External Validity in Empirical Public Finance *

Meng Hsuan Hsieh
Ross School of Business
University of Michigan
rexhsieh@umich.edu

Gerardo Sanz-Maldonado
Department of Economics
University of Michigan
sanzg@umich.edu

Joel Slemrod
Department of Economics
Ross School of Business
University of Michigan
jslemrod@umich.edu

June 5, 2023

Preliminary draft. Not for quotation. Comments welcomed.

Abstract

In recognition of the central role of the elasticity of taxable income (ETI) in the theory of optimal taxation, many recent attempts have been made to measure it, spanning many countries and time periods. Existing methods have, however, generally not taken into account that the ETI is not a primitive parameter, but rather depends on various aspects of a tax system and the non-tax environment. This raises questions about the external validity of ETI estimates based on data in one country (and period) for the ETI in other countries. We propose a new approach to estimate country-specific ETIs with cross-country panel data, based on the correlated random coefficients model, which explicitly expresses the ETI as a function of structural determinants of the tax system and which generates estimates of the ETI for each country that reflects its innate character. Estimating our model on cross-country panel data from OECD countries from 1981 to 2014 about top income shares and tax rates, as well as survey data, we find that countries with greater preference for redistribution and trust in government—and larger countries—have lower ETIs. We close by briefly showing how to extrapolate estimated behavioral elasticities to countries that do not levy a particular tax, using wealth taxation as an example.

JEL Classification: C13, H21

Keywords: Optimal taxation, elasticity of taxable income, correlated random coefficients

*We thank Enrico Rubolino and Daniel Waldenström for providing data to us for our empirical work. We thank Xinyu Chen for careful and extensive data collection and cleaning. We thank Will Boning, Ash Craig, Andreas Hagemann, Florian Gunsilius, Wojciech Kopczuk, and Emmanuel Saez for providing thoughtful feedback. We thank participants in the PF PhD Student Seminar at the University of Michigan, the Michigan Tax Invitational (M-TAXI), and the University of Kentucky for thoughtful comments during this paper's early stages.

1 Motivation and Introduction

A remarkable and promising recent development in empirical public finance has been the proliferation of studies using data from many countries, both developed and developing. Much of the research has been facilitated by the growing accessibility to academics of tax administration data. The proliferation of such studies naturally raises the question of the cross-country external validity of the findings, in particular on the estimates of behavioral responses to tax policies. A lively literature has addressed the question of external validity in the context of randomized controlled trials (RCTs); see, in particular, the dialogue between Deaton and Cartwright (2018) and Duflo (2020). The question of external validity has also been explored with quasi-experimental analyses done on large pools of data. Patterns among these analyses have been documented, in the form of meta analyses, which gather existing studies and seek to establish statistical significance of existing conclusions, or the lack thereof. As examples, see Card, Kluve, and Weber (2010, 2018) for meta analyses in labor economics. In the context of estimating the elasticity of taxable income (ETI) with respect to the net-of-tax rate, which is our focus here, Neisser (2021) conducted a meta analysis of 1,720 estimates reported in 61 studies spanning at least twelve different countries, and concluded that ETI estimates need to be interpreted within the context they are produced from, suggesting that the "right" notion of the ETI depends on the country and time period considered in the study. There, her focus is on how the estimated ETI depends on the estimation technique, data coverage, and publication characteristics.

There are a few cross-country panel studies of the ETI. Rubolino and Waldenström (2019) use aggregate data on top income shares and tax rates to study the ETI with respect to top marginal tax rates, and provide ETI estimates for up to 30 countries spanning 1900 to 2014. The estimated ETI for each country does not, though, depend at all on the data from other countries. They document considerable heterogeneity in the estimated ETI, both across countries and over time, and argue that ETIs are partially driven by shifts in income between high-taxed (labor income) and low-taxed (capital income) tax bases, and are affected by wars and financial crises. Klemm, Liu, Mylonas, and Wingender (2018) analyze data from many OECD countries from 1981 to 2016 to examine if globalization and opportunities for tax evasion or avoidance have increased the ETI over time—which, in turn, implies lower optimal tax rates. They find little evidence to support the hypothesis, and conclude that the ETIs do not exhibit clear patterns over the years examined in the study.

The wide variation in ETI estimates across countries motivates our interest in exploring the issue of external validity. How informative is, for example, an estimate of the ETI in Italy for predicting the likely magnitude of the behavioral response to a rate change in Mexico? What light does the estimated elasticity of reported taxable wealth with respect to annual wealth tax rate, estimated on Norwegian data, shed on the likely behavioral response if the United States were to enact a similar tax? We expect that the ETI (or ETW, in the second example) varies across countries and time periods in systematic ways because, as Slemrod and Kopczuk (2002) discuss, the ETI is not a primitive parameter, but is rather influenced by many tax system aspects, such as the broadness of the tax base and the effectiveness of evasion enforcement. In choosing the tax system parameters simultaneously with the effective progressivity of the tax system, a jurisdiction can be thought of as choosing the ETI simultaneously with its choice of the tax rate schedule. For example, a jurisdiction's chosen top tax rate, and its perceived ETI of top incomes, will depend on the social cost of implementing a broad-based, well-enforced tax system (which will lead to a lower top tax rate and a higher perceived ETI), and on the social preference for equality (which will lead to a higher top tax rate and a lower perceived ETI).

In this paper, we develop a new approach to estimating country- and time-specific ETIs that explicitly recognizes the structural determinants of the ETI. We develop a panel correlated random coefficients (CRC) model to characterize the ETI as a linear function of the tax rate and other observable factors, which—according to the theory of optimal taxation—affect the behavioral response to taxation. We leverage both cross-sectional and within-country, over-time variation in taxable income, tax rates, as well as these observable factors, to estimate the ETI. Our econometric approach allows us to obtain estimates of behavioral response in every jurisdiction at every time period. In doing this, our modeling approach directly addresses the question of external validity in a structural way.

Estimating our model on cross-country panel data from 19 OECD countries form 1981 to 2014 on top income shares and tax rates, as well as survey data on public opinion from the World Values Survey and other country characteristics, we find that countries with greater preference for redistribution and trust in government have lower ETIs. The estimated coefficients on our observable characteristics broadly comport with theoretical predictions from the optimal tax systems literature, particularly those of Slemrod and Kopczuk (2002). Our approach also provides new estimates of jurisdiction-specific ETIs for the top 1% of taxable income earners. Furthermore, our estimates revise the estimate of the average US ETI from 0.240, the estimate based only on US data, to 0.311, when appropriately considering the data from the countries in our sample. Our model attributes this revision largely to the United States' especially low public preference regarding the importance of redistribution, and the high value placed on efficiency in the equity-efficiency trade-off, as measured by the World Values Survey. These factors are counter-weighted by the relatively large population of the US, which puts significant downward pressure on the US

ETI.

We conclude our analysis by showing how the CRC model can be modified to study the expected behavioral response to a policy that is enacted in some jurisdictions but not others, as is the case with wealth taxes. Drawing on the fact that the probability of policy adoption depends on the same factors that determine optimal policy for adopters, we show how one can estimate the expected behavioral response that a non-adopting country should expect. Absent ample comparable cross-country measures of taxable wealth, we describe the approach in full but do not present an empirical application.

The rest of this paper is structured as follows. In Section 2, we describe our setup and introduce the estimation framework. Section 3 describes the data we use for our analysis of the ETI, and presents the results of estimating the ETI of top-income individuals in a large sample of countries. In Section 4, we describe how to use our proposed framework to forecast the anticipated behavioral response of non-adopters of a tax policy, had they implemented it, using the elasticity of taxable wealth (ETW) as an illustration. We conclude in Section 5 with a brief discussion of the policy implications of our method and results.

2 The Empirical Setting and Methodology

We begin by considering a static, cross-jurisdiction setting, where the subscript i indexes jurisdictions. Consider the basic setup

$$\log Y_i = \alpha + \varepsilon_i \log(1-\tau_i) + u_i \ , \tag{1}$$

where $\log Y_i$ is the outcome of interest, the natural log of a measure of taxable income, which depends on the behavioral response of taxpayers to tax policy. The value of τ_i summarizes the relevant tax policy in jurisdiction i. The parameter ε_i captures the responsiveness of $\log Y_i$ to the log of net-of-tax rate, $\log(1-\tau_i)$, which we refer to as the elasticity of taxable income, or ETI (Feldstein, 1999; Saez, Slemrod, and Giertz, 2012).

