Local Governments' Response to Fiscal Shocks: Evidence from Connecticut*

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November 13, 2022

Abstract

The deteriorating fiscal position of municipalities across the United States raises the question which adjustment mechanisms municipalities have at their disposal and what their effects are. We utilize quasi-experimental variation in the year of property tax assessments in the state of Connecticut to provide causal evidence of the fiscal adjustment following a large decline in property values after the Great Financial Crisis. We find that local governments adjust tax rates to maintain stable tax revenues; there is no change in public employment levels and limited adjustments of public services. Our micro data on people's location further allows us to causally estimate the migration elasticity to a change in property tax rates. We find evidence of inter-state migration in response to an increase in property tax rates; and no statistically significant response of intra-state migration. Detailed property and location choice data reveal the elasticity of migration with regard to the property tax bill. An increase in the property tax bill by ten percent leads to an average increase in the migration propensity by about 1.5%.

Keywords: Municipal finance, financial distress, migration, public finance, tax base, fiscal sustainability. *JEL codes*: H30, H71, H72, H75

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1 Introduction

Local governments are an important economic entity in the United States as they account for \$1.6 trn—8.1% of GDP—in public expenditures and 10.0% of employment.[1] Local governments play an instrumental role for the level of local amenities—such as public safety, fire protection, education, administrative support, and infrastructure to their residents. More than that, they provide the basis for community and civic life. In addition, as public sector employers, they employ a large number of employees and are responsible for their employees' retirement and health benefits. The fiscal health of local governments is thus of great importance. Giesecke, Mateen, and Sena (2022) shows that a sizable share of local governments operate with a negative equity position—whether measured in terms of book or market values. That is, future liabilities of local governments exceed future receipts which suggest required fiscal adjustments unless the state and federal government provides substantial support. The consequences of fiscal adjustments are still unclear. Causal identification of the consequences to fiscal adjustments is notoriously difficult.

In this paper we utilize quasi-experimental variation in the year of property tax assessments in the state of Connecticut. Specifically, we focus on the first re-assessment after the Great Financial Crisis. The large decrease in national housing valuation meant that this re-assessment led to a large downward adjustment in the assessment value of properties which effectively constituted a large fiscal shock for local governments. Connecticut law stipulates that properties have to be re-valued according to a strict re-assessment schedule; which makes the timing of the re-assessment of real property quasi-exogenous to the municipality. We use this staggered re-evaluation of properties in our research design. The decline in the tax basis was substantial; with an average decrease of about -8.92% and a decline up to -30.35% for some municipalities.

We find that municipalities in Connecticut insulate themselves from this fiscal shock almost entirely by raising the property tax rate. We find no change in public employment and only a small downward adjustments of public services. As the fiscal shock is

[1]As per the Census of Governments (ASSLGF) in fiscal year 2017 and the 05/2019 BLS Occupational Employment and Wage Statistics (OES), respectively. In fiscal year 2017, they raised approximately \$707 bn in local tax revenues of which property taxes accounted for about \$509 bn. Total own source revenues of local governments amount to \$800 bn USD which corresponds to approximately 4.1% of U.S. GDP and hence about the same magnitude as the total revenues of state governments. Own source revenues predominantly consist of taxes but also include user fees, licensing, and miscellaneous revenue sources.

passed onto residents, we estimate the migration response. We estimate a sizeable and statistically significant effect on net migration. The average tax rate increase of 12.3% led to a decrease in the population by 0.35%—or about 2.5 standard deviations change in population—at a five year horizon. We further document that the net migration is primarily driven by inter-state migration—that is, migration across the state borders of Connecticut. Further, the net migration response results almost entirely from out-migration. We document heterogeneous migration elasticities along the dimensions of age and tenure.

In a separate set of analysis, we construct a merged CoreLogic-Infutor dataset, to estimate the migration elasticity at the individual level. Our detailed data on the location choice and the property tax records allows us to estimate the migration elasticity with respect to the property tax bill. In this setting we instrument the change in the property tax amount by a novel instrument that uses the differential re-valuation in different segments of the property market. We find that for a 10% increase in the property tax amount the migration propensity increases by about 1.5%. Concretely, a city of 100,000 people would lose about 1,500 people.

Related literature: The paper connects to three main strands of the literature. The first strand of literature studies the implications of a fiscal shocks on cities. Myers (2017) argues that cities in California engage in a gambling for resurrection if faced with a large debt burden. Clemens and Veuger (2021) and Green and Loualiche (2020) examine the employment response of state and local government to the fiscal shock and federal relief package in the context of COVID-19. Anzia (2019) shows that increasing pension contributions negatively affect public employment while the study finds no effect on own source revenue. Shoag, Tuttle, and Veuger (2019) focuses on the decline in sales tax revenues after the bankruptcy of big-box retailers. Further James Spiotto made seminal contribution in the study of municipal bankruptcies (Spiotto, 2012b,a). This paper contributes to this literature by causally estimating the fiscal response and migration response to a decline in the tax basis which constitutes a quantitatively large fiscal shock.

The paper also contributes to the literature on optimal location choice, e.g. Qian and Tan (2020), Diamond, McQuade, and Qian (2019), Brueckner and Neumark (2014), Almagro and Domınguez-Iino (2019). We add to this literature by exploring variation in taxation power that originates from the heterogeneity in moving costs across cities. This wedge hinders free migration of residents, which is shown to have substantial welfare costs in Albouy, Behrens, Robert-Nicoud, and Seegert (2019) when local governments control city size. The documentation of the migration pattern and migration elasticity adds to the literature on taxation and migration, as surveyed by Kleven, Landais, Munoz, and Stantcheva (2020). There are two main differences relative to the previous literature. First, we focus on a change in the property tax rates while previous studies were primarily concerned with income tax rates. Second, we are able to estimate average migration response for all individuals whereas previous literature has often focused on subpopulations (Kleven, Saez, Schultz, and Council, 2011; Kleven, Landais, and Saez, 2013; Akcigit, Baslandze, and Stantcheva, 2016).

Lastly, we contribute to the literature on the consequences of the distribution of aggregate shocks between local governments and residents. Hayashi (2020) and Hayashi and Jurow Kleiman (2020) document substantial dead-weight loss in the form of personal bankruptcy and foreclosure when local governments pass the entire fiscal shock onto their residents. Similarly, Wong (2020) finds increased mortgage delinquency and reduced auto consumption as a result of an increase in property taxes. Instead of focusing on households' balance sheets and consumption response we document the migration response. We connect municipality-wide re-assessment decisions to migration outcomes that have important implications for the long-term fiscal sustainability of local governments.

We proceed as follows: Section 2 details the data sources and the data construction. Section 3 contextualizes the financial position of local governments in Connecticut with the financial conditions of municipalities across the United States. Section 4 describes the research design. Section 5 presents and interprets the first set of empirical results and Section 6 provides additional evidence on the migration response. Section 7 concludes.

2 Data

We compile administrative data on the fiscal position of municipalities in Connecticut, including the tax base, property tax rate and additional information from their annual comprehensive financial reports (ACFRs). In addition, we construct a rich panel on about 10 million individuals to study the migration response to a fiscal shock. We summarize the main components of our data here and provide further details in the Data Appendix.

2.1 Data and Sample Selection

Municipal Finance Data Data at the level of individual municipalities is scarce in the United States. While municipalities are legally required to file annual comprehensive financial reports (ACFRs), the publication is irregular at best. We overcome the data scarcity by drawing on administrative data for the state of Connecticut. The state of Connecticut maintains relatively strong financial oversight over its municipalities and as part of this, the Connecticut's Office of Policy Management (OPM) collects and digitizes individually published annual comprehensive financial reports of each municipality and holds the records in a centralized repository. In addition, the OPM publishes detailed information about property tax rates, grand list by property type (assessment value by property type), and the reassessment schedule. Summary statistics for Connecticut is tabulated in Table A.2.

Additional Administrative Records from Connecticut We further obtain administrative data on public and private employment by municipality from Connecticut's Department of labor. We complement this data with demographic characteristics from the decennial population census.

Municipal Bond Data We complement the data set on balance sheet conditions of local governments with municipal bond yields in the primary and secondary market. Primary market information are obtained from Mergent Municipal Bond Database which records issuer characteristics and a large set of bond characteristics. In addition, we obtain secondary market data from MSRB EMMA. MSRB EMMA is a trade repository which records every trade in municipal bond securities since 2005. MSRB EMMA includes the trade time, trade price and implied yield to maturity, as well as, information whether it was a broker to customer trade or broker to broker trade. We only include broker to customer trades in our analysis.

One challenge is to establish the connection between the bond issuance and the bond issuer. While Mergent Bond Database records the issuer name, the match to the financial information of the issuing entity is not straightforward. We draw as much as possible on Moody's historical linkage table. This table is created as part of Moody's ratings activity and documents in great detail whether a local government is the direct issuer or the financial obligor for an issuance. For the remainder, we conduct a careful name matching between the municipal issuers and the townships in Connecticut.

Sample of Individuals The micro-data on migration comes from Infutor. Infutor contains the precise street address, the time frame over which an individual lived at a location, the name of the individual, and information on age and gender. We obtain the address history of residents that resided in Connecticut at some point in time between 1980-2019. Importantly, the data also contains addresses outside of the state of Connecticut which allows us to identify re-locations of individuals from Connecticut to other states in the United States and vice versa.

We examine the data representativeness of the Infutor data by geocoding 23 million addresses and linking it to the county subdivision—a geographically defined area by the Census that corresponds to the townships in Connecticut. We compare the Infutor implied population in 2010 with the corresponding population in the decennial Census.[2] In Figure 1 we find that for every individual in the Census Infutor counts 0.97 individuals. In addition we find that Infutor captures the statistical properties of the Census population count well as indicated by an R-squared of 0.981.

Matched Infutor-CoreLogic Panel We assign a property record for each address in the Infutor data by merging it with the CoreLogic deeds and tax record. The full matching algorithm is described in Section DA.7.1 of the Data Appendix.

[2]Infutor follows only adults 18 years old or above. Hence, we compare it to the corresponding population in the Census.

