

WEALTH TAXATION AND HOUSEHOLD SAVING: EVIDENCE FROM ASSESSMENT DISCONTINUITIES IN NORWAY

Marius A. K. Ring*

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Abstract

I use a quasi-experiment in Norway to examine how households respond to capital taxation. The introduction of a new wealth assessment methodology in 2010 led to geographic discontinuities in household exposure to wealth taxes, along both the extensive and intensive margins. I exploit this novel variation using rich administrative data and a Boundary Discontinuity approach. In contrast to existing work, I find that exposure to wealth taxes has a positive effect on saving as well as a positive effect on labor earnings. For each additional NOK subject to a 1 percent wealth tax, households increase their yearly financial saving by 0.04 NOK. This increase in saving is largely financed by increased labor earnings. My results imply that income effects may dominate substitution effects in household responses to (net-of-tax) rate-of-return shocks, which has important implications for both optimal capital taxation and macroeconomic modeling.

Keywords: Wealth Taxes, Savings, Capital Taxation, Intertemporal Substitution

JEL: G51, D14, D15, H20, H31, E21, J22

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1 Introduction

How households respond to changes in the net-of-tax rate-of-return is crucial to both optimal capital taxation and macroeconomic modeling. In optimal capital taxation, it determines the extent of distortionary effects on saving behavior and labor supply. Quantifying these distortions is necessary for determining the optimal tax policy (Atkinson and Sandmo 1980, Straub and Werning 2019, Saez and Stantcheva 2018). In macroeconomics, it determines the ability of standard representative agent models to explain the aggregate effects of monetary policy (Kaplan, Moll, and Violante, 2018) and informs the importance of new transmission channels (Auclert 2019, Wong 2019). More generally, empirical responses to rate-of-return shocks inform the Elasticity of Intertemporal Substitution (EIS). The EIS is a key parameter in virtually all economic models that involve intertemporal decision-making, but there is no consensus on what it should be.

Despite this broad importance, there is a dearth of applicable empirical evidence. This reflects challenges related to both identification and measurement. Exogenous shocks to the interest rate may have general equilibrium effects that inhibit the identification of the pure rate-of-return effect needed to inform micro-founded models. A potential solution is to exploit variation in capital taxation caused by peculiarities in the tax code to identify partial-equilibrium effects. However, this strategy typically presents two problems. First, one must often compare households who differ on tax-relevant characteristics, such as wealth or gross income, that are also determinants of saving behavior. Second, even if capital taxation were randomly assigned, data limitations may preclude researchers from distinguishing between real saving responses and tax evasion. This is problematic, since evasion responses are uninformative of responses to other rate-of-return shocks, such as interest rate changes or capital taxation when evasion opportunities are restrained.

These empirical challenges are complemented by a long-standing theoretical ambiguity about even the *sign* of saving responses to rate-of-return shocks.¹ This ambiguity is due to countering income and substitution effects from increasing both the absolute and relative price of future consumption. Which effect dominates depends crucially on the EIS, for which the existing range of empirical estimates spans 0 to 2.² This is an “enormous range in terms of its implications for intertemporal behavior and policy” (Best, Cloyne, Ilzetzi, and Kleven, 2020) and includes strikingly different household responses to economic news (Schmidt and Toda, 2019).

In this paper, I use a quasi-experimental setting in Norway that allows me to address the identification and measurement challenges described above. The source of identifying variation in the net-of-tax rate-of-return comes from capital taxation in the form of a wealth tax. While wealth taxation and capital income taxation are equivalent in standard models, wealth taxation differs from capital in-

¹Boskin (1978) indirectly refers to the theoretical ambiguity in his seminal empirical paper: “In brief summary, there is very little empirical evidence upon which to infer a positive relationship (substitution effect outweighing income effect) between saving and the real net rate-of-return to capital. Surprisingly little attention has been paid to this issue—particularly in light of its key role in answering many important policy questions—and those studies which do attempt to deal with it can be improved substantially.”

²In a standard life-cycle model without (non-capital) incomes, the income effect dominates whenever the $EIS < 1$. Including (endogenous) labor income lowers this cutoff to around 0.3 in the model in Section 7, which is calibrated to the empirical setting of this paper.

come taxation by requiring regular assessments of the stock of capital.³ The steps the Norwegian government has taken to make such assessments provides promising quasi-experimental variation in the net-of-tax rate-of-return.

In Norway, wealth taxes are levied annually as a 1 percent tax on taxable wealth that exceeds a given threshold. The relatively low threshold subjects 12 to 15 percent of taxpayers to the wealth tax.⁴ The main components of the tax base are financial wealth and housing wealth. While financial wealth may be assessed at third-party reported market values (which limits the scope for evasion through misreporting), housing wealth must be determined by the tax authorities. In 2010, the tax authorities implemented a new model to assess the housing wealth component. This hedonic pricing model contained municipal fixed effects, which imposed geographic discontinuities in assessed housing wealth even in the absence of any true discontinuities in house prices. These discontinuities provide substantial identifying variation in taxable wealth, and thereby (i) whether households pay a wealth tax and (ii) the amount of wealth taxes they pay. This provides variation in both the marginal and average net-of-tax rate-of-return. I use data on structure-level ownership and location as well as the exact parameters of the hedonic pricing model to implement this identifying variation in a Boundary Discontinuity Design (BDD) approach.

I first consider the effect on yearly financial saving. My estimates imply that for each additional NOK pushed above the tax threshold, and thereby subject to the wealth tax, households *increase* their yearly financial saving by NOK 0.04. These estimates adjust for the mechanical wealth-reducing effects of increased taxation and constitute evidence of behavioral responses to capital taxation that go in the opposite direction of what is typically assumed.⁵ This adjusted saving propensity is four times larger than what is necessary to maintain the same level of wealth after taxes are collected, consistent with households increasing their savings to offset future wealth tax payments.

I find that a majority of the increase in saving is financed by increased labor income. For each additional NOK subject to the wealth tax, households increase total taxable labor income by NOK 0.01. I further find that the effect on labor income is driven entirely by households initially above the wealth tax threshold. These are the households positioned to experience larger income effects. To obtain a better proxy for concurrent labor supply, I isolate salary and self-employment earnings from other sources of labor income, such as pensions. This yields a starker response: For each additional NOK subject to a wealth tax, households increase labor earnings by NOK 0.017. These findings constitute novel evidence of a nontrivial cross-elasticity between the return on capital and the supply of labor. By cumulating the saving and labor income responses over a 5-year treatment period, I find that 50% to 84% of the cumulative saving effect is financed by increased labor incomes.

I continue by presenting new evidence on the effect of capital taxation on portfolio allocation. I first consider the effect on the share of financial wealth invested in the stock market. The perhaps

³This includes [Chamley \(1986\)](#) and [Judd \(1985\)](#). The equivalence comes from assuming homogeneous returns. As an example, a tax on capital income of τ_{CI} of a fixed rate-of-return, r , is equivalent to a wealth tax of $\tau_{CI} \cdot r / (1 + r)$. For further discussion of this equivalence, see, e.g., [Bastani and Waldenström \(2018\)](#) and [Guvenen, Kambourov, Kuruscu, Ocampo, and Chen \(2019\)](#).

⁴This refers to the years 2010–2015, which is the time period I study.

⁵References in the popular press to the potential disincentive effects of wealth or capital taxation are abundant. In economic modeling, the typical assumption is that capital taxation reduces saving; see, e.g., [Saez and Stantcheva \(2018\)](#)

dominant hypothesis is that risk-averse agents will respond to a wealth-tax-induced drop in life time consumption by allocating less of their wealth to risky assets. I find no evidence of any effect on the risky share and can rule out any economically large effects. I then present the hypothesis that the adverse income effect of increased taxation may induce households to enjoy less financial leisure, in the sense that they exert greater effort toward financially optimizing the returns they receive or pay on their deposits or debt. I test this using itemized data on capital incomes that allow me to calculate realized interest rates. I firmly reject the above hypothesis and can rule out any economically large effects.

Given the nonlinear nature of rate-of-return shocks caused by taxing only wealth in excess of a threshold, it is useful to consider the underlying structural parameters governing these responses. Hence, in the last part of this paper, I use a simple multi-period life-cycle model to explore which values of the EIS are consistent with my estimates. I find that in order to replicate treatment effects on savings and labor income growth within the 95% (90%) confidence interval around my empirical results, an EIS below 0.5 (0.3) is needed. This illustrates how my empirical findings can provide a new upper bound for the EIS, which is in the lower range of existing estimates. This finding is robust in the sense that (i) it can be derived from either my savings *or* labor earnings results, and (ii) it is largely insensitive to the value of the Frisch elasticity that governs the elasticity of labor supply.

I use these bounds to simulate savings and labor supply responses to linear rate-of-return shocks to infer the implied uncompensated elasticities. At the 10% level, my empirical findings are inconsistent with parameterizations of a life-cycle model that would produce positive elasticities of saving and labor supply to the rate-of-return.⁶

This paper contributes to three literatures. First, I contribute to the new literature that examines household responses to wealth taxation. This literature has found that wealth taxes reduce the amount of taxable wealth that households report (Seim 2017, Londoño-Vélez and Ávila-Mahecha 2018, Zoutman 2018, Jakobsen, Jakobsen, Kleven, and Zucman 2020, María Durán-Cabré, Esteller-Moré, and Mas-Montserrat 2019, Brülhart, Gruber, Krapf, and Schmidheiny 2019).⁷ However, these findings do not necessarily imply that wealth taxes cause households to save less, as evasion responses may dominate (real) saving responses. Consistent with this ambiguity, I find strikingly different effects when limiting the role for evasion. I limit the role for evasion by (i) focusing on savings in the form of financial wealth, which in Norway is primarily third-party reported and (ii) obtaining identifying variation in wealth tax exposure from below the top 1%, where evasion is less prominent.⁸

By examining real saving responses to (net-of-tax) rate-of-return shocks, I also contribute to the empirical literature aimed at estimating the Interest Elasticity of Saving (see, e.g., Boskin 1978 and

⁶At the cutoff of 0.5 (0.3), the simulated 5-year *uncompensated* elasticity of savings to the net-of-tax rate-of-return is 0.11 (-0.01). For labor supply, it is 0.13 (-0.31).

⁷The literature has either focused completely on evasion (Seim (2017) and Londoño-Vélez and Ávila-Mahecha 2018) or has not distinguished between real and reporting (i.e., evasion) responses to wealth taxation. This fact is stressed by both Zoutman (2018) and Jakobsen et al. (2020) .

⁸Wealth taxes are levied at a relatively low threshold in Norway, and the treatment at hand, namely, increased tax assessment of housing, is particularly well-suited for identifying responses for the moderately wealthy, where housing wealth accounts for a large share of taxable net wealth. (Fagereng, Guiso, Malacrino, and Pistaferri, 2018). Alstadsæter, Johannesen, and Zucman (2019) show that wealth tax evasion primarily occurs above the 99th percentile of the wealth distribution.

Beznoska and Ochmann 2013). This literature has seen few recent contributions, and thereby offers a “paucity of empirical estimates” (Saez and Stantcheva, 2018). Finally, since the outcomes I consider are tightly connected to the Elasticity of Intertemporal Substitution, I contribute to the large empirical literature aimed at estimating it (see, e.g., Best, Cloyne, Ilzetzi, and Kleven 2020, Gruber 2013, Vissing-Jørgensen 2002, Bonaparte and Fabozzi 2017).

Relative to this combined body of work, I make three main contributions. My first contribution is to provide micro-level evidence while comparing households who are similar on socioeconomic observables. While assessed tax assessments change discontinuously at geographic boundaries, these changes are not predictive of changes in other pre-period observables, such as housing transaction prices, wealth, labor income, or education in my preferred BDD specifications. This contrasts with micro-econometric studies that obtain identifying variation in net-of-tax returns by using differential tax treatment that arises from differences in characteristics such as wealth, income, and asset shares.

My second contribution is to also study how (net-of-tax) rate-of-return shocks affect labor earnings. This elasticity is crucial to optimal taxation (see, e.g., Atkinson and Sandmo 1980 and Saez and Stantcheva 2018) and provides an additional moment for parameterizing life-cycle models with endogenous labor supply.

My third contribution is to provide evidence on how shocks to the net-of-tax rate-of-return affect portfolio decisions. This has received little empirical attention, despite its importance for economic modeling. By showing that (i) the risky share of financial wealth and (ii) the realized returns on risk-free assets are unaffected by rate-of-return shocks, I provide justification for treating rates-of-return as exogenous in partial equilibrium.

This paper also provides new evidence of limited evasion responses to wealth taxes. I examine this by considering the amount of excess bunching near the wealth tax threshold. The visual evidence does not favor bunching, which greatly contrasts with previous findings from Denmark, Sweden, Colombia, and Switzerland.⁹ The findings of Seim (2017) and Londoño-Vélez and Ávila-Mahecha (2018) suggest that evasion may be greatly restricted if self-reporting is limited. My findings are consistent with this, suggesting that evasion is addressable by limiting the extent of self-reporting, as Saez and Zucman (2019) argue.

This paper has implications for the growing literature on the effects of household heterogeneity on monetary policy transmission. The importance of this literature relies partially on the premise that standard intertemporal substitution effects are unable to explain the aggregate effects of monetary policy. This premise is validated by my finding that income effects dominate substitution effects in household responses to rate-of-return shocks and that a low EIS is necessary to explain my results.

Finally, this paper contributes to the literature that employs BDD frameworks.¹⁰ My empirical setting features heterogeneous border areas that differ significantly in terms of residential density and treatment discontinuities, which presents some interesting empirical challenges that I explore in detail.

⁹See Jakobsen et al. (2020); Seim (2017); Londoño-Vélez and Ávila-Mahecha (2018); and Brülhart et al. (2019), respectively.

¹⁰See, e.g., Black (1999) and Bayer et al. (2007), who also employ BDD designs to incorporate treatment discontinuities that vary across boundary areas.

My key contribution is to design a simple semiparametric approach that is successful at explaining observable geographic variation in house prices and household characteristics and facilitates graphical presentation of regression estimates.

The paper proceeds as follows. Section 2 discusses the institutional features and assessment model for housing wealth. Section 3 presents a simple two-period theoretical framework that relates tax assessment shocks to rate-of-return shocks, and highlights the theoretical ambiguity of the effects on saving. Section 4 introduces the data, the identification strategy, and the empirical specifications. Section 5 presents the empirical findings. Section 6 explores bunching behavior. Section 7 considers the implied structural parameters in light of a life-cycle model. Section 8 concludes.

2 Institutional Details

2.1 Wealth Taxation in Norway

In Norway, wealth taxes are assessed according to the following formula:¹¹

$$wtax_{i,t} = \tau_t(TNW_{i,t} - Threshold_t)\mathbb{1}[TNW_{i,t} > Threshold_t], \quad (1)$$

where $wtax_{i,t}$ is the amount of wealth taxes incurred during year t and is due the following year. τ_t is the tax rate applied to any Taxable Net Wealth (TNW) in excess of a time-varying threshold. The tax rate, τ , was 1.1% during 2009–2013, 1% in 2014, and 0.85% in 2015.¹² TNW is the sum of taxable assets minus liabilities, where housing wealth is assessed at a discounted fraction of estimated market value (25% for owner-occupied housing).¹³ The tax is assessed on individuals, but married couples are free to shuffle assets and liabilities between them, which effectively taxes married households on the sum of their taxable net wealth in excess of two times the wealth tax threshold.

The market value of all financial assets (debt) held through (borrowed from) domestically registered financial institutions are third-party reported each year. Private-equity wealth, i.e., the value of unlisted stocks, is reported by the stock issuer as part of their financial reporting to the tax authorities.

In this paper, I identify effects from quasi-random variation in $TNW_{i,t}$ that arises due to the implementation of a new methodology to assess the housing wealth component. This identifying variation in $TNW_{i,t}$ affects the marginal rate-of-return households face to the extent that it switches on $\mathbb{1}[TNW_{i,t} > Threshold_t]$ in equation 1, and thereby lowers the marginal net-of-tax return by τ_t . It affects the average rate-of-return to the extent that it lowers the ratio of net-of-tax capital incomes (Pre-Tax Capital Incomes - $wtax_{i,t}$) to $TNW_{i,t}$ by increasing $wtax_{i,t}$. This effect on the average return

¹¹See Subsection A.1 for how this formula is implemented in the data.

¹²Prior to 2009, there were two thresholds. All wealth above the highest threshold was taxed at 1.1%, while the intermediate levels of wealth were taxed at 0.9%. During 2009–2015, the single threshold was gradually increased from NOK 470,000 to 1,250,000 (USD 78,000 to 208,000, using the 2010 USD/NOK exchange rate of around 6.)

¹³Prior to 2008, some other assets were taxable at a discount as well. For example, stocks only entered with 85% of their market value in 2007. During 2008–2015, the only asset class taxed at a discount was real estate. While primary housing (owner-occupied) was taxed at 25%, secondary housing was assessed a tax value of 40%–60% of the estimated market value.

is a combination of intensive and extensive margin effects, while the effect on the marginal return is driven only by extensive margin variation in wealth tax exposure.

In the next section, I describe the model used to assess the housing wealth component in more detail.

2.1.1 Introduction of a Hedonic House Price model

In 2010, the Norwegian tax authorities implemented a major change to how they assess the housing wealth component of Taxable Net Wealth (TNW). Prior to 2010, assessed housing wealth was set to an inflated multiple of the initial tax assessment, which typically corresponded to 30% of construction cost.¹⁴ This approach grew unpopular, because some regions experienced larger house price growth than others. This produced regional disparities in the ratio of assessed housing wealth to observed transaction prices. To rectify this, the tax authorities began assessing housing wealth using a hedonic real estate pricing model that included geographic fixed effects. The implementation of a new assessment methodology was communicated to homeowners in a letter sent out in August 2010. I describe this communication in more detail in Section B.5.

Using a large national dataset on property transactions during 2004–2009, the hedonic pricing model was estimated according to equation 2 below.¹⁵

$$\begin{aligned} \log(\text{Price}_i / \text{Size}_i) &= \alpha_{R,s} + \gamma_{Z,s} + \zeta_{R,s}^{\text{size}} \log(\text{Size}_i) + \zeta_{R,s}^{\text{Dense}} \text{DenseArea}_i \\ &+ \zeta_{1,R,s}^{\text{Age}} \mathbb{1}\{\text{Age}_i \in [10, 19]\} + \zeta_{2,R,s}^{\text{Age}} \mathbb{1}\{\text{Age}_i \in [20, 34]\} \\ &+ \zeta_{3,R,s}^{\text{Age}} \mathbb{1}\{\text{Age}_i \geq 35\} + \varepsilon_i. \end{aligned} \quad (2)$$

Price is the recorded transaction price. *Size* is the size of the house in square meters. The size of the property/lot is not accounted for. *DenseArea* is a dummy for whether the dwelling was located in a cluster of at least 50 housing units. *Age* is number of years since initial construction. The estimation took place separately for each of the three structure types, $s \in \{\text{Detached housing, non-detached housing, condominiums}\}$, and for each region, R . The regions were mainly defined as one of the 20 Norwegian counties or one of the four largest cities (Oslo, Bergen, Stavanger, Trondheim).¹⁶ Municipalities, or within-city districts for the largest four cities, were assigned to within-region price zones, Z , separately for each structure type-region.¹⁷ These price zone fixed effects, $\gamma_{Z,s}$, make up a

¹⁴The tax value of a house would first enter as its construction cost. Then each year the tax value is changed by some percentage; e.g., -5%, 0%, 10%. The practice of using initial construction cost is described in the government budget of 2010: <https://www.statsbudsjettet.no/Statsbudsjettet-2010/Dokumenter/html/Prop-1-L-Skatte--og-avgiftsopplegget-2010-mv---lovendringer/3-Nytt-system-for-formuesverdsetting-av-bolig>

¹⁵The housing price model used to assess house values at year t would include transactions during $t - 5, \dots, t - 1$. When households were given preliminary estimates of their assessed values during 2010, only 2004–2008 data were used. When actual tax values were assigned, 2009 data was included.

¹⁶For non-detached housing and condominiums, for which there were fewer transactions, some counties were combined, presumably to increase sample size in each regression.

¹⁷While I can observe the assignments of Z and R in the appendices of the reports, the underlying process is only briefly described: Municipalities were assigned to price zones depending on “analyses of past price levels” (my translation of a comment in the 2009 report), and non-transacting municipalities were grouped in with low price level municipalities.

key component of the pricing model.

All of the estimated coefficients for a total of 44 regressions are provided in regression output form (see Figure A.5 for an example). These coefficients were then provided to the tax authorities, who applied the estimated coefficients to data from real estate registers and homeowner-verified data on housing characteristics. These assessments were done largely out of sample, as most houses present in 2010 were not transacted during 2004–2009. The following formula was used to assess the tax value of housing:

$$\widehat{TaxVal}_i = 0.25Size_i \cdot \exp(\widehat{\log(Price_i/Size_i)}) \cdot \exp(0.5\hat{\sigma}_{R,s}^2), \quad (3)$$

where $\exp(0.5\hat{\sigma}_{R,s}^2)$ is the concavity adjustment term, with $\hat{\sigma}_{R,s}^2$ being the mean squared error (MSE) of the regression for structure type s in region R .

We can use equations 2 and 3 to write $\log(\widehat{TaxVal}_i)$ as

$$\begin{aligned} \log(\widehat{TaxVal}_i) &= \log(0.25) + \hat{\alpha}_{R,s} + \hat{\gamma}_{R,Z,s} + (1 + \hat{\zeta}_{R,s}^{size}) \log(Size_i) + \hat{\zeta}_{R,s}^{Dense} DenseArea_i \\ &+ \hat{\zeta}_{1,R,s}^{Age} \mathbb{1}\{Age_i \in [10, 19]\} + \hat{\zeta}_{2,R,s}^{Age} \mathbb{1}\{Age_i \in [20, 34]\} + \hat{\zeta}_{3,R,s}^{Age} \mathbb{1}\{Age_i \geq 35\} \\ &+ \log(0.5\hat{\sigma}_{R,s}^2). \end{aligned} \quad (4)$$

From this, we see that that tax assessments will be geographically discontinuous even if past transaction prices are truly smooth. This implies that two identical houses, on different sides of a geographic boundary, may have very different assessments due only to cross-price zone differences in average past transaction prices. For a given structure type, s , the geographic variation within a region, R , comes from $\hat{\gamma}_{R,Z,s}$. Across regions, all of the estimated coefficients change. This provides identifying variation that depends on structure characteristics, such as $Size$ and Age . In Section 4.2, I discuss how I exploit (and isolate) all of this geographic variation.

I collect all the data necessary to replicate the assessed house values from Statistics Norway's reports. In Subsection A.3 in the Appendix, I show how using these coefficients and the real estate registers allows me to accurately predict assessed tax values observable in household tax returns.

[FIGURE 1 about here.]

3 Conceptual framework

The purpose of this section is to present a simple two-period life-cycle model of consumption to relate saving responses to tax-assessment shocks to responses to changes in the net-of-tax rate-of-return, and show how these responses relate to structural parameters.¹⁸ I then show how comparing

Consistent with this, I observe that members of the same price zone tend to have similar past-price levels, and smaller municipalities are more likely to be grouped in with multiple other municipalities within that region, regardless of geographic proximity. (This essentially precludes the use of border areas contained within one price zone to be used for placebo testing. The most intuitive definition of a placebo treatment variable would be the differences in past average transaction prices, but given the assignment rule, there would be very little identifying variation.)

¹⁸In the last section, in which I calibrate a life-cycle model to infer which EIS my results I can rule out, I use a multi-period model with endogenous labor supply. However, the key intuition can be found in this simpler two-period model.

the effects of assessment shocks on the *marginal* versus *average* net-of-tax rates-of-return can help us assess whether tax assessment shocks can be used as instruments for (linear) rate-of-return shocks. Later, in Subsection 5.2.1, I combine the main insights from this model with empirical data to discuss expected heterogeneous responses.

Consider the following simple two-period model, in which households choose how much to consume in each period, C_t and may save S in period 1. I focus on saving responses and assume perfect foresight to keep the model simple. Households have an initial endowment of Y_1 , which can be thought of as initial wealth plus first-period exogenous income, and face exogenous income of Y_2 in period 2. At the end of this section, I discuss the impact of introducing endogenous labor supply. The tax authorities impose a tax τ on taxable net wealth, $W = SR + A$, in excess of a threshold, \bar{W} . A is some premium the tax authorities add to a household's wealth, analogous to the empirical variation in tax assessments for the housing component of net wealth.

Baseline optimization problem.

$$\max_{C_1, C_2, S} U(C_1, C_2, S) = \frac{1}{1-\gamma} C_1^{1-\gamma} + \beta \frac{1}{1-\gamma} C_2^{1-\gamma}, \quad (5)$$

$$\text{s.t.} \quad C_1 + S = Y_1 \quad (6)$$

$$\text{and} \quad C_2 = Y_2 + RS - \tau \mathbb{1}[SR + A - \bar{W} > 0](SR + A - \bar{W}). \quad (7)$$

We can rewrite the constraint for period 2 as:

$$C_2 = Y_2 + SR(1 - \tau \mathbb{1}[SR + A - \bar{W} > 0](SR + A - \bar{W})) + \tau \mathbb{1}[SR + A - \bar{W} > 0](\bar{W} - A),$$

where the last term is virtual income (in period 2), which compensates for the fact that τ is not applied to all savings due to the tax threshold.

Wealth taxes offer a slightly complicated optimization problem, with agents potentially bunching such that $SR + A - \bar{W} = 0$. Since bunching is not an empirically important phenomenon in my setting, and a few key insights are obtainable with a few simplifying approximations, I take the following simpler route. First define $\tilde{R} = R(1 - \tau \mathbb{1}[SR + A - \bar{W} > 0])$ and $\tilde{V} = \tau \mathbb{1}[SR + A - \bar{W} > 0](\bar{W} - A)$. We can then rewrite the budget constraint for period 2 as $C_2 = Y_2 + \tilde{R}S + \tilde{V}$. Then I assume that agents take \tilde{R} and \tilde{V} as given when they optimize, which can be thought of as a linearization of the budget constraint around the empirical means. The problem then becomes:

Simplified optimization problem.

$$\max_{C_1, C_2, S} U(C_1, C_2, S) = \frac{1}{1-\gamma} C_1^{1-\gamma} + \beta \frac{1}{1-\gamma} C_2^{1-\gamma}, \quad (8)$$

$$\text{s.t.} \quad C_1 + S = Y_1 \quad (9)$$

$$\text{and} \quad C_2 = Y_2 + \tilde{R}S + \tilde{V}. \quad (10)$$

Assuming that constraints bind, imposing the first-order condition on S and reorganizing then

leads to the following expression for S :

$$S = \frac{[\beta \tilde{R}]^{\frac{1}{\gamma}} Y_1}{\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}}} - \frac{Y_2 + \tilde{V}}{\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}}}. \quad (11)$$

Suppose \tilde{R} and \tilde{V} are differentiable with respect to the tax-assessment variable, A . Now I assume that agents optimally change their behavior when A affects \tilde{R} and \tilde{V} . Their response can be decomposed, using the chain rule, as the sum of a rate-of-return effect and a virtual income effect:

$$\frac{dS}{dA} = \underbrace{\frac{dS}{d\tilde{R}} \frac{d\tilde{R}}{dA}}_{\text{Rate-of-return Effect}} + \underbrace{\frac{dS}{d\tilde{V}} \frac{d\tilde{V}}{dA}}_{\text{Virtual Income Effect}}. \quad (12)$$

Rate-of-return effect. By reducing the marginal rate-of-return, \tilde{R} , increases in tax assessment, A , cause a “traditional” rate-of-return effect, which I write out below.

$$\frac{dS}{d\tilde{R}} = Y_1 \left(\frac{1}{\gamma} - 1 \right) \frac{[\beta \tilde{R}]^{\frac{1}{\gamma}}}{(\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}})^2} + (Y_2 + \tilde{V}) \frac{1 + \frac{\beta}{\gamma} [\beta \tilde{R}]^{\frac{1}{\gamma}-1}}{(\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}})^2}. \quad (13)$$

The first term in equation 13 gives rise to the theoretical ambiguity in household responses to rate-of-return shocks. Its sign depends on the Elasticity of Intertemporal Substitution, $\frac{1}{\gamma}$. The second term is the “human wealth effect”, whereby an increase in \tilde{R} lowers the net present value of future incomes, $Y_2 + \tilde{V}$, which induces more saving.

We can rewrite the expression for $\frac{dS}{d\tilde{R}}$ above, using the formula for S , to see the overall ambiguity more clearly in the presence of a human wealth effect.

$$\frac{dS}{d\tilde{R}} = \frac{1}{\gamma} \frac{[\beta \tilde{R}]^{\frac{1}{\gamma}}}{(\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}})^2} \left(Y_1 + \frac{Y_2 + \tilde{V}}{\tilde{R}} \right) - \frac{S}{\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}}}. \quad (14)$$

We see now that if savings are sufficiently positive, $S > 0$, and the EIS, $\frac{1}{\gamma}$, is sufficiently small, then this expression is negative.¹⁹

Virtual Income Effect. By affecting \tilde{V} , shocks to tax assessment cause an additional (virtual) income effect:

¹⁹As an example, consider the case in which $\beta \tilde{R} = 1$. Further assume that $\tilde{R} = 1.5$, and, without loss of generality (since it will be divided through), that $Y_2 + \tilde{V} = 1$. $S > 0$ then implies $Y_1 > 1$. In this case, $dS/d\tilde{R} \leq 0$ whenever $\frac{1}{\gamma} \leq 2.5 - \frac{2.5+1/1.5}{Y_1}$. Setting $Y_1 = 1.5$, in other words, that current income and wealth exceeds future (nominal) income and wealth by $\tilde{R} - 1 = 50\%$, yields $1/\gamma \leq 0.38$.

$$\frac{dS}{d\tilde{V}} = -\frac{1}{\tilde{R} + [\beta\tilde{R}]^{\frac{1}{\gamma}}}. \quad (15)$$

The magnitude and sign of this channel depends critically on how A affects \tilde{V} . If we define the average rate of return as \tilde{R}^{avg} , such that $S\tilde{R}^{avg} = S\tilde{R} + \tilde{V}$, then we can rewrite \tilde{V} as $\tilde{V} = S(\tilde{R}^{avg} - \tilde{R})$, which is simply savings multiplied by the difference between the average and marginal rates-of-return. We may therefore write the effect of tax-assessment shocks on virtual income as the following:²⁰

$$\frac{d\tilde{V}}{dA} = S \left(\frac{d\tilde{R}^{avg}}{dA} - \frac{d\tilde{R}}{dA} \right). \quad (16)$$

While these derivatives are not well defined analytically due to the presence of indicator functions, their empirical counterparts can be estimated empirically by considering differential effects of tax-assessment shocks on the marginal versus average net-of-tax rates-of-return. This will be a useful exercise, because the differential effects dictate how my tax-assessment shocks yield a treatment comparable to linear rate-of-return shocks.

Relative importance of income and virtual income effects. To understand the relative importance of these two effects, I rewrite the (decomposed) effect of tax assessment shocks on saving from equation 12 when the EIS is zero to isolate income effects. I use the expression for $dS/d\tilde{R}$ from equation 14, substitute in for $d\tilde{V}/dA$, and reorganize to get:

$$\frac{dS}{dA} = -\frac{S}{\tilde{R} + 1} \left[\underbrace{\left(\frac{d\tilde{R}}{dA} \right)}_{\text{Income Effect}} - \underbrace{\left(\frac{d\tilde{R}}{dA} - \frac{d\tilde{R}^{avg}}{dA} \right)}_{\text{Virtual Income Effect}} \right]. \quad (17)$$

The term denoted “Income Effect” represents the effect of tax assessment on saving through changing a linear rate-of-return. The second term indicates the effect through changing virtual income. This equation suggests that we can evaluate the relative impact of these two channels by comparing the effects of tax-assessment shocks on the marginal versus average rates-of-return. If I find $\mathbb{E}[d\tilde{R}/dA]$ to be twice as large as $\mathbb{E}[d\tilde{R}^{avg}/dA]$, which suggests that half the income effects are offset by opposing virtual income effects. If I find $\mathbb{E}[d\tilde{R}/dA]$ to be only half that of $\mathbb{E}[d\tilde{R}^{avg}/dA]$, this suggests that income effects are amplified by a factor of two.

Endogenous labor supply. In Section B.6 in the Appendix, I modify the existing optimization problem by introducing endogenous labor supply in period 1. The preferences feature a constant

²⁰This assumes that S is not also affected by A in any way that affects V . This is related to the assumption that agents take \tilde{R} and \tilde{V} as given when choosing the optimal amount of S .

Frisch elasticity and additive separability in the (dis)preferences for consumption and labor supply. This added complexity has no effect on the qualitative conclusions in the previous section, but shows that the labor earnings response will be of the same sign as, but smaller in magnitude than, the savings response. The savings response takes the same form, but is scaled up in magnitude. This added responsiveness will depend on the parameters governing labor supply.

4 Empirical

4.1 Identification

I identify household responses to an increased exposure to wealth taxation caused by higher tax assessments on housing. Since this tax assessment is the result of a model that aims to predict housing wealth, more treated households will, by construction, own more expensive homes on average. This may be an important violation of the exclusion restriction, given that housing wealth is known to be an important determinant of household saving behavior, and is likely highly correlated with other important determinants such as income or wealth.

