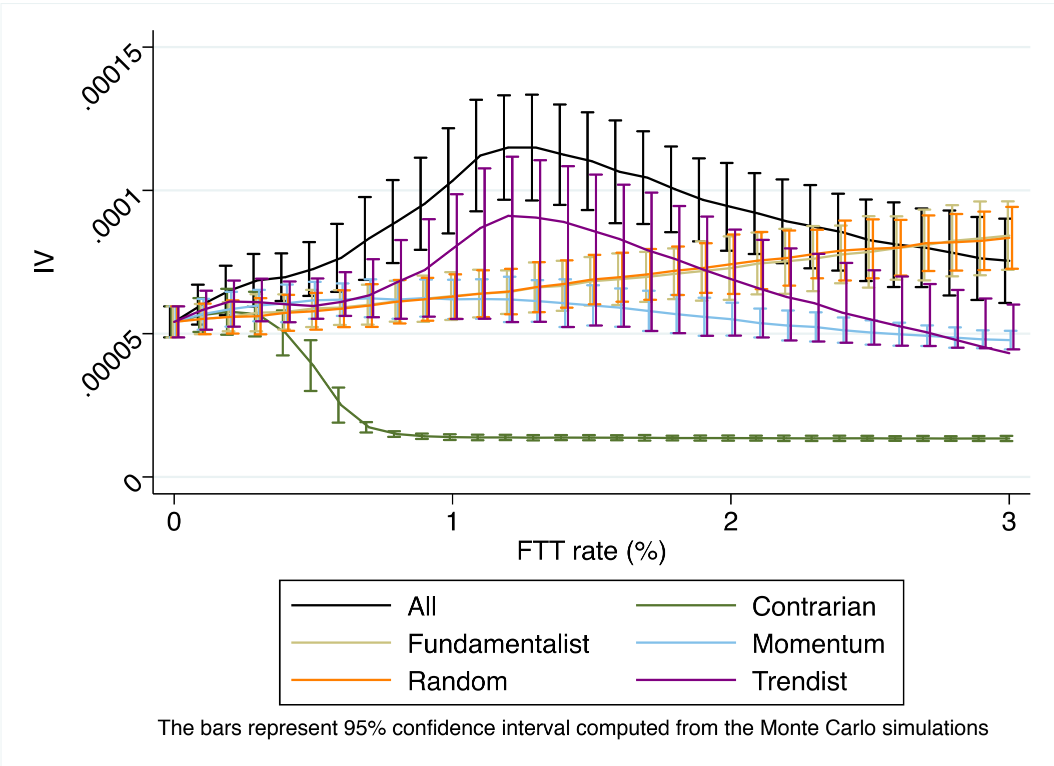
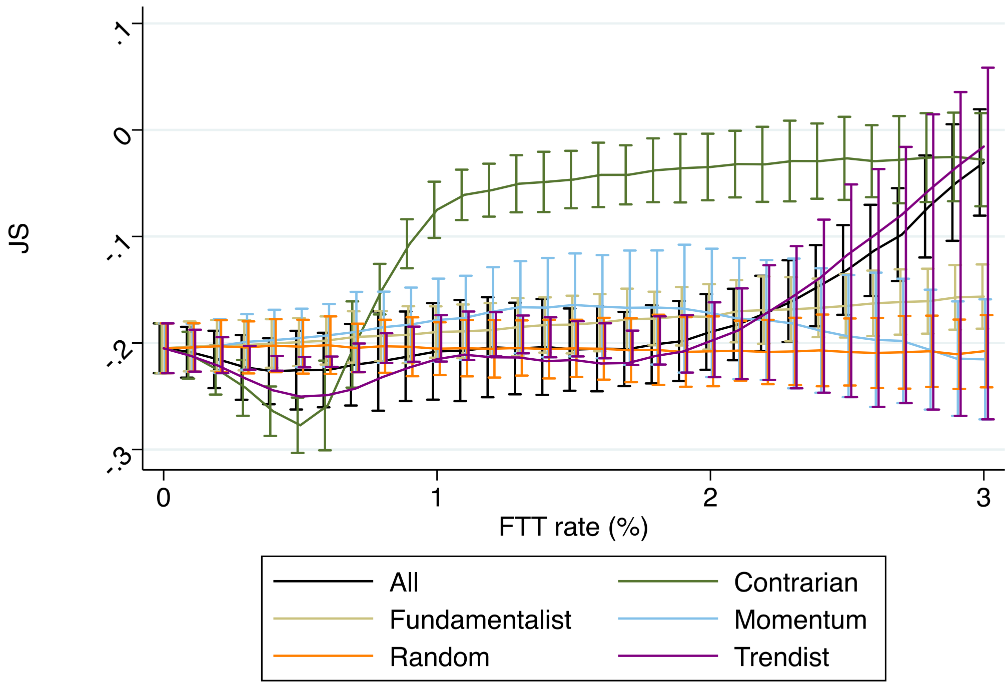


Figure 4.11: Jump ratio



The bars represent 95% confidence interval computed from the Monte Carlo simulations

a zero tax rate,

2. the response of the system to a small change in an already imposed tax.