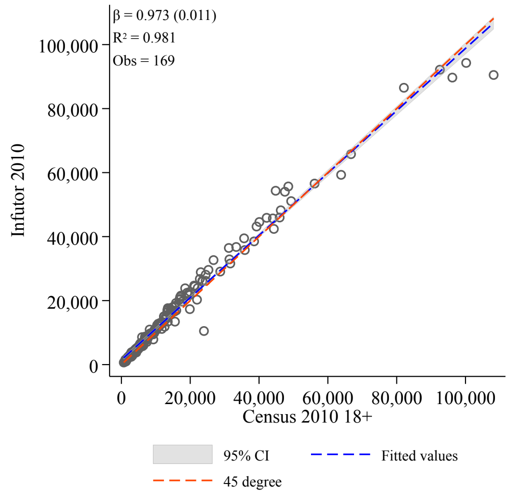


Figure 1 – Infutor Benchmarking

Notes: The Figure plots the population for each of the 169 townships in Connecticut. The x-axis shows the population count of residents at age 18 or above from the decennial Census in 2010 and the y-axis shows the population count from Infutor after assigning each address record to a township.

Race Imputation We use the software library *ethnicolor* to predict race and ethnicity from the first and last name. Ethnicolor is a large neural network trained on Census data, voter registration data, and Wikipedia data. After obtaining the prediction based on names, we calculate the posterior probability of race and ethnicity taking into account the Census tract in which an individual is living following Diamond, McQuade, and Qian (2019).

3 Financial Conditions Across Municipalities in Connecticut

Giesecke, Mateen, and Sena (2022) shows that a sizable share of local governments operate with a negative equity position—whether measured in terms of book or market values. In the following, we show that Connecticut follows the trajectory of the national sample. Further we show that the status-quo of the cross-sectional distribution of financial conditions mirrors those of the national sample. We provide a short introduction to the accounting and the financial indicators of local governments in Section 3.1. Section 3.2 documents the secular development and its association with market based measures for the universe of townships in Connecticut.

3.1 Institutional Background

Accounts and Accounting Local governments manage their finances typically based on funds. Most important is the general fund that covers most of the operational expenditures; other funds—such as, the capital project, debt service, internal service, and enterprise fund—often exist and take on a more specialized role. Every state except for Vermont imposes a statutory or constitutional balanced budget provision on the general fund (NCSL, 2010).[3]

The accounting basis for these funds is *fund accounting* or *modified accrual accounting*. Fund accounting emphasizes cash-flows over solvency and resembles the cash flow statement rather than the profit and loss statement or balance sheet in the corporate context. While the accounts are the primary basis for decision making, local governments are required to publish the statement of net position in their annual comprehensive financial report ("ACFR"). The methodology for the statement of net positions is closer to conventional accrual accounting. The statement of net positions represents assets and liabilities more comprehensively. However, the funds receive most of the attention in the administrative decision-making process. In principle, this hybrid accounting framework allows for large deficits on an accrual basis, i.e. in the ACFRs, as long as it does not materially affect the (cash) balance in the general fund. Pension and other post employment bene-

[3]The balanced budget provision applies with varying degree of stringency as e.g. discussed in Bohn and Inman (1996) and Poterba (1995).

fit commitments are two examples for which the expenditures and the cash flow impact occurs with a large time gap.[4] Thus, the difference between operating expenses and the accrued liability can be large.

Financial Indicators We use two main financial indicators to describe the development of financial conditions. First, the unrestricted net position as a percentage of operating revenues and second the total debt as percentage of the equalized grand list.[5] The unrestricted net position is directly reported in the statement of net position of the ACFR and is an important input into the credit rating.[6] The unrestricted net position consists of three major parts: (i) long-term debt that is not directly associated with capital assets, (ii) pension obligations, and (iii) other post employment benefits ("OPEB"). The portion of long-term debt that is not directly associated with capital assets can be understood as debt that has been issued to fund operating expenses. The use of the unrestricted net position derives its justification under the premise that most of the capital assets are highly illiquid and thus cannot be used to serve the liabilities. It excludes the fraction of liabilities that are directly associated with the capital assets—revenue bonds to fund capital projects is one such example. Further, the unrestricted net position is calculated under an accounting framework that is closer to accrual accounting, that is, the expenditures are accounted for at the time of accrual, not at the time of the cash outflow. The total debt as percentage of the equalized grand list captures the indebtedness relative to the maximum amount of all taxable properties and is another prominent input into the rating of municipal securities.

3.2 Financial Conditions in Connecticut

Connecticut provides a unique opportunity to study the universe of local governments as the state exerts some fiscal oversight. As part of this oversight, the Office of Policy

[4]For a detailed discussion about the actuarial recognition of pension liabilities see e.g. Novy-Marx and Rauh (2011). There is an active debate in the academic literature to what extent the actuarial treatment reflect the economic liability (Brown and Wilcox, 2009).

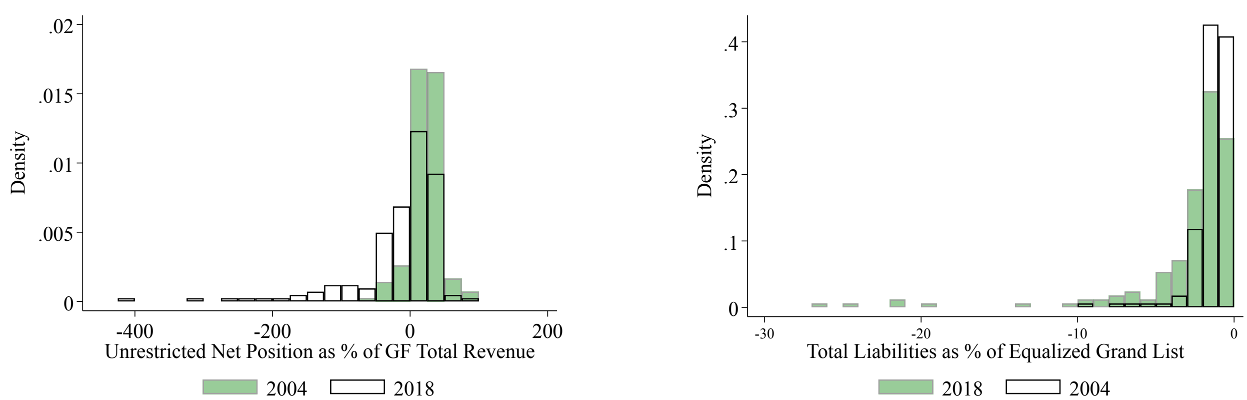
[5]The equalized grand list represents the market value of all taxable properties in a jurisdiction. In comparison to the grand list–the tax basis–it takes the market value of property and thus is unaffected by the methodology that determines the assessment value.

[6]We obtained this information from a conversation with the public finance credit analyst from a major rating agency. Apart from this, the independent think tank "Truth in Accounting" emphasizes the relevance of the unrestricted net position to assess the financial situation of local governments.

Management (OPM) collects the annual comprehensive financial reports (ACFRs). Rather than focusing on a sample we are able to see the whole distribution of financial conditions which includes local governments of various sizes.

The status quo and the trends of the fiscal position resembles broadly the one that we have seen at the national level as described and discussed in Giesecke, Mateen, and Sena (2022). Figure 2 shows an analogous deterioration of the unrestricted net position over total revenues and of total liabilities over the equalized grand list for the time horizon 2004-2018.

Concretely, between 2004—the first year of our data—and 2018 the median unrestricted net position over total expenditures declined from 21.90% to 4.49%. More pronounced is the deterioration at the left tail of the distribution. The 5% percentile shifts from -15.56% to -133.20%. A similar picture about the financial condition also emerges from the total liabilities over the equalized grand list indicator. The median shifts from -1.16% to -1.73% and the 5% percentile shifts from -2.98% to -9.34% between 2004 and 2018. Similar to the results in the nationwide sample of Giesecke, Mateen, and Sena (2022), a substantial share of townships in Connecticut operate with a negative equity position. Out of the 169 townships, 75 (44.4%) report a negative unrestricted net position and 15 (8.9%) report a negative net position in 2018.



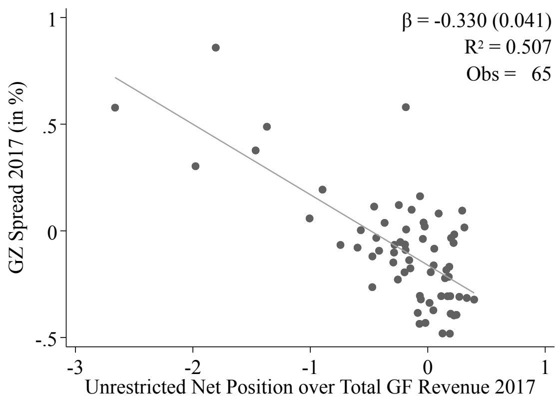
(a) Unrestricted Net Position

(b) Debt / EGL Share

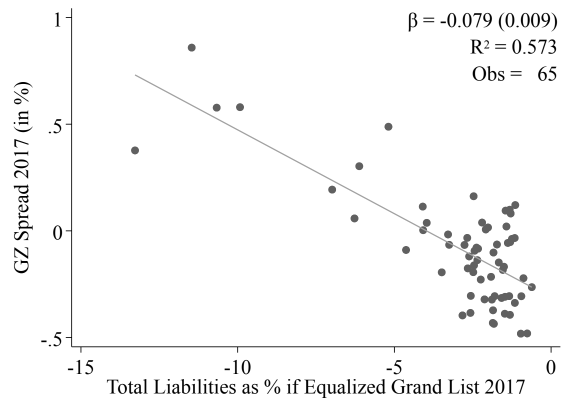
Figure 2 – Financial Conditions Indicators

Notes: Panel (a) shows the unrestricted net position as a share of the the general fund total revenue in 2004 (transparent) and 2018 (green). Panel (b) plots the negative total liabilities (total bonded debt + unfunded OPEB liabilities + unfunded pension liabilities) over the Equalized Grand List (EGL). Data is obtained from the Connecticut's Office for Policy Management.

The cross-sectional variation in the financial indicators is also reflected in the municipal bond yields as shown in Figure 3. We find a tight relationship between the financial indicators and the yield spread as manifested by an R^2 of 50.70% and 57.30% for the unrestricted net position over total revenue and the total debt over equalized grand list, respectively. The tight relationship suggests that other jurisdictional differences are muted in this within state analysis. The cross-sectional variation could in principle reflect relative differences in default risk and/or liquidity risk. Schwert (2017) argues that default risk accounts for 74% to 84% of the average yield spread after adjusting for the tax-exempt status. Thus, we interpret the cross-sectional variation of yields to reflect the difference in default risk rather than a compensation of liquidity risk.