To address this issue, I employ a Boundary Discontinuity Design (BDD) approach. The purpose of this empirical design is to exploit the fact that treatment varies discontinuously at geographic boundaries, which allows me to remove the effects of potential confounders that vary smoothly.

The success of the BDD approach in isolating treatment effects from tax assessment hinges on the following: Potential confounders must vary smoothly at the geographic treatment boundaries. In addition, my parameterization of the BDD regression equations must not confuse smooth variation with geographic discontinuities. This is not straightforward in a setting with treatment discontinuities that vary across boundaries. In the next Subsection, I describe my parameterization in more detail. Throughout the results section, I show that a *correctly* specified BDD framework does not pick up any discontinuities in potential confounders such as housing wealth, pre-period income, or financial wealth. The fact that the identifying variation in my BDD framework is essentially orthogonal to household observables allows me to include a wide range of controls without reducing the amount of residual identifying variation.

Another attractive feature of my empirical setting is that the treatment discontinuities were only recently introduced. This offers two key advantages relative to a setting that identifies effects from a non-time-varying treatment discontinuity. First, it allows me to focus on households who made their residential location choices prior to having any knowledge of the impending wealth-assessment discontinuities.²¹ This addresses the concern that households may have self-selected into lower or higher tax assessment. In addition, it allows me to investigate the parallel-trends assumption by examining the effect of higher tax assessment on pre-period outcome variables.

Another concern when studying the effects of geographically confined increases in taxation is that households may be affected through the effect on local government finances. In Section B.4 in the

²¹(1) Per my investigations, the fact that geographic assessment discontinuities exist is still a little-known fact, even at the time of writing. (2) This wouldn't be a benefit in researching house price capitalization, since a key driver would be selection.

Appendix, I argue that this is unlikely to play a meaningful role in my empirical setting, since wealth taxes are primarily paid by the very wealthiest households, who were not disproportionately affected by this reform. The impact on municipal finances would thus be too small to trigger a meaningful response.

Finally, it is worth noting that this setting will identify partial-equilibrium effects. Since bordering municipalities are typically tightly economically linked, there is little scope for geographic discontinuities in terms of general equilibrium treatment effects. For example, there is little reason to suspect that wages are affected by this treatment, since employers face no frictions in choosing employees from either side of one of the treatment boundaries.

4.2 Empirical Specification

Distance and Boundary Areas. I define the key geographic measure, d_i , as the signed distance, in kilometers, to the closest municipal boundary, where households on the low-assessment side of the borders receive a negative distance, and households on the high-assessment side receive a positive distance.²²

I will refer to boundary areas, b , as sets of households assigned to the same municipal boundary. Within a boundary area, b , households are defined as being on the high-assessment side if the average household within that boundary would see a higher tax assessment on that side.²³ Geographic variables, such as d_i , b , and geographic location, \mathbf{c}_i , are all measured in 2009.

Identifying variation. I define Δ_i as the log increase in tax assessment that arises for household i if it were assessed on the high- instead of the low-assessment side of the border. This variable is a border-area and structure-type-specific (linear) function of $\mathbf{H}_i = \{\log(\text{Size})_i, \text{DenseArea}_i, \{\mathbb{1}[\text{Age}_i \geq a], a = 0, 10, 20, 35\}\}$ and isolates the identifying variation in model-implied tax assessment, $\log(\widehat{\text{TaxVal}}_{i,t})$, to come from cross-border (but within border area) differences in pricing model coefficients, and allows this effect to vary with \mathbf{H}_i , measured as of 2009.

$$\Delta_i \equiv \log(\widehat{\text{TaxVal}}_i) \Big|_{d_i > 0} - \log(\widehat{\text{TaxVal}}_i) \Big|_{d_i < 0} \quad (18)$$

Main reduced-form regression specification. The following regression equation yields the estimator, $\hat{\beta}$, for the reduced-form effect of increased tax assessment on some outcome variable, $y_{i,t}$, measured at year t .

$$y_{i,t} = \beta \log(\widehat{\text{TaxVal}}_i) + g_b(\mathbf{c}_i)\Delta_i + \delta'_{b,s}\mathbf{H}_i + \gamma'_t\mathbf{X}_i + \varepsilon_{i,t}. \quad (19)$$

²²I calculate d_i by minimizing the distance to the nearest residence in a different municipality (or within-city district).

This has the benefit of not assigning households as being close to a border that is vacant on the other side.

²³Within a boundary area, a municipality is defined as being on the high-assessment side if the average detached house (by far the largest group in my sample) in the border area would receive a higher assessment in that area. If there are no differences for single family homes, i.e., they are in the same price region and price zone, I conduct the same exercise for non-detached houses, and if necessary for condominiums.

The inclusion of border-area and structure-type-specific linear controls in housing characteristics, \mathbf{H}_i , isolates the identifying variation in $\log(\widehat{TaxVal}_{i,t})$ to $\mathbb{1}[d_i > 0]\Delta_i$. β thus identifies the effect on households on the high assessment side of the boundary ($\mathbb{1}[d_i > 0]$) of seeing a Δ_i log-point increase

While the estimator for β identifies the effect of a *discontinuous loading* on Δ_i , the the estimated coefficient on $g_b(\mathbf{c}_i)\Delta_i$ is meant to capture the effect of anything that loads continuously on Δ_i . I describe the parameterization of $g_b()$ in more detail below.

To increase precision, and to alleviate concerns that relevant observed heterogeneity is not appropriately controlled for, I include a number of household-level controls, denoted by \mathbf{X}_i , which is a vector of 2009-valued household characteristics: a single dummy, a single dummy interacted with a male dummy, a third-order polynomial in the average age of household adults, $\log(\text{Labor Income})$, $\log(\text{Gross Financial Wealth [GFW]})$ College [Dummy for whether any of the adults have a college degree], a debt dummy, $\log(\text{Debt})$, the share of GFW invested in the stock market [SMW], the log of the tax-return-observed assessed tax value of housing, a dummy for whether the tax returns indicate ownership of other real estate, the log of the assessed value, and finally a dummy for whether the household is reported to own non-listed stocks [PE Dummy]. \mathbf{X}_i is not included as a vector of controls when I examine whether the identifying variation is correlated with pre-treatment household characteristics.

I note that while my specification allows the effect of geographic discontinuities in the estimated coefficients to covary with \mathbf{H}_i (per the definition of Δ_i), estimating border-area-specific coefficients on \mathbf{H}_i accounts for the fact that those with larger houses in more high-priced (border-) areas may have have different (unobservable) characteristics.

In most specifications, observations are pooled by treatment period, where the pre-period is 2004–2009 and the post-period is 2010–2015. Equation 19 is then estimated separately for these periods, allowing the slopes without a t subscript to vary by treatment period. While the initial hypothesis is that the assessment discontinuities are not predictive of differences in pre-period characteristics, outcome variables, $y_{i,t}$, are generally differenced to accommodate this possibility. The main outcome variable that captures saving responses is log-differenced financial wealth. This differencing effectively takes out household fixed effects in the amount of (financial) wealth they hold. This growth rate in financial wealth is not itself (double-) differenced, which is inline with previous papers using the (nondifferenced) log of wealth as the outcome variable while estimating household fixed effects (see, e.g., [Jakobsen et al. \(2020\)](#)).

My main specification imposes equal weights on all observations and clusters at the census-tract level (*grunnkrets*). I provide results using triangular (distance-based) weights for my main results in Table B.2 in the Appendix. Results using different levels of clustering (household and municipality) are reported in Table B.3. Neither standard errors nor estimates are sensitive to these specifications.

Addressing continuous geographic loading on Δ_i . My method for capturing potential confounding heterogeneity is to introduce the term $g_b(\mathbf{c}_i)\Delta_i$. $g_b(\mathbf{c}_i)$ is a border-area-specific function of household i 's location, and is meant to capture geographically heterogeneous loading on Δ_i . Similar

to Dell (2010), I test multiple such specifications. The baseline specification involves controlling for (signed) border distance in kilometers:

$$g_b(\mathbf{c}_i) = \gamma^- \mathbb{1}[d_i < 0]d_i + \gamma^+ \mathbb{1}[d_i > 0]d_i, \quad (20)$$

where γ^- and γ^+ are to be estimated. However, there is considerable heterogeneity in residential density across the border areas in my sample. The extent to which confounding variables change more rapidly, in a geographic sense, in denser urban areas is problematic. I provide a fuller discussion of this issue, and the approaches to addressing it, in Appendix A. I highlight the main aspects of the approaches below.

My preferred specifications address this issue by allowing the slope on border distance to vary parametrically with measures of residential density. The main preferred measure, *Scaled Border Distance*, simply scales border distance (in kilometers) by a measure of average distances in a border area.²⁴ The second preferred measure, *Relative Location*, maps all households onto $[-1, 1]$, where households at 0 are equidistant to the low- and high-side centers.²⁵ As a robustness test, I also allow the slope on border distance to vary by border area. Since this involves the estimation of many slopes, this limits precision and inhibits visual verification.

Two-Stage Least Squares Specification. I implement a fuzzy BDD approach to provide IV estimates of how changes in tax assessment affect a given outcome, $y_{i,t}$. The expectation is that the first-stage coefficient, $\hat{\beta}^{FS}$, is close to one. The coefficient of interest is β^{IV} . Given inclusion of the term $\delta_{b,s}^{FS'} \mathbf{H}_i$, the identifying variation in $\log(\widehat{TaxVal}_i)$ is equal to $\mathbb{1}[d_i > 0]\Delta_i$; i.e., the discontinuous loading on the high-side assessment premium.

$$\log(TaxVal_{i,t}) = \beta^{FS} \log(\widehat{TaxVal}_i) + g_b^{FS}(\mathbf{c}_i)\Delta_i + \delta_{b,s}^{FS'} \mathbf{H}_i + \gamma_t^{FS'} \mathbf{X}_i + \varepsilon_{i,t}^{FS} \quad (21)$$

$$y_{i,t} = \beta^{IV} \log(TaxVal_{i,t}) + g_b^{IV}(\mathbf{c}_i)\Delta_i + \delta_{b,s}^{IV'} \mathbf{H}_i + \gamma_t^{IV'} \mathbf{X}_i + \varepsilon_{i,t}^{IV} \quad (22)$$

Specification to test differences on observables. When testing whether my identifying variation is correlated with pre-treatment observables, I estimate the following equation, which removes socioeconomic controls from the main specification in equation 19. The coefficient of interest is β .

$$y_i = \beta \log(\widehat{TaxVal}_i) + g_b(\mathbf{c}_i)\Delta_i + \delta'_{b,s} \mathbf{H}_i + \varepsilon_i \quad (23)$$

²⁴Specifically, the distance between the two centroids of the two municipalities (or within-city districts) whose residents occupy a given border area, b . This centroid-distance measure is thus b -specific.

²⁵Households at $RelLoc \in [-1, 1]$ must travel (as the crow flies) $RelLoc \cdot X$ km farther to get to the high side than they would to get to the low side, where X is the distance between the centroids of the low and high sides.

4.2.1 Empirical specification relative to the BDD literature

The similarity between my empirical specification and that of the existing BDD literature (e.g., [Black \(1999\)](#) and [Bayer et al. \(2007\)](#)) that incorporates cross-boundary area variation in treatment intensity can be seen by acknowledging that $\mathbb{1}[d_i > 0]\Delta_i$ in equation 19 could be replaced with $\log(\widehat{TaxVal})$ and I would obtain the exact same estimator $\hat{\beta}$. However, writing out the identifying variation as a discontinuous loading, $\mathbb{1}[d_i > 0]\Delta_i$, facilitates a standard Regression Discontinuity Design representation of estimates.²⁶

Beyond this graphical contribution, my approach differs from the existing approach in how it deals with potentially confounding geographic heterogeneity. First, my approach, as highlighted by the main reduced-form specification in equation 19, differs by addressing the fact that the relevant confounders covary with $\mathbb{1}[d_i > 0]\Delta_i$ and not just $\mathbb{1}[d_i > 0]$. The traditional approach is to use a specification similar to the baseline regression specification in equation 19 without directly controlling for geographically smooth heterogeneity, but rather *uniformly* reduce the cutoffs (bands) that determine which observations, i , would be included, based on d_i alone.

Applying the traditional approach to my empirical setting would entail comparing households whose d_i 's were similar in order to limit the potential influence of confounders that covary with d_i . To preserve identifying variation one would then consider households whose d_i s are close to the treatment cutoff of 0. This approach would be unsatisfactory, to the extent that confounders vary more rapidly in areas where treatment discontinuities are larger. If this is the case, then imposing uniform cutoffs implies that the boundary areas that offer the most identifying variation will also have the worst control group. My approach directly addresses this concern.

Second, my approach differs from the traditional approach by addressing rather than discarding geographic heterogeneity in residential density. Addressing heterogeneity in density is important whenever potential confounders may change more rapidly, in a geographic sense, in denser areas. My solution to address this is a useful contribution, since it may be applied to settings where there are many boundary areas that differ significantly, without having to reduce the sample size by dropping boundary areas in order to achieve homogeneity. In Appendix A, I provide examples of how geographic heterogeneity in residential density may invite the false detection of discontinuities in observable characteristics.

4.3 Data

I combine a wide range of administrative registers maintained by Statistics Norway. These contain primarily third-party reported data, and are all linkable through unique de-identified person and property identification numbers. A detailed description of the financial data sources can be found in [Fagereng et al. \(2018\)](#).

Financial data. Data on household financials come from household tax returns. These include

²⁶Prior papers, e.g., [Black \(1999\)](#) and [Bayer et al. \(2007\)](#), do not provide RDD-style figures to illustrate their main empirical findings. [Bayer et al. \(2007\)](#) provide graphical evidence only when using a binary treatment cutoff, but their main estimation strategy leverages the full identifying variation, which allows treatment discontinuities to vary across border areas.

breakdowns of household assets, such as housing wealth, deposits, bonds, mutual funds, listed stocks, and private equity holdings. They also include the sum of household liabilities. I can further distinguish between third-party reported domestic wealth holdings (e.g., domestic deposits) and self-reported foreign holdings of real estate, deposits, and other securities, separately. The tax data include a breakdown of household income, such as self-employment income, wage earnings, pensions, UI income, and the sum of government transfers. They also contain a detailed breakdown of capital income, such as interest income from domestic or foreign deposits, and realized gains or realized losses. These data span 1993 to 2015.

Real estate data. Real estate ownership registers provide end-of-year data on the ownership of each plot of land in Norway. Using de-identified property ID numbers, I can populate each property with the buildings it contains. Then, using structure ID numbers, I can populate each structure with the housing units it contains (e.g., multiple apartments, attached homes, or a single detached house). I can combine this with data on housing unit characteristics, such as size. An attractive feature of the administrative data is that it facilitates the calculation of distances to geographic boundaries at the *structure level* instead of district or census block-level (for examples, see [Dell \(2010\)](#) and [Bayer et al. \(2007\)](#), respectively). These data sources cover 2004 to 2016.

Real estate transaction data. I also use data on real estate transactions to examine past and future transaction prices. This dataset is comparable to the CoreLogic dataset often used in real estate research in the U.S., but can be linked to the other data sources through de-identified property and buyer/seller identification numbers. I collapse the dataset at the property-ID level, keeping information on most recent transaction prior to 2009 and earliest transaction during or after 2010. I restrict the data to transactions noted as being conducted on the open market and thus exclude other events such as bequests or expropriations. This dataset spans 1993 to 2016.

Other data sources. I also use data on demographics from the National Population Register. This contains data on birth year, gender, and marital links. I also obtain data on educational attainment as of 2010 from the National Education Database.

4.3.1 Variable definitions

Gross Financial Wealth (GFW) is the sum of domestic deposits, foreign deposits, bonds held domestically, listed domestic stocks, domestically held mutual funds, non-listed domestic stocks (e.g., private equity holdings), foreign financial assets (stocks, bonds, and other securities), and outstanding claims.²⁷ For a detailed description of wealth variables see Subsection A.1 in the Appendix.

Labor Earnings (LE) is the sum of salaries, wages, and max(self-employment income, 0). Total Taxable Labor Income (TTLI) is the sum of LE, unemployment benefits and other transfers, and pension income.

I measure saving as 1-year log-differences of financial savings (GFW). Log-differencing wealth variables is standard in the wealth tax literature.²⁸ I further follow [Jakobsen et al. \(2020\)](#) in adjusting

²⁷ Foreign deposits and foreign financial assets are self-reported. Outstanding claims are primarily self-reported. Third-party reported components include unpaid wages.

²⁸ [Zoutman \(2018\)](#) considers 1- to 3-year log differences; [Brühlhart et al. \(2019\)](#) consider 3-year log differences; [Jakobsen et al. \(2020\)](#) consider log-values, but incorporate household fixed effects to produce estimated effects on 1- to 8-year

for the “mechanical effects” of increased wealth tax exposure. Absent any behavioral responses, higher wealth tax exposure mechanically reduces wealth by lowering the net-of-tax rate-of-return. To address this, I add wealth taxes incurred during $t - 1$, and thus payable during period t , to savings at time t for all households:

$$\begin{aligned} \text{Adjusted } \Delta \log(GFW_{i,t}) &\equiv \log(GFW_{i,t} + wtax_{i,t-1}) - \log(GFW_{i,t-1}) \\ &\approx \frac{\Delta GFW_{i,t}}{GFW_{i,t-1}} + \frac{wtax_{i,t-1}}{GFW_{i,t-1}}. \end{aligned} \quad (24)$$

The definition of saving above is important to consider for anyone who uses the estimated effects for calibration or inputs into optimal taxation models. Specifically, the implied elasticities arising from regressions that define saving as in 24 must be adjusted in order to serve as a target to calibrate measures of savings growth that include mechanical effects. Alternatively, implied elasticities that incorporate such mechanical effects by not making this adjustment will be provided in the results section.

The majority of my variables will be measured in natural log-points. To accommodate zeros within specific components of financial wealth (e.g., self-reported) or for debt, and to limit the influence of large log-changes caused by small level differences, I shift levels by an inflation-adjusted NOK 10,000 (USD 1,700).²⁹

4.3.2 Sample selection

I only keep households who lived in the same building during 2007–2009, owned at least 90% of their primary residence and had a positive assessed tax value of their house in 2009. In addition, I require that their residence be registered as larger than 50 square meters (approx. 540 square feet). This is to limit the possibility that the size is mismeasured, or that this is not their intended long-term residence. I drop households whose tax records indicate ownership in building co-ops in 2009, due to the lack of data on housing unit assignment within co-ops. I further restrict the sample to only include households with an income above NOK 150,000 (approx. USD 25,000) in 2009, which is well below the poverty limit in Norway. Such households are thus unlikely to be relevant for this study. I further exclude households in which the average age of adults is less than 25 years. I then only keep households with a taxable net wealth (per adult) in 2009 strictly above NOK 0 and below NOK 6,000,000. NOK 6,000,000 corresponds to the 99th percentile of taxable net wealth per adult among the remaining households in 2009. Restricting to positive TNW households is standard in the wealth tax literature, and in my setting implies that the sample is fairly balanced with respect to whether households paid wealth taxes. This restriction leads to 66% of the sample having paid wealth taxes in 2009, and 60%

log-differenced wealth.

²⁹This implies that a reduction in debt from NOK 138,000 (the 50th percentile) to 0 (the 25th percentile) appears as a log-difference of -2.695 rather than -11.835 when using a $\log(1+x)$ specification, which is considerably closer to the true percentage change of -100%. A similarly large magnitude would appear when using the asymptotic sine transformation (asinh), which is employed by [Londoño-Vélez and Ávila-Mahecha \(2018\)](#). There are only negligible differences for similar changes in the main outcome variables. For example, a change in GFW from the 50th to the 25th percentile yields a log-difference of -0.925 compared to a log-difference of -0.951 when using the $\log(1+x)$ specification.

end up paying wealth taxes during 2010–2015. I further trim the sample by removing households with labor incomes above NOK 4,300,000, which corresponds to the 99.95th percentile of the labor income distribution in 2009.

The primary reason for incorporating these upper bounds is that ultra-high income and high net worth households have more complicated balance sheets and likely have access to more evasion technologies. A secondary reason is to increase the ability of income to explain unobserved variation in outcome variables by removing a handful of extreme outliers from the income distribution. In addition, treatment effects will be fairly small relative to existing wealth or incomes for such households, since housing wealth makes up a rather small proportion of total wealth for very wealthy households. This means that I can remove these households without eliminating much identifying variation in, e.g., the fraction of wealth subjected to a wealth tax. Excluding such households has an important additional benefit: Excluding the ultra-wealthy allows sample means to provide more relevant benchmarks for approximating level changes as the product of sample means and estimated log-differences.

An immediate consequence of selecting only households with initial positive taxable net wealth is that the resulting sample has a fairly high average age of 62, and is thus fairly close to retirement. This is close to the average age of 61 in [Jakobsen et al. \(2020\)](#).³⁰ From a theoretical perspective, this suggests that these households are not highly influenced by the human wealth effect in their saving responses to rate-of-return shocks, which is consistent with my empirical results. I would argue that this is not necessarily a concern from an external validity point of view, since savings tend to be concentrated in older households.³¹ A recent report from Statistics Norway shows that the average age of wealth tax payers was 63 years in 2015, and that individuals above 65 years of age account for 48% of wealth tax payers.³²

I also impose some geographic cutoffs. When considering border distance in kilometers, I only consider households within 10 km of the border, which accounts for around 80% of my sample. When using scaled border distance, I consider households within $[-0.6, 0.6]$ (the distance to the border is at most 60% of the distance between the two municipal centroids). This cutoff similarly retains approximately 80% of the sample. The main purpose of this is to allow for the estimation of lower-order polynomials in these distance measures, without giving too much weight to geographic outliers. In Figure A.4 in the Appendix, I show how households are distributed according to the different distance measures. In Tables B.5, B.6 and B.7, I provide results when varying these cutoffs.

5 Results

5.1 A Graphical Overview

In this section, I show graphically how tax values are discontinuous at municipal borders, while past transaction prices and labor incomes appear to behave continuously. These results are presented

³⁰Given population aging, my sample is likely younger. Their sample statistics are based on average pre-period (1982–1985) ages, while my statistics are based on 2009. This is 24 years later on average.

³¹See for example the Federal Reserve Bulletin 09/2017 Vol 103, No. 3, which shows that median net worth is the highest for household whose head is 65–74 years of age. Their median net worth is 5 times larger than households aged 35–44.

³²<https://www.ssb.no/inntekt-og-forbruk/artikler-og-publikasjoner/naer-hver-tredje-over-65-ar-betaler-formuesskatt>

in Figure 2 below.

[FIGURE 2 about here.]

Panel A shows that for a given model-implied treatment discontinuity, Δ_i , assessed housing wealth does indeed rise by close to Δ_i log-points. As expected, the coefficient does not vary significantly other than at the discontinuity, given that only observable characteristics are used for tax assessment.³³ Formal tests of the presence of any discontinuities are performed in Subsection 5.2.

Panels B and C show how past transaction prices (using transactions during 2000-2009) vary geographically. Regardless of which geographic measure is used, these variables do not appear to behave discontinuously at the treatment boundary. I perform formal tests of the presence of discontinuities in Tables 10 and 11 in Subsection 5.9. From Table 10 column (2), we see that if all within-boundary variation in observed transaction prices were attributable to the treatment discontinuities, rather than smooth geographic variation, the jump should be approximately 0.8. However, these plots reveal that we are closer to the ideal scenario of a true jump of 0. Similarly for labor incomes, in Table 11, column (2), we see that if the entire correlation between model-implied tax assessments and incomes were driven by a discontinuity, the observed jump should be approximately 0.15.

In terms of the BDD methodology, an important take-away from these plots is that past transaction prices and labor income change nonlinearly relative to border distance measured in kilometers, but linearly relative to scaled border distance. While visual inspection does not suggest a discontinuity in labor incomes, a formal test in Table 11, column 3, where slopes on border distance (in km) are estimated with side-specific second-order polynomials, shows a discontinuity of 0.1, significant at the 1% level. Thus in order for regression-estimates to agree with our visual inspection, we either need use polynomials of an even higher order or to further limit the sample, both of which would have adverse effects on precision.

The non-linear relationships between observable characteristics and distance in km (first column, rows two and three in Figure 2) appear to be driven by a steeper gradient near the boundary. I find that this is likely driven by the fact that households drawn from near the boundary tend to live in much denser areas. In Figure A.3 in the Appendix, I plot how residential density (log of the number of households residing within 1 km) varies with border distance. Panel A shows that households who live within 1 km of the border have 0.8 log-points (120%) more neighbors than those who live 5 to 10 km away from the border. When instead using scaled border distance as the geographic running variable, this hump-shaped relationship between density and border distance nearly vanishes. This essentially induces more homogeneity in socioeconomic characteristics with respect to the running variable, and thereby (i) makes it possible to account for geographic heterogeneity with a more parsimonious RDD specification and (ii) reduces the external-validity concern that results are only applicable to households in densely populated areas.

Formal tests of a discontinuity using scaled border distance (linear slope on each side) in Table 11, column 4, finds no evidence of a discontinuity, and a point estimate of 0.002. Comparisons of formal

³³The slight positive coefficient may be explained by the fact that tax-return observed $TaxVal$ also includes the value of secondary homes. Some fraction of households will thus have $TaxVal = \bar{TaxVal} + \text{Value of Secondary Home}$. The propensity to own a secondary home is higher for wealthier households, and as we move toward the right on the geographic axis, households get richer.

tests of discontinuities on past transaction prices provide similar results. My parametric approach for accounting for cross-border heterogeneity in density thus appears to be an attractive way to avoid the detection of nonexistent discontinuities without estimating higher-order polynomials in border distance or losing power by focusing on narrow bands around the borders.

5.2 First-Stage Effects on Wealth Tax Outcomes

In this subsection, I provide reduced-form estimates of how changes in (model-implied) tax assessment affects wealth tax outcomes, such as the extensive margin propensity to pay a wealth tax and the amount subject to a wealth tax. These results are necessary to understand the exact treatment that is driving the effects on household saving behavior and labor supply. I show these results graphically in Figure 3. The pre-period (placebo) version of these plots can be found in Figure B.1 in the Appendix.

I also calculate the impact on the marginal and average net-of-tax rates-of-return. The estimates isolate the effect coming through wealth taxation, thereby excluding potential behavioral responses that affect the rate-of-return these households achieve. These estimates and the exact methodologies are provided in Table 1, which uses the scaled border distance specification. Table B.8 in the Appendix provides the version using the unscaled border distance (in km) specification.

In Figure 3, I show clear evidence of a discontinuous treatment effect in terms of the amount subject to a wealth tax (Panel A, rows 1 and 2) and the probability of facing a positive marginal wealth tax rate (Panel B, rows 1 and 2). A 1-log point increase in model-implied tax assessment increases the amount of taxed wealth by between 0.5 and 0.9 MNOK, and increases the propensity to pay a wealth tax by about 25 percentage points, or roughly 42% relative to a mean of 60%.

[FIGURE 3 about here.]

Row 1 uses distance in kilometers as the running variable, and shows larger effects in terms of the amount subject to a wealth tax in Panel A. The reason is likely that households located near the boundary (in terms of kilometers) tend to be drawn from more urban areas (see Figure A.3 in the Appendix.) House prices in more urban areas are higher, which implies that a given percent increase leads to larger level shifts and thereby larger effects on the total amount subject to the wealth tax.

In Table 1, I also include the first-stage effect of increasing model-implied tax assessment on actual (as observed in tax returns) tax assessment, $\log(TaxVal)$. This coefficient is 0.8194 in the full sample, and thus fairly close to 1. A coefficient of 1 would be expected in the absence of moving and ownership of secondary homes (see end of Section 2.1.1 for a discussion of why the coefficient will be less than one). In column (2), I provide the estimates that correspond to Panel B, row 2, in Figure 3. Column (3) shows the effect on the marginal rate-of-return, which is roughly the coefficient in column (1) multiplied by the average wealth tax rate of 1.04%. Column (4) shows the effect on the amount of wealth above the threshold, corresponding to Panel A, row 2, in Figure 3.

[TABLE 1 about here.]

Column (5) provides the effect on the average rate-of-return. We see that the effect on the marginal rate-of-return in column (3) is larger than the effect on the average rate-of-return in column (5). In light

of my conceptual framework introduced in Section 3, this suggests that the income effects associated with changing a linear rate-of-return are generally muted. This implies that any finding that saving increases due to higher tax assessment would be indicative of a low (intertemporal) substitution effect, and in general that my reduced-form findings provide a lower bound of the saving effect of changing a linear rate-of-return (where average and marginal rates are affected equally).³⁴

In general, quasi-first-stage estimates, such as those in Table 1, should be interpreted with some caution, since they may be affected by behavioral responses. For example, if household TNW is extremely elastic with respect to wealth taxation, increased tax assessment may cause households to lower TNW sufficiently to avoid having to pay a wealth tax. Such behavior would push the first-stage estimates toward zero. However, as I will show, behavioral responses are modest. I therefore do not believe that this is a first-order concern, and that this framework thus provides useful quantities with which to compare the subsequent estimates of how increases in tax assessment affect household behavior.

5.2.1 Heterogeneous Responses

The conceptual framework in Section 3 suggests that income effects are amplified (muted) to the extent that the effect on the average rate-of-return is larger (smaller) than the effect on the marginal rate-of-return. Table 1 above suggests that income effects are muted in the full sample of households, as the effect on the marginal rate-of-return is $0.2675/0.1544-1=73\%$ larger. This underlies some significant heterogeneity: In the sample of households initially above the tax threshold, the effect on the marginal rate-of-return is only 19.5% larger than the effect on the average rate-of-return, while in the sample of households initially below, it is 125% larger. I would therefore expect to see more (positive) saving responses in the above-threshold sample.³⁵

The conceptual framework also suggests that income effects are smaller when future incomes, Y_2 , are large relative to initial income and wealth, Y_1 , i.e., when the human wealth effect is larger. In my empirical setting, households whose initial taxable wealth was above the threshold differ from those initially below the threshold in three characteristics, as shown in the summary statistics in Table A.1: (1) They are slightly older (2 years at the mean), but have similar current levels of labor incomes and thus likely face lower future incomes due to retirement. (2) They have more initial wealth as of 2009. These two elements suggest that households with initial taxable wealth above the threshold will save more or dissave less when subjected to increased tax assessment. If both income effects and substitution effects are large, this may offer differential effects (in terms of the sign of the savings

³⁴This assumes that Taxable Net Wealth is the relevant definition of savings, which is done by Jakobsen et al. (2020). Given the definition of TNW in my setting, this is akin to assuming that 25% of housing wealth counts as consumption-planning relevant savings. In the calibration exercise at the end of this paper, I instead define Gross Financial Wealth (GFW) as the main measure of savings. The effect on the average rate-of-return is then scaled up by the ratio of the average TNW to the average GFW (1.741) to 0.27 pp., which is close to the effect on the marginal rate-of-return.

³⁵These qualitative differences hold if we consider returns on Gross Financial Wealth (GFW). The marginal returns are the same, but the average returns must be adjusted, since TNW is typically larger than GFW. The effect on the average rate-of-return on GFW is thus larger. By scaling up the average rate-of-return effect by the ratio of the means of TNW and GFW in the respective samples, we get ratios of the effect on the marginal versus the average rates-of-return of 1.00 ($=0.2675/((1741/1000)*0.1544)$) in the full sample, 0.71 ($=0.2169/((2541/1432)*0.1713)$) in the above-threshold sample, and 1.45 ($=0.3103/((758/466)*0.1312)$) in the below-threshold sample.

response) based on initial taxable wealth.

5.3 Financial Saving

[FIGURE 4 about here.]

In this section, I provide the results on household financial saving. Figure 4 shows the reduced-form results graphically for two of the main specifications. In Table 2, I provide the corresponding results, using an Instrumental Variables (IV) specification, for the full set of geographic running variables. Both Figure 4 and Table 2 consider the effect on wealth-tax adjusted financial saving. The wealth tax adjustment (discussed in Subsection 4.3.1) removes the mechanical effects of increased taxation on savings, essentially by treating tax payments as saving. Table 3 shows results absent this adjustment, and also considers different components of financial wealth.

[TABLE 2 about here.]

Figure 4, Panel A, rows 1 and 2 both show the estimated effect of increased model-implied tax assessment on pre-period financial saving for the full analysis sample. The first row uses (unscaled) border distance in kilometers as the running variable and the second uses scaled border distance. Neither specification can reject the null hypothesis of no pre-trends. The visual evidence is consistent with this conclusion. Panel B, rows 1 and 2 show the effect on financial saving. Both specifications find that a 1-log-point increase in model-implied tax assessment increases saving by approximately 2%. Both discontinuities are significant at the 1% level.

Table 2 provides the regression estimates using the IV specification, where tax-return observed tax assessment ($TaxVal$) is instrumented for by model-implied tax assessment (\widehat{TaxVal}). The first row of results shows the estimated effects of the full sample. The estimates in columns (3) and (4) correspond to the reduced-form estimates in rows 1 and 2, respectively, in Panel B of Figure 4. The effects are consistent across specifications, and significantly different from zero at the 1% level for all but the specification that estimates slopes on border distance separately for each border area (column 5). Some of the specifications suggest that effects are weaker for households initially below the wealth tax threshold. This is consistent with the finding from Table 1 that these households see relatively smaller income effects, since their marginal rate-of-returns is affected considerably more than the average rate-of-return.