Crucially, in (1) we allow the elasticity to be jurisdiction-specific, as opposed to being fixed across all jurisdictions. If all the exogenous variables that affect ε_i, as well as the data-generating process for ε_i, are known, e.g. $\varepsilon_i = a + bW_i$ for some vector of variables W_i, then we can estimate

$$\log Y_i = \alpha + (a + bW_i) \log(1-\tau_i) + u_i \ . \tag{2}$$

Our setting, however, is more complicated than this, because a jurisdiction's choice of τ_i will likely depend on the policy maker's perception of the value of ε_i. In other words, ε_i and $\log(1-\tau_i)$ are correlated. This follows from standard optimal tax theory reasoning, where the elasticity directly influences the marginal efficiency cost of raising a tax rate (Slemrod and Kopczuk, 2002; Kopczuk, 2005). Therefore, other things equal, the higher ε_i is, the lower τ_i should be. This suggests that the estimate of ε_i in (1) is biased. As we will develop in Section 2.1, we can explicitly characterize the form of the bias. On another note, the behavioral response to a change in the tax rate itself is expected to depend on aspects of the tax system, such as the broadness of the tax base and the enforcement effectiveness of the tax system, which are jointly determined along with the marginal tax rate.

The danger of potentially mis-estimating the ETI is even more apparent in assessing policies that are in place in some jurisdictions and not others. From the point of view of optimal taxation, this heterogeneity in adoption is, in principle, driven by the perceived benefit of adoption relative to the perceived cost of implementing such a policy—which depends, inter alia, on the ETI—implying that the adoption of these policies is nonrandom. In our setting, this applies to wealth tax policies. We develop the implications of this reasoning for external validity in Section 4.

In order to incorporate these insights, we develop a conceptual framework for estimating the ETI based on the *correlated random coefficients* (CRC) framework, a term originally coined by Heckman and Vytlacil (1998) for analyses of cross-sectional data. For concreteness, we introduce time into the empirical specification in (1). The panel empirical specification of interest is

$$\log Y_{i,t} = \varepsilon_i \log(1-\tau_{i,t}) + \gamma_i X_{i,t} + u_{i,t} \text{ for each jurisdiction } i \in \{1, \ldots, N\} \; . \tag{3}$$

In the rest of the text, we will refer to (3) as *segmented regressions*, and the $1 \times K$ vector $X_{i,t}$ as observable *factors*. We include a constant term in $X_{i,t}$ to save on notation. We separate $\log(1-\tau_{i,t})$ in (3) from the observable factors (some of which may potentially not vary over time) to highlight ε_i as our parameter of interest. We also clarify that, by segmented regressions, we mean we are estimating (3) separately for each jurisdiction in our data. Notably, in the CRC model we can explicitly express the heterogeneity in our parameter of interest, ε_i, as a function of observable factors. The example considered in Heckman and Vytlacil (1998) is estimating the return to schooling, in a setting where individuals with heterogeneous responsiveness to schooling self-select into a schooling "intensity": people who believe they are more likely to benefit from schooling tend to choose more schooling. In that setting, the CRC model allows the return to schooling to be correlated with the amount of schooling received. In the tax policy context, jurisdictions self-select into the treatment intensity (the tax rate) based on the anticipated behavioral response, ε_i.

We next introduce our panel CRC model, where we show how to express ε_i as a function of the observable factors and the tax rate. The dependence of ε_i on observable factors and the tax rate is a feature of the theory of optimal tax theory we incorporate here. We note that, with panel data, we can avoid imposing stringent requirements on the data, as in Heckman and Vytlacil (1998), who worked with cross-sectional data. They require the existence of instrumental variables for both the random coefficients and regressors, which allowed them to identify the mean of the random coefficients (the equivalent of ε in our exposition). For a full discussion, see Appendix A. For discussions of panel CRC models, see, for example, Wooldridge (2005, 2019).

2.1 Estimation Approach

In this section, we will suppress the time subscript t on our parameter of interest and on covariates to more concisely illustrate details of our estimation approach.

We assume we have a random sample of size N drawn at each time $t \in \{1, \ldots, T\}$. This restriction is almost without loss of generality; additional complications are introduced in unbalanced panels, as discussed in Wooldridge (2019), but we abstract away from these here. The primary goal of our empirical exercise is to recover jurisdiction-specific ETIs, ε_i, as a linear function of a jurisdiction-specific tax rate and observable factors.

We work with the empirical specification described in (3). To begin, we note that a now standard approach, as in Rubolino and Waldenström (2019), estimates ε_i separately for each jurisdiction i. This is what we refer to as segmented regression in (3). Consistently estimating ε_i in the setup of Rubolino and Waldenström (2019) is possible under a conditional moment restriction, i.e. imposing $\mathbb{E}[u_{i,t} \mid X_{i,t}, \log(1-\tau_{i,t})] = 0$ for each time $t \in \{1, \ldots, T\}$. This recovers an estimate of ε_i as if it is a constant over time. Under some rank conditions—namely, so that we require long panels, as captured by the condition $T \geq K + 1$ (Wooldridge, 2005, 2010)—the OLS estimator for ε_i is a consistent, $\sqrt{N}$-asymptotically normal estimator for $\mathbb{E}[\varepsilon_i]$, i.e. the average ETI across jurisdiction i over all time periods $t \in \{1, \ldots, T\}$. This approach, however, does not take into account that the ETI and the tax rate are correlated.

In addition to estimating ε_i, we seek to model the heterogeneity in the ETI explicitly, as a function of data from all jurisdictions simultaneously. Having panel data, we leverage within-jurisdiction variations in observable factors over time, as well as the across-jurisdiction variations in these factors. To do so, we introduce a variation of an estimation technique originally due to Mundlak (1978), who leveraged jurisdiction-specific time averages of time-varying variables and estimated the resulting equation by random effects; see Chamberlain (1982, 1984) and Wooldridge (2010) for additional details. We use cross-sectional averages of observable factors at every time period to model the heterogeneity in the ETIs. In so doing, we attribute cross-jurisdiction heterogeneity in the ETI to a jurisdiction's deviations in observable factors and tax rate, relative to the global averages.

Before we introduce our estimation approach in full, we sketch the logic of our approach here. We assume that the jurisdiction-specific ETI is a random variable, which can be additively separated into two random components. Specifically, we write $\varepsilon_i = \varepsilon + v_{i,t}$, where ε represents the global average ETI over all time periods in the data, and $v_{i,t}$ captures a jurisdiction's deviation from ε at every time period. We assume that $v_{i,t}$ is zero on average at every time period, i.e. $\mathbb{E}[v_{i,t}] = 0$ for all $t \in \{1, \dots, T\}$. Here, it is worth noting that, under this structure of the ETI, the estimate of ε reflects any global trend in tax policy over time. Furthermore, both components of ε_i are random, and depend on the observed data. Under this structure on ε_i, we can write our estimating equation as

$$\log Y_{i,t} = \varepsilon \log(1-\tau_{i,t}) + \gamma X_{i,t} + v_{i,t} \log(1-\tau_{i,t}) + u_{i,t} \text{ for each jurisdiction } i \in \{1, \dots, N\} \ . \quad (4)$$

The foregoing discussion about the theory of optimal taxation suggests that the heterogeneity in the jurisdiction-specific ETIs, v_i, is correlated with observable factors and the tax rate. In other words, $\mathbb{E}[v_{i,t} \mid \log(1-\tau_i), X_i] \neq 0$. This implies we can write (4) as

$$\log Y_{i,t} = \varepsilon \log(1-\tau_{i,t}) + \gamma X_{i,t} + \mathbb{E}[v_{i,t} \mid \log(1-\tau_{i,t}), X_{i,t}] \log(1-\tau_{i,t}) + \tilde{u}_{i,t} \quad (5)$$

for each jurisdiction $i \in \{1, \dots, N\}$, where

$$\tilde{u}_{i,t} = u_{i,t} + \log(1-\tau_{i,t}) \left(v_{i,t} - \mathbb{E}[v_{i,t} \mid \log(1-\tau_{i,t}), X_{i,t}]\right) \ . \quad (6)$$

The model specification described by (5) and (6), is nonlinear in $\log(1-\tau_{i,t})$ and $X_{i,t}$. In what follows, we impose a functional form on the mean of the unobserved heterogeneity, and explain how we consistently estimate the jurisdiction-specific ETIs.