(a) GZ Spread - Unrestricted Net Position



(b) GZ Spread - EGL Share

Figure 3 – Primary Market Bond Spreads

Notes: Panel (a) plots the relationship between the GZ Spread (Gilchrist and Zakrajšek, 2012) for issuances with initial maturity between 5 and 10 years and the unrestricted net position. Panel (b) plots the relationship between the GZ Spread for issuances with maturity between 5 and 10 years and the total liability (total bonded debt + unfunded OPEB liabilities + unfunded pension liabilities) over the Equalized Grand List (EGL). Data is obtained from the Connecticut's Office for Policy Management and primary bond issuance data is from Mergent Municipal Bond Database. The sample contains all townships with bond issuances in fiscal year 2017. Data for 2017 is shown because of data limitations; updates to come.

Connecticut provides an additional unique feature that differentiates its possibility for analysis. The OPM keeps a record of the mill rate, that is, the property tax rate for all of Connecticut's municipalities. This allows us to tabulate the relationship between the financial condition and the level of property taxes as shown in Figure 4. We find a strong negative relationship between the level of property taxes and the fiscal health which indicates that the property tax rate is potentially seen as a viable tool to generate

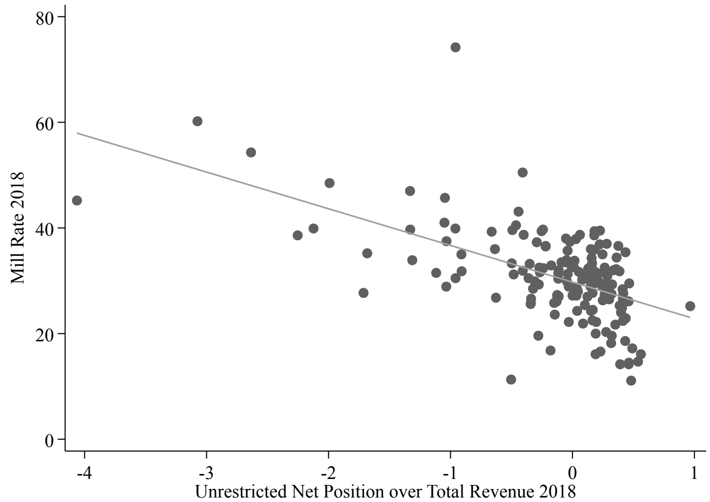


Figure 4 – Fiscal Position and Property Tax Rate

Notes: The figure shows the scatter-plot of the mill rate (property tax rate) and the unrestricted net position over total revenues in 2018. The sample includes the universe of 169 townships in Connecticut and the data come from Connecticut's Office for Policy Management.

additional revenues. Another take-away is that municipalities with weak fiscal health have—on average—already high property tax rates which gives them less room to adjust in the presence of an additional fiscal shock. We will come back to this point in the analysis below.

4 Research Design

The state of Connecticut provides a unique institutional setting that allows for the estimation of causal effects in response to a fiscal shock. We first introduce the law that governs the re-assessment of property and discuss how it translate into our research design.

Property Re-assessment in Connecticut Connecticut's public law stipulates that municipalities have to re-assess all property every *five years* (CT General Statutes, Chapter 203, Sec. 12-62). At the point of re-assessment the assessment value is set at 70% of properties' estimated fair market value.

The re-assessment schedule is centrally determined by the Office of Policy Managements and follows a constant pattern. As a result, about one fifth of all municipalities are due for re-assessment each year. The number of municipalities by re-assessment year after 2010 is tabulated in Table A.1.[7] The timing of the re-assessment is thus exogenous to the municipality. It might still be possible that municipalities across each of the re-assessment years differ from each other in observable and un-observable characteristics which constitutes a potential threat to our research design.[8] We conduct a formal test for covariate balance for a set of observable characteristics. Table 1 reports the results. We cannot reject the null hypothesis for the equality in means at a confidence level of 5% for unemployment and 10% for all other listed covariates. While we cannot exclude the possibility of selection on un-observable characteristics, the balance across observable covariates makes selection on un-observable less likely (Altonji, Elder, and Taber, 2005).

In addition, we check visually for spatial clustering of re-assessment across Connecticut. Figure **??** plots maps about the temporal and spatial pattern of re-assessments post 2010. There is no obviously recognizable pattern which indicates that spatial clustering is less of a concern.

Research Design The staggered re-assessment provides exogenous variation in the timing of realization of changes in market value of real property. In addition, the year of re-assessment determines in which phase of the housing price bust the municipality reset

[7]We find that one township in Connecticut re-assessed after 6 years. This deviation is extremely rare and we found no evidence of systematic deviations. We exclude this unusual observation in our main analysis.

[8]Our inquiry with the Office for Policy Management about the origin of the initial ordering did not lead to any conclusive answer.

	Vintage						F-test
	2011	2012	2013	2014	2015	std.dev.	p-value
Mean Pop. Census	17,814.41	22,565.45	23,973.02	24,701.24	16,195.20	25,324.99	0.49
Mean Median Income	81,670.59	86,456.95	76,930.06	79,859.82	86,003.02	25,682.94	0.44
Mean Share Pop 65+ (%)	15.13	14.83	14.65	15.53	15.67	3.61	0.66
Mean Share Black (%)	5.99	3.00	4.23	3.01	3.62	7.39	0.68
Mean Share College (%)	37.67	39.27	33.90	37.88	41.08	14.39	0.20
Mean Share Hispanic (%)	4.63	4.96	6.86	7.64	5.32	7.55	0.46
Mean Unr. Net as Oper. Rev. (%)	14.32	11.72	12.78	18.07	19.15	22.30	0.56
Unemployment Rate (%)	8.68	7.74	8.79	8.50	7.89	1.80	0.06

Table 1 – Covariate Balance

Notes: Vintage 2011-2016 refers to the fiscal year in which the re-assessment of real property becomes effective. The values in the table represents the mean of the listed covariate. The column std.dev. shows the standard deviation of the covariate across all vintages. The last column tabulates the p-value for a F-test of the equality in means.

the valuation. Hence, not only is the timing of the realization quasi-exogenous but also the treatment intensity. Figure 5 visualizes the main idea by plotting the average realization of the assessment value by cohort of re-assessment. Townships that re-valued in fiscal year 2011 (grand list year 2009) saw little change in the assessment value as the re-evaluation coincided with the early phase in the housing market crash. Starting with the 2012 cohort, assessment were consistently adjusted downwards. The trough was reached with the 2014 cohort, which saw an average downward assessment of -16.1%.[9] Some township in the 2014 experienced significantly larger downward adjustments, with the largest being -30.4%. One remaining concern is that the development in assessment value anticipates the municipalities policy response which introduces an endogeneity problem. Thus, we use the change in national house prices excluding Connecticut as an instrument for treatment intensity.[10]

For the examination of the fiscal response of townships to the bust in the housing market we estimate specifications of the following form:

$$lny_{it} = \delta_t + \delta_i + \delta_{s'} + \sum_{s \in S \setminus 0} \gamma_s \times \Delta lnHPI^{National}_{s=0,s=-5} \times \mathcal{I}_s + \epsilon_{it} \tag{1}$$

where i indexes the municipality and t the year. We include year fixed effects, δ_t, munici-

[9] For the number of townships in each cohort confer Table A.1.

[10] Since re-assessment occurs every five years, we use the change in the national house prices that excludes Connecticut since the last re-assessment, that is, over a five year period.

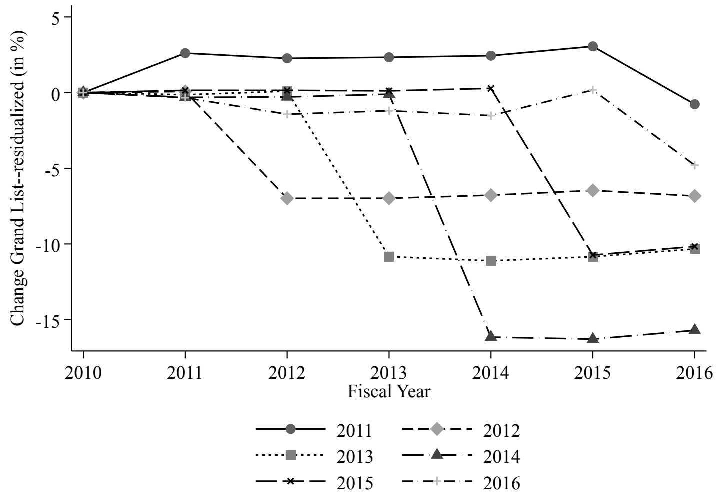


Figure 5 – Assessment Value by Cohort

Notes: The figure shows development of the relative assessment value with respect to the base year 2010 for a group of municipalities that reset in the corresponding year after accounting for the overall deterministic time trend. The sample includes the universe of 169 townships in Connecticut and the data come from Connecticut's Office for Policy Management.

pal fixed effects, δ_i, and event time fixed effects $\delta_{s'}$. $\Delta lnHPI^{National}_{s=0,s=-5}$ measures the change in the national house prices excluding Connecticut between event time 0 and the last reassessment. $\mathcal{I}_s$ is an indicator for event time s with $s \in S\backslash 0$. The coefficients of interest are $\{\gamma_s\}_{s \in S\backslash 0}$.

In the next step we are interested how residents respond to the change in the tax rate. One of the difficulties is that residents may not respond to the treatment contemporaneously. Hence, we have to estimate a specification that can capture a delayed response. We do so by estimating the response to the initial change in the tax rate.[11] We estimate specifications of the following form:

$$lnPop_{it} = \delta_t + \delta_i + \delta_{s'} + \sum_{s \in S\backslash 0} \gamma_s \times \Delta ln\widehat{MillRate}_{s=1,s=0} \times \mathcal{I}_s + \epsilon_{it} \tag{2}$$

$$\Delta lnMillRate_{s=1,s=0} = \delta_t + \delta_i + \delta_{s'} + \sum_{s \in S\backslash 0} \psi_s \times \Delta lnHPI^{National}_{s=0,s=-5} \times \mathcal{I}_s + u_{it} \tag{3}$$

where i indexes the municipality and t the year. We include year fixed effects, δ_t,

[11] We find that after the initial change in the tax rate after the fiscal shock the tax rate is persistent.

municipal fixed effects, δ_i, and event time fixed effects $\delta_{s'}$. $\Delta lnHPI^{National}_{s=0,s=-5}$ measures the change in the national house prices excluding Connecticut between event time 0 and the last re-assessment. $\Delta lnMillRate_{s=1,s=0}$ measures the change in the mill rate (tax rate) between event time zero and one. $\mathcal{I}_s$ is an indicator for event time s with $s \in S\backslash 0$. The coefficients of interest are $\{\gamma_s\}_{s\in S\backslash 0}$.