To infer the implied saving propensity, namely, how many NOK saving increases by for each additional NOK subject to a wealth tax, I perform the following calculation. Table 1 shows that the effect of a 1-log-point increase in $TaxVal$ increases the amount subject to a wealth tax by NOK 489,959, NOK 740,511 and NOK 237,618, for the full, above, and below samples, respectively. To relate these effects to the IV estimates, we must divide these amounts by the first-stage coefficients of 0.8194, 0.8450, and 0.7994, respectively. This addresses the fact that the IV estimates provide estimated effects of increases in $\log(TaxVal)$, while the estimates in Table 1 provides the estimated effects of increases in model-implied $\log(\widehat{TaxVal})$. While the resulting NOK effect on the amount subject to a wealth tax goes into the denominator, the following numbers enter the numerator. I take the estimated effects on the saving rate, 0.0238, 0.0239, and 0.0206, and multiply by the respective sample means of GFW of NOK 1,000,000, NOK 1,432,000, and NOK 466,000, respectively. This

provides propensities (SEs) to increase saving out of increased wealth tax exposure of 0.0398 (0.0149), 0.0391 (0.0198), and 0.0339 (0.0202), respectively, for the three samples.

For the full sample, these numbers suggest that households save approximately 4 NOK per additional NOK of wealth taxes. That includes approximately 1 NOK that goes toward paying the wealth taxes for that year. The residual 3 NOK may be interpreted as additional saving to offset future wealth tax payments. This seems reasonable from a life-cycle perspective, given that the average household is 62 years and thus not far from retirement. Households may therefore want to pay more of the wealth tax (essentially by saving for it) while they have higher incomes and lower costs of labor supply adjustments prior to retirement.

I perform similar calculations to obtain the implied semi-elasticities of saving to the marginal rate-of-return. I divide the estimated coefficients by the (reduced-form) effect on the marginal rate of return, $r^{marginal}$, which itself is divided by the first-stage coefficients in column (1) of Table 1. This provides semi-elasticities of saving with respect to the marginal rate-of-return of -7.2904 (2.2762), -9.3541 (4.7357), and -5.5646 (3.3233), for the full, above, and below samples, respectively. This first estimate may read as follows: A 0.1 percentage-point decrease in the marginal rate-of-return increases the *saving rate* out of financial wealth by 0.73 percentage points. It is worth noting, that while these elasticities are neither compensated nor uncompensated elasticities, as the effect of the average and marginal rates-of-return differ. In Section 7, I infer (bounds on) the underlying uncompensated savings elasticities through the lense of a simple life-cycle model.

I perform a number of robustness tests. In Table B.2, I provide results when using triangular (distance-based) weights. All standard errors provided in the main text are clustered at the census-tract level. In B.3, I provide standard errors when clustering at the household or municipality level. Standard errors are slightly smaller when accounting for correlation in the error term across larger geographic areas (municipalities). In Tables B.5, B.6, and B.7, I provide estimated IV effects when varying the location measure cutoffs for the scaled border distance measure, border distance in KM, and the relative location measure, respectively. Effects are qualitatively similar when varying the bandwidths, but tend to be larger (and more noisily estimated) the narrower the bandwidth.

5.3.1 Decompositions of Financial Saving Effect

In Table 3 below, I consider the effects on saving when not adjusting for wealth tax payments in column (2). In column (3), I further isolate responses to changes in third-party reported domestic deposits. In column (4), I only consider items that include self-reported items, such as foreign wealth and outstanding claims. Column (1) provides results from the baseline definition for reference. I report results using scaled border distance as the geographic running variable.

[TABLE 3 about here.]

Comparing columns (1) and (2) suggests that around $0.149/0.0238=63\%$ of the effect on saving comes from increased accumulation of financial wealth, and 37% comes from increased wealth tax payments. I perform the same exercise as in the previous section to calculate the implied propensities to save out of increased wealth tax exposure. I find that households in the full, above, and below samples increase their savings (SE) by NOK 0.0249 (0.0152), 0.0235 (0.0208), and 0.0205 (0.0202) for

each additional NOK subject to a wealth tax, respectively. The implied semi-elasticities are -4.5641 (2.7875), 5.6359 (4.9706), and 3.3748 (3.3233), respectively.

In column (3), I focus on changes in domestic holdings of deposits, which is the primary (financial) saving vehicle for Norwegian households. Deposits are broadly defined, and include various forms of low-risk savings vehicles offered through banks. From the summary statistics in Table A.1, we see that deposits make up 98% (80%) of financial wealth for the median (mean) household in the full sample, and 94% (77%) for the median (mean) household in the above sample.³⁶

While the estimated effect on deposit growth is not statistically significant, it is important to note that this specification does not account for the mechanical effects of increased wealth taxation. The relevant null hypothesis is therefore not that the effect is zero, but rather the implied mechanical effect on deposits, which is negative. Under the reasonable assumption that wealth taxes are paid out of deposits, the standard no-behavioral-response null hypothesis implies a point estimate of -0.0045.³⁷ This would imply a t -statistic (column 3, full sample) of $(0.0154+0.0045)/0.0099=2.01$.

In column (4), I only consider self-reported items, and find qualitatively similar results. This suggests that even though there is some scope for misreporting responses along asset classes such as foreign wealth, this does not seem to materialize as less reported wealth.

5.4 Debt

In this section, I explore the effects on household debt. Figure 5 shows reduced-form results for the full sample. The first row uses the (unscaled) border distance specification, while the second row uses scaled border distance as the geographic running variable. Panel A finds no evidence of pre-trends in debt accumulation, and Panel B finds no evidence for any effect during the post-period, 2010–2015.

[FIGURE 5 about here.]

In Table 4, I show the results from the IV specifications using the full set of specifications, and provide results separately for the different subsamples. All of the specifications that control for unobserved geographic heterogeneity (columns 3–6) find no evidence that debt increases as a result of higher tax assessment. The coefficients in column (5) suggest that households reduce debt. However, this result cannot be inferred from the other specifications. The finding of little to no effect on debt suggests that marginal savings go toward increasing financial wealth rather than reducing debt. This seems reasonable, since the sample consists of older and wealthier households with fairly little debt.³⁸

³⁶This is higher than in the U.S. Fagereng et al. (2018) provide a comparison of the financial balance sheets of U.S. consumers present in the Survey of Consumer Finances (SCF) and Norwegian households by percentiles of financial wealth. This comparison accounts for the fact that pensions are largely provided by the government and therefore do not appear on household balance sheets. From their Table OA.1, I see that SCF households in the 90th to 95th percentile hold 47% of their (non-private equity) financial wealth in deposits and bonds. The comparable share for Norwegian households found in Table 1A is 78%.

³⁷In Table 1, we see that a 1-log-point increase in TaxVal reduces the average rate-of-return by $0.1544/0.8194=0.1884$ pp. If I assume that wealth taxes are paid out of deposits (rather than out of all of TNW), the reduction in deposits would be $0.1884\% * 1741/722=0.4543\%$, where 1741 is the mean amount of TNW and 722 is the mean amount of deposits, in thousands of NOK, obtained from Table A.1.

³⁸The median household only has NOK 138,000 (USD 23,000) in debt (see Table A.1).

[TABLE 4 about here.]

5.5 Portfolio Allocation

5.5.1 Risky Share of Financial Wealth

In this section I examine the effect of increased tax assessment on the share of financial wealth invested in the stock market. A potential hypothesis is that households take on more risk in order to increase their capital gains (in expectation) and thereby offset the effects of increased taxation. Another hypothesis is that the adverse effect of increased taxation on life-time consumption decreases risk-averse agents', e.g., those with Constant Relative Risk Aversion preferences, willingness to allocate wealth to the stock market. However, I find no evidence of a response in either direction. Figure 6 shows no discontinuities in the (differenced) stock market share.

Focusing on the full sample, I multiply the estimated effect (and the SEs) by the average amount of financial wealth in the sample and divide by the estimated effect on the amount subject to the wealth tax to obtain a propensity to save in stocks out of wealth tax exposure. Given that this effect arises through changes in the stock market share, this would be a propensity to save in stocks, above-and-beyond what would be implied by maintaining a constant risky share. This exercise yields a 95% confidence interval of $\pm 1.96 * 0.0014 * 1000000 / 489959 = [-0.0056, 0.0056]$. If we assume a risk premium of 5%, then the confidence interval on the effect on expected capital gains is $[-0.0003, 0.0003]$. This does not come close to offsetting the effect on yearly wealth tax payments of around 0.0104 per additional NOK subject to the wealth tax.

I perform a similar calculation as in the previous sections to calculate implied (semi-semi) elasticities. A 1-percentage-point decrease in the net-of-tax rate-of-return changes the the stock market share by 0 (0.4288), -0.2348 (0.7828), and 0.2834 (0.5410) percentage points, for the full, above, and below samples, respectively, where standard errors are provided in parentheses. In the full sample, I can thus rule out (at the 95% level) that a 1 percentage point reduction in the net-of-tax return reduces the stock market share by more than 0.84 percentage points and I can rule out an elasticity (dividing the effect by the mean share of financial wealth, and 1 percentage point by an average rate-of-return of 2%) larger than 0.17 in absolute value. Of course, the previous caveat still stands: Given differences in the effects on the marginal and average net-of-tax rate-of-return, these elasticities may differ somewhat from the uncompensated elasticities that would arise from changing a linear tax on wealth or capital income tax.

[FIGURE 6 about here.]

In Table B.4 in the Appendix, I provide results when instead considering a broader measure of the risky share of financial wealth. This measure also includes holdings of non-listed stocks, i.e., private equity. With this definition, the effects suggest a (n almost statistically significant) reduction in risk-taking. For the full sample, a 1 percentage point reduction in the net-of-tax rate-of-return reduces the risky share of financial wealth by 0.8577 (SE=0.5514) percentage points.

[TABLE 5 about here.]

5.5.2 Interest Rates

Below I present the results for realized interest rates on deposits and debt. The hypothesis is that increases in wealth tax payments induces higher effort toward obtaining higher interest rates on deposits or lower interest rates on debt. Figure 7 shows the results graphically, focusing on the scaled border distance specification.

I find no statistically significant effects on the interest rates on either deposits or debt. To examine which effects I can rule out, I focus on the estimated effect on interest rates on deposits for the full sample, using the scaled border distance specification in column (2). This specification yields an (semi-semi) elasticity of $-0.000101/(-0.002675/0.8194)=0.0309$ (SE=0.0380). In other words, the effect of a 1-percentage-point decrease in the marginal net-of-tax rate-of-return on realized returns has a 95% confidence interval of $[-0.0437, 0.1053]$ percentage points.

[FIGURE 7 about here.]

To calculate back-of-the-envelope bounds on the portion of increased wealth tax payments that is offset by realizing better returns on deposits, I perform the following exercise. Multiplying the coefficient in column (2) of -0.000101 (SE=0.000124) by the mean amount of deposits of 0.722 MNOK yields a NOK effect of 73 (89). At the same time, a 1-log-point increase in TaxVal will increase the amount of wealth subject to a wealth tax by $0.49\text{MNOK}/0.8194 \approx 0.6$ MNOK. The propensity to earn more interest out of increased wealth tax exposure is thus 0.000121 (SE=0.000148), which is small relative to the impact on the yearly wealth tax bill of around 0.0104. The upper bound on the 95% confidence interval implies that at most $4\%=(0.000121+1.96*0.000148)/0.0104$ of the increase in the wealth tax bill is offset by higher interest earnings.

[TABLE 6 about here.]

5.6 Labor Income

5.6.1 Total Taxable Labor Income

This section shows the results on household Total Taxable Labor Income (TTLI). This definition of labor income includes transfers, such as UI benefits, labor-related pension payments, and sickness and parental leave benefits. Figure B.3 shows the reduced-form effects for the full sample.

[FIGURE 8 about here.]

Table 7 shows estimated coefficients using different specifications and an IV setup. There is meaningful within-sample variation in the point estimates across the specifications that address geographic heterogeneity (columns 3–6). To calculate implied elasticities and propensities, I take the average coefficient (and standard errors) across these specifications. Performing the same exercises as in the previous sections, I find an implied semi-elasticity (SE) of labor income to the marginal net-of-tax rate-of-return of -2.6190 (1.6388), -7.2798 (3.1996), and 0.0966 (1.6552) for the full, above, and below samples, respectively. A similar exercise yields propensities to earn (pre-tax) of 0.0099 (0.0062), 0.0147 (0.0065), and -0.0009 (0.0150), respectively. Below, In Subsection 5.6.3, I show how these estimates may be used to infer what fraction of the saving effect is financed by increases in labor income.

[TABLE 7 about here.]

5.6.2 Labor Earnings

In this subsection, I focus on pre-tax labor income in the form of salary, wages, and self-employment income. This will prove quite important in my setting, since many of the households in my empirical setting are past retirement age. This means that a large part of their Total Taxable Labor Income (TTLI) is in the form of pensions that are the result of previous (and thereby unaffected) labor supply. The summary statistics in Table A.1 show that for the full sample, the mean of LE is 62% that of the more comprehensively defined TTLI.

Figure 9 shows the results for the full sample using both the unscaled (km) and scaled border distance specification. The plots reveal a clear level shift in the post-period. While there is no stark evidence of a pre-trend, the plots suggest slightly higher earnings growth in the pre-period. To explore this further, I provide the same plots, restricting the sample to those initially above the tax threshold, in Figure B.4. It is reassuring that this sample displays no indication of pre-trends, since this is the subsample driving the overall effect, which we can see in Table 8.

[FIGURE 9 about here.]

This change of definition reveals considerably stronger income responses than what we saw in the previous subsection. For the full sample, the coefficients from the IV regressions in Table 8 are two to four times larger than those using the more comprehensive definition in Table 7. For the above sample, estimated coefficients are around three times larger. This implies that estimated elasticities are correspondingly larger in magnitude. Consistent with results that use the previous definition, there is a noticeable difference in the responses between households initially above versus those initially below the wealth tax threshold.

[TABLE 8 about here.]

Repeating the calculations in the previous subsection yields semielasticities (SEs) of -7.0453 (3.5533), -13.1505 (6.3013), and -2.6535 (4.2765), for the full, above, and below samples, respectively. The implied propensities (SEs) to increase yearly pre-tax earnings out of increased wealth tax exposure are 0.0165 (0.0083), 0.0155 (0.0074), and 0.0159 (0.0257), for the full, above, and below samples, respectively.

Both Tables 9 and 8 reveal much stronger (71% and 65%, respectively) labor earnings responses when using border distance in kilometers versus scaled border distance as the geographic running variable. This is consistent with the finding in Figure 3, that estimated discontinuity in wealth tax exposure (measured in NOK) is 77% larger when using border distance in kilometers. In other words, while the assessment effects are different, the propensities to earn out of wealth tax exposure are similar across specifications.

5.6.3 Labor-financed Savings

This subsection provides some back-of-the-envelope calculations regarding the extent to which saving responses are financed by increased labor earnings.

In Subsection 5.3.1 I found that the propensity to accumulate more financial wealth out of increased wealth tax exposure was 0.0249. If we also account for increased tax payments, this leads to a

cumulative saving propensity over 5 years of $0.0249*5 + 5*1.04\% = 0.1765$. The yearly propensity to increase total taxable labor income of 0.0099 implies a cumulative earnings propensity of $0.0099 + 2*0.0099 + \dots + 5*0.0099=0.1485$. Over the course of 5 years, households will have earned 0.1485 NOK for each additional NOK subject to the wealth tax. If I assume an average marginal tax rate of 40%, this implies increased earnings over a 5-year period of $0.1485*(1-40\%)=0.0891$. Together, these numbers imply that around $0.0891/0.1765 \approx 50\%$ of the increase in saving was financed by increased labor earnings. If I instead use the implied propensity to earn (only salary, wages, and self-employment income) of 0.0150, this labor-financed share is $(5+\dots+1)*0.0165*(1-40\%)/(0.1765)=84\%$.

5.7 Year-by-year Effects

In this section, I decompose the pooled post-period (2010–2015) results by estimating coefficients separately for each year. I plot these results separately for the four main outcome variables in 10 below, using the scaled border distance specification. This is a useful exercise to inform the mechanism behind the observed saving responses. For example, Zoutman (2018) finds that his estimated elasticities are driven by immediate responses. He therefore attributes the high elasticity to changes in reporting behavior, since real responses arising from changes in consumption and labor supply will likely occur gradually. Below, I show that the main estimates are not driven by a single year, which is consistent with real responses caused by gradual consumption and labor supply adjustments.

Panel A considers the effects on financial savings. As a reference, the estimated pooled coefficients from (corresponding Table 2 column (4) are plotted as horizontal lines. We see that the savings effect is persistent across the years, and that the yearly coefficients hover around the pooled coefficient. Panel B similarly shows the yearly estimated effects for the unadjusted saving measure.

Panel C considers the effects on debt. This reveals a somewhat more interesting pattern. The immediate response appears to be to increase debt (or reduce it less), while the opposite seems to be the case toward 2014–2015. This could be consistent with the presence of some constrained households who initially lower their debt payments to pay for their taxes, but eventually respond to the income effect through increasing their savings by paying off their debts.

[FIGURE 10 about here.]

Panel D considers the share of wealth allocated to the stock market. I see no dynamic effects, and all coefficients are close to zero, as are the pooled estimates.

Panel E considers Total Taxable Labor Income (TTLI). The point estimates suggest (although this suggestion may be far from statistically significant) that initial responses are somewhat larger, and that the effects eventually dissipate. This seems highly reasonable, given that the average age of households is 62 (measured in 2009), and the modal age of retirement in Norway is 67; thus I expect the median household to retire during 2014–2015. We see a similar pattern in Panel F, which considers Labor Earnings (LE).

5.8 Subsequent Transaction Prices

In this section, I investigate the effects on subsequent transaction outcomes in terms of the likelihood of selling and the conditional subsequent sales price. I report these results in Table 9.

In columns (4)-(6), I consider extensive margin effects. The treatment in my setting is specific to the house the households own. Households may therefore undo the treatment by selling their house and moving to an area with lower assessments. I do not believe that this is likely, given my impression of limited awareness of the geographic aspects of the pricing model, as well as the likely presence of sizable costs associated with moving. Consistent with this, I find statistically small effects on the propensity to sell. The estimates show that a 1-log-point increase in \widehat{TaxVal} increases the likelihood of selling by 1.2 percentage points, and I can rule out any effects larger than 4.2 percentage points at the 5% level.

In columns (1)-(3), I consider conditional sales prices. The effect of increased tax assessment (which follows the house) on tax prices likely depends on the propensity of potential buyers to be subject to a wealth tax. Since most new homeowners finance their purchases with debt, the net effect of a house purchase on their TNW is highly negative. This is because debt is deducted from TNW in its entirety, while the tax value of the house, on average, corresponds to around 25% of its market value. This causes new home buyers to generally have very low (negative) TNW. Any tax assessment premiums are therefore unlikely to affect these households' immediate wealth tax liabilities. I therefore do not expect the demand side to be highly sensitive to the tax assessments. Consistent with this, I find no effects on subsequent sales prices. The estimated point estimates from the preferred specifications in columns 1 and 3 are rather small, at 0.035 and 0.016.

Since the confidence intervals in columns (1) through (3) are somewhat large, it makes sense to inquire whether the associated confidence intervals include a full capitalization effect. I evaluate this with a back-of-the-envelope calculation. If all potential buyers were well above the wealth tax threshold, then a 10% increase in the tax assessment would increase yearly housing-induced wealth tax liabilities by around 10% times the average wealth tax rate of 0.0104. The NPV effect of this (over 30 years, discounted at 2%) would be $10\% * 0.0104 * (1/0.02 - 1.02^{-30}/0.02) = 2.33\%$, which would be the upper bound for the magnitude of the potential capitalization effect. Using the estimates from column (1), I can rule out an effect outside of $10\% * (0.035 \pm 1.96 * 0.085) = [-1.32\%, 2.02\%]$. Thus, the confidence interval contains $1.32/2.33 = 57\%$ of the (back-of-the-envelope) potential full capitalization effect.

In Table 9, I also report estimated coefficients on the geographic trend controls. The purpose of this is to check whether the estimated coefficients on these variables correspond to initial expectations, which were based on the motivating examples in the empirical specification section. My expectation was that the coefficients on the scaled border distance variable in column (1) would be 1, and the coefficient on the relative location variable in column (3) would be 0.5. The point estimates are indeed very close to this, and statistically indistinguishable at the 5% level.

[TABLE 9 about here.]

5.9 Regression-based Analysis of Pre-treatment Differences

5.9.1 Past Transaction Prices

In this subsection, I examine whether my empirical specifications are identifying discontinuities in past transaction prices. I show that my preferred specifications cannot reject the null of no discontinuity, while more naive approaches *do* identify such discontinuities. I also perform robustness tests by considering different subsets of past transactions.

Column (1) shows that model-implied tax assessment is highly correlated with past transaction prices when only baseline housing characteristics (size, age, dummy for dense area, but not geographic trends) are controlled for. This specification uses both within-boundary and across-boundary-area variation in tax assessment. This correlation remains strong when controlling for these characteristics at the border-area level in column (2), which only uses within-boundary-area variation, but does not address geographic trends.

When addressing geographic heterogeneity by controlling for (unscaled) border distance in KM in column (3), these correlations are reduced considerably, but remain (largely) positive across subsamples. This is consistent with the visual evidence in Figure 2, in which house prices change nonlinearly, which invites the detection of a discontinuity in a linear specification.

Column (4) uses my main preferred geographic running variable, scaled border distance. This removes any statistically significant correlation between tax assessment and past transaction prices across subsamples. Column (5) estimates geographic slopes on border distance at the border-area level. In three out of four subsamples, I cannot reject the null of no correlation, but point estimates are consistently positive and somewhat large. Column (6) corresponds to my second preferred specification, and also consistently retains the null of no correlation between tax assessment and past transaction prices.

This exercise shows that scaled border distance and relative location perform well in keeping the null of no discontinuities, consistent with the visual evidence presented in Figure 2. The fact that estimates are slightly positive—at least in the first two samples—may reflect the fact that many of these transactions would have been present in the sample used to estimate the house price model coefficients. This is especially the case for the second sample, which restricts to transactions during 2004–2009.

[TABLE 10 about here.]

5.9.2 Pre-period Income, Wealth, Debt, and Educational Attainment

In this section, I examine whether tax assessment discontinuities correlate with other pre-period household observables under my different specifications. The specifications in columns (1)-(2) do not address geographic heterogeneity and find a strong correlation between model-implied tax assessment and household observables. These correlations are reduced significantly in column (3), which uses border distance in kilometers as the running variable, but most correlations are still statistically different from zero. This occurs despite allowing the continuous loading on the assessment premium to be nonlinear by including second-order polynomial terms in d_i^{KM} interacted with Δ_i .

My preferred specifications (4) and (6) show very small correlations. They are also fairly precise, in the sense that the standard errors are an order of magnitude smaller than the point estimates in the baseline specifications (columns (1)–(2)). Column (5), which estimates border-specific slopes on border distance, also performs reasonably well, except for a marginally significant (at the 10% level) correlation with having a college degree.

To illustrate the success of my approach in removing the correlation between tax treatment and household characteristics, consider the correlation between $\log(\widehat{TaxVal})$ and $\log(\text{Labor Income})$. Column (1) shows that when not addressing geographic heterogeneity at all, a 1-log-point increase in tax assessment is associated with 28.8% higher labor incomes. Addressing geographical confounders using my main preferred specification in column (4), I find that this correlation is reduced to 0, and I can rule out a correlation larger (in magnitude) than 5.5 percentage points at the 5% level.

[TABLE 11 about here.]

6 Bunching

In this section, I examine the extent to which households bunch around the wealth tax threshold. The primary reason for this is to investigate the likely extent of evasion or avoidance opportunities. If these are abundant and not costly, I would expect to see sizable bunching (excess mass) around the wealth tax threshold. If this is indeed the case, one might worry that households can partially “untreat” themselves through these means. For example, if it is not costly for households to lower their wealth tax burden by moving financial assets that are observed by tax authorities into harder-to-tax assets, such as cash, the response I observe in terms of growth in financial wealth may be a lower bound of the actual effect on savings.³⁹ This is not a concern for the qualitative conclusions of this paper, but it is nevertheless useful to evaluate, since sizable bunching would suggest that the true saving responses may be even higher.

I show my results in Figure 11 below. Panel A shows the results for my full analysis sample, and Panel B shows results for the full sample of Norwegian taxpayers. I follow the approach of Chetty, Friedman, Olsen, and Pistaferri (2011) to perform the analysis.

The visual evidence is quite clear, in that there is no sizable bunching around the wealth tax threshold in either sample. Panel B estimates a statistically significant excess mass around the threshold, but the visual evidence is not very supportive. In Panel B, the excess mass, $b = 0.097$, means that there is 9.7% extra mass in the NOK 5,000 bin to the left of the kink. This number is calculated using the methodology of Chetty et al. (2011), and the assumptions closely resemble those made by Seim (2017). First, a counterfactual distribution is calculated by fitting a 7th order polynomial to all points bins outside $[-40k, 15k]$. Then the relative number of bunchers, $N(\%)$, is calculated as the relative difference between the number of agents in the empirical and counterfactual distributions within $[-40k, 15k]$. Then all of the bunchers are assumed to be bunching one bin to the left of the threshold. Multiplying $N(\%)$ by the number of NOK 5,000 bins in $[-40k, 15k]$ then yields b .

³⁹I do expect that withdrawing deposits to store as cash is quite costly for households. Even though it could reduce wealth taxes by 1 cent per dollar, it would also preclude them from any interest earnings of (on average) 2 cents, leading to a net loss.

Multiplying b by NOK 5,000 tells us that 5,000 b less TNW is being reported due to the wealth tax threshold. In relative terms, given an average threshold during this period of NOK 830,000, and $b = 0.097$, this implies that 0.05843% of TNW is being misreported. Since the average wealth tax rate during this sample period (2011–2014) was 1.075%, this yields a net-of-tax rate elasticity of taxable wealth (following the definition in Seim (2017)) of $0.05853\% / (0.01075 / (1 - 0.01075)) = 0.054$. When translated to an elasticity with respect to a net-of-tax rate-of-return of 2%, the elasticity becomes $0.05853\% / (0.01075 / (2\%)) = 0.0010$.

[FIGURE 11 about here.]

7 Implied Structural Parameters

In this section, I use a simple life-cycle model to examine which value of the Elasticity of Intertemporal Substitution (EIS) is most consistent with my empirical findings. The model environment is simple; It only contains the core elements necessary to replicate my empirical results and the shock to wealth tax exposure. Agents choose both how much to save and how much to work, and they're shocked by more aggressive wealth taxation in such a way that the effect on the marginal and average net-of-tax rates-of-return may differ.

7.1 A simple life-cycle model

Consider the following life-cycle model with perfect foresight. The model features a constant EIS, $\frac{1}{\gamma}$, and a constant Frisch elasticity of labor supply, $\frac{1}{\nu}$.

$$\begin{aligned} \max_{\{c_t, s_{t+1}\}_{t=0}^T} \quad & \sum_{t=0}^T \beta^t \left(\frac{1}{1-\gamma} c_t^{1-\gamma} - \psi \frac{l_t^{1+\nu}}{1+\nu} \right) \\ \text{s.t. } c_t + s_{t+1} \quad & = y_t + l_t w_t \end{aligned} \tag{25}$$

$$+ s_t R(1 - \tau \mathbb{1}[s_t R + A - \bar{w} > 0]) + (A - \bar{w}) \tau \mathbb{1}[s_t R + A - \bar{w} > 0]. \tag{26}$$

ψ is the (dis)utility weight on labor supply, and β is the discount factor. The endogenous variables are c_t, l_t, s_{t+1} for $t \geq 0$. Unearned income (pensions), y_t and initial wealth, s_0 , are exogenous. \bar{w} is the threshold applicable to all taxable wealth, savings with returns ($s_t R$) plus assessed housing wealth, A .

Define $\tilde{R}_t = R(1 - \tau \mathbb{1}[s_t R + A - \bar{w} > 0])$ and $\tilde{V}_t = s^* \tau \mathbb{1}[s_t R + A - \bar{w} > 0]$. The budget constraint can be written as

$$c_t = y_t + l_t w_t + s_t \tilde{R}_t + \tilde{V}_t - s_{t+1}. \tag{27}$$

I assume that households respond to changes in \tilde{R}_t and \tilde{V}_t . I shut off the feedback mechanism of how changes in s_t can affect \tilde{R}_t and \tilde{V}_t . This eliminates bunching around the tax threshold, and allows me to solve the model using the (binding) first-order conditions and the lifetime budget constraint.

I do not model precautionary savings motives or bequests directly. Instead, I assume that households live until they are 100 years old. This ensures that households do not dissave too quickly, and therefore still hold meaningful savings around the average (empirical) age of death in Norway, which is around 85 years.⁴⁰

7.2 Simulation and Calibration

I assume that households act according to the model in the previous section, and simulate their responses to shocks to \tilde{R}_t and \tilde{V}_t , for $t \geq 1$, from a baseline $\tilde{R}_t = 1.02$ and $\tilde{V}_t = 0$. I simulate the responses in terms of their saving behavior and labor supply for EIS-Frisch combinations, $(\frac{1}{\gamma}, \frac{1}{\nu})$. The (dis)utility weight on labor supply, ψ , is calibrated to ensure that simulated labor earnings at $t = 0$ equal observed after-tax labor earnings in 2009 and the consumption share of total incomes (labor earnings plus exogenous income) equals 80%.⁴¹ I set $\beta = 0.98$.

Similar to [Jakobsen et al. \(2020\)](#), I model the responses of a representative agent. This agent sees shocks to \tilde{R}_t and \tilde{V}_t corresponding to those found for the full sample in Table 1, assuming a shock to $\log(\widehat{TaxVal}) = 0.5$. This implies $\Delta\tilde{R}_t = 0.13375$ pp. and $\Delta\tilde{V}_t = s_t(\Delta\tilde{R}_t^{avg} - \Delta\tilde{R}_t) = s_t(-0.001544 * (1741/1000) * 0.5 - (-0.002675 * 0.5))$ for $t \geq 1$,⁴² where the s_t used to determine $\Delta\tilde{V}_t$ is the s_t chosen absent the shock.

Savings, s_t , in my model corresponds to Gross Financial Wealth (GFW). Labor earnings corresponds to salary and self-employment income. I set exogenous income, y_t , equal to the difference between total taxable income and labor earnings in 2009 whenever the agent's age is strictly below retirement age. This difference corresponds approximately to the average amount of pension income. Starting at retirement age, exogenous income (pension income) increases by 50% of the after-tax 2009 average of labor earnings. I induce retirement by making wages drop to zero over a 5-year period that starts at retirement age.

7.3 Simulated Treatment Effects

The benchmark empirical treatment effect on savings corresponds to a 0.5 log-point increase in tax assessment. My empirical estimates on savings growth (GFW) imply a yearly effect of $0.5 * 0.0149$ percentage points each year, when not adjusting for the mechanical effects of increased taxation in Table 3. When cumulated over a 5-year period, this implies an effect of $5 * 0.5 * 0.0149 = 0.0373$ (SE = $5 * 0.5 * 0.0091 = 0.0228$). The lower bound of the 95% confidence interval is -0.0074.

[FIGURE 12 about here.]

⁴⁰Absent any mortality risk, this corresponds to (1) assuming that the bequest elasticity equals the EIS, and (2) that the strength of the (warm-glow) bequest motive ensures that households wish to bequeath an amount large enough to finance their own planned consumption for 15 years, given a continued flow of exogenous income.

⁴¹Choosing a consumption share of 80% ensures that agents choose labor supply close to the empirical average in the sample. Setting it to 100%, for example, leads to very large (unshocked) labor supply in order to save enough to finance a higher level of consumption.

⁴²The effect on \tilde{R}^{avg} is scaled up by the ratio of the sample means of TNW and GFW (1741/1000), since the first-stage estimate of -0.001544 is based on using TNW as the wealth base, but the model defines wealth as GFW. This accounts for the fact that the relative (return) effect is larger when GFW (which is smaller than TNW) is defined to be the stock of savings.

The benchmark empirical treatment effect for labor earnings is the following. I find that a 0.5 log-point increase in labor earnings increases labor earnings (salaries and self-employment income) by 0.5×0.0230 percentage points each year. The cumulative effect of this in terms of total earnings is $0.5 \times 0.0230 \times (5+4+3+2+1)$, since the first-year effect cumulates over 5 years, and so on. This gives a cumulative effect of 0.1725 ($SE = 0.5 \times 0.0116 \times (5+4+3+2+1) = 0.087$). In other words, over 5 years, treated households earned 17.25% more than untreated households. The lower bound of the 95% confidence interval is 0.002.

In Figure 12, I plot the Frisch-EIS combinations (with the disutility weight on labor supply being calibrated) that provide treatment effects corresponding to the lower bound of the 95% confidence intervals of the cumulative treatment effects in green. The orange line similarly represents the lower part of the 90% confidence intervals. Any EIS-Frisch combinations *above* these lines yield simulated treatment effects below the respective confidence intervals. In this figure, we see that either the labor earnings effect or the savings effect can be used to pin down similar bounds for the EIS, which only weakly depend on the Frisch elasticity.

[FIGURE 13 about here.]

In Figure 13, I plot the simulated cumulative treatment effects as a function of the EIS, assuming a Frisch elasticity of 0.5. It's clear from the figure that it is difficult to parameterize the simple life-cycle model I use in a way that exactly replicates my point estimates. This feature is not particularly robust to the assumptions of the model. For example, if we force the agent to pay a large bequest at death, increase β , or make other adjustments that increase the income effect, then the blue line will shift slightly upward. Similarly, we can make the blue line shift downward by lowering the income effect, for example, by shortening the life-span of the agent.