In formally presenting our estimation framework, we now proceed to write everything in vector form. In what follows, we suppress the time subscript by "stacking" observations over time. We write $Z_i = (\{\log(1-\tau_{i,t})\}_{t=1}^T, \{X_{i,t}\}_{t=1}^T)'$, which is a $(K+1) \times T$ matrix. Following the logic in (2), we assume $\mathbb{E}[v_i \mid Z_i] = a + bZ_i'$, in the spirit of Mundlak (1978). By the law of iterated expectations, $\mathbb{E}[v_i] = \mathbb{E}[\mathbb{E}[v_i \mid Z_i]] = a + b\mathbb{E}[Z_i]$, implying, because $\mathbb{E}[v_i] = 0$, $a = -b\mathbb{E}[Z_i]$, and therefore $\mathbb{E}[v_i \mid Z_i] = b(Z_i - \mathbb{E}[Z_i])$. This means we can write our estimating equation as

$$\log Y_i = Z_i'\beta + b(Z_i - \mathbb{E}[Z_i]) \log(1-\tau_i) + \tilde{u}_i \text{ for each jurisdiction } i \in \{1, \dots, N\} \ , \quad (7)$$

where $Y_i = (Y_{i,1}, \ldots, Y_{i,T})'$ denotes a $T \times 1$ vector of taxable incomes, $\log(1-\tau_i) = (\log(1-\tau_{i,1}, \ldots, \log(1-\tau_{i,T}))'$ denotes a $T \times 1$ vector of log net-of-tax rates, $\beta = (\varepsilon, \gamma)'$ is a $(K+1) \times 1$ vector of coefficients, b is a $T \times (K+1)$ matrix of coefficients, and $\tilde{u}_i = (\tilde{u}_{i,1}, \ldots, \tilde{u}_{i,T})'$. In practice, for estimation, we replace the population mean by the sample mean, i.e. $\mathbb{E}[Z_i]$ is replaced by $\frac{1}{N}\sum_{1 \leq i \leq N} Z_i$.

Our estimation framework in (7) entails three consequences in practice. First, to characterize the cross-jurisdiction heterogeneity in the ETIs, we leverage cross-sectional variations in the tax rate and observable factors at every time period of our data. In particular, this implies that the coefficient b in (7) measures how much the deviations in the tax rate and observable factors in a jurisdiction, relative to the global averages, contribute to its anticipated behavioral response. Second, in our estimation strategy, we imposed restrictions on the conditional distribution of jurisdiction-specific heterogeneity, $v_{i,t}$. Specifically, $v_{i,t}$ depends on both the tax rate and the set of observable factors. This is a special case of the identification argument via exchangeability conditional on covariates, described in Altonji and Matzkin (2005), which allows us to point-identify the average heterogeneity in the ETIs in our approach. Third, from (7), we have $\mathbb{E}[\tilde{u}_i \mid Z_i] = 0$ by direct verification. By this moment restriction, we can estimate (7) consistently via a standard pooled OLS approach. Further note that $\mathbb{E}[\tilde{u}_i\tilde{u}_i'] = \mathbb{E}[u_i u_i' + \log(1-\tau_u)'\tilde{v}_i\tilde{v}_i' \log(1-\tau_i)]$, where $\tilde{v}_i = v_i - \mathbb{E}[v_i \mid Z_i]$.

We make two additional observations about our approach. First, by a direct application of the Frisch-Waugh-Lovell theorem, we can explicitly characterize the bias of the estimated ETI in the segmented regressions (3)—which ignore the correlation between $\log(1-\tau_i)$ and ε_i—by thinking of them as misspecified models for estimating the ETI. The bias depends on the covariance between residualized taxable income and the residualized tax rate, where we residualize using the set of chosen observable factors. For more details, see Appendix B. Second, from (6), the residual in our empirical specification is composed of two terms. The first term comes from explaining a jurisdiction's taxable income using its tax rate. In estimating the ETI of jurisdiction i, our approach minimizes the residual from explaining jurisdiction i's taxable income using its tax rate, and not that of other jurisdictions. The second term involves the residual from estimating the true unobserved heterogeneity term using the observable factors. In particular, the second term depends on the observable factors we choose.

By way of remark, we can alternatively model the heterogeneity term $v_{i,t}$ by exploiting within-country, over-time variations in observable factors and tax rate. In practice, this means in modelling $\mathbb{E}[v_i \mid Z_i] = b(Z_i - \mathbb{E}[Z_i])$, we replace $\mathbb{E}[Z_i] = \frac{1}{T}\sum_{1 \leq t \leq T} Z_{i,t}$ for all jurisdictions $i \in \{1, \ldots, N\}$. This arises from imposing an alternative assumption that $\mathbb{E}[v_{i,t}] = 0$ for all jurisdictions $i \in \{1, \ldots, N\}$. This modelling assumption allows us to estimate the global average ETI as a time-varying function of observable factors and tax rate, but we give up estimating the heterogeneity in ETI as a time-varying function. We note that there is no assumption on the heterogeneity term that allows us to estimate the hetereogeneity by utilizing *both* cross-country and within-country, over time variations in observable factors and tax rate.

In summary, our empirical approach proceeds as follows. We first identify some set of covariates that we hypothesize will affect the outcome variables and/or the behavioral response of that variable to a tax policy. We estimate (7) to identify ε_i for every jurisdiction i. For inference on the estimated coefficients in (7), we utilize heteroskedasticity-robust standard errors; alternatively, we could construct the "stepdown" bootstrap confidence intervals as described in Romano and Wolf (2005). This is valid as we jointly test the multiple hypothesis about the ETIs across jurisdictions. For inference on the predicted ETIs for each jurisdiction, we construct bootstrap standard errors. Specifically, we resample at the jurisdiction level in order to construct the sampling distributions of predicted ETIs for each jurisdiction. We construct 95% confidence intervals by taking the 2.5th and 97.5th percentiles of the resulting sampling distributions. We then compute standard errors by dividing by four the difference between the ends of the confidence interval.

3 Estimating the Top Income ETI

We now turn to our application of the econometric methodology we have described—explaining the top income share as a function of the top tax rate. In what follows, we say more about the model specification, describe our data sources, and present estimates from our proposed methodology.

3.1 Model Specification

In this section we describe the structural model we propose for the simultaneous choice a country makes, explicitly, about the top tax rate and, implicitly, about the elasticity of taxable income. This specification will guide the choice of observable factors used to estimate the ETI according to the method developed in Section 2.

First, we recognize, as suggested by the theory of optimal taxation, that the top tax rate is likely to be a function of both the social value of redistribution $\Omega_{i,t}$ and the elasticity of taxable income ε. With this in mind, we characterize the top tax rate as a linear function of these two factors. In turn, we model the elasticity of taxable income according to the logic in Slemrod and Kopczuk (2002), which suggests that the ETI is itself implicitly a chosen parameter, subject to influence by the social preference for redistribution as well as factors that govern the tax administration's ability to institute a broad-based and well-enforced tax system, captured here by the term $\gamma_{i,t}$.

$$\log(1-\tau_{i,t}) = \pi + \pi_1\Omega_{i,t} + \pi_2\varepsilon_i + w_{i,t} \tag{8}$$

$$\varepsilon_i = \varepsilon + b_1\Omega_{i,t} + b_2\gamma_{i,t} + \omega_{i,t} \tag{9}$$

In the framework described in Section 2.1, $\Omega_{i,t}$ and $\gamma_{i,t}$ constitute the components of $X_{i,t}$, along with the top marginal tax rate from the vector $Z_{i,t}$. This characterization of the ETI and top marginal tax rates suggests that both policy instruments are driven by a set of common factors captured in $X_{i,t}$. Our econometric framework accounts for this. We emphasize that our framework allows us to remain agnostic about the functional form of the correlation between the ETI and the top marginal tax rate. As such, we do not assume that the relationship is linear per se. Instead, we make the less restrictive assumption that the conditional expectation of the idiosyncratic heterogeneity term in the ETI (v_i in the framework of Section 2.1) is linear in observed characteristics, which we model according to (9) as $b_1\Omega_{i,t} + b_2\gamma_{i,t}$, along with an extra term for the tax rate to account for any residual unobserved correlation between expected country-specific ETIs and the top marginal tax rate.

Because our estimation relies on panel data, we need to make a decision about how to handle country-specific heterogeneity in the ETI and the top share of income. We allow for country fixed effects in the outcome variable, as well as linear time trends that vary across countries. These are meant to capture secular trends in top income shares that differ across countries, as well as the country-specific average top income share. That said, such modeling decisions are not strictly necessary, although useful in our setting, and our framework extends to alternative specifications. Note that our specification does not feature fixed effects in the ETI equation. The assumption of a single intercept is necessary for the cross-sectional comparisons that we would like to make. In making this modeling decision, our assumption is that all country-specific heterogeneity in the ETI is captured by the tax rate and the elements of $X_{i,t}$: we require that different countries with the same observable characteristics will have the same expected ETI.