Event time It is important to note that there is a time gap between re-assessment year—sometimes called the grand list year—and the fiscal year in which the fiscal impact of the re-assessment is realized. Let us consider the following example. Suppose the grand list year is 2009. The re-assessment would then typically be conducted in the fall of 2009. The notice about the new assessment value and the corresponding tax amount is sent out in spring 2010. The property tax is due in fall 2010—either in the form of a lump sum or in the form of installments. Thus, the realization of the fiscal consequences of the re-assessment falls into the fiscal year 2010/2011.[12] In the paper the fiscal year 2010/2011 is referred to as 2011. For the estimation of the fiscal impact 2011 is taken to be the first year after treatment. For the migratory response calendar year 2010 is used as the first year after treatment as notices about the new assessment and tax amount are disseminated.

[12]The fiscal year for municipalities in Connecticut starts on July 1 and ends June 30 of the following year.

5 Empirical Results

How do local governments respond if they face a large fiscal shock? The state of Connecticut with its unique institutional characteristic allows us to causally estimate the response of local governments and the response of residents. We first discuss the fiscal response in Section 5.1 before we discuss the migration response of residents in Section 5.2.

5.1 Fiscal Response

When prices in the national housing market started to decline post 2006, it had profound spillovers into Connecticut's housing market.[13] Municipalities had to adjust the assessment value to reflect the decline in the market value of real property according to the timing of the re-assessment schedule. The downward adjustment in the assessment value corresponds to an erosion in the tax base of municipalities. We use the timing and the magnitude of the first revaluation post Great Financial Crisis (GFC) to estimate the fiscal response.

In the first step of our research design, we estimate the pass-through of change in national real estate value on the assessment value. The assessment value is tied—by public law—to the change in the market value of real property. In principle, the change in the market value could reflect two components: (i) decline due to fundamentals as e.g. to the changing credit conditions post GFC, (ii) changes that reflects anticipated policy changes, e.g. changes in property taxes. We try to carefully separate these two components by instrumenting the change in assessment values by the decline in the national housing market since the last re-assessment

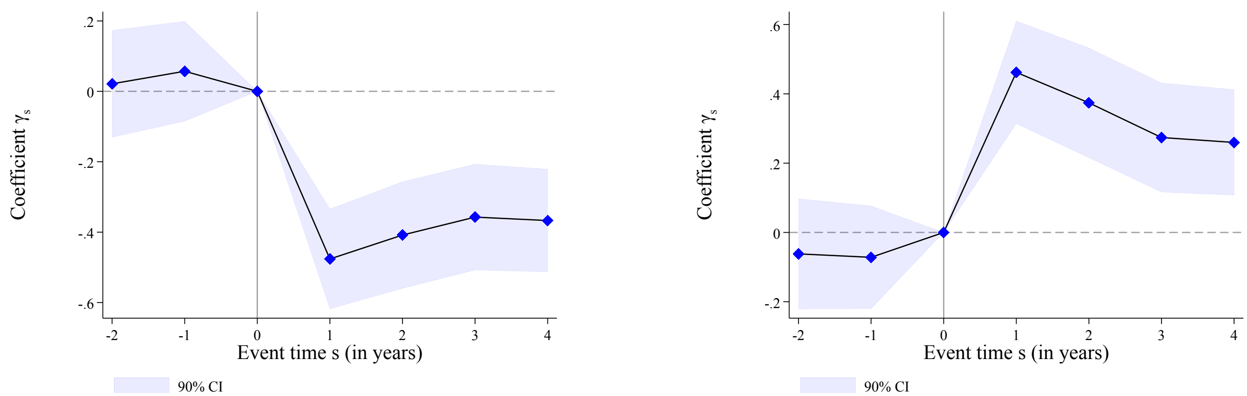
Figure 6a presents the coefficient of the pass-through from the national housing market to the tax base of townships in Connecticut. We find a large and statistically significant impact of -0.48 on the net grand list—in the first fiscal year.[14] Moreover, the effect is persistent which we expect since there are no major changes to the tax base until the next

[13] Vansteenkiste (2007), Malone (2017) document the importance of inter-regional spill-over in housing markets.

[14] If property prices in Connecticut followed the national house price trend, we would expect a coefficient of one. However, the assessment value is composed of a variety of asset classes, e.g. industrial, commercial and residential properties and land, which observed differential dynamics post GFC. Even within residential properties there was significant variation across property types, a fact that we use in the research design for the micro data.

re-assessment.[15]

The tax base is the reference point for taxation. In the absence of any adjustment, the decline in the tax base had translated one-to-one in a decline in tax revenues. Townships in Connecticut have significant discretion about the tax rate that they set. Hence, the first outcome of interest is to examine the tax rate response. The corresponding coefficient is displayed in 6b. We find a large and statistically significant tax rate increase. Interestingly, the tax rate increase is of similar magnitude as the coefficient on the tax base which means that the revenue impact is almost entirely offset. We confirm this intuition formally in a separate specification in Column (3) of Table A.4. Indeed, we find no statistically significant revenue impact for year one and year two after the re-assessment; only in year three we start seeing a small negative effect on overall tax revenues.



(a) Change Grand List

(b) Mill Rate Adjustment

Figure 6 – Fiscal Shock

Notes: Both panels display the coefficient estimates of specification (1). Panel (a) uses the log tax basis as the outcome. The sign of the coefficient is inverted for readability. Panel (b) used the log mill rate as the outcome. The sample includes the universe of 169 townships in Connecticut and the data on the fiscal position and the re-assessment schedule is obtained from Connecticut's Office of Policy Management.

We further study other adjustment margins. One of the conjectures is that municipalities issue additional long-term debt in response to a fiscal shock. Alternatively, the state government could provide additional intergovernmental revenues to absorb part of the fiscal shock. We test for both conjectures formally in column (4) and column (5) of Table A.4 and find no evidence of such.

[15]In principle, the tax basis can change between re-assessment years due to the addition of new properties. However, this does not affect the tax base in a material way.

Besides the adjustments on the revenue side, municipalities have the option to adjust expenditures. This often comes in form of changes to public employment or education expenditures. Connecticut with its rich data sources allows to test for this. Table A.5 reports the results on per pupil expenditures (education), average public employment (headcount), and average wages in public employment. While there is no differential changes in public employment and average wages, we found a quantitatively large but imprecisely estimated change in per pupil expenditures. In the first year after the downward assessment, per pupil expenditures fall on average by -5.2% as a result to the fiscal shock. Three years after, the effect increases to about -10.0%. This is a substantial decrease and not surprising since educational expenditures account for an average share of 68.3% (median of 68.6%) of general government expenditures.[16]

5.2 Migration Response

While local government mostly insulate themselves from the revenue impact of the erosion in the tax base, residents carry the full burden of the shock. As unemployment rises and income declines as a result of the Great Recession, the tax rate on the properties rises. Hayashi (2020) and Wong (2020) show that the pass-through of economic shocks onto residents can impose a significant financial burden. Residents may instead chose to reduce housing cost by choosing cheaper location by trading-off other amenities; such as, social capital and educational opportunities (Bilal and Rossi-Hansberg, 2018).

We explore the migration response as a consequence of the property tax increases in the following. After documenting the net migration response we use the granularity of our micro-data to document the different margins of migration and the heterogeneity in the migration response which we later connect to the heterogeneous moving costs in Section **??**.

Net Migration Response We estimate specification (2) and (3) based on aggregated data at the township level, that is, we create a longitudinal dataset at the township-year level. The first outcome variable is total population; hence, we estimate the effect on net migration. Figure 7 shows the estimates visually. After three years, we find a statistically

[16]For a breakdown of the main expenditure and revenue categories among the 169 townships in Connecticut see Table A.3.

significant decline in total population. To put the magnitude into context: the average avg. tax rate increase of 12.3% led to a decrease in the population by 0.35%—or about 2.5 standard deviations change in population—at a five year horizon—a sizable response.