This section shows that in a simple life-cycle model, we need a fairly small value of the EIS to rationalize the empirical findings. We could also replicate low-EIS behavior by exogenously imposing harsh consumption adjustment frictions, e.g., that $c_t \geq c_0$ for $t \geq 1$. In such an environment, the responses to wealth taxation become uninformative of the EIS.

7.4 Implied Uncompensated Elasticity of savings to the Net-of-tax Rate-of-return

In Figure 14, I simulate the effects of a reduction in the (net-of-tax) rate-of-return for different values of the EIS. In this (partial-equilibrium) model, it does not matter whether the rate-of-return is reduced by capital taxation or monetary policy. The blue and green lines correspond to the EIS that produced simulated treatment effects in Figure 13 corresponding to the lower bound of the confidence intervals of my empirical findings at the 90% and 95% levels, respectively.⁴³

[FIGURE 14 about here.]

I also plot the treatment effects for two other values of the EIS. The solid line assumes an EIS of 1, corresponding to log-utility in consumption. The dashed line corresponds to one of the lower values of the EIS needed to calibrate the model in Jakobsen et al. (2020) to their empirical estimates. Given an average gross rate-of-return of 1.02 (assumed in the model and consistent with summary statistics),

⁴³The EIS cutoffs are slightly different based on whether we look at the savings results or labor earnings results. I therefore take the average EIS for a given confidence level.

we can find the implied *uncompensated* elasticities to the net-of-tax rate-of-return by reading off (the negative of) the value on the y-axis for a given line when the x-axis takes a value of 0.02. From Panel A, we see that the implicit uncompensated 5-year savings elasticity consistent with our empirical findings are below 0.10 and 0.02 at the 95% and 90% level, which can be read off of the green and blue lines, respectively. The implied elasticity when the EIS equals zero, which is the EIS that comes closest to explaining my results, is -0.42 .

Finally, Figure 14 also highlights the strikingly different responses to, for example, tax-induced, rate-of-return shocks contained within the set of commonly used values of the EIS. A 2-percentage-point reduction in the rate-of-return leads to a dissaving of 59% ($=\exp(-0.9)-1$) if the EIS is 2, but an increase in savings of almost 50% ($=\exp(0.4)-1$) if the EIS is zero. In the middle, we have an EIS of around 0.3 that gives barely any response at all. Research into the saving responses to capital taxation and the underlying parameters that drive these responses therefore seems particularly prudent to inform tax policy, even in the short to medium term.

8 Discussion

In this paper, I address an important and long-standing question in economics, namely, how household savings and labor income respond to capital taxation. Despite the importance of this question in terms of how it may inform a range of economic models, and in particular tax policy, there exists very little empirical evidence that is applicable to these models. This is in part due to a lack of exogenous identifying variation in the rate-of-return and capital taxation, but also to the difficulty of isolating real responses from evasion and avoidance effects. By using a novel source of identifying variation in wealth tax exposure in an empirical setting in which observed responses are unlikely to be driven by evasion, I make an important contribution to this literature. An additional contribution lies in the novel examination of theoretically important margins of adjustment, such as labor earnings and portfolio allocation.

My results indicate that the distortionary effects of capital taxation may go in the opposite direction of what is typically assumed.⁴⁴ In addition, capital taxation may encourage households to supply more labor. This is important for policymakers to consider when considering the optimal mix of capital and labor income taxation. My findings suggest that capital taxation may offset some of the distortionary (tax-revenue-reducing) effects of labor income taxation on labor income. However, it is important to note that my findings focus on distortionary effects that arise in partial equilibrium in the household sector. Wealth taxation, and capital taxation in general, may have potentially adverse general equilibrium effects or effects that operate through the corporate sector that are not considered in this paper.

My results on the savings effects of wealth taxation are qualitative different (and even of a different sign) from the previous empirical literature. The likely explanation is that my empirical setting, with largely third-party reported measures of savings, comes closer to estimating savings effects rather

⁴⁴Saez and Stantcheva (2018) consider feasible elasticities of capital to the net-of-tax rate-of-return to be 0.25, 0.5, and 1.

than strategic tax responses. Elasticities estimated elsewhere in the literature likely include evasion or avoidance responses, and will thus be larger (and may even be of a different sign) than pure savings elasticities. In Denmark, for example, only households in the top 1% to 2% of the wealth distribution paid a wealth tax. Around half of these households are business owners with potentially sizable evasion opportunities, since business wealth is self-reported. In Switzerland, financial wealth is completely self-reported by taxpayers.

I know of no obvious reason why the finding of a positive as opposed to a negative effect of wealth taxes on saving is would be driven by characteristics specific to Norway. If anything, the presence of more generous pension and social insurance programs should create an economic environment in which savings motives, and thus income effects, would be weaker in Norway and more easily dominated by the substitution effects associated with rate-of-return shocks.

At face value, the finding of a *positive* effect on savings is somewhat surprising. However, as I showed in the previous section, nonnegative saving responses to a negative rate-of-return shock can be generated by plausible parameterizations of a life-cycle model. For example, the estimate of 0.1 in [Best, Cloyne, Ilzetzi, and Kleven \(2020\)](#) would, in the model calibrated to my empirical setting, produce simulated saving responses that take a positive sign. A value for the EIS of 0.1 is also contained in the confidence bounds around the empirical estimates of the EIS for stockholders in [Vissing-Jørgensen \(2002\)](#). This further highlights the possibility of positively signed responses to adverse rate-of-return shocks.

Finally, as discussed in the introduction, my findings strengthen the premise upon which the recent macro-heterogeneity literature is built. In particular, my findings point to a larger role for the partial-equilibrium mechanism of [Auclert \(2019\)](#) and the general-equilibrium mechanisms of [Kaplan, Moll, and Violante \(2018\)](#) in explaining aggregate responses to monetary policy. In addition, my results are driven by older, wealthier households, which suggests that these households may respond in the opposite way to that of a representative agent, highlighting the need to study the behavior of younger, constrained households, as in [Wong \(2019\)](#), in which the mortgage refinancing channel is important.

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FIGURE 1: MODEL-IMPLIED GEOGRAPHIC VARIATION IN TAX ASSESSMENT FOR A STANDARD HOUSE

This figure shows the logarithm of the 2010 assessed tax value of an identical single-family home assessed as if it were located inside one of the municipalities below, predicted using the coefficients in the tax authorities' hedonic pricing model. Each distinct (shade of) color corresponds to a bin of \widehat{TaxVal} with a width of 0.3 log-points. I assume a house size of 130 m^2 , an age of 25–34 years, and a location in an area defined as densely populated. The assessed log tax value has a mean of 13.30 and a standard deviation of 0.37, across (equal-weighted) municipalities. For municipalities with within-city districts making up separate price zones, I assign the unweighted average tax assessments for the purpose of this illustration.

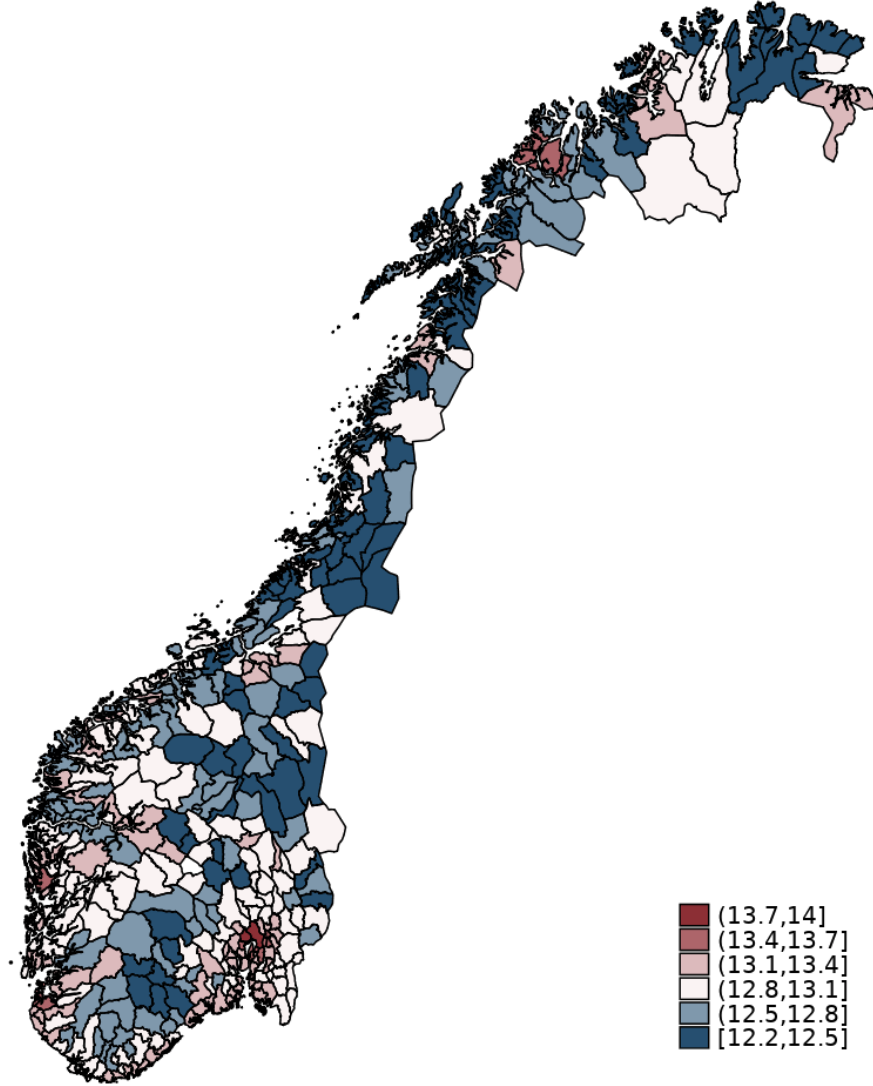


FIGURE 2: ASSESSED TAX VALUES AND OBSERVABLE CHARACTERISTICS

The graphs below show the effect on actual tax assessment (as observed in tax returns), past transaction prices, and pre-treatment incomes of living in a boundary region where hedonic pricing model coefficients imply a 1-log-point assessment premium on the high-assessment side. Panel A considers log tax assessment in 2010 to verify the treatment discontinuity. Panel B considers the smoothness of observed past log transaction prices (2000–2009). Panel C considers log labor incomes (TTLI) in 2009. The effects are estimated separately for geographic bins, according to the different location measures. The top row uses distance in kilometers, where households on the low-assessment side are given a negative distance. The second row uses (similarly signed) distance scaled by the distance between the two municipal centroids. Bins with less than 1% of observations are not plotted. The size of the circles corresponds approximately to the relative size of that bin in the estimation sample. Estimated coefficients stem from estimating a coefficient on Δ_i in equation 23 separately for d_i bins, rather than estimating coefficients on $\log(\overline{TaxVal}_i)$ and $g_b(c_i)\Delta_i$. This specification includes a vector of housing controls, but no household characteristics. Panel B includes all homeowners present during 2009 who purchased their home during 2000–2009, and is not subject to the main sample restrictions. A robustness exercise is performed in Table 10.

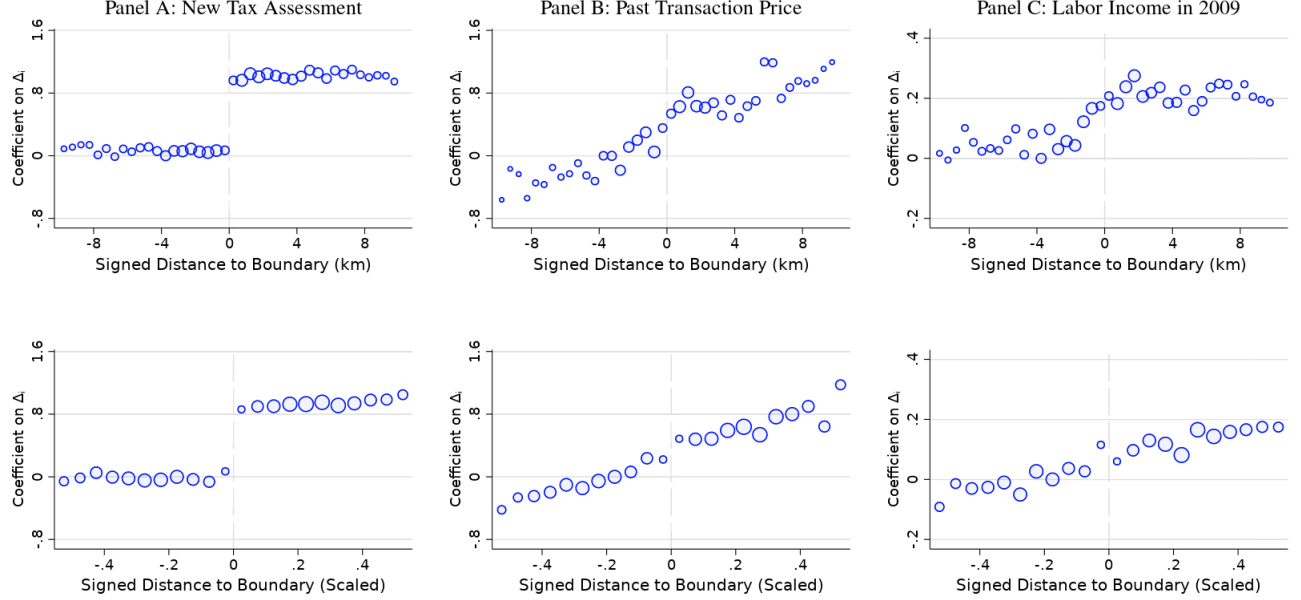


FIGURE 3: GRAPHICAL PRESENTATION OF THE REDUCED-FORM EFFECTS ON WEALTH TAX EXPOSURE

This graph shows the reduced-form effects of increased tax assessment on (A) how much of household savings is subject to a wealth tax, i.e., the amount of wealth above the tax threshold, and (B) whether household pays a wealth tax. These outcomes are measured during 2010–2015. The first row uses distance in kilometers, where households on the low-assessment side are given a negative distance. The second row uses (similarly signed) distance scaled by the distance between the two municipal centroids. The fitted lines and discontinuities correspond to reduced-form regressions using the regression specification in equation 19. 95% confidence bands are represented by dashed lines. All panels consider post-period saving outcomes for the full sample of households with initial positive taxable net wealth in 2009. Scatter-points stem from estimating a coefficient on Δ_i using equation 19 separately for d_i bins, rather than estimating coefficients on $\log(\widehat{TaxVal}_i)$ and $g_b(c_i)\Delta_i$. The size of each circle corresponds approximately to the relative number of observations in that bin.

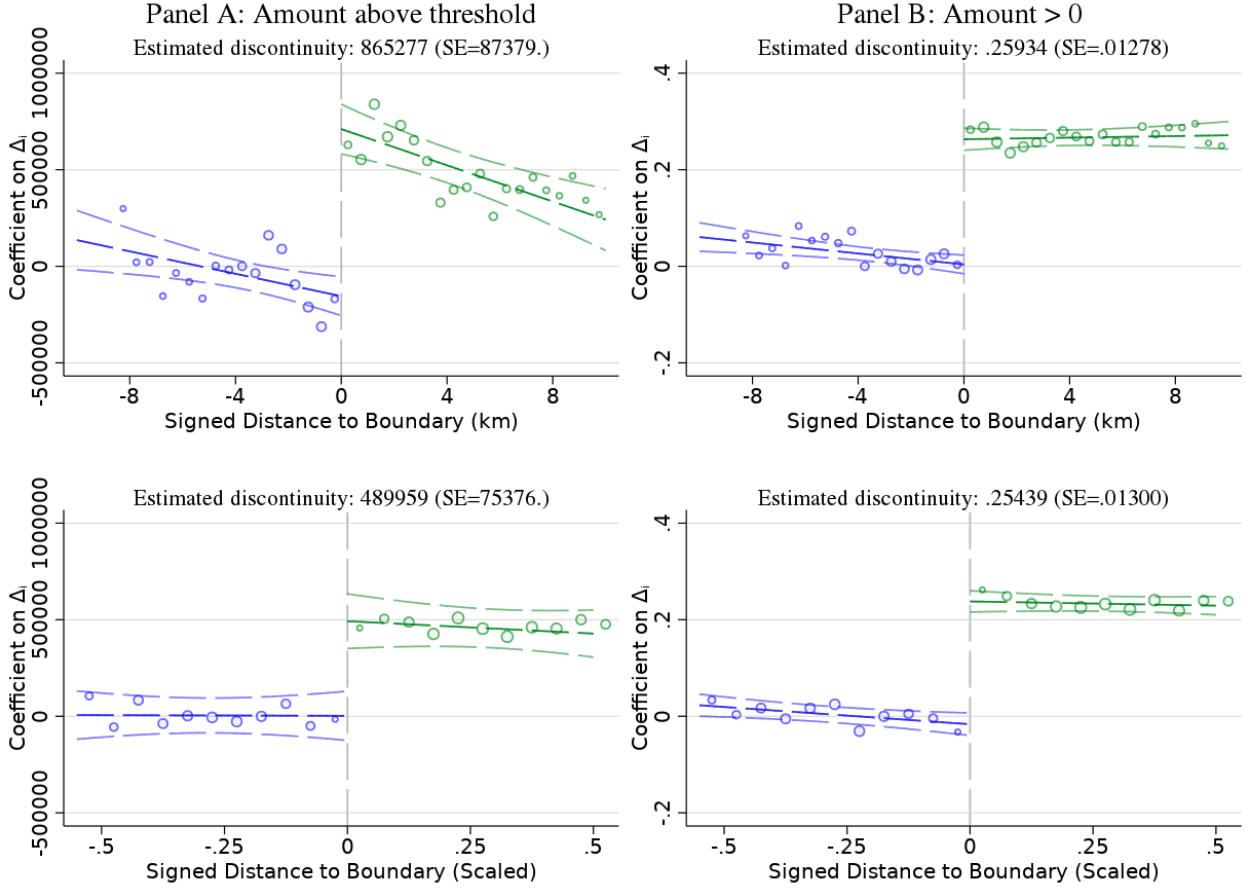


FIGURE 4: GRAPHICAL PRESENTATION OF THE EFFECTS OF
INCREASED TAX ASSESSMENT ON FINANCIAL SAVING

The graphs below show the reduced-form effect on savings of living in a boundary region where households face a 1-log-point tax assessment premium on the high-assessment side. This effect is estimated separately for geographic bins, according to the different location measures. The discontinuities at zero represent the estimated reduced-form causal effect of a 1-log-point increase in (model-implied) tax assessment on household savings, measured as yearly log-differences of Gross Financial Wealth, adjusted for wealth tax payments. Panel A considers pre-period outcomes (2004–2009), and Panel B considers post-period outcomes (2010–2015). The first row uses distance in kilometers, where households on the low-assessment side are given a negative distance. The second row uses (similarly signed) distance scaled by the distance between the two municipal centroids. The fitted lines and discontinuities correspond to reduced-form regressions using the regression specification in equation 19. 95% confidence bands are represented by dashed lines. All panels consider the full sample of households with initial positive taxable net wealth in 2009. Scatter-points stem from estimating a coefficient on Δ_i using equation 19 separately for d_i bins, rather than estimating coefficients on $\log(TaxVal_i)$ and $g_b(c_i)\Delta_i$. The size of each circle corresponds approximately to the relative number of observations in that bin.

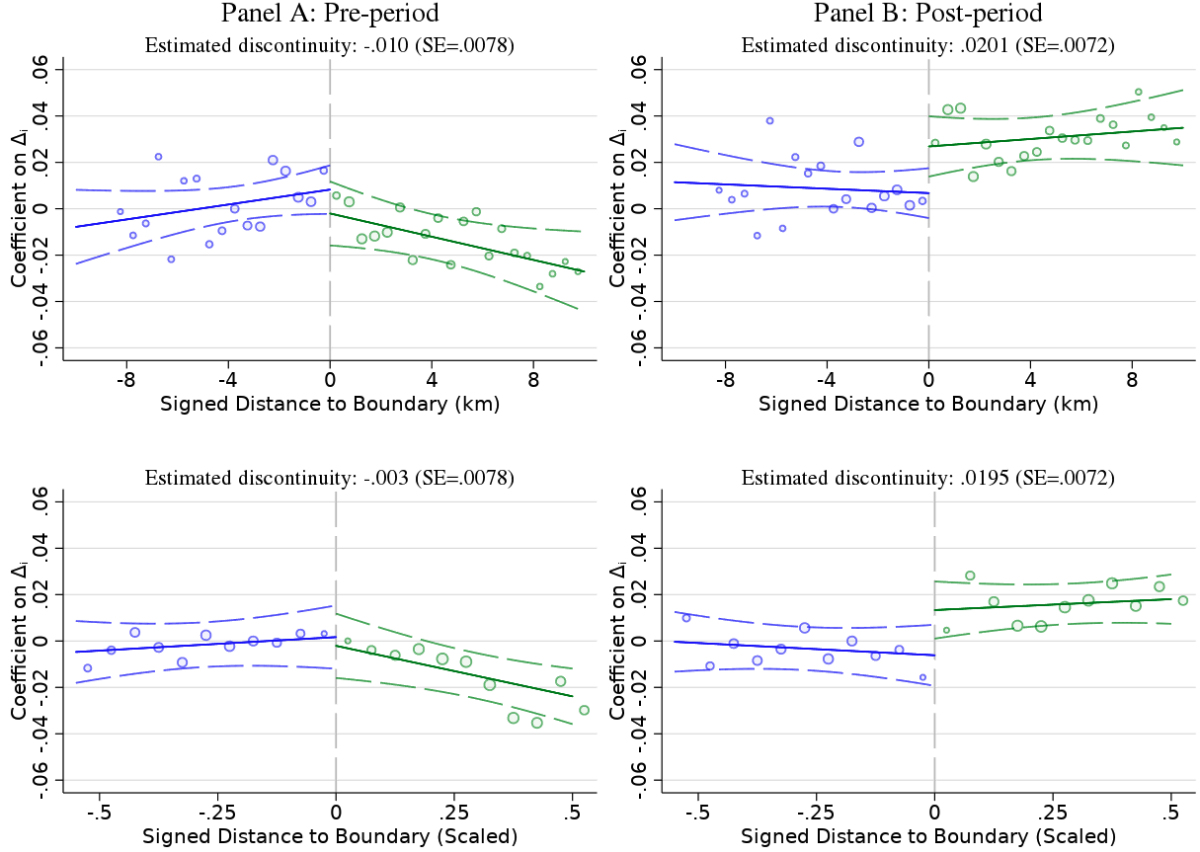


FIGURE 5: DEBT

The graphs below show the effect on log-differenced debt of living in a boundary region where households face a 1-log-point tax assessment premium on the high-assessment side. This effect is estimated separately for geographic bins, according to the different location measures. The discontinuities at zero represent the estimated reduced-form causal effect of a 1-log-point increase in (model-implied) tax assessment on household debt. Panel A considers pre-period outcomes (2004–2009), and Panel B considers post-period outcomes (2010–2015). The first row uses distance in kilometers, where households on the low-assessment side are given a negative distance. The second row uses (similarly signed) distance scaled by the distance between the two municipal centroids. The fitted lines and discontinuities correspond to reduced-form regressions using the regression specification in equation 19. 95% confidence bands are represented by dashed lines. All panels consider the full sample of households with initial positive taxable net wealth in 2009. Scatter-points stem from estimating a coefficient on Δ_i using equation 19 separately for d_i bins, rather than estimating coefficients on $\log(TaxVal_i)$ and $g_b(c_i)\Delta_i$. The size of each circle corresponds approximately to the relative number of observations in that bin.

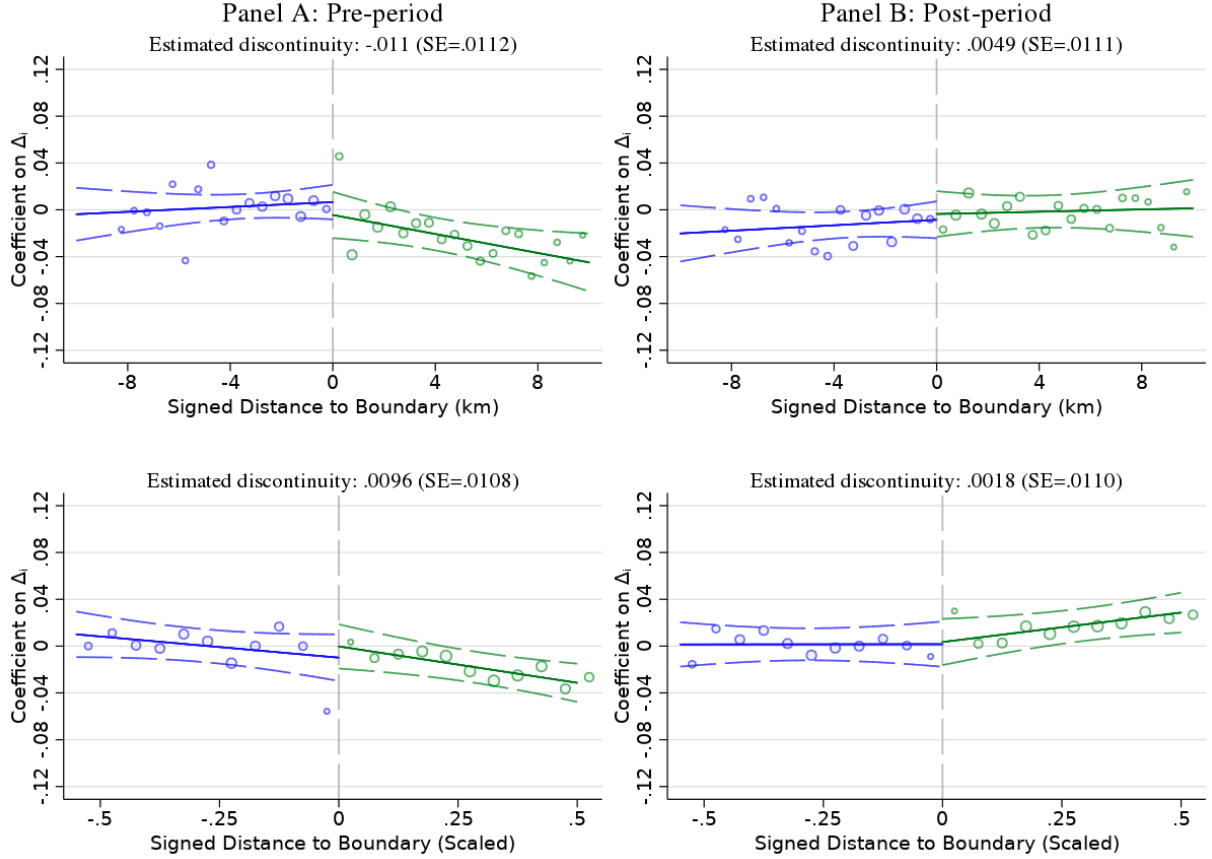


FIGURE 6: STOCK MARKET SHARE

The graphs below show the effect on the one-year differenced stock market share of living in a boundary region where households face a 1-log-point tax assessment premium on the high-assessment side. The stock market share is the ratio of mutual funds and listed domestic stocks to GFW. This effect is estimated separately for geographic bins, according to the different location measures. The discontinuities at zero represent the estimated reduced-form causal effect of a 1-log-point increase in (model-implied) tax assessment on household savings, measured as yearly log-differences of Gross Financial Wealth, adjusted for wealth tax payments. Panel A considers pre-period outcomes (2004–2009), and Panel B considers post-period outcomes (2010–2015). The first row uses distance in kilometers, where households on the low-assessment side are given a negative distance. The second row uses (similarly signed) distance scaled by the distance between the two municipal centroids. The fitted lines and discontinuities correspond to reduced-form regressions using the regression specification in equation 19. 95% confidence bands are represented by dashed lines. All panels the full sample of households with initial positive taxable net wealth in 2009. Scatter-points are estimated using the specification in equation 19, excluding geographic trend controls, g , allowing the coefficient on Δ_i to vary by bin. The size of each circle corresponds approximately to the number of observations in that bin.

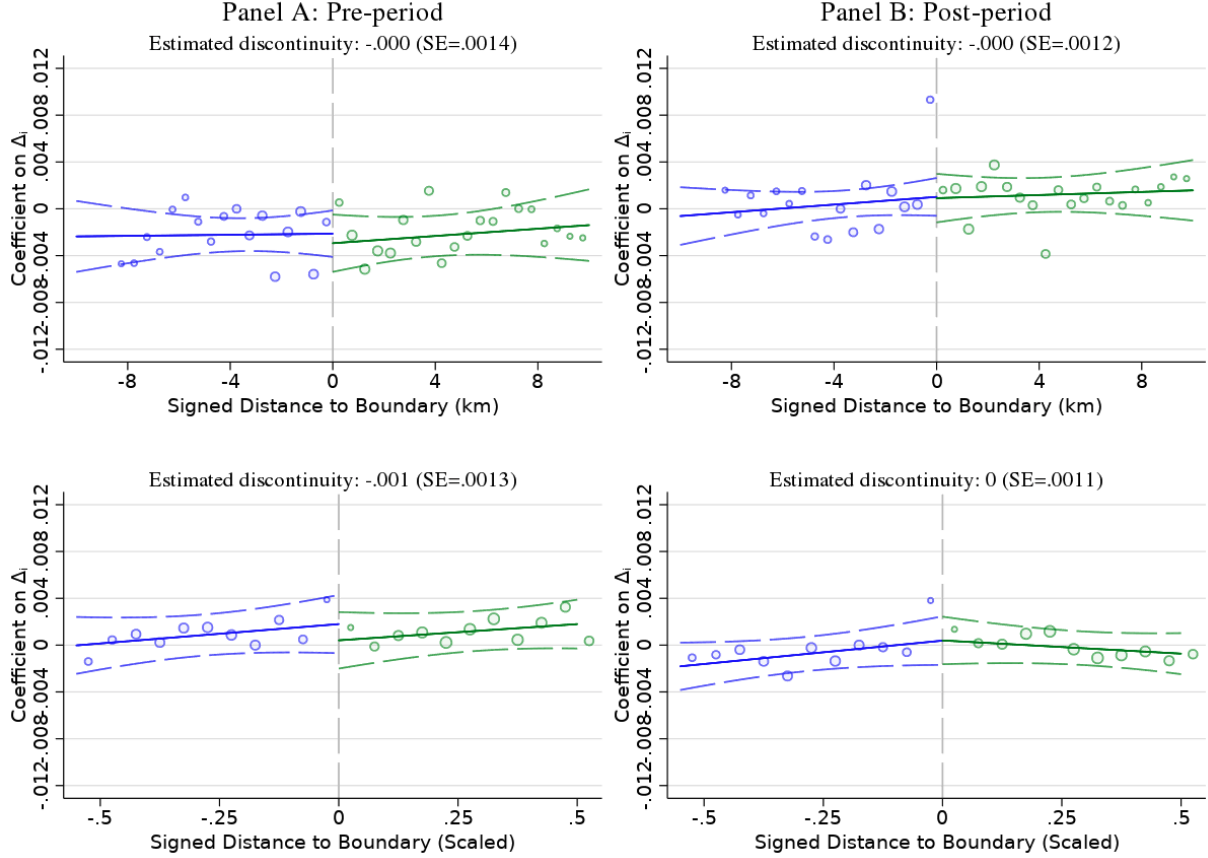


FIGURE 7: INTEREST RATES ON DEPOSITS AND DEBT

The dependent variable is 1-year differenced realized interest rates on deposits (left) and debt (right). This graph only considers households with taxable net wealth above the wealth tax threshold in 2009 (full sample). The discontinuities at zero represent the estimated causal effect of a 1-log-point increase in tax assessment, and correspond to the estimated coefficients in Table 6, columns (1) and (3) for the left- and right-hand side figures, respectively. Both graphs use scaled border distance as the geographic running variable.

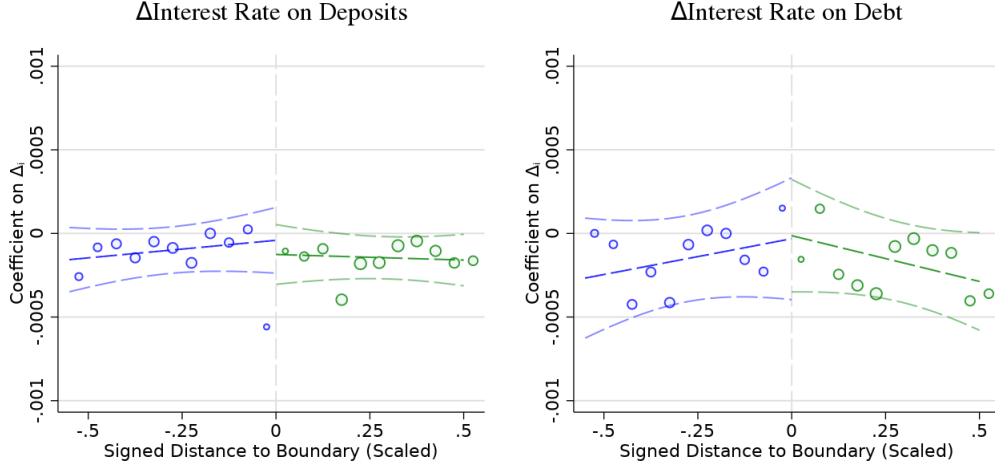


FIGURE 8: TOTAL TAXABLE LABOR INCOME

The graphs below show the effect on 1-year log-differenced Total Taxable Labor Income (TTLI) of living in a boundary region where households face a 1-log-point tax assessment premium on the high-assessment side. This effect is estimated separately for geographic bins, according to the different location measures. The discontinuities at zero represent the estimated reduced-form causal effect of a 1-log-point increase in (model-implied) tax assessment on household savings, measured as yearly log-differences of Gross Financial Wealth (GFW), adjusted for wealth tax payments. Panel A considers pre-period outcomes (2004–2009), and Panel B considers post-period outcomes (2010–2015). The first row uses distance in kilometers, where households on the low-assessment side are given a negative distance. The second row uses (similarly signed) distance scaled by the distance between the two municipal centroids. The fitted lines and discontinuities correspond to reduced-form regressions using the regression specification in equation 19. 95% confidence bands are represented by dashed lines. All panels consider the full sample of households with initial positive taxable net wealth in 2009. Scatter-points stem from estimating a coefficient on Δ_i using equation 19 separately for d_i bins, rather than estimating coefficients on $\log(TaxVal_i)$ and $g_b(c_i)\Delta_i$. The size of each circle corresponds approximately to the relative number of observations in that bin.