Combining these insights with our model from Section 2, we arrive at our estimating equation:

$$\log Y_{i,t} = \varepsilon\log(1-\tau_{i,t}) + b(Z_{i,t} - \mathbb{E}[Z_{i,t}])\log(1-\tau_{i,t}) + X'_{i,t}\beta + \alpha_i D_i + tD_i + \tilde{u}_{i,t}\ , \tag{10}$$

where $Y_{i,t}$ is the top 1% share of reported top taxable income, $X_{i,t}$ is data for $\Omega_{i,t}$ and $\gamma_{i,t}$, $Z_{i,t}$ is $X_{i,t}$ combined with our top net-of-tax rate $\log(1-\tau_{i,t})$ as defined in Section 2.1, and D_i denotes the set of dummy variables for countries. As described in Section 2.1, the expectation in (10) is taken with respect to countries at every time period. With this setup in mind, the estimated coefficients map back to the structural model for the ETI in (9): ε is the average ETI across countries over time, and b governs the influence of the observable characteristics in Z_i on a country's ETI relative to others at any point in time. Finally, note that ε in (10) is equivalent to ε in (7).

3.2 Data

We implement the econometric model described in the previous section with data for the top percentile share of pre-tax reported income, the marginal tax rate for the top percentile earner, and indices of country characteristics that are contained in $Z_{i,t}$.

Our analysis relies on a panel of 19 countries for the years 1981 through 2014, and largely draws on Rubolino and Waldenström (2019). Data on the top percentile shares of national "fiscal" income come from the World Inequality Database (WID.world, 2022). The measure of fiscal income from the WID is intended to capture the component of taxable income that is reported in income tax filings. This definition of income is attractive for the estimation of the ETI under its interpretation as a measure of the fiscal externality caused by the behavioral response to changes to marginal tax rates. One drawback of using this measure is that it includes realized capital gains, which are in many cases not subject to the same tax rate as ordinary income. This raises omitted variable concerns in so far as changes in the top tax rate are correlated with changes in the capital gains rate. Rubolino and Waldenström (2019) address this concern and note that, for a subset of countries where capital gains-adjusted top shares are available, exclusion of capital gains in the top income share does not meaningfully change estimates for the ETI. When estimates of the top income share are missing from the WID data, we impute using linear interpolation. Country-year observations with missing top income share values at the beginning or end of the sample period are excluded from our analysis.

Top tax rates are taken from Rubolino and Waldenström (2019), and are supplemented by data from the OECD tax table I.7 for more recent years (OECD (2023)). After taking logs of the top share of reported income and the marginal net-of-tax rate, the interpretation of the coefficient ε is the now-standard elasticity of taxable income; see Saez, Slemrod, and Giertz (2012) for an extended discussion.

For the elements $X_{i,t}$ that capture the perceived benefits of redistribution as well as the costs of enforcing a broad and well-enforced tax base, we first construct indicators based on survey responses from the World Values Survey (WVS). These indicators are constructed as follows. Each question is associated with an index. First, we pull the individual survey responses from the WVS website. Then, for each question, we calculate the weighted mean of the responses within each country and wave. We assign this value to the index for all years within each survey wave. For the years in between survey waves, or any years where the question was not asked in a particular country, we linearly interpolate based on the values from the prior time the question was asked and the next time the question was asked. Any early-year missing values are carried back from the first time the question was asked, and any tail-year missing values are carried forward from the last time the question was asked. In the rare cases where a particular survey question was never asked in a country, we assign the average survey value across countries. The mean and standard deviation for each of the constructed indexes in our analysis sample are reported in Table 1.

3.2.1 Social Attitudes toward Redistribution

Following the logic of Slemrod and Kopczuk (2002), we look for measures of the social demand for tax progressivity and for measures of the social cost of achieving progressivity. We discuss each in turn below.

Our first indicator comes from a Likert scale that assesses respondents' beliefs that engaging in redistribution is an essential part of democracy. We believe that this question most directly elicits citizens' preferences about redistribution and the social value of redistributive taxation. The question is posed as follows:

> **Question 1.** Many things are desirable, but not all of them are essential characteristics of democracy. Please tell me for each of the following things how essential you think it is as a characteristic of democracy. Use this scale where 1 means "not at all an essential characteristic of democracy" and 10 means it definitely is "an essential characteristic of democracy"
>
> **a.** Governments tax the rich and subsidize the poor.

Although Question 1 appeals to respondents' ideal role of government, the following two questions are posed in a way that appeals to the proper role of government relative to the status quo. Question 2.a is particularly interesting because we believe that it captures the public's views regarding the relative importance of equity and efficiency, which is an important object for the study of optimal taxes; we refer to the index created by this question as "Efficiency over Equity." We will refer to the second as "Own over Government Responsibility." The questions are worded as follows:

> **Question 2.** Now I'd like you to tell me your views on various issues. How would you place your views on this scale? 1 means you agree completely with the statement on the left; 10 means you agree completely with the statement on the right; and if your views fall

Table 1: Sample Statistics

Country	Statistic	Top 1% Share of Pre-Tax Income	Top Marginal Tax Rate	Population in 2000 (thousands)	Redistribution Essential to Democracy	Efficiency over Equity	Own over Government Responsibility	Justifiable to Cheat on Taxes	Confidence in Government	Government Right to Collect Info.
Australia	Mean	0.070	0.498	19,053	6.050	5.465	5.139	2.322	1.148	1.027
	St. Dev.	0.015	0.046	0.000	0.002	0.302	0.092	0.405	0.081	0.000
	N	34	34	34	34	34	34	34	34	34
Canada	Mean	0.121	0.324	31,100	6.135	6.139	4.526	2.185	1.332	0.778
	St. Dev.	0.022	0.066	0.000	0.091	0.539	0.502	0.149	0.015	0.000
	N	34	34	34	34	34	34	34	34	34
Denmark	Mean	0.054	0.386	5,337	6.293	6.609	4.394	2.128	1.526	0.910
	St. Dev.	0.004	0.081	0.000	0.000	0.212	0.210	0.278	0.045	0.000
	N	30	34	34	34	34	34	34	34	34
Finland	Mean	0.064	0.414	5,168	6.988	5.394	4.560	2.461	1.224	1.153
	St. Dev.	0.021	0.073	0.000	0.000	0.974	0.388	0.399	0.035	0.000
	N	29	34	34	34	34	34	34	34	34
France	Mean	0.091	0.549	61,137	5.948	5.133	4.304	2.928	1.055	0.758
	St. Dev.	0.008	0.078	0.000	0.000	0.157	0.320	0.298	0.008	0.000
	N	34	34	34	34	34	34	34	34	34
Germany	Mean	0.114	0.508	82,187	7.171	5.242	5.761	2.477	1.050	0.574
	St. Dev.	0.015	0.045	0.000	0.097	1.011	0.743	0.345	0.156	0.000
	N	34	34	34	34	34	34	34	34	34
Ireland	Mean	0.079	0.488	3,791	6.408	5.954	4.596	2.652	1.223	0.905
	St. Dev.	0.020	0.073	0.000	0.000	0.516	0.275	0.337	0.000	0.000
	N	34	34	34	34	34	34	34	34	34
Italy	Mean	0.082	0.516	57,719	6.712	5.860	5.630	2.259	1.040	0.985
	St. Dev.	0.011	0.092	0.000	0.000	0.099	0.156	0.194	0.007	0.000
	N	29	34	34	34	34	34	34	34	34
Japan	Mean	0.097	0.487	126,729	6.497	5.638	6.892	1.452	1.165	0.905
	St. Dev.	0.014	0.115	0.000	0.000	0.259	0.196	0.063	0.040	0.000
	N	30	34	34	34	34	34	34	34	34
Korea	Mean	0.087	0.453	46,838	7.481	6.006	6.344	1.633	1.373	0.745
	St. Dev.	0.018	0.111	0.000	0.020	0.666	1.644	0.082	0.083	0.000
	N	34	34	34	34	34	34	34	34	34
Netherlands	Mean	0.060	0.600	15,907	6.102	5.983	4.814	2.679	1.280	1.270
	St. Dev.	0.006	0.081	0.000	0.000	0.256	0.239	0.423	0.026	0.000
	N	34	34	34	34	34	34	34	34	34
New Zealand	Mean	0.078	0.409	3,802	5.469	5.329	4.924	2.206	1.084	1.137
	St. Dev.	0.017	0.113	0.000	0.000	0.078	0.153	0.155	0.243	0.000
	N	34	34	34	34	34	34	34	34	34
Norway	Mean	0.072	0.478	4,492	6.848	5.610	5.016	2.706	1.625	0.594
	St. Dev.	0.026	0.083	0.000	0.000	0.319	0.401	0.450	0.087	0.000
	N	34	34	34	34	34	34	34	34	34
Portugal	Mean	0.076	0.470	10,335	5.989	4.856	4.799	2.983	1.030	0.758
	St. Dev.	0.017	0.112	0.000	0.000	0.332	0.277	0.695	0.016	0.000
	N	25	34	34	34	34	34	34	34	34
Spain	Mean	0.091	0.492	40,016	7.023	5.217	6.219	2.252	1.121	0.967
	St. Dev.	0.011	0.054	0.000	0.000	0.207	0.297	0.362	0.098	0.000
	N	32	34	34	34	34	34	34	34	34
Sweden	Mean	0.071	0.633	8,872	6.423	5.847	4.017	2.287	1.402	0.789
	St. Dev.	0.020	0.118	0.000	0.000	0.573	0.764	0.232	0.090	0.000
	N	33	34	34	34	34	34	34	34	34
Switzerland	Mean	0.095	0.420	7,266	6.887	4.615	3.687	2.307	1.542	0.725
	St. Dev.	0.010	0.024	0.000	0.003	0.266	0.503	0.177	0.106	0.000
	N	34	34	34	34	34	34	34	34	34
United Kingdom	Mean	0.114	0.453	59,522	6.307	5.816	4.758	2.368	1.001	1.240
	St. Dev.	0.028	0.082	0.000	0.000	0.541	0.350	0.266	0.026	0.000
	N	34	34	34	34	34	34	34	34	34
United States	Mean	0.173	0.384	282,158	5.016	6.118	4.075	1.987	1.243	0.967
	St. Dev.	0.038	0.065	0.000	0.010	0.546	0.617	0.159	0.043	0.000
	N	34	34	34	34	34	34	34	34	34
All	Mean	0.090	0.472	45,865	6.408	5.623	4.971	2.330	1.235	0.905
	St. Dev.	0.033	0.110	64,447	0.586	0.678	0.988	0.492	0.203	0.196
	N	616	646	646	646	646	646	646	646	646