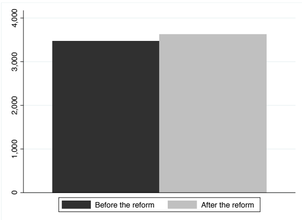
We do this by letting the simulation run for a predetermined number of periods (6000) and then adjusting the tax rate accordingly. In the interest of brevity, we focus on the tax rate of 1%, which has the advantage of being located in the middle of the range studied in the previous sections. For the first scenario, we change the tax rate from 0% to 1%, whereas for the second we adjust the tax rate from 1% to 1.1% and 0.9%, respectively.

The results of the analysis can be seen in Figure 4.12, which shows pre-averaged impulse response functions – an average of given variables 100 periods before the reform and 100 periods after the reform, respectively.[11] The subfigures show that a very small changes from 1% to 1.1% or from 1% to 0.9% do not have a significant effect on any of the relevant variables. However, the message is more complicated when we change the tax rate from 0% to 1%. It is obvious that in the very short period after its introduction, the tax does not have an significant effect on the volume. However, the statistics of the price process are affected almost immediately. This result shows that one should not

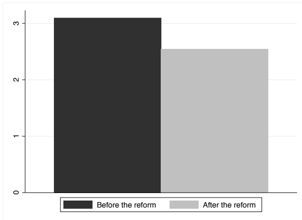
[11] As before, we run each scenario 200 times and compute averages across these runs.

Figure 4.12: Comparative statics

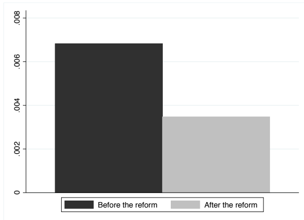
(a) 0 to 1% – Volumes



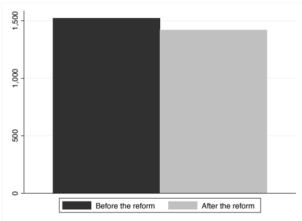
(b) 0 to 1% – Kurtosis



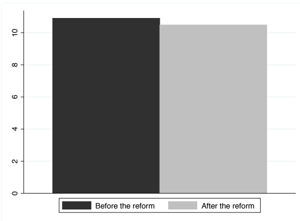
(c) 0 to 1% – St.Dev.



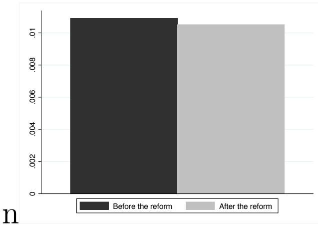
(d) 1 to 1.1% – Volumes



(e) 1 to 1.1% – Kurtosis

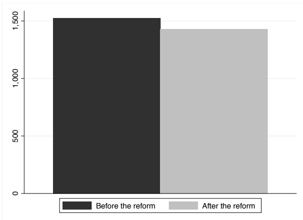


(f) 1 to 1.1% – St.Dev.

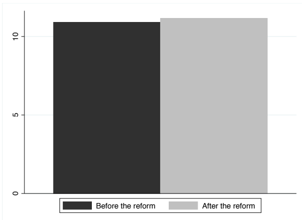


n

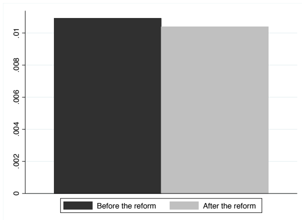
(g) 1 to 0.9% – Volumes



(h) 1 to 0.9% – Kurtosis



(i) 1 to 0.9% – St.Dev.



confuse transaction volume with liquidity. Although these two variables are very often correlated, they are not identical.[12] Our result implies that the traded volume is not a good proxy measure for market risk. It cannot be used to assess the overall market volatility (as represented by the standard deviation), nor its decomposition into Gaussian and non-Gaussian volatility. It is argued that market orders generally contain at least three times more information about the price formation process than limit orders (Lehalle & Laruelle, 2013). Our findings corroborate this hypothesis by showing that what matters for volatility are directed market orders and not their overall amount.