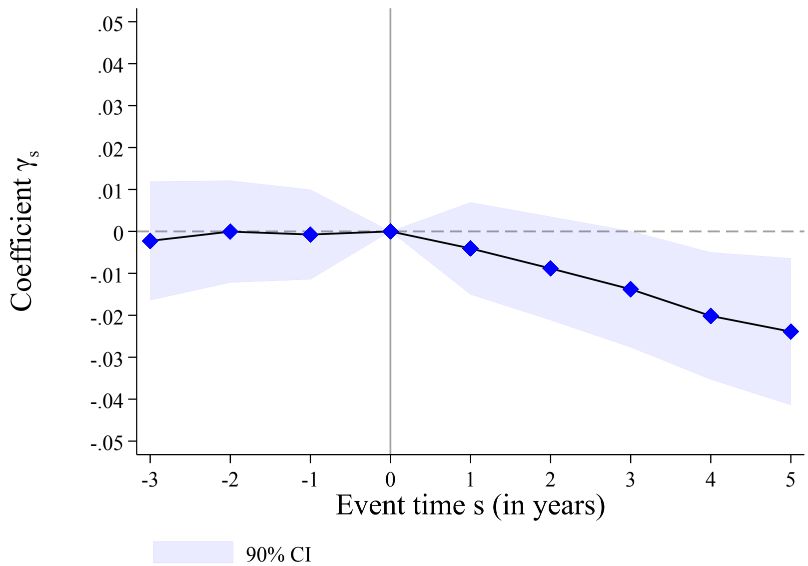
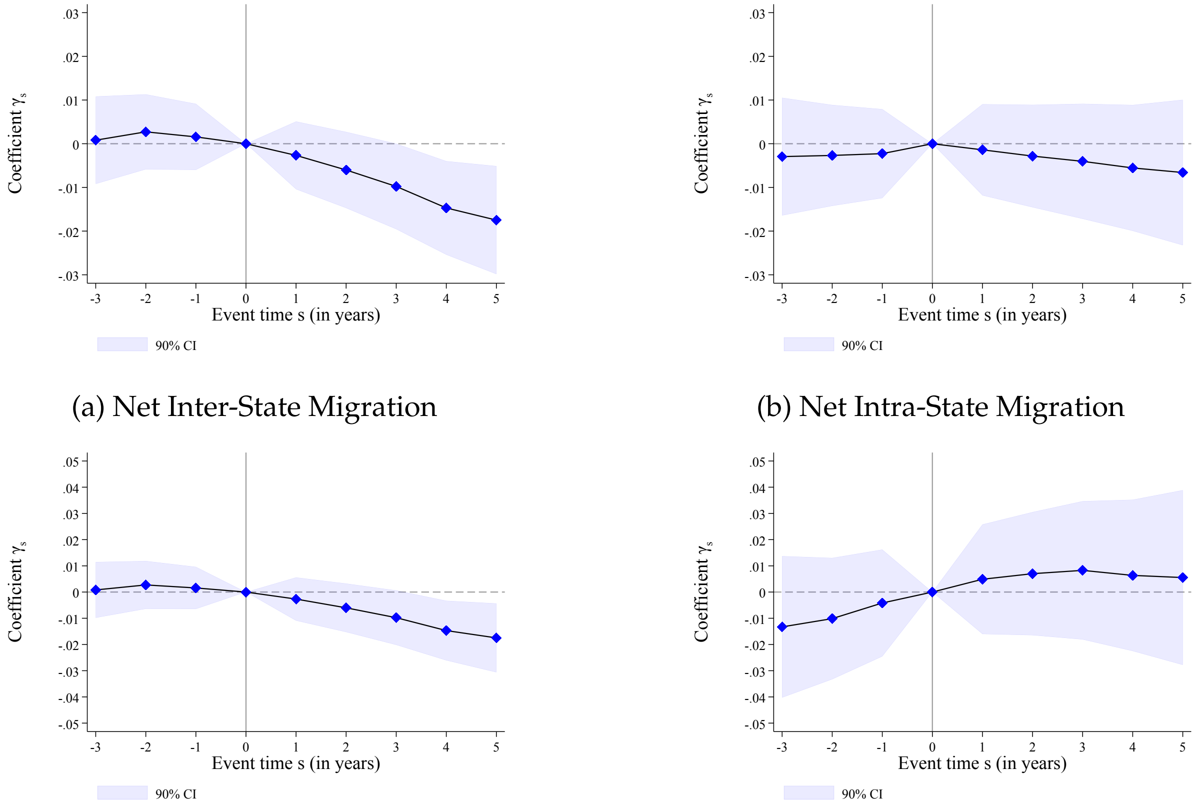


Figure 7 – Net Migration

Notes: The figure plots the estimates of specification (2) and (3) with total population as the outcome variable. Blue shaded area corresponds to the confidence interval at the 90% significance level. Numerical estimates are tabulated in Table A.6, Column (1).

Migration Margins The net migration response is the most policy-relevant margin for the assessment of fiscal sustainability as the market value in the housing market—and hence the tax basis—is driven by the demand and supply of housing units. To better understand the migration dynamics, we investigate net inter-state vs. net intra-state and out-migration vs. in-migration margins separately.

Figure 8a displays the statistically significant response of inter-state migration. In contrast, we do not find statistically significant net migration within the state of Connecticut as shown in 8b. This is not surprising given that townships in Connecticut are exposed to a similar trend in real estate prices; even though the precise timing differs across townships. We further show that the point estimates point towards migration that is driven predominantly by a change in outflows as shown in Figure 8c rather than a change in inflows as presented in Figure 8d. Tables A.6, Columns (2)-(4) tabulate the numerical estimates.



(a) Net Inter-State Migration

(b) Net Intra-State Migration

(c) Gross Out-Migration

(d) Gross In-Migration

Figure 8 – Migration Breakdown

Notes: The figures plots the estimates of specification (2) and (3). Panel (a) uses net-interstate migration as the outcome variable. Panel (b) uses net-intrastate migration as the outcome variable. Panel (c) uses gross out-migration as the outcome variable. Panel (d) uses gross in-migration as the outcome variable. Blue shaded area corresponds to the confidence interval at the 90% significance level. Numerical estimates are tabulated in Table A.6, Column (2)-(4).

Migration Response Heterogeneity We further document the the migration heterogeneity along some important dimension, that is, age and tenure. The observed heterogeneity in migration propensity is important to assess the fiscal sustainability of local governments; the migration propensity ultimately determines the taxing power that local governments have over its jurisdictions.

Along the age dimension we observe the largest propensity to migrate in the prime age—that is adults between 30 and 59 years of age. A lower migration intensity is observed for the age category of 60 and above. Figure A.2 displays the estimates visually and Table A.8 tabulates the estimates.

We take tenure—the number of years at a specific location—as a proxy for the social capital that a person has accumulated at a location. We estimate the net-migration elasticity and display the estimates in Figure A.3. Interestingly, the migration elasticity between tenure bins $[0, 4)$ and $[4, 10)$ shows no substantial difference. We do observe, however, a much lower migration propensity for people with tenure of 10 years and above. Table A.8 tabulates the numerical estimates.

Consequences of Migration In the following we provide suggestive evidence about the consequences of the net population decline.

The net out-migration of people decreases the demand for housing units, however, the housing supply—at least, in the intermediate term—is relatively stable. While we do not expect necessarily a large amount of vacancies, we may expect a cooling in the housing market and a corresponding decline in the market value of properties.

Figure 9 shows the drop in the house prices for single family residential. Interestingly, the decline becomes more pronounced in year two and three which is consistent with the lag that we observe in the migration pattern. It is important to note that this decline is independent of the decline in the national house price market and the decline due to the policy change as this precedes the event timing. This provides suggestive evidence that the net out-migration led to a under-performance in property values—and hence, a further weakening of the tax base.[17] The numerical estimates are tabulated in Table A.9, Column (1). Column (2) shows robustness to the use of the all-home house price index.

Robustness of Migration Estimates We show robustness of the net migration result by using the zip code level data from the Statistics of Income (SOI) from the Internal Revenue Service.[18] First, we match the zip-code into Census tabulated areas (ZCTA). Second, we use the geo correspondence engine which is available at the Missouri Census Data Center https://mcdc.missouri.edu/applications/geocorr.html to match the ZCTA to county

[17]We observe a relatively weak recovery of Connecticut's house prices in comparison to its neighboring states, that is, New York, Rhode Island, and Massachusetts, which corroborates this interpretation

[18]Zip code level data from the Statistics of Income (SOI) is publicly available at: https://www.irs.gov/statistics/ soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi

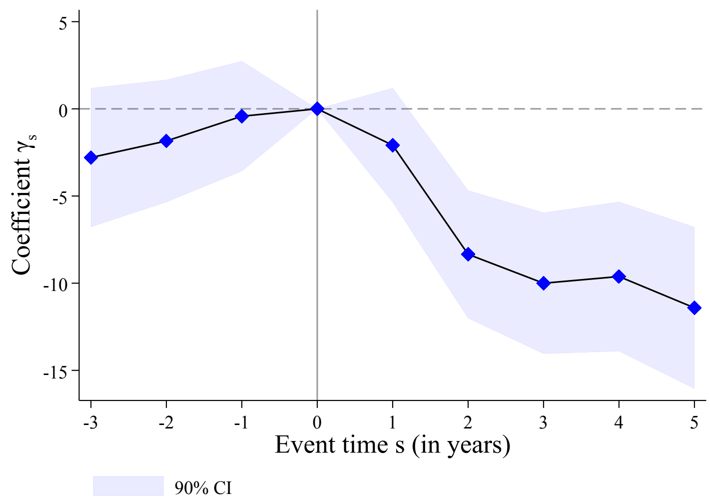


Figure 9 – Single Family Residential HPI

Notes: The figures plots the estimates of specification (2) and (3) with the median house price of single family resident gross as the outcome variable. The sample includes the the 169 townships in Connecticut and the data come from Connecticut's Office of Policy Management and Zillow. Numerical estimates are tabulated in Table A.9

subdivision which correspond to the legal boundaries of townships in Connecticut. In accordance with many population estimates, we use the number of dependents on the tax filing as a proxy for the residential population in a municipality. We acknowledge that this is only a coarse approximation of the residential population. Further we acknowledge that the described geo-merging is not flawless. For instance, a zipcode does not always have a corresponding ZCTA and ZCTAs often have to be allocated to multiple townships based on the relative area. Table A.10 presents the estimates. Despite these challenges we find migration elasticity estimates that are comparable in magnitude to those presented above. The estimates, however, are less precisely estimated which is not surprising given that the number of dependents in the tax data is only a coarse proxy of population and the imperfect matching heuristic that we employ.

6 Micro Evidence of Migration Response

We provide further micro-evidence on the migration response by examining the change in tax amount on individual properties. In Section 5 we show that municipalities stabilize the tax revenue at the aggregate level by adjusting the tax rate. The stabilization at the the municipal level leaves substantial variation at the property level. First, the tax base at the municipal level includes industrial and commercial properties, as well as, land. Second, it is well document that there is substantial variation in the assessment of individual property (Berry, 2021; Amornsiripanitch, 2020; Avenancio-León and Howard, 2019). As a result, the stabilization of total tax revenue does not imply a stable property tax bill for individual properties. In the following, we estimate the migration response using the detailed micro data from the merged CoreLogic-Infutor panel.

For the estimation, we cannot rely on the change in the property tax amount since this is itself a function of future house prices which introduces an endogeneity problem. Thus, similar to the previous research design, we use the development in the national house prices since the last re-assessment to instrument for the change in the re-assessment value. Specifically, we use the development in the national house prices for the specific property category to which a property belongs. After the Great Financial Crisis, various property categories experienced differential price paths; we use this variation and the insight from the estimates in Section 5 to instrument for the change in the property tax amount.