Notes: For each of the questions defined in Section 3.2, this table displays the average and standard deviation of the survey indicators used in our analysis sample. Sample counts reflect the impact of interpolation and extrapolation. Note that we interpolate, but do not extrapolate, the missing top 1% share values. Survey indicators are both interpolated for between-wave years, and extrapolated for beginning and end years. Population counts are kept constant across years based on their values in 2000. Sources: Top income shares and population counts are from WID.world (2022). Top marginal tax rates are from Rubolino and Waldenström (2019), supplemented with data from OECD (2023). Survey indices are calculated based on World Values Survey data.

somewhere in between, you can choose any number in between.

a. Incomes should be made more equal (1) vs. We need larger income differences as incentives for individual effort (10)

b. Government should take more responsibility to ensure that everyone is provided for (1) vs. People should take more responsibility to provide for themselves (10)

3.2.2 Measures of the Social Cost of Redistribution

We turn next to measures of the social cost of achieving a progressive tax system. One aspect of this is the prevalence of tax evasion. As a measure of a country's attitudes toward evasion, we consider the average responses to the following question, with the idea that the higher is people's willingness to evade taxes, the higher will be this cost.

Question 3. Please tell me for each of the following actions whether you think it can always be justified (10), never be justified (1), or something in between, using this card.

- Cheating on taxes if you have a chance.

Next, we consider direct survey evidence on confidence in government, which arguably lowers the cost of implementing a progressive tax system:

Question 4. I am going to name a number of organizations. For each one, could you tell me how much confidence you have in them: is it a great deal of confidence (4), quite a lot of confidence (3), not very much confidence (2) or none at all (1)?

a. The government

Additionally, we construct a measure to capture respondents' beliefs about privacy. Beliefs about privacy matter for the social cost of achieving progressivity because access to taxpayer information facilitates the implementation of an equitable tax system. The less the public believes that the government has a right to access private information, the more difficult it may be to implement, for example, robust third-party information reporting programs. Our measure is based on the following question:

Question 5. Do you think that the your country's government should (4) or should not (1) have the right to do the following:

a. Collect information about anyone living in this country without their knowledge

Finally, we consider one non-survey-based characteristic of a country, its population, on the grounds that smaller countries will likely have more open economies, and more open economies will tend to have higher ETIs, due to its facilitation of migration of factors and other tax bases. We use the log of population in 2000, ignoring its drift over time.

3.3 Benchmarks

If the goal of our analysis were to simply describe the nature and extent of ETI heterogeneity across countries, one might want to run "segmented" regressions in the spirit of (1) separately for each country, and potentially for separate time periods. Indeed, this is the exercise at the heart of Rubolino and Waldenström (2019). As a benchmark, we regress our preferred measure of the logged top share of income against the log net-of-tax rate for each of the countries in our data set. The resulting estimates are reported in Column 1 of Table 2 along with heteroskedasticity-and-auto-correlation robust standard errors. Keep in mind that, as discussed above, these estimates are biased to the extent that tax rates are chosen in part based on policy makers' perceptions of the ETI, and these perceptions are correlated with the true ETI. The US estimate is 0.240, lower than the overall world average of 0.293, and broadly in line with the evidence summarized in Saez, Slemrod, and Giertz (2012). These estimates are also broadly in line with those presented by Rubolino and Waldenström (2019). Note that many of the segmented ETI estimates are imprecise due to the limited amount of within-country variation in some countries for the top marginal tax rate. This suggests that a pooled estimation may yield improved precision, depending on how much one can learn about one country's elasticity from other countries' experiences.

Estimating separate segmented regressions for each country presumes a stark answer to the question of how much can be learned from analysis of data in other countries: nothing at all. At the other extreme, one can estimate a pooled regression assuming that there is a common ETI for all countries, essentially treating other countries' data as providing additional information about a common elasticity. If we do that while allowing for country fixed effects and country-specific linear time trends for the top taxable income, we estimate an ETI of 0.294, which is unsurprisingly almost exactly the simple average of cross-country segmented elasticities.

3.4 CRC Estimation

We argue that the CRC framework we have developed is an informative middle ground between the segmented regression approach and the pooled approach assuming a common ETI everywhere, and one that can avoid the bias that arises from ignoring the correlation between elasticities and the chosen top tax rate and is consistent with optimal tax theory. In this section we present the

Table 2: ETI Estimates

Country	Segmented ETIs	CRCM Mean
Australia	0.590	0.350
	(0.143)	(0.208)
Canada	0.484	0.401
	(0.087)	(0.237)
Denmark	-0.205	0.399
	(0.105)	(0.308)
Finland	0.065	0.262
	(0.401)	(0.476)
France	0.433	0.383
	(0.074)	(0.237)
Germany	0.310	0.339
	(0.110)	(0.363)
Ireland	0.409	0.531
	(0.423)	(0.226)
Italy	0.195	0.359
	(0.039)	(0.182)
Japan	0.171	0.205
	(0.312)	(0.184)
Korea	-0.251	0.167
	(0.099)	(0.300)
Netherlands	-0.161	0.221
	(0.186)	(0.318)
New Zealand	0.639	0.539
	(0.208)	(0.409)
Norway	0.484	0.210
	(0.325)	(0.329)
Portugal	0.328	0.507
	(0.067)	(0.256)
Spain	0.186	0.188
	(0.187)	(0.261)
Sweden	0.276	0.325
	(0.108)	(0.231)
Switzerland	0.755	0.037
	(0.668)	(0.646)
United Kingdom	0.611	0.331
	(0.176)	(0.309)
United States	0.240	0.311
	(0.157)	(0.431)
Mean	0.293	0.319

Notes: This table shows how ETI estimates compare across segmented regressions and our CRCM model. CRCM mean estimates are computed as $\varepsilon + b(\mathbb{E}_i[Z_{i,t}] - \mathbb{E}[Z_{i,t}])$ from (10). Standard errors for the segmented estimates are heteroskedasticity-and-autocorrelation-robust. Standard errors for the CRCM estimates are computed using 30,000 iterations of the bootstrap procedure. Specifically, we take the bootstrap 95 percentile confidence interval ends and divide their differences by four.

results of the pooled analysis according to the CRC model outlined in Section 2, according to the specification describe in Section 3.1.

Following the framework in Section 2, the coefficients of the ETI equation are identified based on over-time variation in the differences between each country's observable characteristics and the global mean of each characteristic at each period in time. The intercept of the ETI equation is interpreted as the predicted ETI of a country that is "average" with respect to our observable characteristics at any point in time. Further, our regression coefficients can be interpreted as the effect of a relative change in observable characteristics on a country's ETI. With this interpretation in mind, we note that our model is able to explain, for example, why the United States has an ETI that differs from Norway's, as a function of the difference between the observable characteristics of each country.