4.7 Conclusion

The main goal of this paper was to open a discussion on a heretofore ignored relationship between financial transaction taxes and price jumps. We argued that looking at the

[12]We thank J.Doyne Farmer for this point.

effect of FTTs on realized variance as a measure of volatility is insufficient as it does not convey enough information. Our point was that an increase in the variance itself does not necessarily mean less stable markets, because realized variance can be decomposed into two parts—Gaussian variance and price jumps. As we have shown, the variance may go up through an increase in Gaussian variance, while the contribution of price jumps may go down, decreasing the kurtosis of the return distribution. This result seems to be driven by the different responses of individual trader types to the tax. More precisely, the relative share of fundamentalist activity in our model is an increasing function of the tax rate.

Given that there is a sizeable literature on hedging against Gaussian variance, this result implies that different tax rates have qualitatively different impact on the efficiency of these formulae, and through this, the functioning of the markets. Our paper thus indicates that future research into FTTs needs to take into account the relationship between variance of the price process and the number of price jumps. We believe that our work opens interesting avenues for further research about the relationship between FTTs and price jumps relevant from both academic and policy point of view.

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Appendix

Table 4.1 presents a regression analysis of the response of different trader groups to the tax. In this table, τ denotes the level of the tax rate, while d denotes group dummies, which take a value of 1 if the tax was imposed on that particular group and 0 otherwise.

Table 4.1: Response of different trader types to the tax

	(1) Quadratic variation		(2) Integrated variation	
$\tau \cdot d_{all}$	1.35e-07	(1.41)	1.95e-07	(1.71)
$\tau^2 \cdot d_{all}$	6.34e-09***	(4.75)	7.16e-09***	(4.53)
$\tau^3 \cdot d_{all}$	-4.83e-11***	(-7.18)	-5.56e-11***	(-6.97)
$\tau^4 \cdot d_{all}$	8.97e-14***	(8.06)	1.02e-13***	(7.71)
$\tau \cdot d_{cont}$	-6.34e-07***	(-6.60)	-7.01e-07***	(-6.15)
$\tau^2 \cdot d_{cont}$	2.74e-09*	(2.05)	1.97e-09	(1.24)
$\tau^3 \cdot d_{cont}$	-1.52e-12	(-0.23)	5.13e-12	(0.64)
$\tau^4 \cdot d_{cont}$	-7.11e-15	(-0.64)	-1.96e-14	(-1.49)
$\tau \cdot d_{fund}$	7.85e-08	(0.82)	9.00e-08	(0.79)
$\tau^2 \cdot d_{fund}$	-3.37e-11	(-0.03)	-7.92e-11	(-0.05)
$\tau^3 \cdot d_{fund}$	5.61e-13	(0.08)	7.58e-13	(0.09)
$\tau^4 \cdot d_{fund}$	-9.43e-16	(-0.08)	-1.26e-15	(-0.10)
$\tau \cdot d_{mom}$	1.65e-07	(1.72)	2.07e-07	(1.82)
$\tau^2 \cdot d_{mom}$	-9.26e-10	(-0.69)	-1.56e-09	(-0.99)
$\tau^3 \cdot d_{mom}$	6.88e-14	(0.01)	2.74e-12	(0.34)
$\tau^4 \cdot d_{mom}$	3.20e-15	(0.29)	-3.00e-16	(-0.02)
$\tau \cdot d_{rand}$	5.42e-08	(0.56)	6.24e-08	(0.55)
$\tau^2 \cdot d_{rand}$	1.84e-10	(0.14)	2.57e-10	(0.16)
$\tau^3 \cdot d_{rand}$	3.02e-14	(0.00)	-6.49e-14	(-0.01)
$\tau^4 \cdot d_{rand}$	-1.21e-15	(-0.11)	-1.38e-15	(-0.10)
$\tau \cdot d_{trend}$	-2.31e-07*	(-2.41)	-2.44e-07*	(-2.14)
$\tau^2 \cdot d_{trend}$	8.19e-09***	(6.14)	9.55e-09***	(6.04)
$\tau^3 \cdot d_{trend}$	-5.08e-11***	(-7.55)	-6.03e-11***	(-7.55)
$\tau^4 \cdot d_{trend}$	8.70e-14***	(7.81)	1.03e-13***	(7.77)
d_{all}	4.58e-05***	(22.79)	5.53e-05***	(23.22)
d_{cont}	5.32e-05***	(26.47)	6.45e-05***	(27.05)
d_{fund}	4.50e-05***	(22.38)	5.42e-05***	(22.74)
d_{mom}	4.54e-05***	(22.59)	5.46e-05***	(22.92)
d_{rand}	4.51e-05***	(22.42)	5.43e-05***	(22.77)
d_{trend}	4.76e-05***	(23.68)	5.77e-05***	(24.21)
Observations	186		186	
Adjusted R^2	0.998		0.998	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$