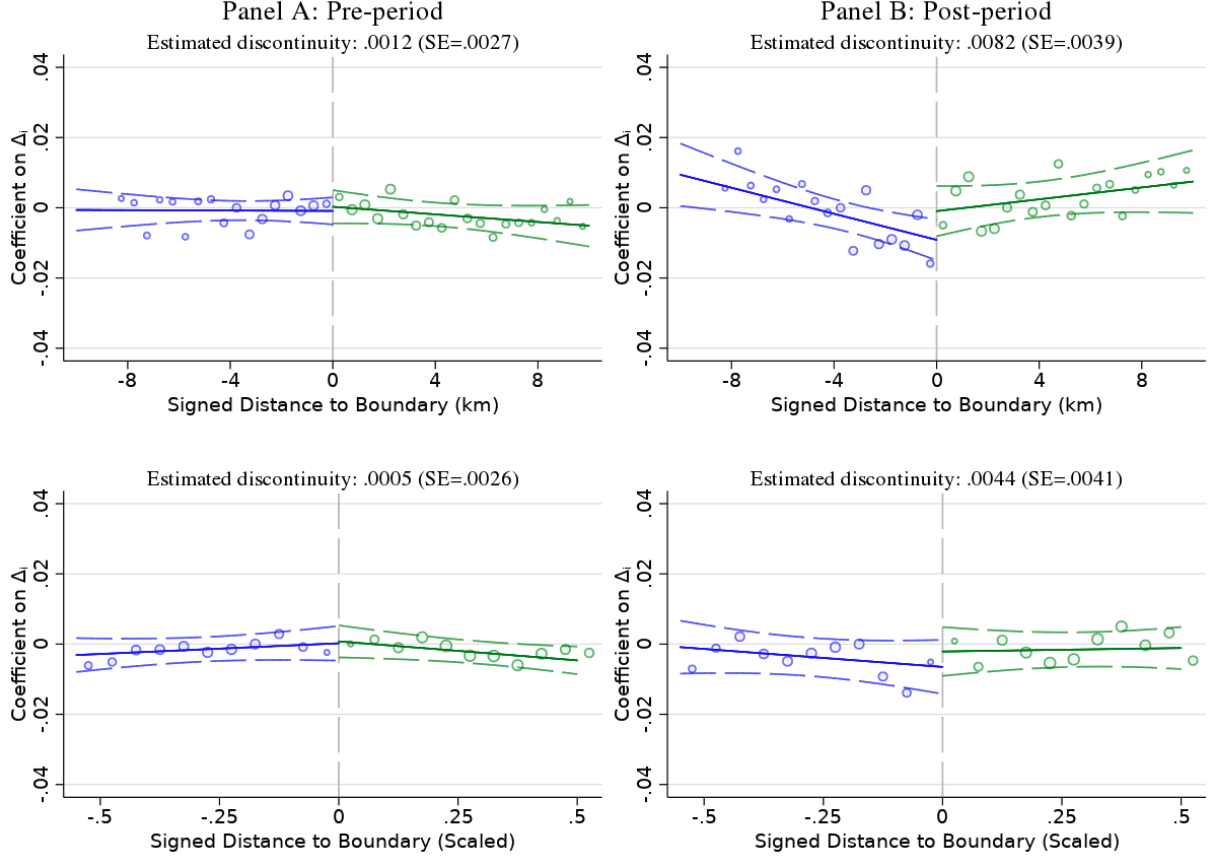


FIGURE 9: LABOR EARNINGS

The graphs below show the effect on 1-year log-differenced Labor Earnings (LE) of living in a boundary region where households face a 1-log-point tax-assessment premium on the high-assessment side. LE is the sum of wage earnings, salaries, and max(self employment income,0). This effect is estimated separately for geographic bins, according to the different location measures. The discontinuities at zero represent the estimated reduced-form causal effect of a 1-log-point increase in (model-implied) tax assessment on household savings, measured as yearly log-differences of Gross Financial Wealth, adjusted for wealth tax payments. Panel A considers pre-period outcomes (2004–2009), and Panel B considers post-period outcomes (2010–2015). The first row uses distance in kilometers, where households on the low-assessment side are given a negative distance. The second row uses (similarly signed) distance scaled by the distance between the two municipal centroids. The fitted lines and discontinuities correspond to reduced-form regressions using the regression specification in equation 19. 95% confidence bands are represented by dashed lines. All panels consider the full sample of households with initial positive taxable net wealth in 2009. Scatter-points stem from estimating a coefficient on Δ_i using equation 19 separately for d_i bins, rather than estimating coefficients on $\log(TaxVal_i)$ and $g_b(c_i)\Delta_i$. The size of each circle corresponds approximately to the relative number of observations in that bin.

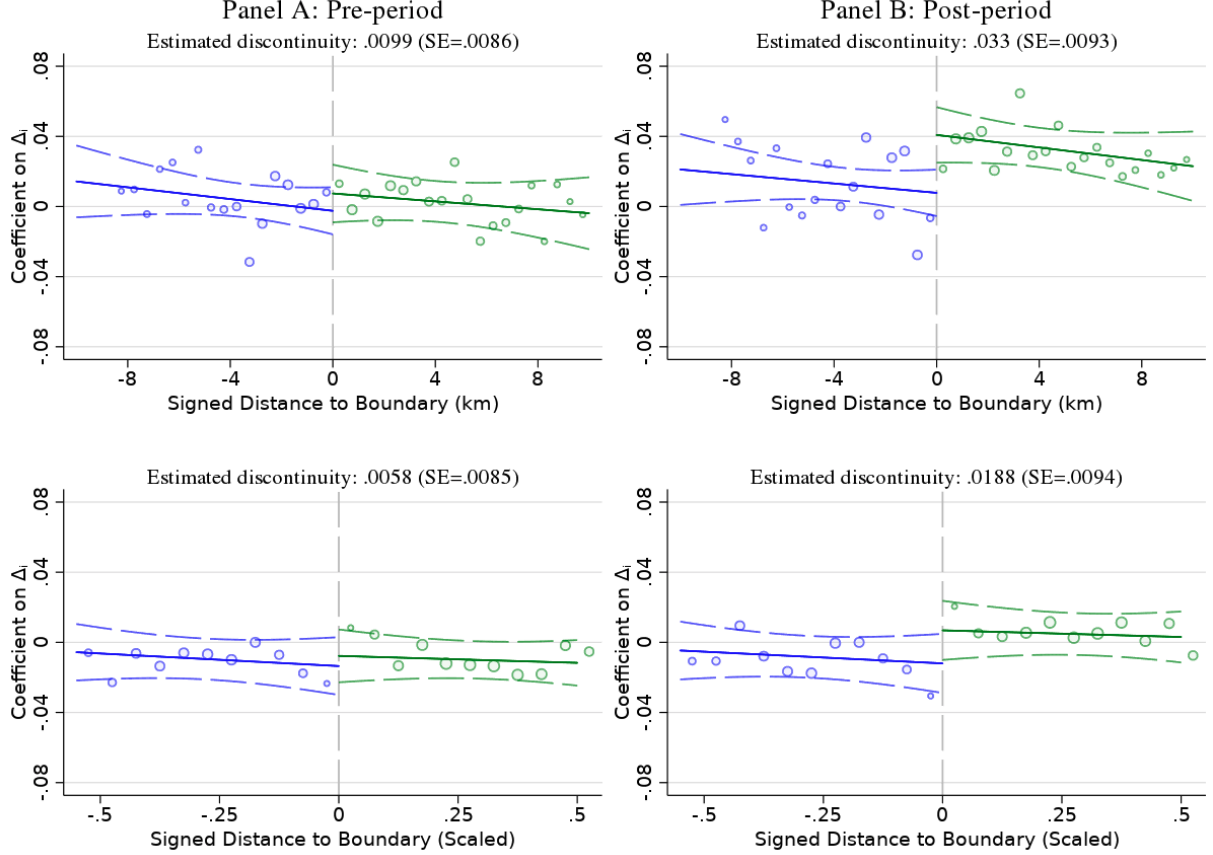


FIGURE 10: YEARLY DECOMPOSITION OF ESTIMATED (REDUCED-FORM) EFFECTS

In this graph, I allow the estimated discontinuities, $\hat{\beta}$, to vary by year. Otherwise, the specifications are identical to those in column (4) of the respective tables, which includes the scaled border distance control. Standard errors are clustered at the census-tract level, and plots indicate 95% confidence intervals for the point estimates. Coefficients are estimated in two different samples: *Full sample* corresponds to all households in the analysis sample, and the *Above sample* is the sample of households with Taxable Net Wealth above the wealth tax threshold in 2009. The blue solid (green dashed) line corresponds to the pooled regression estimates for the Full (Above) sample.

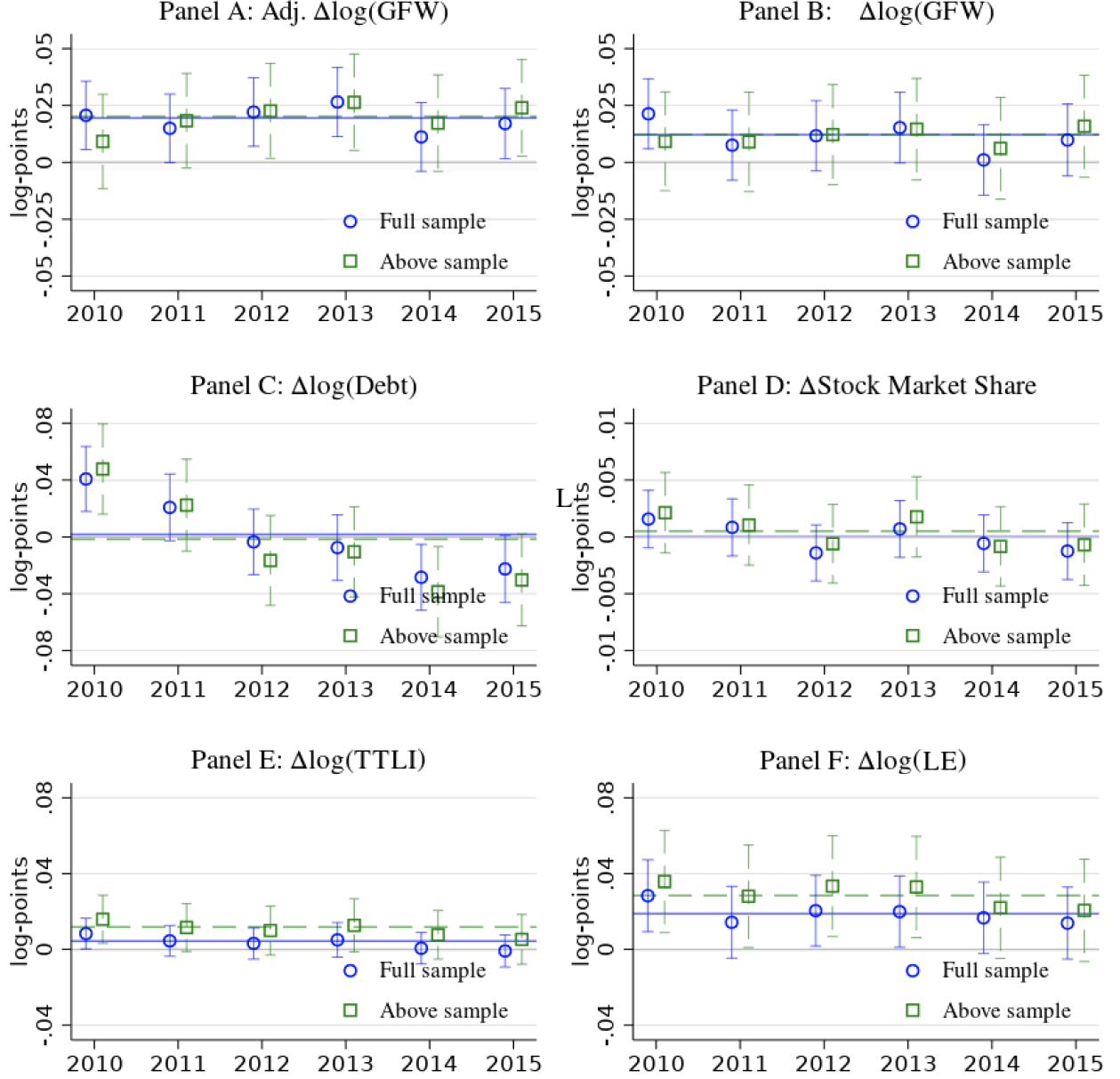


FIGURE 11: DISTRIBUTION OF HOUSEHOLDS AROUND THE WEALTH TAX THRESHOLD

These figures show the distribution of taxable net wealth around the wealth tax threshold. Households are divided into NOK 5,000 bins, and households at zero have $[0, 5000)$ NOK in excess of the threshold. Panel A considers the full analysis sample, where thresholds are multiplied by two for married couples, and only couples with a non-changed marital status are included. Panel B considers the full sample of Norwegian taxpayers, where the analysis is done at the individual level. Plots and estimates are produced using the .ado file provided by [Chetty, Friedman, Olsen, and Pistaferri \(2011\)](#). The counterfactual distribution (green line) is constructed by fitting a 7th degree polynomial on all bins outside $[-40,000, 15,000]$. b is the estimated excess mass inside $[-40,000, 15,000]$, normalized to be in the bin directly to the left of the threshold. Bootstrapped standard errors are in parenthesis. The analyses use pooled data for 2011–2014. The sample period is restricted due to limited sample years in which the relevant net wealth variable, `nto_form`, is not bottom-coded at the level of the tax threshold.

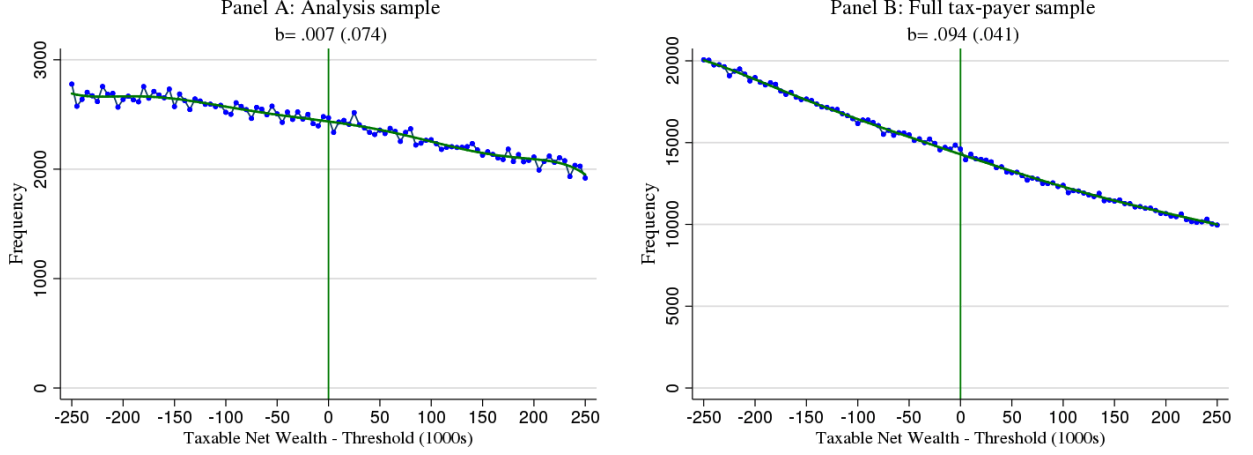


FIGURE 12: THE FRISCH-EIS COMBINATIONS THAT PROVIDE SIMULATED TREATMENT EFFECTS INSIDE THE EMPIRICAL CONFIDENCE INTERVALS

This figure shows the EIS and Frisch elasticity combinations that yield simulated cumulative treatment effects on savings (or labor earnings) over a 5-year period that correspond to the lower bound of the 95 percent confidence interval of my empirical findings. The baseline shock corresponds to a 0.5 log-point increase in tax assessment. EIS–Frisch combinations above the lines yield simulated treatment effects *below* the confidence intervals of my empirical findings.

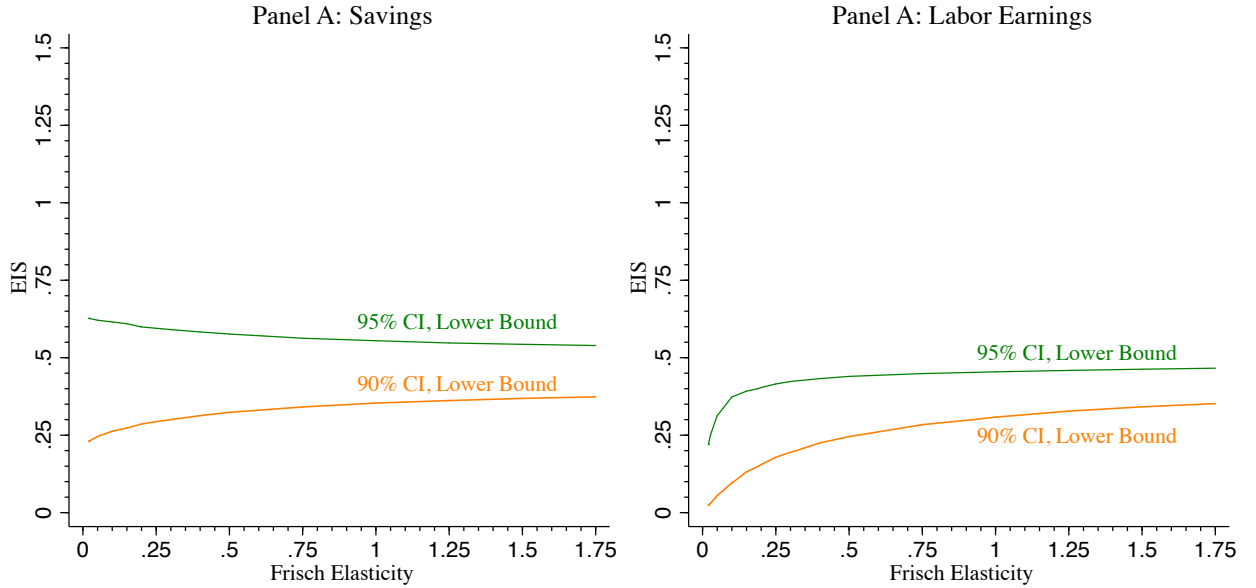


FIGURE 13: SIMULATED TREATMENT EFFECTS AS A FUNCTION OF THE EIS

This figure shows the simulated cumulative treatment effect (blue line) as a function of the EIS, assuming a Frisch elasticity of 0.5. The baseline shock corresponds to a 0.5 log-point increase in tax assessment. The green dashed line corresponds to the empirical point estimate, while the green shaded area constitutes the 95% confidence interval. The first column considers the effect on savings growth, while the second column considers the effect on earnings growth.

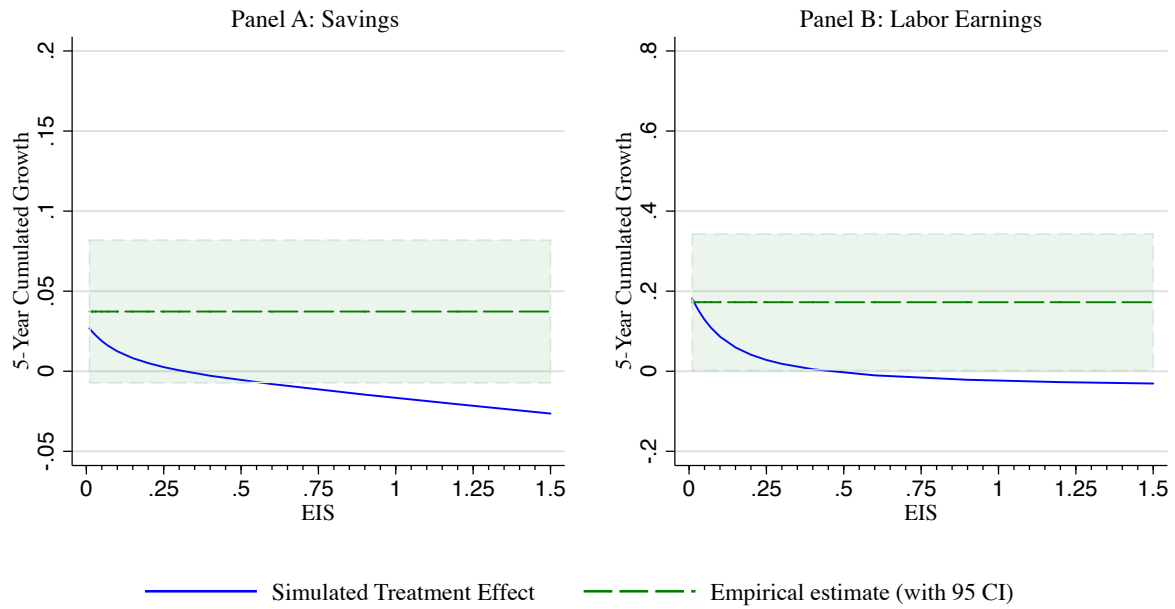
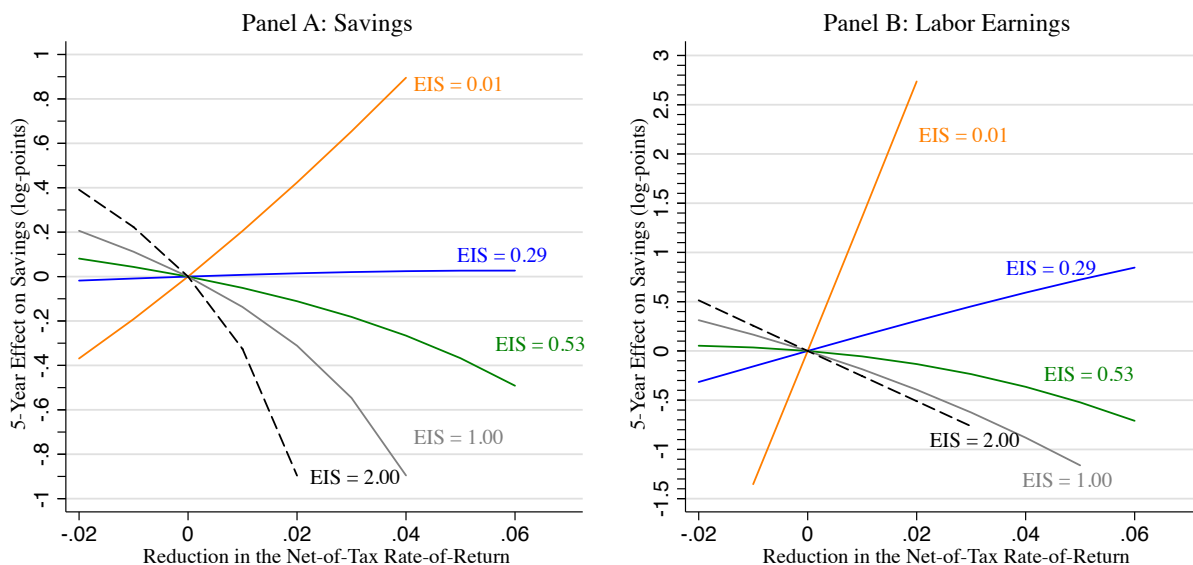


FIGURE 14: SIMULATED SAVING RESPONSES TO REDUCING THE NET-OF-TAX RATE-OF-RETURN

This figure shows the simulated 5-year effect (in log points) of reducing the net-of-tax rate-of-return for different values of the EIS, assuming a Frisch elasticity of 0.5. Given a gross rate-of-return of 1.02 (assumed in the model), we can find the implied *uncompensated* savings elasticities to the net-of-tax rate-of-return by reading off (the negative of) the value on the y-axis for a given line when the x-axis takes a value of 0.02. In Panel A (Panel B), these values are 0.42, 0.01, -0.11, -0.31, and -0.90 (2.74, 0.31, -0.13, -0.40, and -0.51) for an EIS of 0.01, 0.29, 0.53, 1.00, 2.00, respectively.



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TABLE 1: FIRST STAGE EFFECTS ON WEALTH TAX OUTCOMES

This table provides the reduced-form using scaled border distance as the geographic measure in equation 19. Column (1) considers the tax value of housing, as observed in tax returns. Column (2) considers the effect on being above the wealth tax threshold. Column (3) considers the effect on the marginal rate-of-return, by isolating extensive margin effects from wealth taxation. This is done by defining the dependent variable as $-\tau_t \mathbb{1}[TNW_{i,t} > Threshold_t]$. Column (4) examines the effect on the amount above the wealth tax threshold, $\mathbb{1}[TNW_{i,t} > Threshold_t](TNW_{i,t} - Threshold)$. Column (5) isolates the effect of increased wealth taxation on the average rate-of-return. This is done by defining the dependent variable as $-\tau_t \mathbb{1}[TNW_{i,t} > Threshold_t](TNW_{i,t} - Threshold)/TNW_{i,t}$, which is evaluated as 0 if $TNW_{i,t} \leq 0$. pp is short for percentage points, and indicates that coefficients (SEs) are multiplied by 100. Standard errors, provided in parentheses, are clustered at the census-tract level.

		Extensive Margin		Extensive and intensive margin	
	$\log(TaxVal)$	$\mathbb{1}[TNW > Threshold]$	$r^{marginal}$ (pp.)	AmountAbove	$r^{average}$ (pp.)
	(1)	(2)	(3)	(4)	(5)
FULL SAMPLE					
$\log(\widehat{TaxVal})$	0.8194*** (0.0316)	0.2545*** (0.0130)	-0.2675*** (0.0136)	489959*** (75376)	-0.1544*** (0.0083)
$F(\hat{\beta} = 0)$	672	383	388	42	347
HOUSEHOLDS ABOVE TAX THRESHOLD IN 2009					
$\log(\widehat{TaxVal})$	0.8450*** (0.0440)	0.2047*** (0.015926)	-0.2159*** (0.0166)	740511*** (120820)	-0.1713*** (0.0111)
$F(\hat{\beta} = 0)$	369	165	168	38	239
HOUSEHOLDS BELOW TAX THRESHOLD IN 2009					
$\log(\widehat{TaxVal})$	0.7994*** (0.0414)	0.2957*** (0.0196)	-0.3103*** (0.0205)	237618*** (48691)	-0.1312*** (0.0103)
$F(\hat{\beta} = 0)$	373	227	230	24	162
Scaled Border Distance	Yes	Yes	Yes	Yes	Yes

TABLE 2: THE (IV) EFFECT OF INCREASED TAX ASSESSMENT
ON HOUSEHOLD FINANCIAL SAVING BEHAVIOR

This table shows the effect of changing tax assessment on financial saving during 2010–2015. $\log(TaxVal)$ is instrumented with the model-implied variation in tax assessment. Column (1) does not address geographic heterogeneity, and does not allow slopes on housing characteristics, H_i , to vary at the border-area level. Column (2) allows slopes to vary at the border-area level, but does not address within-border area geographic heterogeneity. Columns (3)–(6) address geographic heterogeneity according to the main IV specification in equation 21. Column (4) corresponds to the preferred (scaled) border distance measure. Census-tract-level clustered standard errors are in parentheses. Sample size is in brackets. F is the Kleinbergen-Paap rk-F statistic of the first-stage regression. One, two, and three stars indicate that estimates are statistically different from zero at the 10, 5, and 1 percent level, respectively.

$\log(GFW_t + wtax_{t-1}) - \log(GFW_{t-1})$	(1)	(2)	(3)	(4)	(5)	(6)
FULL SAMPLE						
$\log(TaxVal)$	0.0229*** (0.0011)	0.0252*** (0.0038)	0.0231*** (0.0083)	0.0238*** (0.0089)	0.0270** (0.0127)	0.0232*** (0.0080)
N	[1842603]	[1842508]	[1459917]	[1472113]	[1472113]	[1649409]
F	40411	2960	845	683	326	837
HOUSEHOLDS INITIALLY ABOVE THRESHOLD						
$\log(TaxVal)$	0.0176*** (0.0014)	0.0235*** (0.0050)	0.0183* (0.0109)	0.0239** (0.0121)	0.0535*** (0.0185)	0.0291*** (0.0113)
N	[1013476]	[1013369]	[817054]	[817214]	[817214]	[912464]
F	27576	1770	496	376	163	420
HOUSEHOLDS INITIALLY BELOW THRESHOLD						
$\log(TaxVal)$	0.0291*** (0.0016)	0.0265*** (0.0057)	0.0234* (0.0129)	0.0216* (0.0129)	-0.0003 (0.0169)	0.0166 (0.0111)
N	[829127]	[829022]	[642762]	[654804]	[654804]	[736853]
F	24703	1940	430	374	189	463
Controls						
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Housing Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
– Border specific	–	Yes	Yes	Yes	Yes	Yes
Border Distance Controls						
– KM	–	–	Yes	–	–	–
– Scaled	–	–	–	Yes	–	–
– Border specific	–	–	–	–	Yes	–
Relative Location Controls	–	–	–	–	–	Yes

TABLE 3: DECOMPOSITION OF FINANCIAL SAVING RESPONSE

In this table, I provide the IV effects using different measures of financial savings. Column (1) uses the baseline definition, which adjusts for wealth tax payments. Column (2) does not account for wealth tax payments. (3) Only considers domestically held (and thus third-party reported) holdings of deposits. (4) Only considers self-reported wealth items: foreign financial assets and outstanding claims. Reduced-form standard errors are provided in parentheses, and are clustered at the census-tract level.

	Adj. $\Delta \log(GFW)$	Unadj. $\Delta \log(GFW)$	$\Delta \log(\text{Dom. Deposits})$	$\Delta \log(\text{Self-Rep. GFW})$
	(1)	(2)	(3)	(4)
FULL SAMPLE				
$\log(TaxVal)$	0.0238*** (0.0089)	0.0149 (0.0091)	0.0154 (0.0099)	0.0254*** (0.0096)
HOUSEHOLDS INITIALLY ABOVE THRESHOLD				
$\log(TaxVal)$	0.0239** (0.0121)	0.0144 (0.0127)	0.0093 (0.0141)	0.0254 (0.0160)
HOUSEHOLDS INITIALLY BELOW THRESHOLD				
$\log(TaxVal)$	0.0216* (0.0129)	0.0131 (0.0129)	0.0201 (0.0139)	0.0229** (0.0097)
Controls				
Household Characteristics	Yes	Yes	Yes	Yes
Housing Characteristics	Yes	Yes	Yes	Yes
– Border specific	Yes	Yes	Yes	Yes
Border Distance Controls				
– Scaled	Yes	Yes	Yes	Yes

TABLE 4: DEBT

This table shows the effect of tax assessment on log-differenced debt during 2010–2015. $\log(TaxVal)$ is instrumented with the model-implied variation in tax assessment. Column (1) does not address geographic heterogeneity, and does not allow slopes on housing characteristics, H_i , to vary at the border-area level. Column (2) allows slopes to vary at the border-area level, but does not address within-border area geographic heterogeneity. Columns (3)–(6) address geographic heterogeneity according to the main IV specification in equation 21. Column (4) corresponds to the preferred (scaled) border distance measure. Census-tract-level clustered standard errors are in parentheses. Sample size is in brackets. F is the Kleinbergen-Paap rk-F statistic of the first-stage regression. One, two, and three stars indicate that estimates are statistically different from zero at the 10, 5, and 1 percent level, respectively.