Table 3 shows the results of this exercise, with heteroskedasticity-and-autocorrelation-robust standard errors reported. The explanatory variables are standardized, so the coefficients can be interpreted as the effect on the ETI of a one standard deviation increase in the difference between a country's observable characteristic and the cross-country average at a point in time. The first coefficient reported in this table is the intercept of our ETI equation. This coefficient implies an average ETI in our sample of 0.319. Other coefficient estimates capture how the explanatory factors explain the cross-section of country ETIs.

The estimates generally comport with the theoretical predictions associated with the optimal ETI model from Slemrod and Kopczuk (2002). As society increasingly values redistribution, the marginal benefit of collecting taxes efficiently grows, so ETIs are expected to decline. This dynamic is captured by the negative coefficient associated with "Redistribution is essential to democracy", and the positive coefficient associated with the "efficiency over equity" factor. The "own over government" responsibility factor is associated with a negative coefficient, as expected. The "justifiability of cheating on taxes" factor, which is associated with the perceived private costs of evasion, is associated with lower ETIs, although this coefficient estimate is not significant. The confidence in government measure captures the costs of implementing a broad and well enforced tax system and is, as expected, associated with lower ETIs. The framework in Slemrod and Kopczuk (2002) suggests that the less people believe that the government has the right to collect information about anybody in their country, the higher the cost of administering a broad tax base, and the higher the ETI. This is borne out in a negative coefficient on the "government right to collect information" measure. We find that, holding all other observable characteristics fixed, lower taxes are associated with higher ETIs. Finally, we find that population size is inversely related to the ETI, consistent with the idea that smaller countries are on average more open, and openness

Table 3: CRCM Regression Estimates

	ε_i
ε	0.319***
	(0.090)
Redistribution is essential	−0.055
	(0.054)
Efficiency over Equity	0.112**
	(0.048)
Own over Government Responsibility	−0.012
	(0.063)
Confidence in Government	−0.165**
	(0.080)
Justifiability of cheating on taxes	−0.007
	(0.031)
Government right to collect info	−0.082
	(0.066)
$\log(1-\tau)$	0.015
	(0.019)
Logged Population in 2000	−0.109*
	(0.060)
Observations	616
R^2	0.920
Adjusted R^2	0.913
Residual Std. Error	0.101 (df = 564)
F Statistic	127.949*** (df = 51; 564)

Notes: *** p<0.01, ** p<0.05, * p<0.10.
Coefficient estimates are from the regression specification detailed in (10). Explanatory variables are standardized before regression. Standard errors are heteroskedasticity-and-autocorrelation-robust. Specifically, we use Newey-West standard errors with three lags.

increases ETI by facilitating migration of tax bases. It also potentially reflects the economies of scale associated with centralized tax administration in large countries.

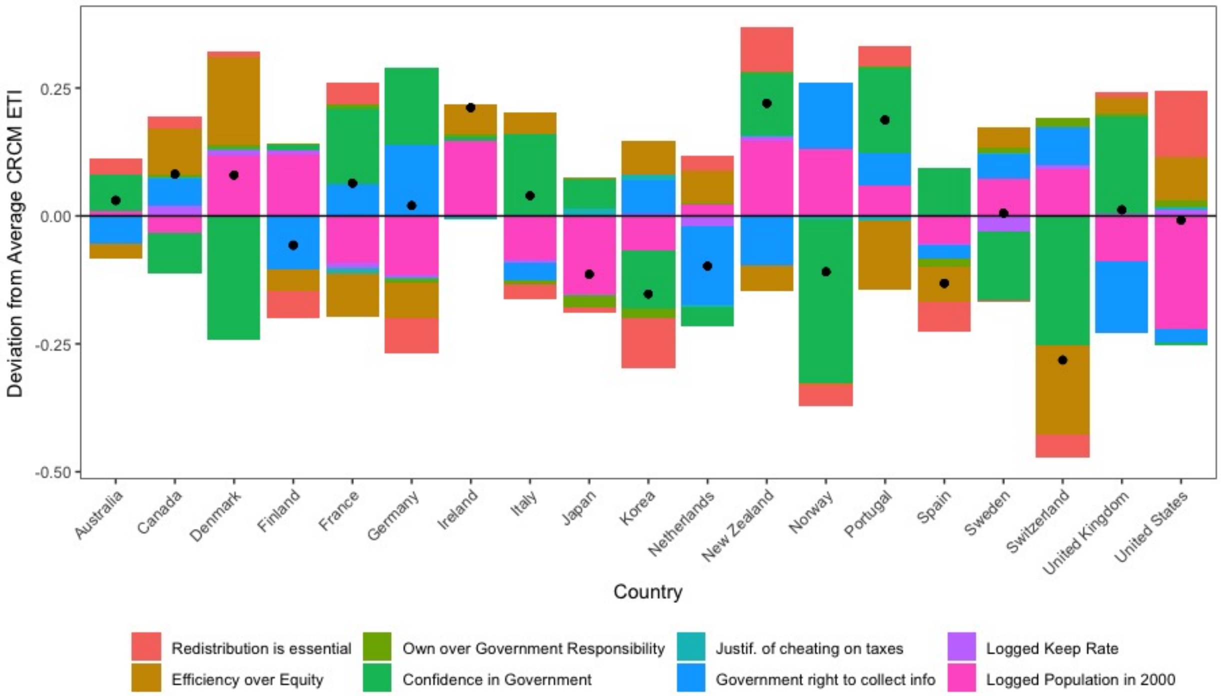
We now have all of the ingredients needed to estimate conditional ETIs for each country in each time period. The estimated ETI for each country is presented in column 3 of Table 2. Note that these estimates are in some cases substantially different from those reported in column 1 of Table 2. Take, for example, the United States. The estimated ETI for the US using only US data, i.e. according to the segmented estimation procedure, is 0.240. Using the CRC model we estimate the average US ETI to be 0.311, somewhat higher than the estimate from the segmented procedure. This revision reflects the fact that our estimation strategy accounts for the bias in the ETI discussed previously. It also occurs because we require each country's estimated ETI to follow the estimated linear function of the factors we have selected. Figure 1 shows that the estimated US ETI via our method is slightly lower than the average over all countries. This prediction is the product of opposing forces. For one, the US is an outlier in the public value of redistribution, putting a lower value on it than the OECD average by more than two standard deviations. In addition, Americans are more likely to prioritize the importance of efficiency in the equity-efficiency trade-off, and report lower trust in government than the average country in our sample. Both of these factors indicate a significantly higher-than-average US ETI. However, they are counter-weighted by the role of country size: the relatively large US population leads to a reduction in the predicted ETI of around 0.2, leading to an estimated ETI of 0.311.

4 External Validity Between Adopters and Non-Adopters—With an Application to Wealth Taxation

We turn now to a setting where only some jurisdictions levy a given tax, and those that do levy different rates (and have different definitions of the tax base). What can we learn about the elasticity of the tax base with respect to the tax rate of the countries that do not levy such a tax?

This setting is not purely hypothetical; in particular, it applies to an annual wealth tax. In 1990, twelve European (mostly OECD) countries levied an annual tax on net wealth. By 2018, only four—France, Norway, Spain, and Switzerland—levied such a tax, while in 2018, France replaced its annual wealth tax with a tax only on immovable property, leaving only three. In 2019, two prominent contenders for the US Democratic presidential nomination proposed such a tax. Analyses of its likely impact often cited evidence drawn from these three countries—from where else could such evidence be drawn? However, following the logic of the previous section, there is reason to believe that a wealth tax is adopted in those countries in which the net social

Figure 1: Contribution of Factors to Deviations from the Average World ETI



Notes: This figure depicts the role that country-level factor deviations play in explaining the departure of country-specific average ETIs from the cross-country average ETI. This difference is equivalent to $\mathbb{E}[\varepsilon_i|Z_{i,t}] - \varepsilon$. Effect sizes are determined by the product between the average country-level difference from the cross-country factor mean (i.e. $\mathbb{E}_i[Z_{i,t} - \mathbb{E}_t[Z_{i,t}]]$) and the coefficient estimates shown in Table 3. The components above the zero line represent the role of factors that put upward pressure on a country's ETI, and the components below the zero line are factors that put downward pressure on the ETI. The black points depict the net effect of all factors on $\mathbb{E}[\varepsilon_i] - \varepsilon$.

benefit is relatively high, the determinants of which include a relatively low behavioral response and therefore efficiency cost[1], as well as a relatively high demand for tax progressivity, given that wealth taxes are levied on a highly skewed base and usually feature a high exemption level. But, because there are other factors that influence the probability of adoption, one cannot be sure, *a priori*, that the behavioral response in adopters is lower than in non-adopters.