We create property categories in a data driven way by relying various house and lot attributes using a k-means clustering algorithm.[19] The clusters are based on characteristics such as number of bedrooms, number of bathrooms, building area, building age, assessed amount and most recent tax amount paid. Importantly, these clusters are defined *across* cities, not within cities. Each of the individual dimensions of the clusters are standardized and equi-weighted in the k-means algorithm. The standardized cluster means are reported in Figure A.13. The number of clusters is determined by the "elbow" method. Figure 10 shows the outcome of the clustering for the township of Waterbury with a total of 7 clusters.

[19]This approach is similar to Song (2021) which uses a clustering approach to obtain a nation-wide sample on minimum lot restrictions and finds that it proxies actual minimum lot restrictions in a validation dataset well.

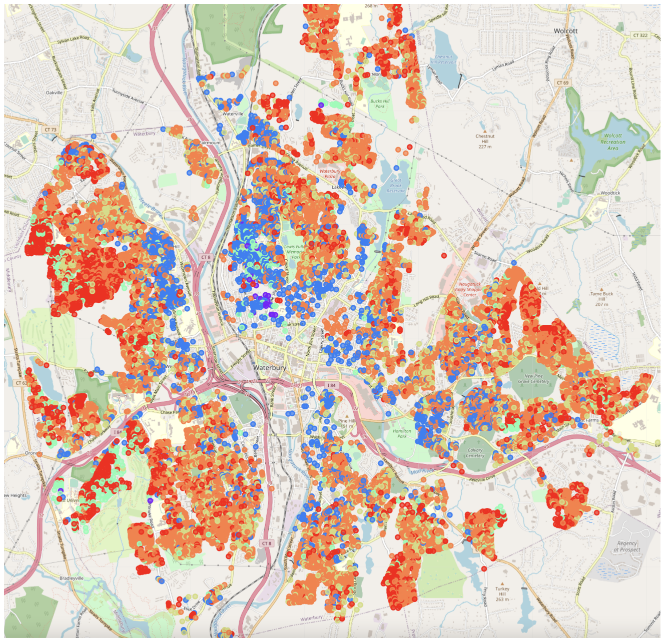


Figure 10 – Example - Clustering in Waterbury

Notes: The figures shows the clustering for the example of Waterbury, CT. Each color represents a cluster of property. The clusters are obtained from a k-means algorithm.

We then create price indices for each cluster. The price index is derived using a repeat sales price method with smoothing. Therefore, the main condition on the validity of our index is that the quality of housing remains roughly constant over time. The representativeness of the repeat sales should not be a problem since we have a large number of observations. The repeat sales index follows Case and Shiller (1987) in weighting observations inversely based on the duration between repeat home sales. The evolution of price indices by cluster and the overall price index through this method is shown in Figure A.4.[20] The price index, $I^{c(i)}$ for a house i in cluster $c(i)$ serves as an instrument for the change in the property tax after appropriate normalization. Appendix B.7.1 provides a formal derivation of the instrument. Concretely, the first stage is given by:

$$dln\text{PropertyTaxAmount}_{i,t+1} = \delta_{c(i)\times t} + \delta_l + \beta \left(dlnI^{c(i)}_{t+1} - ln\left(\sum_{c\in C} \frac{I^{c(i)}_{t+1}}{I^{c(i)}_{t}} \hat{s}^c_{lt} \right) \right) + X_i + \eta_{i,t,t+1} \tag{4}$$

[20]Figure A.5 compares a monthly version of our index with Zillow's house price index for the state of Connecticut. Despite different methodologies our index tracks Zillow's index very well.

where i indexes an individual's property and $I_{t+1}^{c(i)}$ is the index value of cluster c to which the property belongs. $I_t^{c(i)}$ is the index value for properties in cluster c in the year of the prior re-assessment. s_{lt}^c is the relative share of assessment value for property cluster c in municipality l, δ_l is a municipal fixed effect and $\delta_{c(i)\times t}$ is a cluster $\times$ year fixed effect.

With the instrument at hand, we estimate the migration response in a linear probability model in the second stage:

$$\mathcal{I}_{it}^{MOVE} = \delta_{c(i)\times t} + \delta_l + \sum_{s\in S} \gamma_s \times \mathcal{I}_s \times \Delta ln\widehat{\text{PropertyTaxAmount}}_{i,s,s+1} + X_i + \epsilon_{it} \tag{5}$$

where $\mathcal{I}_{it}^{MOVE}$, is a dummy variable which takes the value of one once the first movement has been recorded, $\delta_{c(i)\times t}$ is a cluster $\times$ year fixed effect, δ_l is a municipal fixed effect and $\Delta ln\widehat{\text{PropertyTaxAmount}}_{i,s,s+1}$ is the predicted change in the property tax amount from the first stage. X_i captures additional control variables.

In contrast to the township level migration estimates, this specification uses the change

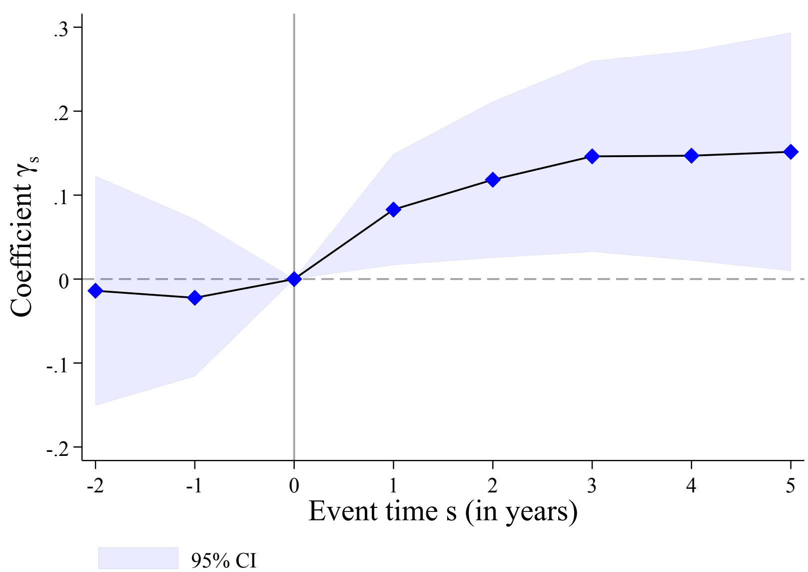


Figure 11 – Micro Migration Propensity

Notes: The figure plots the estimates of specification (5) and (4) with the indicator that indicates a move as the outcome variable. Blue shaded area corresponds to the confidence interval at the 95% significance level. Numerical estimates are tabulated in Table A.12. Standard errors are two-way clustered at the township and cluster level.

in the property tax amount. Thanks to an arcane assessment process and a revaluation of substantial magnitude post Great Financial Crisis, the induced variation is large. As municipals tried to stabilize their tax revenues as shown above, the individual property tax amount depends on the type of property, as well as, the fraction of other property classes and their price development in the township. The estimates of the first stage in Table A.11 confirm that the instrument in Equation (4) is relevant, as evidenced by a t-stat of 9.41.

The estimates of the second stage are plotted in Figure 11. All coefficients are estimated with respect to event time zero. The estimates for the two preceding years suggest no statistically significant different migration dynamics between people in properties that experience a positive or negative change in the property tax amount, which provides some re-assurance that migration dynamics do not differ in the absence of treatment. After treatment, the differential migration response slowly builds up between event time zero and three. The estimates reach a plateau at about 0.15. To put this magnitude into context, for a 10% increase in the property tax amount, we estimate an increased migration propensity of about 1.5%. Concretely, a city of 100,000 people would lose about 1,500 people.

7 Conclusion

Local governments are an important economic entity in the United States. Prior work by Giesecke, Mateen, and Sena (2022) shows that a sizable share of local governments operate with a negative equity position—whether measured in terms of book or market values—which suggests required fiscal adjustments unless the state and federal government provides fiscal support. What are the consequences of fiscal adjustments? This paper we utilize quasi-experimental variation in the year of property tax assessments in the state of Connecticut to estimate the consequences of a fiscal adjustment causally. The large decrease in national housing valuations post Great Financial Crisis constituted a large fiscal shocks to local governments. We find that municipalities in Connecticut insulate themselves by raising the property tax rate and only make marginal adjustments in public services. As the fiscal shock is passed onto residents, we estimate a sizeable and statistically significant effect on net migration. We further document that the net migration is primarily driven by inter-state migration—that is, migration across the state borders of Connecticut. Further, the net migration response results almost entirely from out-migration. Thus, offsetting the immediate fiscal shock with higher property taxes comes at a cost at longer horizons. While the municipal level analysis conflates many factors, we estimate the individual migration response to the property tax amount drawing on merged CoreLogic and Infutor data. We estimate an increased migration propensity of about 1.5% to an increase in the property tax amount by 10%. An immediate next step is modeling the interaction between governments and location choice decisions for residents. In particular, governments may tend to balance their budgets by taking advantage of higher moving costs among its residents, increasing taxes if amenities are relatively valuable. On the margin, however, increased taxes do lead to some out-migration. A loss of residents and the associated tax base has implications for fiscal sustainability. Future research should explore the implications on fiscal sustainability for local governments across the United States.