$\Delta \log(Debt)$	(1)	(2)	(3)	(4)	(5)	(6)
FULL SAMPLE						
$\log(TaxVal)$	0.0300*** (0.0016)	0.0265*** (0.0058)	0.0057 (0.0128)	0.0022 (0.0135)	-0.0356* (0.0189)	-0.0060 (0.0119)
N	[1842624]	[1842529]	[1459935]	[1472130]	[1472130]	[1649429]
F	40414	2960	845	683	326	836
HOUSEHOLDS INITIALLY ABOVE THRESHOLD						
$\log(TaxVal)$	0.0296*** (0.0022)	0.0249*** (0.0080)	0.0153 (0.0170)	-0.0019 (0.0186)	-0.0408 (0.0276)	-0.0025 (0.0168)
N	[1013495]	[1013388]	[817070]	[817229]	[817229]	[912482]
F	27580	1770	496	375	162	419
HOUSEHOLDS INITIALLY BELOW THRESHOLD						
$\log(TaxVal)$	0.0307*** (0.0024)	0.0286*** (0.0082)	-0.0040 (0.0189)	0.0098 (0.0194)	-0.0162 (0.0246)	-0.0024 (0.0164)
N	[829129]	[829024]	[642764]	[654806]	[654806]	[736855]
F	24704	1940	430	374	189	463
Controls						
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Housing Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
– Border specific	–	Yes	Yes	Yes	Yes	Yes
Border Distance Controls						
– KM	–	–	Yes	–	–	–
– Scaled	–	–	–	Yes	–	–
– Border specific	–	–	–	–	Yes	–
Relative Location Controls	–	–	–	–	–	Yes

TABLE 5: STOCK MARKET SHARE

This table shows the effect of tax assessment on the (one-year differenced) Stock Market Share (SMS) during 2010–2015. $\log(TaxVal)$ is instrumented with the model-implied variation in tax assessment. Column (1) does not address geographic heterogeneity, and does not allow slopes on housing characteristics, H_i , to vary at the border-area level. Column (2) allows slopes to vary at the border-area level, but does not address within-border area geographic heterogeneity. Columns (3)–(6) address geographic heterogeneity according to the main IV specification in equation 21. Column (4) corresponds to the preferred (scaled) border distance measure. Census-tract-level clustered standard errors are in parentheses. Sample size is in brackets. F is the Kleinbergen-Paap rk-F statistic of the first-stage regression. One, two, and three stars indicate that estimates are statistically different from zero at the 10, 5, and 1 percent level, respectively.

ΔSMS	(1)	(2)	(3)	(4)	(5)	(6)
FULL SAMPLE						
$\log(TaxVal)$	0.0004** (0.0002)	0.0004 (0.0006)	-0.0001 (0.0014)	0.0000 (0.0014)	-0.0012 (0.0020)	0.0001 (0.0012)
N	[1835781]	[1835687]	[1454510]	[1466682]	[1466682]	[1643325]
F	41089	3022	857	698	332	850
HOUSEHOLDS INITIALLY ABOVE THRESHOLD						
$\log(TaxVal)$	0.0008*** (0.0002)	0.0010 (0.0008)	0.0004 (0.0018)	0.0006 (0.0020)	-0.0010 (0.0029)	0.0007 (0.0017)
N	[1008692]	[1008586]	[813160]	[813335]	[813335]	[908140]
F	28321	1818	509	387	166	430
HOUSEHOLDS INITIALLY BELOW THRESHOLD						
$\log(TaxVal)$	-0.0004 (0.0003)	-0.0004 (0.0009)	-0.0011 (0.0022)	-0.0011 (0.0021)	-0.0015 (0.0028)	-0.0009 (0.0017)
N	[827089]	[826985]	[641250]	[653253]	[653253]	[735094]
F	24962	1952	431	378	192	466
Controls						
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Housing Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
– Border specific	–	Yes	Yes	Yes	Yes	Yes
Border Distance Controls						
– KM	–	–	Yes	–	–	–
– Scaled	–	–	–	Yes	–	–
– Border specific	–	–	–	–	Yes	–
Relative Location Controls	–	–	–	–	–	Yes

TABLE 6: EFFECTS OF INCREASED TAX ASSESSMENT ON
INTEREST RATES ON DEPOSITS AND DEBT

This table shows the IV effects on realized interest rates on deposits and debt. Realized interest rates for $X \in \{\text{Deposits, Debt}\}$ are calculated as $\text{Interest}(X)_{i,t}/(0.5X_{i,t} + 0.5X_{i,t-1})$. Only households with debt in excess of NOK 10,000 are included when examining the interest rate on debt. Standard errors are provided in parentheses, and are clustered at the census-tract level. Sample sizes are provided in brackets.

	Interest Rates on Deposits			Interest Rates on Debt		
	(1)	(2)	(3)	(4)	(5)	(6)
FULL SAMPLE						
$\log(\text{TaxVal})$	-0.000145 (0.000119)	-0.000101 (0.000124)	-0.000131 (0.000107)	0.000156 (0.000216)	0.000023 (0.000228)	0.000046 (0.000197)
N	[1230385]	[1240695]	[1390122]	[725506]	[726694]	[812642]
F	983	798	976	670	540	628
HOUSEHOLDS INITIALLY ABOVE THRESHOLD						
$\log(\text{TaxVal})$	-0.000032 (0.000154)	-0.000023 (0.000167)	-0.000074 (0.000147)	0.000379 (0.000393)	-0.000053 (0.000439)	-0.000262 (0.000409)
N	[689009]	[689150]	[769440]	[291170]	[286855]	[318960]
F	566	428	483	271	197	204
HOUSEHOLDS INITIALLY BELOW THRESHOLD						
$\log(\text{TaxVal})$	-0.000390** (0.000193)	-0.000218 (0.000181)	-0.000224 (0.000159)	0.000057 (0.000255)	0.000137 (0.000262)	0.000224 (0.000212)
N	[541270]	[551446]	[620587]	[434182]	[439676]	[493528]
F	504	438	535	455	378	464
Controls						
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Housing Controls	Yes	Yes	Yes	Yes	Yes	Yes
– Border specific	Yes	Yes	Yes	Yes	Yes	Yes
Border Distance (KM)	Yes	–	–	Yes	–	–
Border Distance (Scaled)	–	Yes	–	–	Yes	–
Relative Location Control	–	–	Yes	–	–	Yes

TABLE 7: TOTAL TAXABLE LABOR INCOME

This table shows the effect of tax assessment on log-differenced Total Taxable Labor Income (TTLI) during 2010–2015. Labor Income is defined as the sum of wage earnings, self-employment earnings, pensions, and unemployment income. $\log(TaxVal)$ is instrumented with the model-implied variation in tax assessment. Column (1) does not address geographic heterogeneity, and does not allow slopes on housing characteristics, H_i , to vary at the border-area level. Column (2) allows slopes to vary at the border-area level, but does not address within-border area geographic heterogeneity. Columns (3)–(6) address geographic heterogeneity according to the main IV specification in equation 21. Column (4) corresponds to the preferred (scaled) border distance measure. Census-tract-level clustered standard errors are in parentheses. Sample size is in brackets. F is the Kleinbergen-Paap rk-F statistic of the first-stage regression. One, two, and three stars indicate that estimates are statistically different from zero at the 10, 5, and 1 percent level, respectively.

$\Delta \log(Labor\ Income)$	(1)	(2)	(3)	(4)	(5)	(6)
FULL SAMPLE						
$\log(TaxVal)$	0.0049*** (0.0006)	0.0032 (0.0021)	0.0094** (0.0045)	0.0053 (0.0050)	0.0132* (0.0074)	0.0063 (0.0045)
N	[1844488]	[1844392]	[1461364]	[1473585]	[1473585]	[1651083]
F	40163	2968	839	681	327	837
HOUSEHOLDS INITIALLY ABOVE THRESHOLD						
$\log(TaxVal)$	0.0053*** (0.0009)	0.0026 (0.0033)	0.0161** (0.0065)	0.0139* (0.0075)	0.0325*** (0.0115)	0.0119* (0.0072)
N	[1014776]	[1014669]	[818080]	[818244]	[818244]	[913625]
F	27346	1754	494	375	164	420
HOUSEHOLDS INITIALLY BELOW THRESHOLD						
$\log(TaxVal)$	0.0039*** (0.0008)	0.0037 (0.0026)	-0.0015 (0.0059)	-0.0036 (0.0063)	-0.0041 (0.0082)	0.0005 (0.0053)
N	[829712]	[829607]	[643184]	[655247]	[655247]	[737367]
F	24628	1961	427	374	188	465
Controls						
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Housing Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
– Border specific	–	Yes	Yes	Yes	Yes	Yes
Border Distance Controls						
– KM	–	–	Yes	–	–	–
– Scaled	–	–	–	Yes	–	–
– Border specific	–	–	–	–	Yes	–
Relative Location Controls	–	–	–	–	–	Yes

TABLE 8: THE EFFECTS OF INCREASED TAX ASSESSMENT
ON LABOR EARNINGS

This table shows the effect of tax assessment on log-differenced labor income, excluding pensions and transfers, during 2010–2015. Labor Income is defined as the sum of wage earnings, self-employment earnings, pensions, and unemployment income. $\log(TaxVal)$ is instrumented with the model-implied variation in tax assessment. Column (1) does not address geographic heterogeneity, and does not allow slopes on housing characteristics, H_i , to vary at the border-area level. Column (2) allows slopes to vary at the border-area level, but does not address within-border area geographic heterogeneity. Columns (3)–(6) address geographic heterogeneity according to the main IV specification in equation 21. Column (4) corresponds to the preferred (scaled) border distance measure. Census-tract-level clustered standard errors are in parentheses. Sample size is in brackets. F is the Kleinbergen-Paap rk-F statistic of the first-stage regression. One, two, and three stars indicate that estimates are statistically different from zero at the 10, 5, and 1 percent level, respectively.

$\Delta \log(\text{Salary and Self-E. Income})$	(1)	(2)	(3)	(4)	(5)	(6)
FULL SAMPLE						
$\log(TaxVal)$	0.0162*** (0.0013)	0.0159*** (0.0049)	0.0379*** (0.0108)	0.0230** (0.0116)	0.0233 (0.0158)	0.0263*** (0.0099)
N	[1844488]	[1844392]	[1461364]	[1473585]	[1473585]	[1651083]
F	40163	2968	839	681	327	837
HOUSEHOLDS INITIALLY ABOVE THRESHOLD						
$\log(TaxVal)$	0.0166*** (0.0017)	0.0194*** (0.0069)	0.0528*** (0.0149)	0.0336** (0.0161)	0.0290 (0.0225)	0.0386*** (0.0142)
N	[1014776]	[1014669]	[818080]	[818244]	[818244]	[913625]
F	27346	1754	494	375	164	420
HOUSEHOLDS INITIALLY BELOW THRESHOLD						
$\log(TaxVal)$	0.0149*** (0.0019)	0.0112* (0.0064)	0.0133 (0.0154)	0.0103 (0.0166)	0.0094 (0.0215)	0.0134 (0.0137)
N	[829712]	[829607]	[643184]	[655247]	[655247]	[737367]
F	24628	1961	427	374	188	465
Controls						
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Housing Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
– Border specific	–	Yes	Yes	Yes	Yes	Yes
Border Distance Controls						
– KM	–	–	Yes	–	–	–
– Scaled	–	–	–	Yes	–	–
– Border specific	–	–	–	–	Yes	–
Relative Location Controls	–	–	–	–	–	Yes

TABLE 9: SUBSEQUENT TRANSACTION OUTCOMES

This table provides the effects of a 1-log-point increase in \widehat{TaxVal} on transaction outcomes during 2010–2016. Columns (1)–(3) consider log transaction prices, and columns (4)–(6) examine extensive margin effects, in terms of a dummy that takes the value 1 if the house the household lived in during 2009 was transacted during 2010–2016. Standard errors are provided in parentheses, and are clustered at the census-tract level.

	log(Transaction Price)			Sales Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\widehat{TaxVal})$	0.035 (0.085)	0.239*** (0.084)	0.016 (0.072)	0.002 (0.003)	0.004 (0.003)	0.002 (0.002)
$\mathbb{1}[d_i < 0] * d_i^{scaled} * \Delta_i$	0.955*** (0.167)			0.005 (0.006)		
$\mathbb{1}[d_i > 0] * d_i^{scaled} * \Delta_i$	1.096*** (0.215)			0.004 (0.006)		
$\mathbb{1}[d_i < 0] * d_i^{KM} * \Delta_i$		0.050*** (0.015)			0.0003 (0.0004)	
$\mathbb{1}[d_i > 0] * d_i^{KM} * \Delta_i$		0.042*** (0.015)			-0.0002 (0.0004)	
$RelativeLocation_i * \Delta_i$			0.592*** (0.060)			0.003* (0.002)
N	44666	45422	50203	1553563	1540201	1740546
R ²	0.5381	0.5337	0.5257	0.1931	0.1972	0.1943
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Housing controls (Border spec.)	Yes	Yes	Yes	Yes	Yes	Yes
Geo-Controls						
– Scaled Border Distance	Yes	–	–	Yes	–	–
– KM Border Distance	–	Yes	–	–	Yes	–
– Relative Location	–	–	Yes	–	–	Yes

TABLE 10: THE CORRELATION BETWEEN TREATMENT AND
OBSERVED TRANSACTION PRICES AFTER INCLUDING GEOGRAPHIC CONTROLS

This table reports estimated coefficients from a regressing log housing transaction prices on the log of model-implied tax assessment. Past transaction prices are obtained from the real estate transaction register, covering all real estate transactions during 1993–2017. The sample is limited to households who, in 2009, lived in a house that was transacted during 1993–2009. Panels (A)–(B) consider all households who owned a house during 2009; Panels (A) and (C) restrict the sample to households in the main analysis sample. Panels (B) and (D) restricts the sample to transactions occurring during 2004–2009, the same sample period during the estimation of the house price model coefficients. Column (1) does not address geographic heterogeneity, and does not allow slopes on housing characteristics, H_i , to vary at the border-area level. Column (2) allows slopes to vary at the border-area level, but does not address within-border area geographic heterogeneity. Columns (3)–(6) address geographic heterogeneity according to the main reduced-form specification in equation 19. Column (4) corresponds to the preferred (scaled) border distance measure. Standard errors are provided in parentheses, and are clustered at the census-tract level. Sample sizes are provided in brackets.

$\log(\text{Transaction Price})$	(1)	(2)	(3)	(4)	(5)	(6)
(A) All homeowners, 2000–2009						
$\log(\widehat{\text{TaxVal}})$	1.273*** (0.017) [206712]	0.769*** (0.051) [206280]	0.293*** (0.108) [206280]	0.086 (0.102) [199841]	0.148 (0.091) [199841]	0.148 (0.094) [199841]
(B) All homeowners, 2004–2009						
$\log(\widehat{\text{TaxVal}})$	1.258*** (0.020) [134304]	0.800*** (0.062) [133843]	0.422*** (0.121) [133843]	0.115 (0.121) [129608]	0.171* (0.102) [129608]	0.144 (0.110) [129608]
(C) Analysis sample, 2000–2009						
$\log(\widehat{\text{TaxVal}})$	1.457*** (0.040) [40211]	0.773*** (0.110) [39649]	-0.067 (0.244) [39649]	-0.061 (0.224) [38639]	0.252 (0.202) [38639]	-0.109 (0.211) [38639]
(D) Analysis sample, 2004–2009						
$\log(\widehat{\text{TaxVal}})$	1.490*** (0.071) [18021]	0.946*** (0.172) [17429]	0.265 (0.332) [17429]	-0.086 (0.333) [17035]	0.332 (0.322) [17035]	-0.420 (0.322) [17035]
Controls						
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Housing Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
– Border specific	–	Yes	Yes	Yes	Yes	Yes
Border Distance Controls						
– KM, KM ²	–	–	Yes	–	–	–
– Scaled	–	–	–	Yes	–	–
– Border specific	–	–	–	–	Yes	–
Relative Location Controls	–	–	–	–	–	Yes

TABLE 11: THE CORRELATION BETWEEN TREATMENT AND HOUSEHOLD CHARACTERISTICS
AFTER INCLUDING GEOGRAPHIC CONTROLS

This table reports the correlation between model-implied tax assessment, $\log(\widehat{TaxVal})$, and 2009 socioeconomic characteristics: Income, GFW, debt, and education. College is a dummy equal to one if one of the household members (excluding children) has a college degree. Columns (1)-(4) add different sets of controls. Column (1) includes the baseline controls: structure-type-specific slopes on $\log(\text{size})$, the dense population dummy, and age bracket indicators. Column (2) interacts the baseline controls with border area fixed effects. Column (3) further includes a control for the distance to border within a border area, estimated separately for each side, and interacted with Δ_i (border area and structure-type-specific $\log(\text{difference})$ in average assessed house prices between the sides of the border). Column (4) includes the relative location control, also interacted with Δ_i . These two variables are defined in detail in the text. Standard errors are provided in parentheses, and are clustered at the census-tract level.

	(1)	(2)	(3)	(4)	(5)	(6)
<hr/>						
	log(Labor Income)					
$\log(\widehat{TaxVal})$	0.288*** (0.005)	0.153*** (0.013)	0.067* (0.040)	-0.000 (0.028)	-0.039 (0.034)	0.002 (0.023)
	<hr/>					
	log(Gross Financial Wealth)					
$\log(\widehat{TaxVal})$	0.629*** (0.012)	0.409*** (0.035)	0.255*** (0.095)	-0.030 (0.070)	0.110 (0.086)	0.002 (0.064)
	<hr/>					
	Stock Market Share					
$\log(\widehat{TaxVal})$	0.045*** (0.002)	0.028*** (0.005)	0.053*** (0.014)	0.000 (0.010)	0.010 (0.013)	0.002 (0.009)
	<hr/>					
	log(Debt)					
$\log(\widehat{TaxVal})$	0.502*** (0.015)	0.350*** (0.046)	0.180 (0.143)	0.092 (0.099)	-0.009 (0.125)	0.097 (0.082)
	<hr/>					
	College					
$\log(\widehat{TaxVal})$	0.239*** (0.005)	0.194*** (0.015)	0.159*** (0.040)	0.019 (0.028)	0.056* (0.033)	0.028 (0.024)
<hr/>						
Controls						
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Housing Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
– Border specific	–	Yes	Yes	Yes	Yes	Yes
Border Distance Controls						
– KM, KM ²	–	–	Yes	–	–	–
– Scaled	–	–	–	Yes	–	–
– Border specific	–	–	–	–	Yes	–
Relative Location Controls	–	–	–	–	–	Yes
<hr/>						

A Data and Empirical Appendix

A.1 Wealth Variables

- Deposits is the sum of deposits in norwegian banks (TR 4.1.1). This includes savings and checking accounts, and accounts with higher interest and limitations on the timing/number of withdrawals. Information on deposit holdings are reported directly from banks to the tax authorities.
- Stock Market Wealth (SMW) is the sum of listed domestic stocks (4.1.7.1), mutual fund (equity) holdings (4.1.4), other taxable capital abroad (TR 4.6.2). The first two items are third-party reported. The third is largely self-reported and includes foreign financial securities (excl. deposits in foreign banks).
- Private Equity (PE) is the value of directly held unlisted stocks (TR 4.1.8). These are reported by the stock issuer as part of their annual tax returns.
- GFW is the sum of SMW, deposits, deposits in foreign banks (TR 4.1.9), PE, bonds (TR 4.1.5 and TR 4.1.7.2), and outstanding claims (TR 4.1.6). Outstanding claims contain unpaid wages (reported by the firm) and loans to friends and family (self-reported).
- TaxVal is the tax value of housing wealth (TR 4.3.2).
 - This is the sum of the tax value of primary housing (which is what I instrument for) and the tax value of secondary housing.
 - If TaxVal is missing, but GFW or Total Taxable Labor Income (TTLI) is not (2.7% of observations), it is first replaced with the average of the lag and lead. If the lead is missing, it is replaced with the lag, if the lag is missing, it is replaced with zero. This addresses the concern that housing transactions may render TaxVal missing, but that repeated missing values most likely indicates non-ownership.
 - When taking logs, the base is shifted (for all wealth variables, by NOK 10,000 or approximately USD 1,667), which retains households who sold their house in the sample (by avoiding $\log(0)$ returning missing values). For the other variables, it ensures that small level changes do not lead to extreme log-differences (e.g., an increase in GFW from NOK 1 to NOK 100 (\approx \$17) would otherwise lead to a log-difference of 4.7).
 - This process thus ensures that households who might sell their house in response to the treatment remain in the sample.
- TGW is the sum of GFW, TaxVal, holiday homes, forest property and other property (TR 4.3.3, TR 4.3.4, TR 4.3.5), real estate held abroad (TR 4.6.1), capital in housing coops (TR 4.5.3), home contents/moveable property (TR 4.2).
- TNW is TGW minus debt (TR 4.8).
 - the taxable net wealth definition used by the tax authorities to calculate wealth taxes also include less-frequently used posts TR 4.4 and TR 4.5, which are not in my data. To calculate wealth tax payments, the net wealth variable “netto formue” (nto_form) from the FD-Trygd database is used instead, as it includes all such posts. I also use this to create dummy variables indicating whether a household is above the wealth tax threshold. The

nto_form variable is not available for 2015. I then use the previous definition of TNW to calculate *wtax*.

- The variable nto_form is also bottom-coded for many years (displaying zeros if no wealth taxes are paid), which is not an issue for the first-stage analyses since those only need taxable wealth *in excess of the tax threshold*. However, when this variable is used for the bunching analysis, I must limit the analyses to years in which it is not bottom-coded.
- The median relative difference $(TNW - nto_form)/(0.5 \cdot TNW + 0.5 \cdot nto_form)$ for 2014 (when there is no bottom-coding) is 0, and the 10th and 90th percentiles are -0.0386 and 0.0543, respectively.
- $wtax$ is $\tau_t(nto_form - Threshold_t)$ for all years except 2015, when it equals $\tau_t(TNW - Threshold_t)$.
- Stock Market Share (SMS) is the ratio of SMW to GFW. Risky Share is $(SMW + PE)/GFW$.
- The foreign share (Foreign/GFW) is defined as (deposits in foreign banks plus other taxable capital abroad)/GFW.
- The deposit share (Deposits/GFW) is the ratio of deposits (in norwegian banks) to GFW.

A.2 Defining the geographic running variable

My setting includes many border areas that differ significantly in terms of residential density. While neighbors may be kilometers away in the arctic northern parts of Norway, they may only be meters away in rural Oslo. This is problematic when pooling boundary areas in order to obtain precision, because for a fixed differential, Δ_i , house prices must change more rapidly whenever the border area is smaller. When pooling boundary-areas, by construction, households closer to the border (in kilometers) will be drawn from smaller (denser) areas,⁴⁵ where the slope of house prices will be steeper. I provide a graphical example of the issue in Figure A.6 in the Appendix. This example shows that despite geographically smooth—even linear—house prices within a border area, a pooled regression may easily detect discontinuities due to strong nonlinearities arising.

Below, I describe a simple motivating example in which house prices move linearly within border areas, and the geographic slope varies only with two key characteristics: the difference in average house prices (Δ) and residential density.

Fix a boundary area, b , populated by households, i . Assume that true house prices, p , move linearly along some geographic measure, k : $p_i = p(k(\mathbf{c}_i)) = \xi_b k_i = \xi_b k(\mathbf{c}_i)$. We can think of k as border distance in kilometers. There are two sides, $S = L, H$. Assume that $\mathbb{E}[k(c_i)|i \in S] = k(\mathbb{E}[c_i|i \in S])$ (a linearity assumption)⁴⁶. Then the mean price in S equals the price at $k()$ valued at the centroid of S : $\mathbb{E}[p_i|i \in S] = p(k(\mathbb{E}[\mathbf{c}_i|i \in S]))$, since p is linear in k . Define the coordinate centroid of side S as $\mathbf{c}_S = \mathbb{E}[\mathbf{c}_i|i \in S]$. Applying the formula for a line, given two points, we get that the slope of p on $k(\mathbf{c}_i)$ is $(p(k(\mathbf{c}_H)) - p(k(\mathbf{c}_L)))/(k(\mathbf{c}_H) - k(\mathbf{c}_L))$.

Define Δ_b as the difference in mean house prices: $\Delta_b = \mathbb{E}[p_i|i \in H] - \mathbb{E}[p_i|i \in L]$, and the centroid distance, $CD_b = k(\mathbf{c}_H) - k(\mathbf{c}_L)$, and we can write the slope of prices, p , on our geographic measure,

⁴⁵In Panel A of Figure A.3, I show that households located near the boundary (in terms of kilometers) live in much denser areas than those farther away.

⁴⁶In reality, this is more of an approximation, as coordinates generally will not map linearly into border distance.

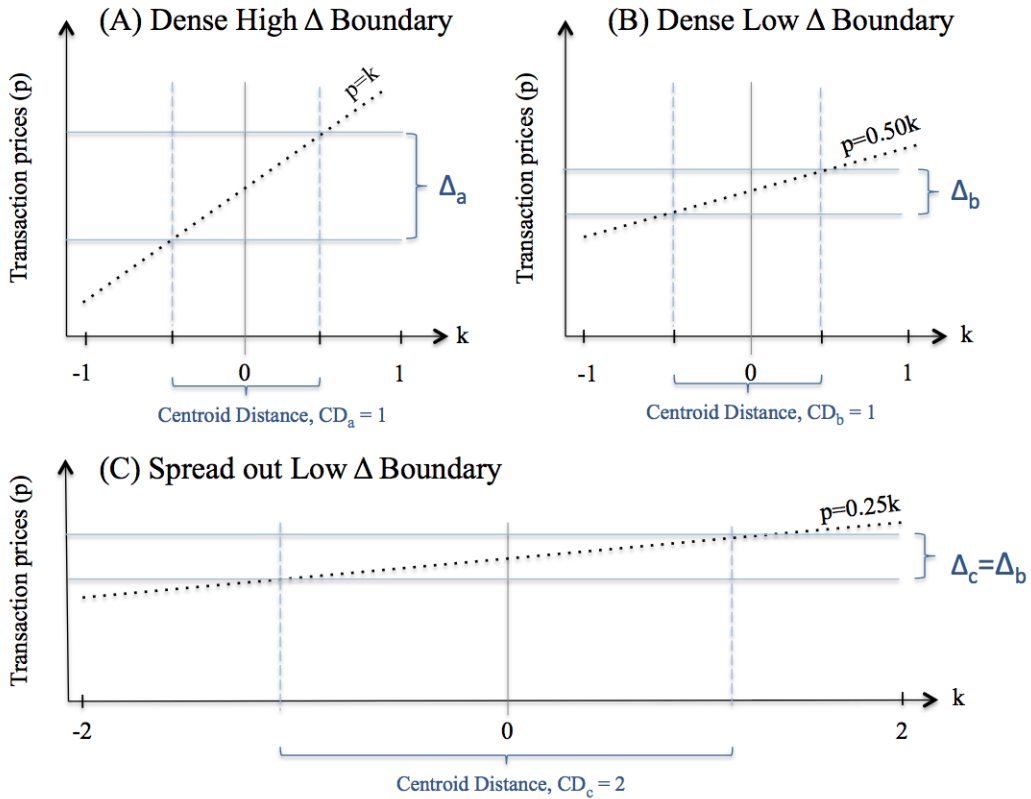
k , as Δ_b/CD_b .

$$p_i = \frac{k_i}{CD_b} \Delta_b$$

This example contains the two key elements: (1) house prices have larger geographic gradients when the differences in averages are higher and (2) more dense (less scattered) areas have larger geographic gradients. I illustrate this in Figure A.1. The boundary regions in (A) and (B) differ only in that the average prices in (A) are 1 price unit higher in (A). Boundary regions (B) and (C) differ only in that (C) is spread out geographically (all g_i s in C are twice that in B). In all three cases, the slope of prices, p , on our geographic measure, k , is simply Δ_b/CD_b . Below, I outline four approaches based on this example.

FIGURE A.1: BORDER AREA HETEROGENEITY: MOTIVATING EXAMPLE

This figure provides some simple examples to motivate my empirical specifications. I plot house prices (dotted lines) against a geographic measure (e.g., border distance) for three hypothetical border areas. The geographic slope of house prices is linear within each border area. Panels A and (B) differ only in that the difference in average house prices between each side of the boundary is higher in (A) than in (B). Panels B and (C) differ only in that (C) is more spread out, while the differences in averages is still the same. The commonality between all border areas, b , is that the slope of house prices on the geographic measure is Δ_b/CD_b , where CD_b is the distance between the centroids of the two sides of a given boundary area, b .



Approach 1 (Benchmark: Border Distance in km). This approach uses signed border distance, d_i , as the relevant within-boundary area geographic measure: $k(c_i) = d_i$. It ignores heterogeneity in residential density by assuming a (normalized) centroid distance, $CD_b = 1$. This invites the problem of nonlinear slopes on d_i , which are potentially very steep near boundaries in a pooled regression. This

can be visualized by envisioning the slope of house prices on g when pooling border areas (B) and (C). I provide an example of what this might look like when pooling multiple border areas in Figure A.6. This issue also becomes apparent in the results section. Despite this, it serves as a useful benchmark for the other approaches.

$$(\text{Unscaled}) \text{ Border Distance term: } g_b(\mathbf{c}_i) = \gamma \cdot d_i \quad (28)$$

Approach 2 (Scaled Border Distance). This approach also uses signed border distance, d_i , but incorporates the heterogeneity in density by scaling the measure by $CD_b = \text{Dist}(\mathbf{c}_{b,H}, \mathbf{c}_{b,L})$. The following term then captures the within-border area geographic variation in house prices, where the expectation is that $\hat{\gamma} = 1$.

$$\text{Scaled Border Distance term: } g_b(\mathbf{c}_i) = \gamma \cdot \frac{d_i}{CD_b} \quad (29)$$

Approach 3 (Relative Location). I set $k()$ equal to the differential distance to the centroids of the L versus H side of the boundary. This provides, in meters, how much closer c_i is to \mathbf{c}_H than \mathbf{c}_L : $k(c_i) = \text{Dist}(\mathbf{c}_i, \mathbf{c}_{b,L}) - \text{Dist}(\mathbf{c}_i, \mathbf{c}_{b,H})$. In this setting, $k(\mathbf{c}_H) - k(\mathbf{c}_L) = 2 \cdot \text{Dist}(\mathbf{c}_{b,H}, \mathbf{c}_{b,L})$. I omit this scaling by 2, which leads to the expectation that $\hat{\gamma} = \frac{1}{2}$.

$$\text{Relative Location term: } g_b(\mathbf{c}_i) = \gamma \cdot \frac{\text{Dist}(\mathbf{c}_i, \mathbf{c}_{b,L}) - \text{Dist}(\mathbf{c}_i, \mathbf{c}_{b,H})}{\text{Dist}(\mathbf{c}_{b,H}, \mathbf{c}_{b,L})} \in [-\gamma, \gamma] \quad (30)$$

The Relative Location variable is novel in the BDD setting. It is based on the hypothesis that the true house price for some sampled house within a boundary area is a weighted average of estimated average house prices on each side of a boundary, where weights are assigned based on how much closer (or less far away) a house is located to the centroids of the estimation samples on the two sides.⁴⁷

Approach 4 (Border-specific slopes). Finally, I set $k()$ equal to signed border distance, $d(\mathbf{c}_i) = d_i$ where households on the low-assessment side receive $k < 0$. I estimate slopes separately for each border area, and thus do not scale by CD_b , since this does not vary within a border area.

$$\text{Border-specific Border Distance: } g_b(\mathbf{c}_i) = \gamma_b \cdot d_i \quad (31)$$

While the motivating example does not contain side-specific slopes, I follow the standard approach in the RDD literature and allow slopes γ to be estimated separately for $d_i < 0$ and $d_i > 0$ in approaches 1, 2, and 4.

In the specifications using border distance, there is a concern that treated units on one side of the border may indeed be very far away from any control units on the other side. This may be caused by housing clusters near a border, where the other side of the border is vacant due to the presence of a forest or mountain. If this happens frequently enough, observable characteristics may seem discontinuous, even if they truly are smooth (and even linear) along other dimensions of proximity,

⁴⁷I use the centroids of all *residences* to proxy for the centroid of the actual estimation sample. Some areas see very few or no housing transactions; thus using all residences provides a more widely applicable measure.

such as (unobservable) travel distance. I partially address this concern by measuring border distance as the distance to the nearest owner-occupied residences on the other side of the border.⁴⁸ This nearest-neighbor approach also avoids some computational issues in calculating border distance when borders take complicated forms, since I can calculate border distance by minimizing the distance to residences in neighboring municipalities.⁴⁹

A.3 Model-implied v. Actual Tax Value of Housing Wealth

In Figure A.2 below, I show the mapping in a scatter-plot format from model-implied tax assessments to the actual tax assessments of housing wealth observed in the tax returns.

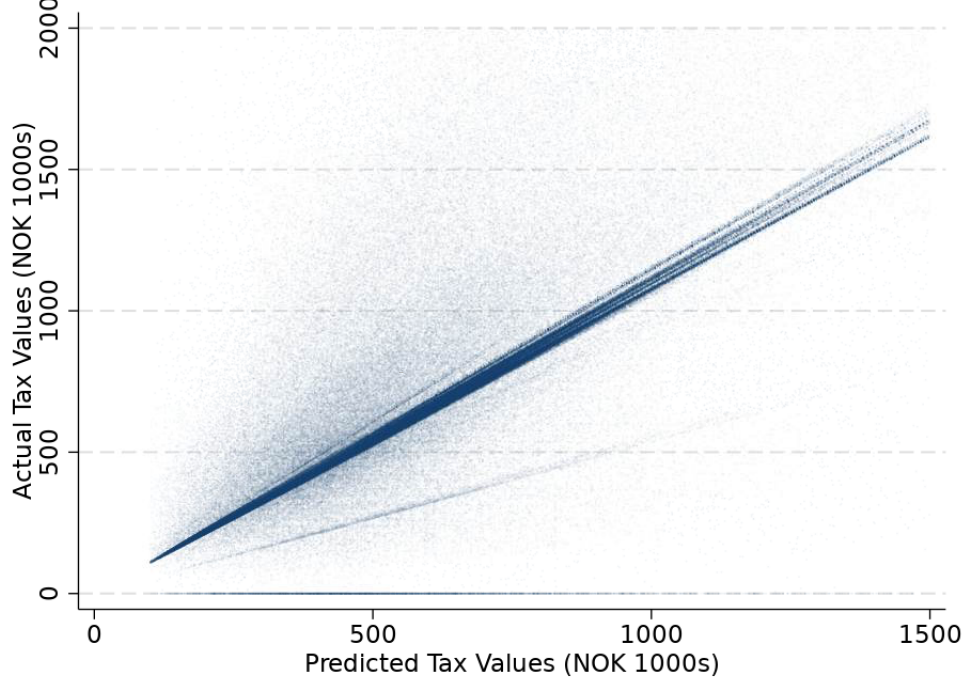
The actual tax values may differ from predicted tax values for a few reasons. First, the coefficients I use are based on estimating equation 2 on 2004–2008 data. These are, to the best of my knowledge, the same coefficients that were used to inform households of their new tax assessments *during* 2010. When assessing tax values after the end of the tax year, the coefficients were re-estimated on a dataset that also included 2009 data. Thus the inclusion of more data would slightly impact the coefficients and the assessed tax values. Second, the amount of housing wealth observed in the tax returns, $TaxVal$ (no hat), also includes the value of secondary homes, while I estimate model-predicted tax values, \widehat{TaxVal} , only considering primary residences. This leads to a few cases in which $TaxVal > \widehat{TaxVal}$. Third, households may have moved during 2010. Finally, they may have filed a complaint regarding the tax assessment. While assessed tax values are meant to equal $0.25\times$ market value, households who can document that their assessment exceeds $0.30\times$ market value may have the assessment lowered to $0.30\times$ market value, but not to $0.25\times$. In other words, even if the assessment is 20% too high, there are no incentives to complain. This ensures that the possibility of households' complaining does not materially lower the explanatory effect of the model coefficients on actual tax assessments.