To see that behavioral responses may not necessarily be "monotone", let the social benefit of adopting a tax, B_i, be equal to $\delta X_i + e_i$, where X_i is a vector of observable factors and e_i is a set of unobservable factors. Then, one can estimate a linear probability or probit model to see which factors matter for adoption, using either the current 3-country adopter set or the circa 1990 12-country adopter set (or, perhaps, an ordered probit, with three outcomes: never adopted, adopted

[1]Note that Scandinavian countries are also noted for the quality and accessibility of tax administration data. This is almost certainly correlated with factors that affect optimal tax policy, which raises another fascinating issue. What if credible studies of tax elasticities are more likely to be done in countries with high-quality, accessible-to-academics, data? This could cause bias in meta analyses of ETI studies, such as Neisser (2021).

but later abolished, and current adopters). On average, non-adopters will have negative values of δX_i. One could rank the non-adopters by the value of δX_i to see which are marginal and which are far from adoption. In addition, for any jurisdiction i, one could see which elements of X_i are responsible for the non-adoption.

The econometric approach outlined in Section 2.1, as applied only to the set of adopters, can shed light on the behavioral response of non-adopters *had they* implemented a wealth tax. This claim is part of a larger discussion of external validity in the CRC model literature, e.g. Heckman, Schmierer, and Urzua (2010), who argue the CRC model, as applied to cross-sectional data, maps to the Roy model (Roy, 1951), which is equivalent to the potential outcomes framework (Vytlacil, 2002). This feature allows us to express the ETW, ε_i, in terms of treated and untreated potential outcomes. We note, however, that this discussion is limited to cross-sectional data, and our approach does not map identically to the discussion in Heckman and Vytlacil (1998).

However, using data of the adopters, we can still learn the anticipated behavioral responses of non-adopters *had* they implemented a wealth tax. In the context of ETW, as argued above, countries with higher perceived ETW are less likely to implement a wealth tax, due to increased social costs of implementation. Our interest is to measure the change in the behavioral response before and after a wealth tax policy is implemented. We take a causal interpretation of the regression specification (7). Recalling that the estimated ETI admits the form

$$\hat{\varepsilon}_i = \frac{\partial \log Y_i}{\partial \log(1-\tau_i)} = \hat{\varepsilon} + \hat{b}\tilde{Z}_i' \ ,$$

where $\hat{\varepsilon}$ denotes the estimated average ETI over time within each country, $\hat{b}$ denotes the estimated effect each *demeaned* observable factor contributes to the jurisdiction-specific ETI, and $\tilde{Z}_i' = \left(Z_i' - \frac{1}{N}\sum_{1\leq i\leq N} Z_i'\right)$.

We impose the assumption that, had the non-adopters implemented a wealth tax, the estimated cross-country average ETI, $\hat{\varepsilon}$, remains the same. While this is not an innocuous assumption, it is plausible in our context. The estimated $\hat{\varepsilon}$ does not take into account the costs of implementing a wealth tax, but rather explains the effect of *having* a wealth tax on behavioral response, everything else held constant. Had a non-adopter implemented a wealth tax, we model its anticipated behavioral response in the presence of a wealth tax as a function of the demeaned observable factors $\tilde{Z}_i'$. From the set of adopters, we can learn how the observable factors affect the jurisdiction-specific ETI.

Alas, the requisite data for assessing the elasticity of taxable wealth are much scarcer compared to those for the ETI—there is just a handful of studies on this subject, notwithstanding the limited number of countries implementing such taxes, both sets identified and described in **?**. In fact, **?** collects a number of empirical studies that examine how individuals respond to the incentives created by a net wealth tax. Particularly of note is the substantial variation in the magnitudes of the ETW estimates. While the studies discussed therein are based in different countries, the estimates vary enormously. They attribute these dramatic variations to differences in tax system designs, contexts, and methodologies used in the studies. As noted by the authors, the existing studies on the estimates of ETW are limited in both time horizons considered, and methods are limited to differences-in-differences approaches. Because we lack sufficient comparable cross-country measures of taxable wealth, we do not present estimates of ETW in this paper, and encourage future researchers to apply this method to this or other appropriate questions.

5 Conclusion

We develop a new econometric framework for estimating the elasticity of taxable income that utilizes data from many countries, while recognizing that the behavioral response will vary systematically across countries in ways suggested by the theory of optimal taxation. In particular, because the elasticity of taxable income is not a model primitive, it depends, among other things, on the social preference for equality and the social cost of implementing a broad, well-enforced tax system. We describe the interdependence between the ETI and tax rate using the conditional random coefficients (CRC) framework. Applying this framework to study the ETI among top income earners in 19 OECD countries, we find that our model yields an average ETI of 0.319. We find a number of results that are consistent with predictions of optimal tax theory: for example, the ETI declines as society increasingly values redistribution and decreases as citizens place more trust in government, which captures the costs of implementing a broad and well enforced tax system.

We further argue that, in the scenario where a policy is implemented in some jurisdictions and not others, the CRC framework can be formulated to use evidence from the sample of adopters to estimate what the behavioral response would be among the non-adopters, were they to implement such a policy.

We offer this method as an initial step toward rigorously distilling the lessons to be learned from evidence about tax systems, and the behavioral response to these systems, from other countries, and possibly other times. To be sure, meta analysis has a similar objective. Unlike meta analysis, however, our approach draws from the insights in the theory of optimal taxation, which teaches us that the tax rate structure depends both on society's distributional preferences and the social cost of achieving progressivity. This implies that a jurisdiction's elasticity of the tax base and its top tax rate are determined simultaneously by these factors. Our approach delivers jurisdiction-specific estimates of the elasticity of response, and generates estimates of what exogenous characteristics of the jurisdiction affect both the elasticity and top tax rate chosen. Thus, it provides a rigorous answer to the question of to what extent an estimated behavioral response can be extrapolated to other countries.

One clear next step in this agenda is developing a robust set of factors that explains why tax systems and behavioral elasticities vary across countries and time. In this version, we have focused on measures of citizen attitudes rather than policy manifestations of these attitudes. For example, we have used a survey measure of how people feel about personal privacy vis-a-vis the government, rather than how extensive third-party information reporting is, which undoubtedly depends on attitudes toward privacy. Another step would be to extend the sample of countries considered beyond the OECD set to developing countries. Almost certainly this would introduce greater variation in the factors affecting chosen tax systems and observed elasticities, which would improve the model's predictive power, but it would also add countries where data availability and quality are in general inferior, which is problematic. Finally, the method described here should be applied to explaining how changes in country characteristics over time have affected the changes over time in top shares, tax rates, and elasticities.

References

Altonji, J. G. and R. L. Matzkin (2005): "Cross Section and Panel Data Estimators for Nonseparable Models with Endogenous Regressors," *Econometrica*, 73, 1053–1102.

Card, D., J. Kluve, and A. Weber (2010): "Active Labour Market Policy Evaluations: A Meta-Analysis," *The Economic Journal*, 120, F452–F477.

——— (2018): "What works? A Meta Analysis of Recent Active Labor Market Program Evaluations," *Journal of the European Economic Association*, 16, 894–931.

Chamberlain, G. (1982): "Multivariate Regression Models for Panel Data," *Journal of Econometrics*, 18, 5–46.

——— (1984): "Chapter 22 Panel Data," in *Handbook of Econometrics*, Elsevier, vol. 2, 1247–1318.

Cinelli, C. and C. Hazlett (2020): "Making Sense of Sensitivity: Extending Omitted Variable Bias," *Journal of the Royal Statistical Society Series B-Statistical Methodology*, 82, 39–67.

Deaton, A. and N. Cartwright (2018): "Understanding and Misunderstanding Randomized Controlled Trials," *Social Science & Medicine*, 210, 2–21.

Duflo, E. (2020): "Field Experiments and the Practice of Policy," *American Economic Review*, 110, 1952–73.

Feldstein, M. (1999): "Tax Avoidance and the Deadweight Loss of the Income Tax," *Review of Economics and Statistics*, 81, 674–680.

Heckman, J., D. Schmierer, and S. Urzua (2010): "Testing the Correlated Random Coefficient Model," *Journal of Econometrics*, 158, 177–203.

Heckman, J. and E. Vytlacil (1998): "Instrumental Variables Methods for the Correlated Random Coefficient Model: Estimating the Average Rate of Return to schooling When the Return is Correlated with Schooling," *Journal of Human Resources*, 974–987.

Klemm, M. A. D., M. L. Liu, V. Mylonas, and P. Wingender (2018): "Are Elasticities of Taxable Income Rising?" .

Kopczuk, W. (2005): "Tax Bases, Tax Rates and the Elasticity of Reported Income," *Journal of Public Economics*, 89, 2093–2119.

Mundlak, Y. (1978): "On the Pooling of Time Series and Cross Section Data," *Econometrica*, 46, 69–85.