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Tables and Figures:

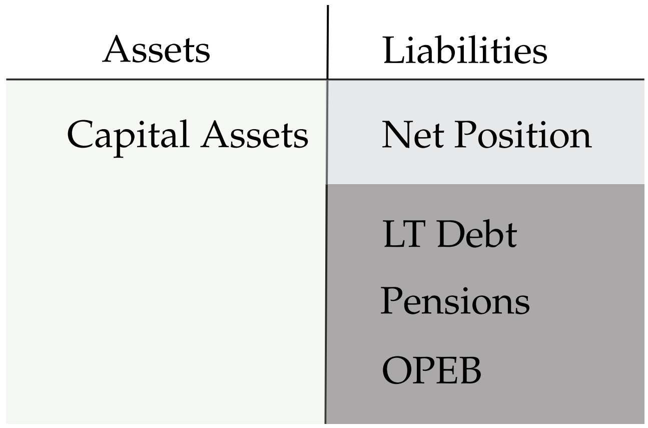


Figure A.1 – Schematic Balance Sheet

Reassessment year	Count
2011	17
2012	20
2013	47
2014	38
2015	46
2016	1
Total	169

Table A.1 – Assessment Schedule Summary Statistics

Notes: The table tabulates the counts of townships by the first re-assessment year after 2010. The sample includes the universe of 169 townships in Connecticut and the data comes from Connecticut's Office for Policy Management.

	mean	p25	p50	p75	count
Unr. Net. Pos. as of Op. Rev 2004 (%)	22.68	11.18	21.90	38.43	169
Unr. Net. Pos. as of Op. Rev 2018 (%)	-13.84	-27.57	4.49	24.90	169
Total Liability as of EGL 2004 (%)	-1.42	-1.69	-1.16	-0.82	169
Total Liability as of EGL 2018 (%)	-2.90	-2.90	-1.73	-0.98	169
Tax Rate 2006 (in mill)	27.65	22.90	27.00	32.04	169
Tax Rate 2018 (in mill)	30.71	26.80	30.50	34.40	169
Share Hispanic (Census 2010) (%)	6.14	2.46	3.42	5.88	169
Share Black (Census 2010) (%)	3.80	0.66	1.30	2.88	169
Share Age 65+ (Census 2010) (%)	15.20	12.80	14.92	17.19	169
Share College (Census 2010) (%)	37.66	26.57	37.17	44.79	169
Population (Census 2010)	21148.50	5485.00	12683.00	25709.00	169
Per Capita Income (Census 2010)	39866.55	31652.00	37324.00	43400.00	169

Table A.2 – Connecticut - Summary Statistics

Notes: The sample comprises all 169 municipalities (townships) in Connecticut. Data is obtained from the Office of Policy Management of Connecticut. The table follows the sign convention that liabilities are expressed as a negative values. The tax rate is expressed in mills; i.e., one mill corresponds to 1$ in taxes for every 1000$ of assessed property value.

	mean	p25	p50	p75	count
Expenditures (in % as of total)					
Share Education	68.30	63.56	68.57	73.62	169
Share Operating	31.70	26.38	31.43	36.44	169
Revenues (in % as of total)					
Share Property Tax Revenue	74.71	67.10	75.98	83.16	169
Share Intergovernmental Revenue	21.80	13.25	21.06	30.03	169
Share Other Revenue	3.48	2.29	3.04	4.21	169

Table A.3 – Connecticut - General Fund Summary Statistics

Notes: The table tabulates the main expenditure and revenue categories in the general fund of municipalities in Connecticut. The sample comprises all 169 municipalities (townships) in Connecticut. Data is obtained from the Office of Policy Management of Connecticut.

	(1) Log Grand List	(2) Log Mill Rate	(3) Log Tax Revenue	(4) Log LT Debt	(5) Intergov. Rev.
$\mathcal{I}_{s=-3}\times$ lnHPI	-0.0299	0.0465	-0.0254	0.912	-0.173
	(0.0901)	(0.0942)	(0.0507)	(0.610)	(0.263)
$\mathcal{I}_{s=-2}\times$ lnHPI	0.0214	-0.0618	-0.0481	0.0372	-0.00184
	(0.0905)	(0.0946)	(0.0510)	(0.613)	(0.265)
$\mathcal{I}_{s=-1}\times$ lnHPI	0.0570	-0.0717	-0.0221	-0.155	-0.0121
	(0.0845)	(0.0884)	(0.0476)	(0.573)	(0.247)
$\mathcal{I}_{s=+1}\times$ lnHPI	-0.476***	0.462***	-0.0160	0.0494	-0.0728
	(0.0845)	(0.0883)	(0.0476)	(0.572)	(0.247)
$\mathcal{I}_{s=+2}\times$ lnHPI	-0.408***	0.374***	-0.0375	-0.788	-0.147
	(0.0902)	(0.0943)	(0.0508)	(0.611)	(0.264)
$\mathcal{I}_{s=+3}\times$ lnHPI	-0.357***	0.274***	-0.103**	-0.935	-0.238
	(0.0897)	(0.0937)	(0.0505)	(0.607)	(0.262)
Within Adj. R^2	0.442	0.431	0.0242	0.00399	-0.00668
Town FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
LnPop10 Weight	✓	✓	✓	✓	✓
Observations	2197	2197	2197	2177	2197

Table A.4 – Fiscal Outcomes

Notes: The table presents estimates of specifications (3) and (2). The outcome variable is indicated by the respective column header. The sample includes the universe of 169 townships in Connecticut. Information on long-term debt is only available for a subset of townships. *,**, *** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

	(1) Log Per Pupil Exp.	(2) Log Public Employment	(3) Log Mean Public Wage
$\mathcal{I}_{s=-3} \times$ lnHPI	0.0884	-0.0671	0.0956
	(0.0700)	(0.103)	(0.0784)
$\mathcal{I}_{s=-2} \times$ lnHPI	0.0280	-0.0115	0.0205
	(0.0704)	(0.103)	(0.0789)
$\mathcal{I}_{s=-1} \times$ lnHPI	0.0107	-0.0695	0.0859
	(0.0656)	(0.0963)	(0.0735)
$\mathcal{I}_{s=+1} \times$ lnHPI	-0.0522	0.0331	-0.0204
	(0.0656)	(0.0962)	(0.0735)
$\mathcal{I}_{s=+2} \times$ lnHPI	-0.0724	0.0406	-0.0742
	(0.0701)	(0.103)	(0.0786)
$\mathcal{I}_{s=+3} \times$ lnHPI	-0.0994	0.0121	-0.0516
	(0.0692)	(0.102)	(0.0775)
$\mathcal{I}_{s=+4} \times$ lnHPI	-0.106	0.0119	-0.0854
	(0.0670)	(0.0983)	(0.0751)
Within Adj. R^2	0.0110	-0.00661	0.00618
Town FE	✓	✓	✓
Year FE	✓	✓	✓
LnPop10 Weight	✓	✓	✓
Observations	2197	2197	2197

Table A.5 – Service Outcomes

Notes: The table presents estimates of specifications (3) and (2). The outcome variable is indicated by the respective column header. The sample includes the universe of 169 townships in Connecticut. *,**, *** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

	Net Migration	Net Inter-State Migration	Net Intra-State Migration	Gross Out Migration	Gross In Migration
$\mathcal{I}_{s=-3} \times \Delta\text{lnMillRate}_{s=1}$	-0.00000875	0.000614	-0.000525	0.000614	-0.00504
	(0.00842)	(0.00614)	(0.00820)	(0.00652)	(0.0157)
$\mathcal{I}_{s=-2} \times \Delta\text{lnMillRate}_{s=1}$	0.00133	0.00254	-0.00113	0.00254	-0.00518
	(0.00722)	(0.00526)	(0.00703)	(0.00559)	(0.0134)
$\mathcal{I}_{s=-1} \times \Delta\text{lnMillRate}_{s=1}$	-0.00000396	0.00151	-0.00148	0.00151	-0.00162
	(0.00636)	(0.00464)	(0.00619)	(0.00492)	(0.0118)
$\mathcal{I}_{s=1} \times \Delta\text{lnMillRate}_{s=1}$	-0.00462	-0.00254	-0.00209	-0.00254	0.00269
	(0.00652)	(0.00476)	(0.00635)	(0.00505)	(0.0121)
$\mathcal{I}_{s=2} \times \Delta\text{lnMillRate}_{s=1}$	-0.00987	-0.00569	-0.00417	-0.00569	0.00243
	(0.00734)	(0.00535)	(0.00714)	(0.00568)	(0.0136)
$\mathcal{I}_{s=3} \times \Delta\text{lnMillRate}_{s=1}$	-0.0150*	-0.00926	-0.00580	-0.00926	0.00207
	(0.00826)	(0.00603)	(0.00804)	(0.00640)	(0.0154)
$\mathcal{I}_{s=4} \times \Delta\text{lnMillRate}_{s=1}$	-0.0214**	-0.0142**	-0.00735	-0.0142**	0.0000477
	(0.00907)	(0.00662)	(0.00884)	(0.00703)	(0.0169)
$\mathcal{I}_{s=5} \times \Delta\text{lnMillRate}_{s=1}$	-0.0250**	-0.0169**	-0.00820	-0.0169**	-0.000357
	(0.0105)	(0.00766)	(0.0102)	(0.00813)	(0.0195)
Town FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
IV	✓	✓	✓	✓	✓
LnPop10 Wgt.	✓	✓	✓	✓	✓
Observations	1680	1680	1680	1680	1680

Table A.6 – Migration Outcomes

Notes: The table presents estimates of specifications (3) and (2). The outcome variable is indicated by the respective column header. The sample includes the universe of 169 townships in Connecticut. *,**, *** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

	Net Migration Age 0-29yrs	Net Migration Age 30-59yrs	Net Migration Age 60+yrs
$\mathcal{I}_{s=-3} \times \Delta\text{lnMillRate}_{s=1}$	0.00212	-0.00640	0.00429
	(0.00211)	(0.00609)	(0.00558)
$\mathcal{I}_{s=-2} \times \Delta\text{lnMillRate}_{s=1}$	0.00156	-0.00285	0.00263
	(0.00181)	(0.00522)	(0.00479)
$\mathcal{I}_{s=-1} \times \Delta\text{lnMillRate}_{s=1}$	0.000787	-0.00142	0.000634
	(0.00159)	(0.00460)	(0.00422)
$\mathcal{I}_{s=1} \times \Delta\text{lnMillRate}_{s=1}$	0.000180	-0.00334	-0.00146
	(0.00163)	(0.00472)	(0.00432)
$\mathcal{I}_{s=2} \times \Delta\text{lnMillRate}_{s=1}$	0.000121	-0.00741	-0.00258
	(0.00183)	(0.00531)	(0.00486)
$\mathcal{I}_{s=3} \times \Delta\text{lnMillRate}_{s=1}$	0.00138	-0.0121**	-0.00435
	(0.00207)	(0.00598)	(0.00548)
$\mathcal{I}_{s=4} \times \Delta\text{lnMillRate}_{s=1}$	0.00163	-0.0167**	-0.00633
	(0.00227)	(0.00657)	(0.00602)
$\mathcal{I}_{s=5} \times \Delta\text{lnMillRate}_{s=1}$	0.00243	-0.0185**	-0.00895
	(0.00263)	(0.00760)	(0.00696)
Town FE	✓	✓	✓
Year FE	✓	✓	✓
IV	✓	✓	✓
LnPop10 Wgt.	✓	✓	✓
Observations	1680	1680	1680