⁴⁸The exact algorithm for calculating the distance variables is provided in the Appendix.

⁴⁹Complex borders may require linearization or division of the border into a finite set of points. This could lead to sizable approximation errors, in relative terms, for households very close to the border.

FIGURE A.2: VERIFYING THE HOUSE PRICE MODEL COEFFICIENTS

This figure plots actual assessed tax values against tax values predicted using the real estate data and coefficients from the hedonic pricing model. The Y-axis has the actual tax values that are retrieved from individuals' tax returns for 2010, presumably based on the coefficients from the model estimated with 2004–2009 data. The X-axis has predicted tax values based on 2009 real estate data and coefficients estimated with 2004–2008 data, which are the same coefficients used in providing preliminary tax values to households in during 2010. Predicted and actual values may differ for the following main reasons: (1) coefficients changed due to the inclusion of 2009 data in the estimation sample; (2) households can move or have a complaint approved that assessed tax values are too high; or (3) households may own a second home.



A.4 Calculating distances

For each household i , d_i^U is the signed distance, in meters, to the nearest residential building in a different municipality (or within-city district), m'_i , with which m_i shares a border which is not in the ocean or a fjord.^{50,51} In the following, m is referred to as a municipality, where, for purposes of brevity, I denote within-city districts in the largest 4 cities as municipalities. Household i is then assigned to the border area $b_i = m_i \cup m'_i = m'_i \cup m_i$. Household i is defined to be in the low-assessment side, if the average household in b_i would receive a lower assessment, were it assessed as if it were in m_i . If the assessment would be higher in m_i , household i lives on the high-assessment side. If they are equal, the household (and all households in this border area) is dropped from the sample. If household i lives in the low (high) assessment side, d_i^U is signed to be negative (positive).

For all municipal pairs, m, m' , distance between their housing centroids is calculated. A centroid is the vector average of the coordinates of all owner-occupied houses in a municipality. This disregards

⁵⁰All distances are calculated as the euclidean distance between coordinate vectors measured in meters. This assumes that the world is flat, which seems like a reasonable approximation for distances between neighboring municipalities. This assumption speeds up the time it takes to calculate a large combination of distances required to find the nearest household in a different municipality.

⁵¹For computational reasons, only one building per 100 square-meter square in neighboring municipalities is retained, and the search is conducted over a grid of the coordinates of these “representative” buildings.

which b_i you belong to. This number then enters in the denominator when scaling d_i^U to get the scaled (and signed) border distance, d_i .

A.5 Descriptive Figures and Tables

FIGURE A.3: RESIDENTIAL DENSITY AROUND BORDERS

This graph shows how residential density varies with border distance. Density is defined at the household level as the log of the number of households living within 1 km. The figures plot estimated coefficients of living in a given distance bin. The regressions include the baseline housing controls $\mathbf{H}_{i,2009}$, but these are not allowed to vary at the border-area level. Panel A uses distance in kilometers, and Panel B uses scaled distance. All households in the analysis sample (with Taxable Net Wealth ≥ 0 in 2009) are included.

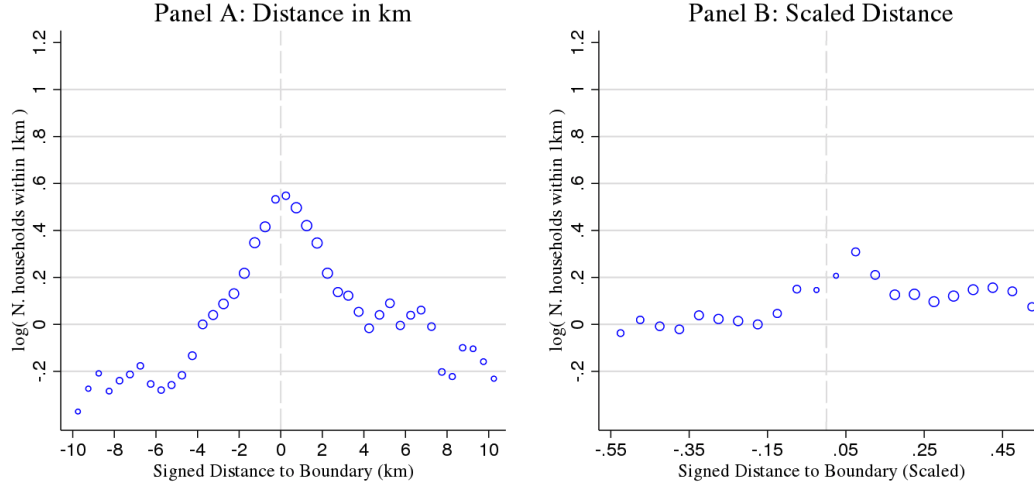


FIGURE A.4: GEOGRAPHIC DISTRIBUTION OF HOUSEHOLDS

This figures provides histograms illustrating the distribution of households in the analysis sample according to the different distance measures. All households in the analysis sample (with taxable net wealth ≥ 0 in 2009) are included, except those with distance measures outside the visible range of the graphs. Panel A uses (signed) distance in kilometers, Panel B uses scaled distance, and Panel C uses relative location, where the darker shade indicates membership in the high-assessment side of the boundary.

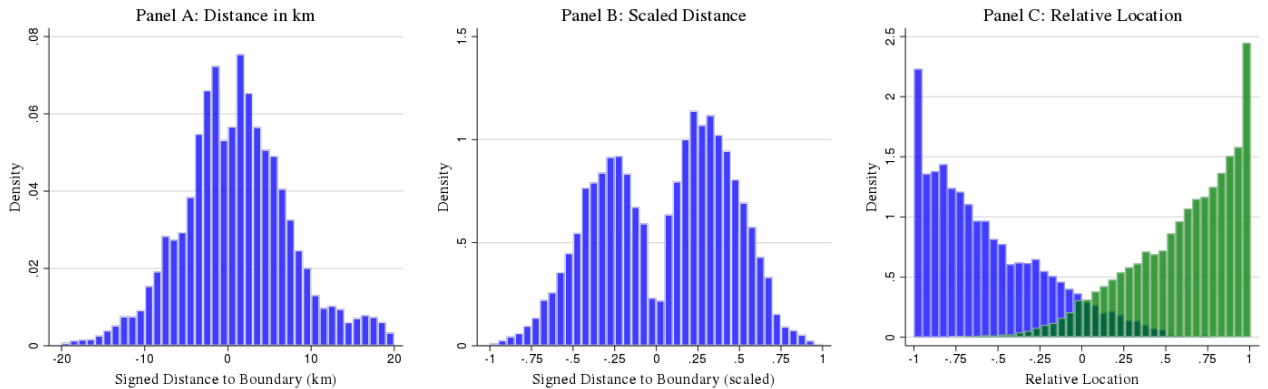


FIGURE A.5: EXAMPLE OF DATA SOURCE FOR HOUSE PRICE MODEL COEFFICIENTS

The regression output below is for s =detached homes, in the price region, R , corresponding to Aust-Agder county. Estimated coefficients are: $\alpha_R = 11.83711$, $\gamma_1 = 0$, $\gamma_2 = -0.15054$,..., $\gamma_7 = -0.72255$, $\zeta_R^{size} = -0.38555$, $\zeta_R^{Dense} = 0.06373$, $\zeta_{1,R}^{Age} = 0$, $\zeta_{2,R}^{Age} = -0.09434$,..., $\zeta_{4,R}^{Age} = -0.21287$, and $\sigma_R = 0.28800$.

Notater 39/2010

Reestimering av modell for beregning av boligformue

Eneboliger i Aust-Agder

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The REG Procedure

Model: MODEL1

Dependent Variable: lnkvmpri

Number of Observations Read 4196

Number of Observations Used 4196

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value
Pr > F				
Model	16	312.92646	19.55790	235.79
<.0001				
Error	4179	346.63448	0.08295	
Corrected Total	4195	659.56094		
Root MSE	0.28800	R-Square	0.4744	
Dependent Mean	9.35767	Adj R-Sq	0.4724	
Coeff Var	3.07774			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	11.83711	0.07555	156.68	<.0001
lnareal	1	-0.38555	0.01447	-26.65	<.0001
tett	1	0.06373	0.01197	5.33	<.0001
aar1	1	-0.43694	0.01599	-27.33	<.0001
aar2	1	-0.36403	0.01544	-23.57	<.0001
aar3	1	-0.26966	0.01494	-18.05	<.0001
aar4	1	-0.09556	0.01496	-6.39	<.0001
aar5	1	-0.05457	0.01537	-3.55	0.0004
alder2	1	-0.09434	0.01954	-4.83	<.0001
alder3	1	-0.21329	0.01615	-13.21	<.0001
alder4	1	-0.21287	0.01475	-14.43	<.0001
sone2	1	-0.15054	0.01850	-8.14	<.0001
sone3	1	-0.26613	0.02581	-10.31	<.0001
sone4	1	-0.24332	0.01699	-14.32	<.0001
sone5	1	-0.36361	0.02706	-13.44	<.0001
sone6	1	-0.43013	0.02127	-20.23	<.0001
sone7	1	-0.72255	0.02323	-31.10	<.0001

Statistisk sentralbyrå

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FIGURE A.6: EXAMPLE OF NONLINEARITIES IN A POOLED BOUNDARY REGION

I create this example as followings. First create 100 border areas, indexed by b . Each border area has a length of $200 \cdot b$, and thus a centroid distance in thousands, e.g., kilometers, (CD) of $100b/1000$. Each b has 100 households, equidistantly populated in $G=[-100b, 100b]$. Within each b , house prices move linearly according to their location, $g \in G$: $p = \frac{\Delta}{100} \cdot g$. By construction, the mean difference between houses with $g < 0$ (low side) and $g > 0$ (high side) is constant across b s, and is Δ . I set Δ to 1. In the first plot, I provide a binscatter of p s against g , separately for $b = 10, 25, 50, 75, 100$. In the second plot, I perform a pooled binscatter of p , for $b \in \{10, 25, 50, 75, 100\}$. The red line is a second-order RD polynomial, estimated separately for each side, allowing for a discontinuity at zero. Point estimates correspond to the within-bin means for 20 equal-sized bins.

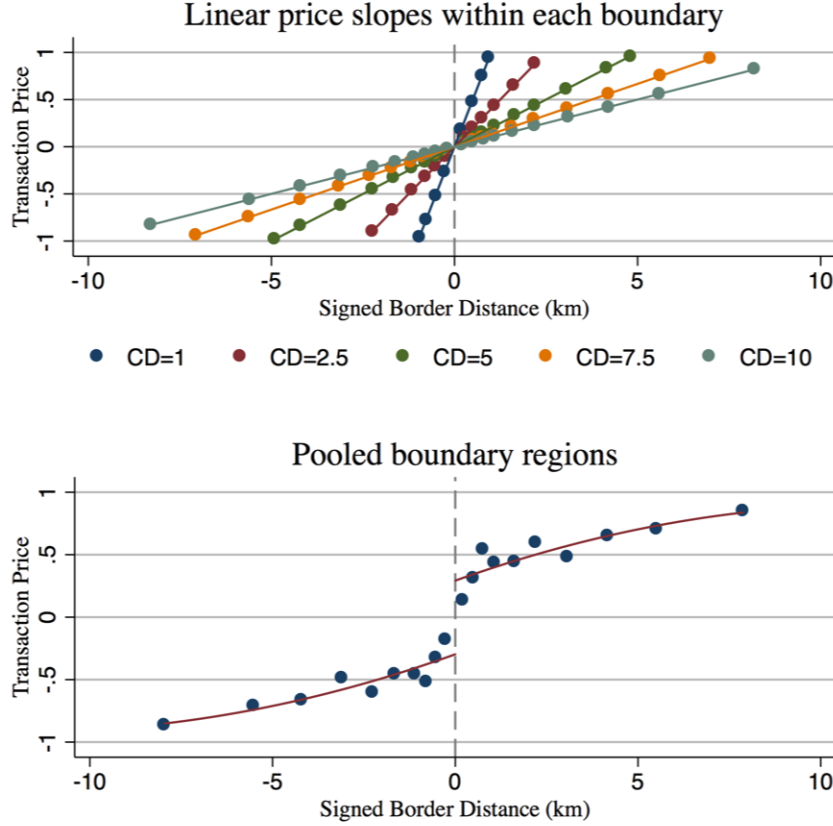


TABLE A.1: SUMMARY STATISTICS BY INITIAL WEALTH

Summary statistics are provided for households in the sample. Only households who are assigned a signed border distance variable are included. GFW is Gross Financial Wealth. GFW , *censored* indicates that GFW is winsorized (censored) at the 95th percentile. TGW is Taxable Gross Wealth. TNW is TGW minus Debt. Labor Earnings (LE) is the sum of wage and salary earnings and max(self employment income, 0). Total Taxable Labor Income ($TTLI$) is the sum of LE , UI benefits and other transfers, and labor-related pension income. SMW is the sum of mutual-fund holdings, direct holdings of listed domestic stocks and financial securities (excl. deposits) held abroad. $TaxVal$ is the assessed tax value (housing wealth) observed in the tax returns. $wtax$ is the amount of wealth taxes paid. $wtax/GFW$ is set to be the $\min(wtax/GFW, 1)$. RiskyShare is the ratio of SMW plus non-listed stocks (e.g., private equity) to GFW . *Foreign/GFW* is the share of GFW that is held abroad. *Self-rep/GFW* is the share of GFW that belongs to self-reported asset classes, such as outstanding claims and foreign assets. $wtax > 0$ is a dummy for whether a household paid wealth taxes. r , *Deposits* is the realized (symmetric) return on deposits. r , *Debt* is similarly defined, but excludes households who in either the current or subsequent period had $Debt < 10,000$. Further information on the wealth variables can be found in Subsection A.1 in the Appendix.

	Full sample					Households above wealth tax threshold in 2009					Households below wealth tax threshold in 2009							
	N	mean	sd	p25	p50	p75	N	mean	sd	p25	p50	p75	N	mean	sd	p25	p50	p75
2010–2015																		
GFW	1820892	1177	2300	224	580	1321	1005096	1739	2859	491	1026	2014	815796	484	933	117	284	579
GFW, censored	1820892	1000	1109				1005096	1432	1235				815796	466	589			
Debt	1820892	510	1035	0	138	617	1005096	417	1144	0	6	332	815796	625	869	71	385	813
TGW	1772724	2261	2765	970	1550	2600	977374	2967	3369	1353	2100	3437	795350	1394	1314	750	1097	1648
TNW	1772724	1741	2559	586	1181	2157	977374	2541	3061	1139	1837	3022	795350	758	1154	285	638	1081
TTLI	1824466	692	483	378	579	891	1007252	698	526	365	567	887	817214	685	424	392	595	895
LE	1824466	429	566	0	203	741	1007252	405	602	0	60	676	817214	459	515	0	355	793
SMW	1820892	151	559	0	0	82	1005096	225	717	0	8	153	815796	59	223	0	0	31
Deposits	1820892	722	970	153	408	916	1005096	1029	1154	308	700	1337	815796	343	448	87	215	445
TaxVal	1780154	828	706	466	659	969	981670	908	805	495	707	1062	798484	730	545	436	609	865
wtax	1819622	11	25	0	2	13	1004801	18	30	2	10	22	814821	2	9	0	0	1
2004–2009																		
TaxVal	1873872	406	222	257	367	511	1038598	434	237	277	391	544	835274	371	196	236	340	471
2010–2015																		
SMW/GFW	1805548	0.108	0.202	0.000	0.000	0.118	995132	0.115	0.203	0.000	0.008	0.135	810416	0.099	0.199	0.000	0.000	0.092
RiskyShare	1805548	0.164	0.266	0.000	0.006	0.224	995132	0.189	0.282	0.000	0.032	0.282	810416	0.133	0.242	0.000	0.000	0.152
Deposits/GFW	1805548	0.803	0.291	0.690	0.977	1.000	995132	0.772	0.308	0.615	0.944	1.000	810416	0.841	0.264	0.780	1.000	1.000
Foreign/GFW	1805548	0.008	0.054	0.000	0.000	0.000	995132	0.009	0.058	0.000	0.000	0.000	810416	0.006	0.049	0.000	0.000	0.000
Self-rep/GFW	1805548	0.025	0.106	0.000	0.000	0.000	995132	0.030	0.113	0.000	0.000	0.000	810416	0.019	0.096	0.000	0.000	0.000
wtax/GFW	1797249	0.009	0.036	0.000	0.005	0.011	990509	0.012	0.037	0.004	0.009	0.013	806740	0.006	0.035	0.000	0.000	0.004
wtax>0	1819622	0.600	0.490	0.000	1.000	1.000	1004801	0.817	0.387	1.000	1.000	1.000	814821	0.332	0.471	0.000	0.000	1.000
2009																		
r, Deposits	315208	0.0202	0.0116	0.0117	0.0203	0.0274	174786	0.0237	0.0108	0.0174	0.0244	0.0299	140422	0.0158	0.0111	0.0075	0.0148	0.0218
r, Debt	196473	0.0441	0.0144	0.0384	0.0433	0.0499	79305	0.0408	0.0169	0.0361	0.0416	0.0485	117168	0.0464	0.0118	0.0397	0.0441	0.0508
Age (hh. avg)	315328	61.93	13	53.0	62.0	71.0	174814	64.08	13	55.0	64.0	73.0	140514	59.25	13	50.0	59.0	68.0

B General Appendix

B.1 Additional figures

FIGURE B.1: GRAPHICAL PRESENTATION OF THE REDUCED-FORM EFFECTS ON PRE-PERIOD WEALTH TAX EXPOSURE

This graph shows the reduced-form effects of increased tax assessment on the following pre-period outcomes: (A) How much of household savings is subject to a wealth tax, i.e., the amount of wealth above the tax threshold; (B) Whether or not a household pays a wealth tax. These outcomes are measured during 2010–2015. The first row uses distance in kilometers, where households on the low-assessment side are given a negative distance. The second row uses (similarly signed) distance scaled by the distance between the two municipal centroids. The fitted lines and discontinuities correspond to reduced-form regressions using the regression specification in equation 19. 95% confidence bands are represented by dashed lines. All panels consider post-period saving outcomes for the full sample of households with initial positive taxable net wealth in 2009. Scatter-points stem from estimating a coefficient on Δ_i using equation 19 separately for d_i bins, rather than estimating coefficients on $\log(\overline{TaxVal}_i)$ and $g_b(c_i)\Delta_i$. The size of each circle corresponds approximately to the relative number of observations in that bin.

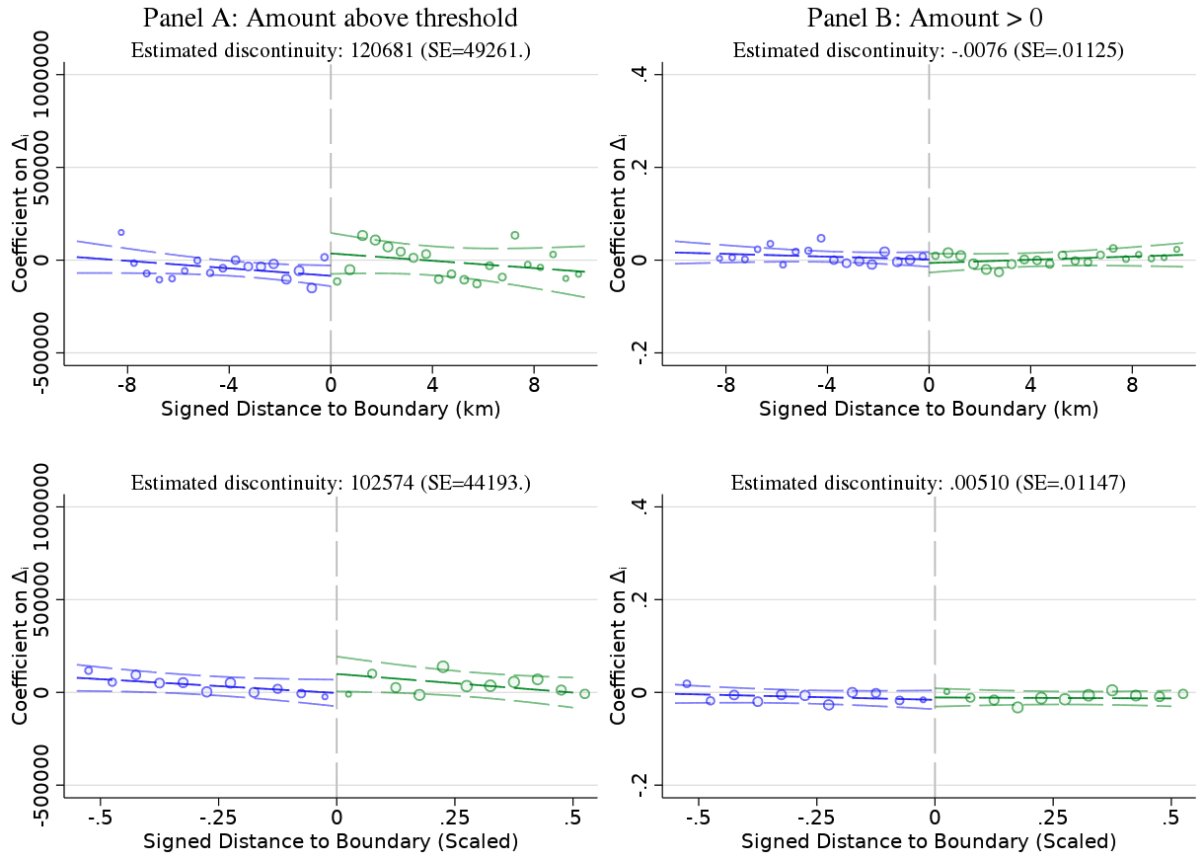
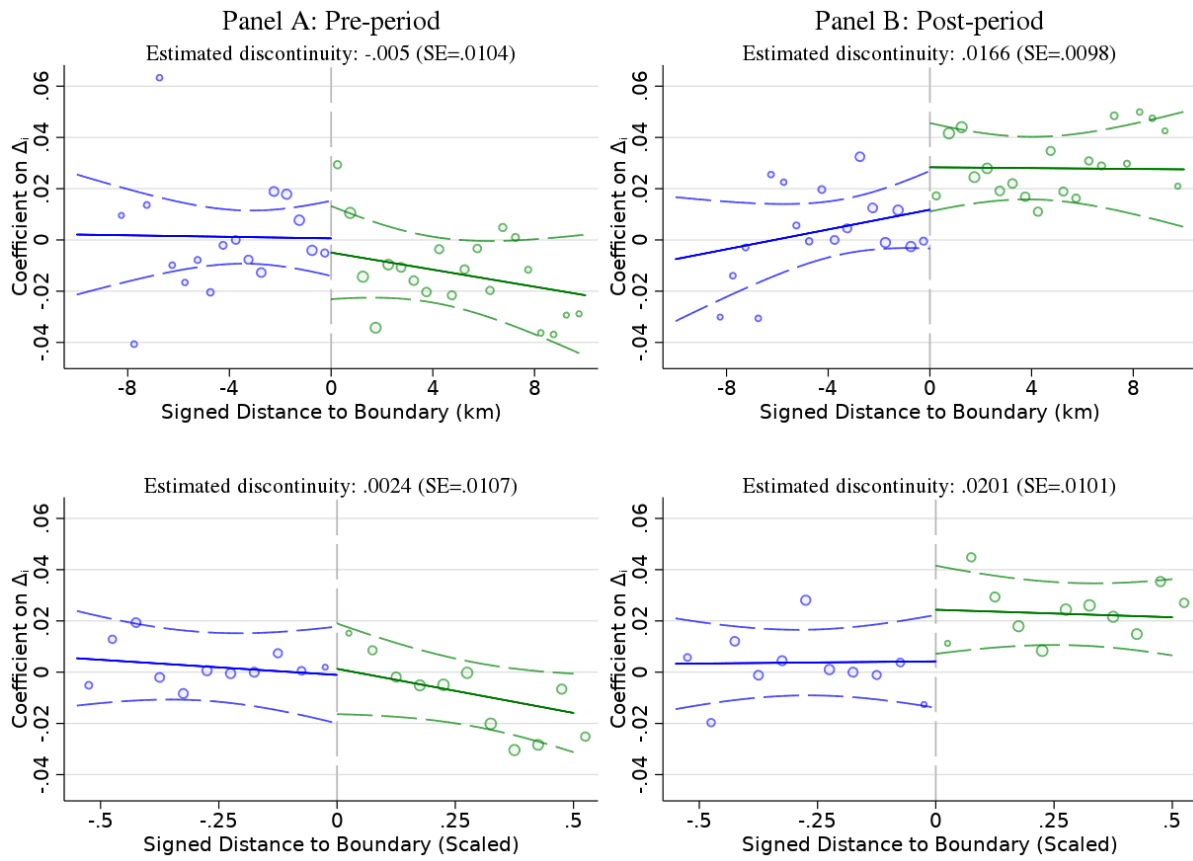


FIGURE B.2: GRAPHICAL PRESENTATION OF THE EFFECTS OF
INCREASED TAX ASSESSMENT ON FINANCIAL SAVING
Above Sample



B.2 Additional results figures

FIGURE B.3: TOTAL TAXABLE LABOR INCOME
SUBSAMPLE: HOUSEHOLDS INITIALLY ABOVE TAX THRESHOLD

The dependent variable is 1-year log-differenced TTTL. This figure provides results for the sample of households above the tax threshold in 2009. See description in Figure 8.

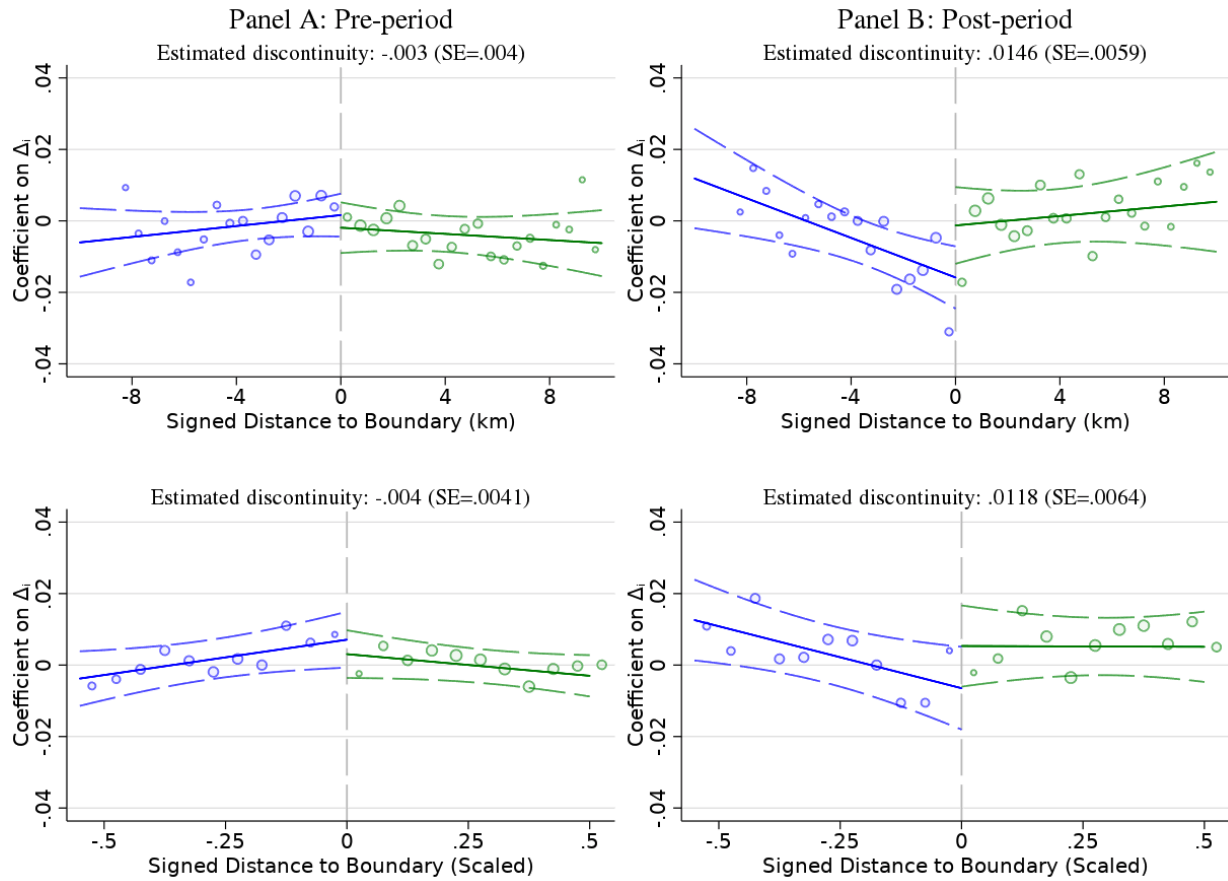
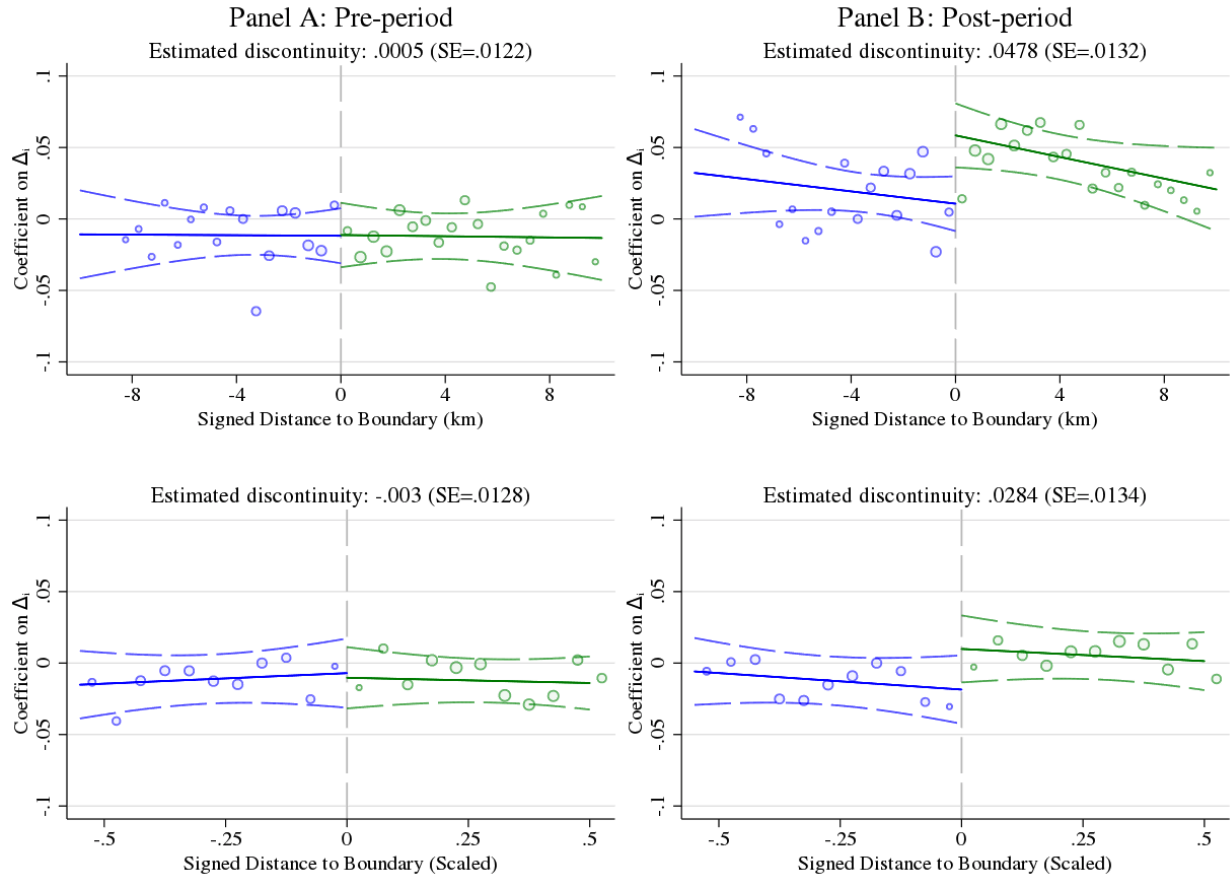


FIGURE B.4: LABOR EARNINGS
 SUBSAMPLE: HOUSEHOLDS INITIALLY ABOVE TAX THRESHOLD

The dependent variable is 1-year log-differenced Labor Earnings (LE), which is the sum of salaries, wages, and max(self employment income,0). This figure provides results for the sample of households above the wealth tax threshold in 2009. See description in Figure 9.