Neisser, C. (2021): "The Elasticity of Taxable Income: A Meta-Regression Analysis," *The Economic Journal*, 131, 3365–3391.

OECD (2023): *Taxing Wages 2023*.

Romano, J. P. and M. Wolf (2005): "Exact and Approximate Stepdown Methods for Multiple Hypothesis Testing," *Journal of the American Statistical Association*, 100, 94–108.

Roy, A. D. (1951): "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, 3, 135–146.

Rubolino, E. and D. Waldenström (2019): "Trends and Gradients in Top Tax Elasticities: Cross-Country Evidence, 1900–2014," *International Tax and Public Finance*, 26, 457–485.

Saez, E., J. Slemrod, and S. H. Giertz (2012): "The Elasticity of Taxable Income with Respect to Marginal Tax Rates: A Critical Review," *Journal of Economic Literature*, 50, 3–50.

Slemrod, J. and W. Kopczuk (2002): "The Optimal Elasticity of Taxable Income," *Journal of Public Economics*, 84, 91–112.

Vytlacil, E. (2002): "Independence, Monotonicity, and Latent Index Models: An Equivalence Result," *Econometrica*, 70, 331–341.

WID.world (2022): "World Inequality Database," .

Wooldridge, J. M. (2005): "Fixed-Effects and Related Estimators for Correlated Random-Coefficient and Treatment-Effect Panel Data Models," *Review of Economics and Statistics*, 87, 385–390.

——— (2010): *Econometric Analysis of Cross Section and Panel Data*, MIT Press.

——— (2019): "Correlated Random Effects Models with Unbalanced Panels," *Journal of Econometrics*, 211, 137–150.

A CRC in the Cross-Sectional Case

For ease of exposition, consider the case where we do not have covariates in (1), and consider the cross-sectional case. We note that our discussion is without loss of generality, in the sense that including covariates and generalizing the discussion to the case of panel data are straightforward extensions.

To start, we note that, under (11) and the correlation structure of ε_i and $\log(1-\tau_i)$ with $u_{i,t}$, ε_i cannot be consistently estimated by OLS. To estimate ε_i consistently, we get rid of correlation between ε_i, $\log(1-\tau_i)$ and u_i, we project ε_i and $\log(1-\tau_i)$ onto sets of potentially identical factors that we think best explain the variations across jurisdictions. Formally, we have the system of linear models

$$Y_i^p = \varepsilon_i \log(1-\tau_i^p) + u_i \ , \tag{11}$$

$$\log(1-\tau_i^p) = Z_{1,i}\pi + U_i \ , \tag{12}$$

$$\varepsilon_i = \Phi' Z_{2,i}' + V_i \ , \tag{13}$$

where Y_i^p is the top p-th percentile share of reported income, $\log(1-\tau_i^p)$ is the log of the marginal net-of-tax rate for the top p-th percentile earner, $Z_{1,i}$ and $Z_{2,i}$ are exogenous determinants of the marginal net-of-tax rate and the ETI, respectively. $u_{i,t}$, U_i, and V_i are the error terms. We note that ε_i in (13) is a *perceived* ETI: it is unobserved.

In any given cross section, our estimation approach recovers ε_i indirectly by estimating parameters Φ and π according to the three-step procedure described in Heckman and Vytlacil (1998). We summarize the procedure here for completeness. Note that combining (11), (12), and (13) gives

$$Y = (\pi_1' Z_1' Z_2)\Phi_1 + (\pi_2' Z_1' Z_2)\Phi_2 + \cdots + (\pi_K' Z_1' Z_2)\Phi_K + \eta \ , \tag{14}$$

where $\eta \coloneqq Z_1\pi U + V\Phi' Z_2' + VU + u$. This equation suggests a procedure for deriving consistent estimates of Φ. Specifically, we first estimate (12) via seemingly unrelated regression (SUR). Then, running OLS of $Y_{i,t}^p$ on $\hat{\pi} Z_{1,i,t} Z_{2,i,t}$ yields the desired parameter estimates $\hat{\Phi}$ which can be used to back out the conditional expectation of ε_i. Note that standard error correction procedure is discussed in Heckman and Vytlacil (1998, Appendix B).

Note that the error term in (14) is a linear combination of the errors in equations (11) through (13). Therefore, consistent estimation through the procedure described above requires the following set of assumptions:

Assumption A.1. 1. (Strict exogeneity) $\mathbb{E}[u_i \mid \log(1-\tau_i^p), Z_{1,i}, Z_{2,i}] = \mathbb{E}\, u_i = 0$.

2. $\mathbb{E}[U_i \mid Z_{1,i}, Z_{2,i}] = 0$.

3. $\mathbb{E}[V_i \mid Z_{1,i}, Z_{2,i}] = 0$.

4. $\mathbb{E}[V_i U_i \mid Z_{1,i}, Z_{2,i}]$ is some function independent of $Z_{1,i}$ and $Z_{2,i}$.

The first of the four assumptions is the standard strict exogeneity assumption in unobserved-effects models; in particular, this rules out the possibility of omitted variables bias. The second and third assumptions are exogeneity conditions for the first-stage equations. The last of these assumptions is perhaps the most difficult to describe, but it in essence posits that the covariance of the errors in (12) and (13) are unrelated to the instruments. In our setting, this assumption states that, for example, the covariance between the error terms is the same in countries that prize redistribution as in those that don't.

B Auxiliary Results

We provide relevant details for the claim made in the main text about characterizing the bias of the estimated ETIs in segmented regressions, (3). The overarching idea is to view (3) as a misspecified model relative to (7). The parameter of interest is ε in (3), which we call the "segmented ETI" in short. By way of notation, the point estimate of the "segmented ETI" is denoted $\hat{\varepsilon}_{\text{ols}}$, and the point estimate of ε in (7) is denoted $\hat{\varepsilon}_{\text{crc}}$.

To see the intuition of characterizing this bias, we briefly describe the case where we have *one* observable factor. The descriptions below are based on standard arguments we use for characterizing omitted variables bias. By a direct application of the Frisch-Waugh-Lovell theorem, $\hat{\varepsilon}_{\text{ols}}$ is numerically equivalent to the point estimate of ε in the following specification:

$$(\log Y_{i,t})^{\perp} = \varepsilon_i (\log(1-\tau_{i,t}))^{\perp} + u_{i,t} \ \text{ for each jurisdiction } i \in \{1, \dots, N\} \ , \tag{15}$$

where $x^{\perp}$ denotes the residuals from projecting the covariate x onto the controls $X_{i,t}$. For simplicity, let $\tilde{Y}$ The bivariate regression in (15) yields

$$\hat{\varepsilon}_{\text{ols}} = \frac{\operatorname{Cov}((\log Y_{i,t})^{\perp}, (\log(1-\tau_{i,t}))^{\perp})}{\operatorname{Var}((\log(1-\tau_{i,t}))^{\perp})} \ . \tag{16}$$

The residualized log outcome can equivalently be obtained from applying the Frisch-Waugh-Lovell theorem to (7), i.e.

$$(\log Y_{i,t})^{\perp} = \varepsilon_i(\log(1-\tau_{i,t}))^{\perp} + b((Z_i - \mathbb{E}[Z_i])\log(1-\tau_i))^{\perp} + \tilde{u}_{i,t} \ . \tag{17}$$

We therefore obtain a sensitivity decomposition of

$$\hat{\varepsilon}_{\text{ols}} = \varepsilon_{\text{crc}} + \hat{b}_{\text{crc}} \frac{\operatorname{Cov}\left((\log(1-\tau_{i,t}))^{\perp}, ((Z_i - \mathbb{E}[Z_i])\log(1-\tau_i))^{\perp}\right)}{\operatorname{Var}((\log(1-\tau_{i,t}))^{\perp})} \ , \tag{18}$$

i.e. the OLS estimate of the "segmented ETI" has the bias characterized by the second term, which involves the estimates of the ETI heterogeneity terms, and the covariance between residualized taxable income and the residualized tax rate. *Ex-ante*, the sign of the bias of ε_{ols} is unclear.

Note that we can only apply (18) to characterize the bias of our estimates of segmented ETIs when there is *one observable factor*. We can calculate the bias explicitly by replacing $\mathbb{E}[Z_i]$ by its sample counterpart, $\frac{1}{N}\sum_{1\leq i\leq N} Z_i$.

To analyze the bias in our case, where we have multiple observable factors, we rely on partial R^2 parametrizations, as shown in equations (7), (8), and (13) of Cinelli and Hazlett (2020). Applying those readily available equivalent formulae, using the `sensemakr` package made available by the authors, we find that the CRC estimates revises the segmented estimates *uwpards*; specifically, the segmented estimates are negatively biased, by roughly 0.0593.