B.3 Additional Results Tables

TABLE B.1: ROBUSTNESS: EXCLUDING 2015 AND CONTROLLING FOR PROPERTY TAX RATE

This table provides the main (reduced-form) results when controlling for municipal property tax rates and excluding 2015.

	Adj. $\Delta \log(GFW)$	$\Delta \log(\text{Debt})$	ΔSMS	$\Delta \log(\text{TTLI})$	$\Delta \log(\text{LE})$
	(1)	(2)	(3)	(4)	(5)
FULL SAMPLE					
$\log(\widehat{\text{TaxVal}})$	0.0211*** (0.0077)	0.0004 (0.0123)	0.0003 (0.0014)	0.0044 (0.0045)	0.0191 (0.0119)
Prop. Tax (%)	-0.0062* (0.0032)	-0.0009 (0.0051)	-0.0009 (0.0006)	0.0024* (0.0014)	0.0086*** (0.0028)
N	[1232832]	[1232845]	[1229001]	[1234293]	[1234293]
HOUSEHOLDS INITIALLY ABOVE THRESHOLD					
$\log(\widehat{\text{TaxVal}})$	0.0219** (0.0107)	-0.0131 (0.0180)	0.0017 (0.0018)	0.0135** (0.0066)	0.0344*** (0.0127)
Prop. Tax (%)	-0.0056 (0.0041)	0.0025 (0.0067)	-0.0003 (0.0008)	0.0008 (0.0020)	0.0122*** (0.0043)
N	[685156]	[685168]	[682439]	[686177]	[686177]
HOUSEHOLDS INITIALLY BELOW THRESHOLD					
$\log(\widehat{\text{TaxVal}})$	0.0192* (0.0107)	0.0173 (0.0182)	-0.0013 (0.0021)	-0.0042 (0.0057)	0.0038 (0.0168)
Prop. Tax (%)	-0.0064 (0.0046)	-0.0029 (0.0063)	-0.0015** (0.0007)	0.0054*** (0.0018)	0.0055 (0.0042)
N	[547581]	[547582]	[546467]	[548022]	[548022]
Geo-Controls					
Scaled Border Distance	Yes	Yes	Yes	Yes	Yes

TABLE B.2: ROBUSTNESS: MAIN IV ESTIMATES USING TRIANGULAR WEIGHTS

This table provides regression results when the main IV regression specifications are run with triangular weights. For the case of scaled border distance, $d_i^{scaled} \in [-0.6, 0.6]$, weights are assigned as $1 - \text{abs}(d_i^{scaled}/0.6)$. For the relative location measure, $RL_i \in [-1, 1]$, weights are assigned as $1 - \text{abs}(RL_i)$.

	Adj. $\Delta \log(GFW)$		$\Delta \log(Debt)$		Δ Stock Market Share		$\Delta \log(TTLL)$		$\Delta \log(LE)$	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Full sample										
$\log(TaxVal)$	0.0264*** (0.0102)	0.0254*** (0.0086)	0.0022 (0.0135)	-0.0060 (0.0119)	0.0000 (0.0014)	0.0001 (0.0012)	0.0061 (0.0056)	0.0074 (0.0048)	0.0263*** (0.0126)	0.0230*** (0.0104)
N	1472113	1649293	1472130	1649429	1466682	1643325	1473585	1650966	1473585	1650966
Households above tax threshold in 2009										
$\log(TaxVal)$	0.0345*** (0.0137)	0.0261*** (0.0120)	-0.0019 (0.0186)	-0.0025 (0.0168)	-0.0004 (0.0022)	-0.0008 (0.0020)	0.0164* (0.0085)	0.0107 (0.0074)	0.0307* (0.0178)	0.0320*** (0.0158)
N	817214	912399	817229	912482	813335	908075	818244	913560	818244	913560
Households below tax threshold in 2009										
$\log(TaxVal)$	0.0170 (0.0145)	0.0183 (0.0117)	0.0098 (0.0194)	-0.0024 (0.0164)	0.0003 (0.0023)	0.0001 (0.0018)	-0.0038 (0.0069)	0.0038 (0.0058)	0.0206 (0.0181)	0.0161 (0.0139)
N	654804	736802	654806	736855	653253	735043	655247	737315	655247	737315
Geo-Controls										
Scaled Border Distance	Yes	–	Yes	–	Yes	–	Yes	–	Yes	–
Relative Location	–	Yes	–	Yes	–	Yes	–	Yes	–	Yes

TABLE B.3: ROBUSTNESS: SIGNIFICANCE AND STANDARD ERRORS OF MAIN REDUCED-FORM RESULTS USING DIFFERENT LEVELS OF CLUSTERING

Table reports estimated standard errors on $\log(\widehat{TaxVal})$ using different levels of clustering. All regressions are reduced-form, and consider post-period (2010–2015) outcomes.

Level of clustering	Adj. $\Delta \log(GFW)$		$\Delta \log(Debt)$		ΔSMS		$\Delta \log(TTLI)$		$\Delta \log(LE)$	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Full sample										
Household	0.0195*** (0.0076)	0.0182*** (0.0063)	0.0018 (0.0113)	-0.0047 (0.0093)	0.0000 (0.0012)	0.0001 (0.0010)	0.0044 (0.0043)	0.0049 (0.0036)	0.0191** (0.0091)	0.0214*** (0.0075)
Census tract	0.0195*** (0.0073)	0.0182*** (0.0063)	0.0018 (0.0111)	-0.0047 (0.0093)	0.0000 (0.0012)	0.0001 (0.0010)	0.0044 (0.0041)	0.0049 (0.0035)	0.0188** (0.0095)	0.0207*** (0.0078)
Municipality	0.0195*** (0.0073)	0.0182*** (0.0060)	0.0018 (0.0104)	-0.0047 (0.0091)	0.0000 (0.0013)	0.0001 (0.0011)	0.0044 (0.0039)	0.0049 (0.0033)	0.0188** (0.0105)	0.0207*** (0.0075)
Households above tax threshold in 2009										
Household	0.0201* (0.0108)	0.0230** (0.0090)	-0.0016 (0.0163)	-0.0020 (0.0135)	0.0005 (0.0017)	0.0006 (0.0014)	0.0118* (0.0069)	0.0094* (0.0057)	0.0290** (0.0132)	0.0316*** (0.0110)
Census tract	0.0201** (0.0102)	0.0230*** (0.0089)	-0.0016 (0.0157)	-0.0020 (0.0133)	0.0005 (0.0017)	0.0006 (0.0014)	0.0118* (0.0064)	0.0094* (0.0057)	0.0284** (0.0135)	0.0306*** (0.0112)
Municipality	0.0201** (0.0091)	0.0230*** (0.0075)	-0.0016 (0.0158)	-0.0020 (0.0132)	0.0005 (0.0015)	0.0006 (0.0012)	0.0118** (0.0059)	0.0094* (0.0051)	0.0284** (0.0122)	0.0306*** (0.0101)
Geo-Controls										
Scaled Border Distance	Yes	–	Yes	–	Yes	–	Yes	–	Yes	–
Relative Location Controls	–	Yes	–	Yes	–	Yes	–	Yes	–	Yes

TABLE B.4: EFFECT ON THE RISKY SHARE OF GROSS FINANCIAL WEALTH
THAT INCLUDES NON-LISTED STOCKS AND FOREIGN-HELD
FINANCIAL ASSETS (EXCL. FOREIGN DEPOSITS)

This table shows the (IV) effect of tax assessment on the (one-year differenced) share of wealth allocated to “risky assets” (Risky Share) during 2010–2015. Risky Assets is defined as the sum of listed and non-listed stocks. This implies $RiskyShare \geq SMS$.

$\Delta RiskyAssets/GFW$	(1)	(2)	(3)	(4)	(5)	(6)
FULL SAMPLE						
$\log(TaxVal)$	-0.0003 (0.0002)	-0.0005 (0.0008)	-0.0006 (0.0017)	-0.0028 (0.0018)	-0.0035 (0.0026)	-0.0019 (0.0016)
N	[1835781]	[1835687]	[1454510]	[1466682]	[1466682]	[1643325]
F	41012	3021	857	697	331	849
HOUSEHOLDS INITIALLY ABOVE THRESHOLD						
$\log(TaxVal)$	-0.0001 (0.0003)	0.0009 (0.0011)	-0.0014 (0.0023)	-0.0024 (0.0026)	-0.0030 (0.0039)	-0.0019 (0.0023)
N	[1008692]	[1008586]	[813160]	[813335]	[813335]	[908140]
F	28269	1819	509	386	165	430
HOUSEHOLDS INITIALLY BELOW THRESHOLD						
$\log(TaxVal)$	-0.0009*** (0.0003)	-0.0020* (0.0011)	-0.0006 (0.0027)	-0.0035 (0.0026)	-0.0035 (0.0035)	-0.0021 (0.0021)
N	[827089]	[826985]	[641250]	[653253]	[653253]	[735094]
F	24918	1955	432	379	193	466
Controls						
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Housing Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
– Border specific	–	Yes	Yes	Yes	Yes	Yes
Border Distance Controls						
– KM	–	–	Yes	–	–	–
– Scaled	–	–	–	Yes	–	–
– Border specific	–	–	–	–	Yes	–
Relative Location Controls	–	–	–	–	–	Yes

TABLE B.5: BANDWIDTH ROBUSTNESS, SCALED BORDER DISTANCE.

This table shows the results from the main IV specification, using different cutoffs for scaled border distance. bw=0.9 implies retaining all households with a scaled border distance inside [-0.9,0.9]. The main specification uses bw=0.6. All specifications consider outcomes during the post-period of 2010–2015.

Bandwidth	Adj. $\Delta \log(GFW)$ (1)	$\Delta \log(GFW)$ (2)	$\Delta \log(Debt)$ (3)	ΔSMS (4)	$\Delta \log(TTLI)$ (5)	$\Delta \log(LE)$ (5)
Full sample						
bw = .9	0.0199** (0.0078)	0.0110 (0.0080)	-0.0032 (0.0119)	0.0002 (0.0012)	0.0044 (0.0044)	0.0311*** (0.0100)
bw = .8	0.0208*** (0.0079)	0.0118 (0.0081)	-0.0020 (0.0121)	0.0000 (0.0012)	0.0027 (0.0044)	0.0305*** (0.0102)
bw = .7	0.0212*** (0.0080)	0.0123 (0.0082)	-0.0027 (0.0124)	0.0003 (0.0013)	0.0027 (0.0045)	0.0295*** (0.0105)
bw = .5	0.0204** (0.0100)	0.0110 (0.0102)	0.0067 (0.0153)	0.0007 (0.0016)	0.0054 (0.0056)	0.0293** (0.0125)
bw = .4	0.0247** (0.0119)	0.0147 (0.0122)	0.0081 (0.0179)	0.0003 (0.0019)	0.0043 (0.0066)	0.0200 (0.0146)
bw = .3	0.0390** (0.0156)	0.0282* (0.0159)	-0.0081 (0.0236)	-0.0010 (0.0025)	0.0121 (0.0086)	0.0353* (0.0193)
bw = .2	0.0647** (0.0253)	0.0526** (0.0256)	0.0015 (0.0365)	-0.0013 (0.0037)	0.0121 (0.0135)	0.0647** (0.0275)
Households above tax threshold in 2009						
bw = .9	0.0201* (0.0104)	0.0114 (0.0109)	-0.0004 (0.0160)	0.0015 (0.0016)	0.0094 (0.0066)	0.0412*** (0.0136)
bw = .8	0.0201* (0.0106)	0.0111 (0.0111)	-0.0018 (0.0164)	0.0014 (0.0017)	0.0060 (0.0066)	0.0375*** (0.0138)
bw = .7	0.0178* (0.0107)	0.0085 (0.0113)	-0.0086 (0.0168)	0.0014 (0.0017)	0.0058 (0.0067)	0.0347** (0.0143)
bw = .5	0.0263* (0.0135)	0.0168 (0.0142)	0.0088 (0.0210)	0.0008 (0.0023)	0.0147* (0.0085)	0.0350** (0.0177)
bw = .4	0.0395** (0.0161)	0.0292* (0.0169)	0.0036 (0.0251)	-0.0008 (0.0027)	0.0137 (0.0102)	0.0161 (0.0205)
bw = .3	0.0526** (0.0214)	0.0415* (0.0223)	-0.0118 (0.0340)	-0.0045 (0.0036)	0.0270** (0.0134)	0.0474* (0.0281)
bw = .2	0.0875** (0.0376)	0.0733* (0.0387)	0.0148 (0.0585)	-0.0052 (0.0060)	0.0204 (0.0227)	0.1084** (0.0481)
Households below tax threshold in 2009						
bw = .9	0.0194* (0.0114)	0.0102 (0.0113)	-0.0048 (0.0174)	-0.0018 (0.0019)	-0.0010 (0.0055)	0.0195 (0.0148)
bw = .8	0.0214* (0.0115)	0.0122 (0.0114)	-0.0006 (0.0176)	-0.0023 (0.0019)	-0.0006 (0.0056)	0.0218 (0.0149)
bw = .7	0.0235** (0.0119)	0.0146 (0.0119)	0.0057 (0.0182)	-0.0016 (0.0019)	-0.0015 (0.0058)	0.0235 (0.0153)
bw = .5	0.0149 (0.0142)	0.0055 (0.0142)	0.0005 (0.0215)	0.0002 (0.0023)	-0.0045 (0.0070)	0.0215 (0.0180)
bw = .4	0.0074 (0.0176)	-0.0021 (0.0176)	0.0151 (0.0260)	0.0008 (0.0028)	-0.0049 (0.0084)	0.0290 (0.0215)
bw = .3	0.0146 (0.0225)	0.0043 (0.0223)	0.0016 (0.0319)	0.0017 (0.0037)	-0.0036 (0.0106)	0.0222 (0.0285)
bw = .2	0.0423 (0.0331)	0.0328 (0.0329)	0.0141 (0.0440)	0.0026 (0.0049)	0.0104 (0.0149)	0.0296 (0.0373)

TABLE B.6: BANDWIDTH ROBUSTNESS, BORDER DISTANCE (KM)

This table shows the results from the main IV specification, using different cutoffs for scaled border distance. bw=10 implies retaining all households with a border distance, in km, inside [-10,10]. The main specification uses bw=10. All specifications consider outcomes during the post-period of 2010–2015.

Bandwidth	Adj. $\Delta \log(GFW)$ (1)	$\Delta \log(GFW)$ (2)	$\Delta \log(Debt)$ (3)	ΔSMS (4)	$\Delta \log(TTLI)$ (5)	$\Delta \log(LE)$ (5)
Full sample						
bw = 14	0.0228*** (0.0070)	0.0111 (0.0072)	0.0022 (0.0109)	0.0012 (0.0012)	0.0057 (0.0039)	0.0322*** (0.0091)
bw = 12	0.0226*** (0.0077)	0.0102 (0.0079)	0.0059 (0.0118)	0.0005 (0.0013)	0.0055 (0.0042)	0.0367*** (0.0101)
bw = 8	0.0252*** (0.0094)	0.0119 (0.0097)	0.0101 (0.0145)	0.0001 (0.0016)	0.0110** (0.0050)	0.0379*** (0.0120)
bw = 6	0.0327*** (0.0109)	0.0179 (0.0113)	0.0025 (0.0176)	-0.0005 (0.0019)	0.0102* (0.0059)	0.0290** (0.0143)
bw = 4	0.0436*** (0.0139)	0.0285** (0.0143)	0.0156 (0.0216)	-0.0023 (0.0023)	0.0109 (0.0075)	0.0319* (0.0174)
bw = 2	0.0361 (0.0251)	0.0184 (0.0258)	-0.0276 (0.0396)	-0.0055 (0.0041)	-0.0002 (0.0132)	0.0650** (0.0307)
bw = 1	-0.0238 (0.0549)	-0.0504 (0.0573)	0.0132 (0.0860)	-0.0170* (0.0099)	-0.0239 (0.0283)	0.0278 (0.0684)
Households above tax threshold in 2009						
bw = 14	0.0184** (0.0093)	0.0073 (0.0098)	0.0017 (0.0147)	0.0014 (0.0015)	0.0126** (0.0057)	0.0437*** (0.0124)
bw = 12	0.0183* (0.0101)	0.0071 (0.0106)	0.0058 (0.0159)	0.0009 (0.0017)	0.0127** (0.0060)	0.0482*** (0.0136)
bw = 8	0.0218* (0.0123)	0.0101 (0.0130)	0.0194 (0.0195)	0.0003 (0.0020)	0.0164** (0.0073)	0.0489*** (0.0165)
bw = 6	0.0381*** (0.0142)	0.0245 (0.0150)	0.0051 (0.0226)	-0.0017 (0.0024)	0.0187** (0.0085)	0.0324* (0.0190)
bw = 4	0.0460** (0.0179)	0.0329* (0.0190)	-0.0115 (0.0279)	-0.0031 (0.0030)	0.0166 (0.0109)	0.0288 (0.0231)
bw = 2	0.0302 (0.0301)	0.0190 (0.0321)	-0.0476 (0.0479)	-0.0044 (0.0048)	-0.0050 (0.0180)	0.0231 (0.0356)
bw = 1	0.0005 (0.0595)	-0.0184 (0.0636)	0.0195 (0.0853)	-0.0091 (0.0090)	-0.0057 (0.0317)	0.0414 (0.0634)
Households below tax threshold in 2009						
bw = 14	0.0245** (0.0109)	0.0119 (0.0109)	0.0045 (0.0163)	0.0007 (0.0019)	-0.0035 (0.0053)	0.0126 (0.0135)
bw = 12	0.0243** (0.0118)	0.0107 (0.0118)	0.0080 (0.0174)	0.0000 (0.0020)	-0.0040 (0.0059)	0.0197 (0.0145)
bw = 8	0.0246* (0.0144)	0.0091 (0.0144)	0.0010 (0.0211)	-0.0004 (0.0025)	0.0009 (0.0064)	0.0148 (0.0174)
bw = 6	0.0190 (0.0174)	0.0025 (0.0174)	0.0050 (0.0255)	0.0012 (0.0030)	-0.0034 (0.0077)	0.0148 (0.0217)
bw = 4	0.0376* (0.0221)	0.0197 (0.0220)	0.0529* (0.0311)	-0.0019 (0.0038)	0.0043 (0.0098)	0.0251 (0.0267)
bw = 2	0.0422 (0.0405)	0.0169 (0.0398)	0.0316 (0.0579)	-0.0057 (0.0070)	0.0036 (0.0185)	0.1192** (0.0530)
bw = 1	-0.0978 (0.1304)	-0.1517 (0.1346)	0.0493 (0.1747)	-0.0276 (0.0232)	-0.0623 (0.0601)	-0.0352 (0.1548)

TABLE B.7: BANDWIDTH ROBUSTNESS, RELATIVE LOCATION

This table shows the results from the main IV specification, using different cutoffs for scaled border distance. bw=0.5 implies retaining all households with Relative Location in inside [-0.5,0.5]. The main specification uses bw=1.0. All specifications consider outcomes during the post-period of 2010–2015.

Bandwidth	Adj. $\Delta \log(GFW)$ (1)	$\Delta \log(GFW)$ (2)	$\Delta \log(Debt)$ (3)	ΔSMS (4)	$\Delta \log(TTLI)$ (5)	$\Delta \log(LE)$ (5)
Full sample						
bw = .9	0.0223*** (0.0082)	0.0129 (0.0084)	-0.0090 (0.0128)	-0.0002 (0.0013)	0.0059 (0.0046)	0.0230** (0.0103)
bw = .8	0.0217** (0.0088)	0.0121 (0.0091)	-0.0034 (0.0140)	0.0003 (0.0014)	0.0040 (0.0051)	0.0206* (0.0109)
bw = .7	0.0250*** (0.0095)	0.0152 (0.0098)	-0.0038 (0.0149)	-0.0000 (0.0015)	0.0058 (0.0054)	0.0182 (0.0113)
bw = .6	0.0312*** (0.0104)	0.0201* (0.0107)	0.0047 (0.0164)	-0.0012 (0.0017)	0.0094 (0.0060)	0.0188 (0.0127)
bw = .5	0.0326*** (0.0117)	0.0221* (0.0120)	-0.0090 (0.0180)	-0.0010 (0.0018)	0.0127* (0.0066)	0.0280** (0.0134)
bw = .4	0.0321** (0.0130)	0.0196 (0.0133)	-0.0154 (0.0193)	-0.0002 (0.0020)	0.0134* (0.0072)	0.0181 (0.0149)
bw = .3	0.0352** (0.0146)	0.0205 (0.0150)	-0.0283 (0.0235)	-0.0000 (0.0022)	0.0086 (0.0083)	0.0213 (0.0171)
Households above tax threshold in 2009						
bw = .9	0.0259** (0.0118)	0.0157 (0.0124)	-0.0071 (0.0185)	-0.0000 (0.0019)	0.0110 (0.0074)	0.0383** (0.0152)
bw = .8	0.0218* (0.0127)	0.0115 (0.0134)	-0.0018 (0.0202)	-0.0000 (0.0021)	0.0068 (0.0080)	0.0349** (0.0164)
bw = .7	0.0234* (0.0137)	0.0126 (0.0145)	0.0004 (0.0218)	-0.0003 (0.0022)	0.0045 (0.0085)	0.0281 (0.0174)
bw = .6	0.0292** (0.0148)	0.0174 (0.0158)	0.0074 (0.0234)	-0.0018 (0.0024)	0.0088 (0.0092)	0.0195 (0.0189)
bw = .5	0.0367** (0.0169)	0.0252 (0.0179)	-0.0057 (0.0268)	-0.0027 (0.0026)	0.0138 (0.0100)	0.0217 (0.0208)
bw = .4	0.0256 (0.0182)	0.0116 (0.0192)	0.0033 (0.0288)	-0.0025 (0.0030)	0.0228** (0.0105)	0.0240 (0.0225)
bw = .3	0.0326 (0.0211)	0.0152 (0.0225)	-0.0225 (0.0381)	-0.0026 (0.0034)	0.0167 (0.0126)	0.0251 (0.0283)
Households below tax threshold in 2009						
bw = .9	0.0197* (0.0116)	0.0109 (0.0115)	-0.0051 (0.0170)	-0.0006 (0.0018)	0.0009 (0.0056)	0.0079 (0.0143)
bw = .8	0.0215* (0.0124)	0.0127 (0.0124)	0.0005 (0.0187)	-0.0001 (0.0020)	0.0006 (0.0061)	0.0082 (0.0152)
bw = .7	0.0174 (0.0131)	0.0084 (0.0130)	0.0030 (0.0194)	-0.0005 (0.0021)	0.0057 (0.0065)	0.0109 (0.0155)
bw = .6	0.0182 (0.0144)	0.0081 (0.0143)	0.0120 (0.0219)	-0.0008 (0.0023)	0.0083 (0.0074)	0.0232 (0.0174)
bw = .5	0.0111 (0.0156)	0.0012 (0.0155)	-0.0006 (0.0228)	0.0005 (0.0024)	0.0103 (0.0081)	0.0400** (0.0180)
bw = .4	0.0192 (0.0171)	0.0072 (0.0169)	-0.0159 (0.0247)	0.0026 (0.0027)	0.0012 (0.0089)	0.0208 (0.0202)
bw = .3	0.0194 (0.0187)	0.0057 (0.0186)	-0.0098 (0.0278)	0.0028 (0.0030)	-0.0002 (0.0094)	0.0232 (0.0215)

TABLE B.8: FIRST-STAGE EFFECTS ON WEALTH TAX OUTCOMES: USING DISTANCE IN KM

This table provides the reduced-form estimates that uses border distance in km (as opposed to scaled border distance) as the geographic measure. Column (1) considers the tax value of housing, as observed in tax returns. Column (2) considers the effect on being above the wealth tax threshold. Column (3) considers the effect on the marginal rate-of-return, by isolating extensive margin effects from wealth taxation. This is done by defining the dependent variable to be $-\tau_t \mathbb{1}[TNW_{i,t} > Threshold_t]$. Column (4) examines the effect on the amount above the wealth tax threshold, $\mathbb{1}[TNW_{i,t} > Threshold_t](TNW_{i,t} - Threshold)$. Column (5) isolates the effect of increased wealth taxation on the average rate-of-return. This is done by defining the dependent variable as $-\tau_t \mathbb{1}[TNW_{i,t} > Threshold_t](TNW_{i,t} - Threshold)/TNW_{i,t}$, which is evaluated as 0 if $TNW_{i,t} \leq 0$. pp is short for percentage points, and indicates that coefficients (SEs) are multiplied by 100. Standard errors, provided in parentheses, are clustered at the census-tract level.

		Extensive margin		Extensive and intensive margin	
	$\log(TaxVal)$	$\mathbb{1}[TNW > Threshold]$	$r^{marginal}$	AmountAbove	$r^{average}$
	(1)	(2)	(3)	(4)	(5)
Full sample					
$\log(\widehat{TaxVal})$	0.872693*** (0.030300)	0.259342*** (0.012781)	-0.002724*** (0.000133)	865278*** (87379)	-0.001898*** (0.000082)
$F(\hat{\beta} = 0)$	830	412	419	98	539
Households above tax threshold in 2009					
$\log(\widehat{TaxVal})$	0.906123*** (0.041042)	0.157144*** (0.014319)	-0.001654*** (0.000149)	1158019*** (135316)	-0.001737*** (0.000103)
$F(\hat{\beta} = 0)$	487	120	123	73	284
Households below tax threshold in 2009					
$\log(\widehat{TaxVal})$	0.827092*** (0.040108)	0.386843*** (0.020063)	-0.004059*** (0.000209)	375749*** (58352)	-0.002017*** (0.000115)
$F(\hat{\beta} = 0)$	425	372	378	41	309
Border Distance Controls – KM	Yes	Yes	Yes	Yes	Yes

B.4 Effect on municipal finances

Households in high-taxation municipalities may see the negative income effect partially offset by a higher provision of public goods or a lowering of municipal fees. While this may generally be a cause for concern, I argue that this effect is likely negligible in my empirical setting for the following key reasons: First, wealth taxes are disproportionately paid by the very wealthy, who were not disproportionately affected by this reform given that housing wealth accounts for a very small fraction of net worth for the very wealthy (see [Fagereng, Guiso, Malacrino, and Pistaferri \(2018\)](#)). Thus, changes in tax assessments are not likely to lead to meaningful changes in the aggregate amount of wealth tax revenues in a given municipality. In addition, wealth taxes account for only 10% of aggregate municipal tax revenues, and drops to only 4% of when considered relative to aggregate municipal total incomes. Finally, due to the government's revenue equalization scheme, increasing per capita tax revenues by 1 NOK lowers transfers from the central government by 0.6 NOK. Therefore, even if wealth tax revenues do change, the effect on local public services would be likely muted, due to a limited effect on municipality finances. Calculations that I present below, suggest that a municipality where assessed tax values of

housing are 0.5 log points higher will have 0.26% more revenue.⁵² Thus any reasonable bounds on household sensitivity to municipal finances suggest that the effect will be negligible.

B.5 Communication of policy change

The implementation of a new methodology to assess housing wealth was primarily communicated in a letter sent to all homeowners in August of 2010. The letter was titled “Information for the calculation of new tax values for residential properties,”⁵³ and provided registered information about the house, namely structure type, construction year and size. Home-owners were asked to verify and possibly correct this information, either by postal service or online. At the same time, “tax calculators” were made available online on the tax authorities’ website, where households could enter the characteristics of their home and see their estimated new tax value. This tax value differed somewhat from the actual assessed values, since the online calculators used pricing coefficients based on 2004–2008 transaction data, while the final assessment for 2010 used coefficients based on 2004–2009 data. The fact that a new assessment methodology was introduced was therefore salient, and the effect on a household’s wealth tax base (TNW) was already available in the early fall of 2010. On December 15 2010, preliminary tax information (“tax cards”) was sent out to all tax payers, containing estimated taxes to be paid for that year, which included the new housing assessment and TNW. Households should thus have been aware of the financial impact of the new assessment methodology before Christmas of 2010 at the latest.

The tax authorities’ website states that tax values are assessed as the size of the home multiplied with a price-per-square meter coefficient, which is based on Statistics Norway’s real estate transaction statistics: “Boligens boligverdi er lik boligens areal multiplisert med kvadratmeterpris basert på statistikk over omsatte boliger.” (March 2019). See [the tax authorities’ website](#). No details provided on the exact methodology.

B.6 Two-period model with endogenous labor supply

Consider the modified household optimization problem. $L \geq 0$ is hours worked in period 1, W is the exogenous hourly wage, $\frac{1}{\nu} > 0$ is the Frisch elasticity, and $\psi > 0$ is the (dis)utility weight on labor

⁵²I use the distribution of wealth tax payers from SSB (<https://www.ssb.no/statbank/table/08231/tableViewLayout1/>), and assume that this distribution holds for all municipalities. In my empirical setting, a 0.5 log point increase in *TaxVal* increases the amount subject to a wealth tax by 478,000 for households initially above the wealth tax threshold. This increases wealth tax payments by approximately 5,000. Using the distribution of wealth taxpayers, I increase everyone’s tax payments by 5,000, and find an increase in total tax payments of 25%. Assume that this occurred in one municipality, but not its neighbor. Since the municipal share of the wealth tax is only 64%, the high-side municipality now has $0.64 \cdot 0.25 = 16\%$ more wealth tax revenue. The wealth tax’s share of tax revenue is 10%. Thus the high-side will have 1.6% more tax revenue, but only $1.6\% \cdot 40\% = 0.64\%$ more total revenue, since tax revenues account for 40% of total incomes on average. Only 40% of this difference will pass through after applying the government revenue equalization scheme, leaving only 0.26% more revenue for the high-assessment side municipality.

⁵³My own translation.

supply. Y_1 , and Y_2 are the exogenous incomes in periods 1 and 2, respectively.

$$\begin{aligned} \max_{C_1, C_2, S, L} \quad & U(C_1, C_2, S, L) = \frac{1}{1-\gamma} C_1^{1-\gamma} - \psi \frac{L^{1+\nu}}{1+\nu} + \beta \frac{1}{1-\gamma} C_2^{1-\gamma} \\ \text{s.t.} \quad & C_1 + S = Y_1 + LW \\ \text{and} \quad & C_2 = Y_2 + \tilde{R} + \tilde{V} \end{aligned} \quad (32)$$

The first-order conditions with respect to S , together with the budget constraints, imply that:

$$S = \frac{[\beta \tilde{R}]^{\frac{1}{\gamma}} (Y_1 + LW)}{\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}}} - \frac{Y_2 + \tilde{V}}{\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}}}. \quad (33)$$

The first-order conditions with respect to L , together with the budget constraints, imply that:

$$dL \cdot W = \frac{\gamma[Y_1 + LW - S]^{-\gamma-1} W^2}{(\psi \nu L^{\nu-1} + \gamma[Y_1 + LW - S]^{-\gamma-1} W^2)} dS \equiv f dS. \quad (34)$$

Since $\psi \nu L^{\nu-1} > 0$, and $C_1 = Y_1 + LW - S > 0$, this implies that the labor earnings response is a fraction, $f \in (0, 1)$, of the savings response to rate-of-return shocks.

I now totally differentiate equation 33 with respect to \tilde{R} and substitute $dL \cdot W$ for the expression in equation 34, and solve for $dS/d\tilde{R}$ to get:

$$\frac{dS}{d\tilde{R}} = \left(1 - f \frac{[\beta \tilde{R}]^{\frac{1}{\gamma}}}{\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}}}\right)^{-1} \left((Y_1 + LW) \frac{1-\gamma}{\gamma} \frac{[\beta \tilde{R}]^{\frac{1}{\gamma}}}{(\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}})^2} + (Y_2 + \tilde{V}) \frac{1 + \frac{\beta}{\gamma} [\beta \tilde{R}]^{\frac{1}{\gamma}-1}}{(\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}})^2} \right). \quad (35)$$

I then totally differentiate 33 with respect to \tilde{V} , and substitute $dL \cdot W$ with the expression in equation 34, and solve for $dS/d\tilde{V}$ to get:

$$\frac{dS}{d\tilde{V}} = \left(1 - f \frac{[\beta \tilde{R}]^{\frac{1}{\gamma}}}{\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}}}\right)^{-1} \left(-\frac{1}{\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}}} \right). \quad (36)$$

The expressions for $dS/d\tilde{R}$ and $dS/d\tilde{V}$ are qualitatively similar to the case without endogenous labor supply, but are scaled up (in magnitude), since $(1 - f[\beta \tilde{R}]^{\frac{1}{\gamma}}/(\tilde{R} + [\beta \tilde{R}]^{\frac{1}{\gamma}}))^{-1} > 1$. The expression for the rate-of-return sensitivity in equation 35 now also contains labor earnings as period 1 income. There is therefore no change in the qualitative conclusions drawn in the case with only exogenous (labor) income. The new insight is that the effect on labor earnings should be of a same sign as, but smaller in magnitude than, the effect on savings.