Table A.7 – Migration Heterogeneity By Age

Notes: The table presents estimates of specifications (3) and (2). The outcome variable is indicated by the respective column header. The sample includes the universe of 169 townships in Connecticut. *,**, *** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

	Net Migration Tenure [0-4) yrs	Net Migration Tenure [4-10) yrs	Net Migration Tenure 10 yrs
$\mathcal{I}_{s=-3} \times \Delta\text{lnMillRate}_{s=1}$	-0.00208	-0.000671	0.00221
	(0.00310)	(0.00394)	(0.00564)
$\mathcal{I}_{s=-2} \times \Delta\text{lnMillRate}_{s=1}$	0.00157	-0.000169	0.000226
	(0.00265)	(0.00337)	(0.00484)
$\mathcal{I}_{s=-1} \times \Delta\text{lnMillRate}_{s=1}$	0.00189	0.000190	-0.00208
	(0.00234)	(0.00297)	(0.00426)
$\mathcal{I}_{s=1} \times \Delta\text{lnMillRate}_{s=1}$	-0.00158	-0.00300	-0.000621
	(0.00240)	(0.00305)	(0.00437)
$\mathcal{I}_{s=2} \times \Delta\text{lnMillRate}_{s=1}$	-0.00444	-0.00536	-0.000916
	(0.00270)	(0.00343)	(0.00491)
$\mathcal{I}_{s=3} \times \Delta\text{lnMillRate}_{s=1}$	-0.00756**	-0.00808**	-0.000821
	(0.00304)	(0.00386)	(0.00553)
$\mathcal{I}_{s=4} \times \Delta\text{lnMillRate}_{s=1}$	-0.00923***	-0.0118***	-0.00214
	(0.00334)	(0.00424)	(0.00608)
$\mathcal{I}_{s=5} \times \Delta\text{lnMillRate}_{s=1}$	-0.00995**	-0.0118**	-0.00443
	(0.00386)	(0.00491)	(0.00703)
Town FE	✓	✓	✓
Year FE	✓	✓	✓
IV	✓	✓	✓
LnPop10 Wgt.	✓	✓	✓
Observations	1680	1680	1680

Table A.8 – Migration Heterogeneity By Tenure

Notes: The table presents estimates of specifications (3) and (2). The outcome variable is indicated by the respective column header. The sample includes the universe of 169 townships in Connecticut. *,**, *** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

	HPI SFR	HPI All Homes
$\mathcal{I}_{s=-3} \times \Delta\text{lnMillRate}_{s=1}$	-2.792	-3.782
	(2.371)	(2.498)
$\mathcal{I}_{s=-2} \times \Delta\text{lnMillRate}_{s=1}$	-1.843	-2.452
	(2.087)	(2.219)
$\mathcal{I}_{s=-1} \times \Delta\text{lnMillRate}_{s=1}$	-0.423	-0.296
	(1.876)	(1.992)
$\mathcal{I}_{s=1} \times \Delta\text{lnMillRate}_{s=1}$	-2.087	-0.782
	(1.948)	(2.064)
$\mathcal{I}_{s=2} \times \Delta\text{lnMillRate}_{s=1}$	-8.344***	-7.578***
	(2.181)	(2.314)
$\mathcal{I}_{s=3} \times \Delta\text{lnMillRate}_{s=1}$	-10.00***	-9.045***
	(2.408)	(2.562)
$\mathcal{I}_{s=4} \times \Delta\text{lnMillRate}_{s=1}$	-9.617***	-8.897***
	(2.550)	(2.715)
$\mathcal{I}_{s=5} \times \Delta\text{lnMillRate}_{s=1}$	-11.41***	-11.60***
	(2.759)	(2.940)
Town FE	✓	✓
Year FE	✓	✓
IV		
LnPop10 Wgt.	✓	✓
Observations	1550	1567

Table A.9 – House Prices

Notes: The table estimates specifications (3) and (2) with the house price index on single family residential in Column (1) and the house price index on all homes in Column (2). The sample includes the universe of 169 townships in Connecticut and the data on the assessment value and the mill rate come from Connecticut's Office of Policy Management and the house price indices from Zillow. The specification is estimated on a subset of municipality-year observation for which house price indices are available. *,**, *** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

	Net Migration (IRS)
$\mathcal{I}_{s=-3} \times \Delta\text{lnMillRate}_{s=1}$	-0.00148
	(0.0268)
$\mathcal{I}_{s=-2} \times \Delta\text{lnMillRate}_{s=1}$	0.0162
	(0.0230)
$\mathcal{I}_{s=-1} \times \Delta\text{lnMillRate}_{s=1}$	0.0132
	(0.0202)
$\mathcal{I}_{s=1} \times \Delta\text{lnMillRate}_{s=1}$	-0.0156
	(0.0207)
$\mathcal{I}_{s=2} \times \Delta\text{lnMillRate}_{s=1}$	-0.0235
	(0.0233)
$\mathcal{I}_{s=3} \times \Delta\text{lnMillRate}_{s=1}$	-0.0255
	(0.0263)
$\mathcal{I}_{s=4} \times \Delta\text{lnMillRate}_{s=1}$	-0.0258
	(0.0289)
$\mathcal{I}_{s=5} \times \Delta\text{lnMillRate}_{s=1}$	-0.0492
	(0.0334)
Town FE	✓
Year FE	✓
IV	✓
LnPop10 Wgt.	✓
Observations	1680

Table A.10 – Robustness - Net Migration

Notes: The table estimates specifications (3) and (2) with the total population as the outcome variable. Total population is constructed from the number of dependents claimed in the income tax filings. The sample includes the universe of 169 townships in Connecticut. *,**, *** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

	(1)
	$\Delta ln\text{TaxAmount}_{s=1}$
Instrument	0.207***
	(0.0222)
Town FE	✓
Observations	858516

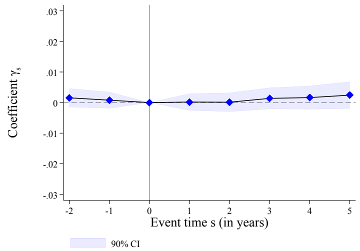
Table A.11 – Micro Migration First Stage

Notes: The tabulates the estimates of the first stage with the instrument constructed as described in Equation (4). Standard errors are two-way clustered at the township and cluster level. *,**, *** indicates significance at the 0.1, 0.05, 0.01 level, respectively.

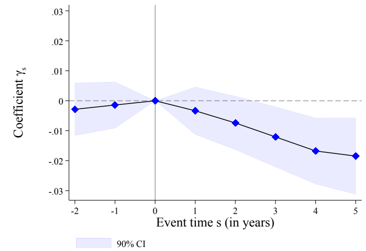
	(1) Migration Indicator
$\mathcal{I}_{s=-2} \times \Delta ln\text{TaxAmount}_{s=1}$	-0.0139
	(0.0697)
$\mathcal{I}_{s=-1} \times \Delta ln\text{TaxAmount}_{s=1}$	-0.0223
	(0.0477)
$\mathcal{I}_{s=1} \times \Delta ln\text{TaxAmount}_{s=1}$	0.0828**
	(0.0337)
$\mathcal{I}_{s=2} \times \Delta ln\text{TaxAmount}_{s=1}$	0.118**
	(0.0475)
$\mathcal{I}_{s=3} \times \Delta ln\text{TaxAmount}_{s=1}$	0.146**
	(0.0580)
$\mathcal{I}_{s=4} \times \Delta ln\text{TaxAmount}_{s=1}$	0.147**
	(0.0637)
$\mathcal{I}_{s=5} \times \Delta ln\text{TaxAmount}_{s=1}$	0.152**
	(0.0724)
Town FE	✓
Year $\times$ Cluster FE	✓
Cluster	Township $\times$ Year
Observations	7058138

Table A.12 – Micro Migration Propensity Estimates

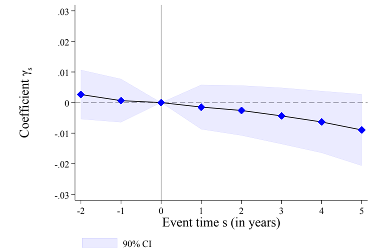
Notes: The table tabulates the estimates of specification (5) and (4) with the indicator variable, that takes on the value of one if a move has been recorded and zero otherwise, as the outcome variable. Numerical estimates are tabulated in Table A.12. Standard errors are two-way clustered at the township and cluster level. *,**, *** indicates significance at the 0.1, 0.05, 0.01 level, respectively.



(a) Age 18-29 yrs



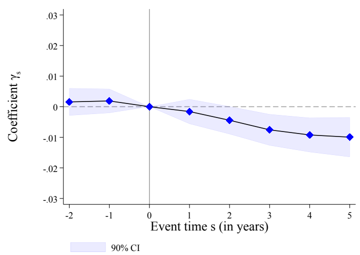
(b) Age 30-59 yrs



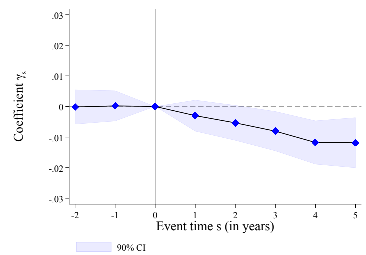
(c) Age 60 + yrs

Figure A.2 – Net Migration by Age

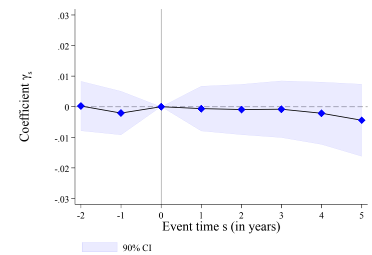
Notes: Panel (a) - (c) show the estimates of specification (3) and (2) with total population as an outcome variable by age category. All age categories are calculated in 2010 given the observed year of birth. Blue shaded areas indicate the confidence interval at the 90% significance level.



(a) Tenure 0-4 yr



(b) Tenure 4-10 yr



(c) Tenure 10 yr +

Figure A.3 – Net Migration by Tenure

Notes: Panel (a) - (c) show the estimates of specification (3) and (2) with total population as an outcome variable by tenure category. Tenure is defined as the number of years since the last move was registered for a specific person. Blue shaded areas indicate the confidence interval at the 90% significance level.

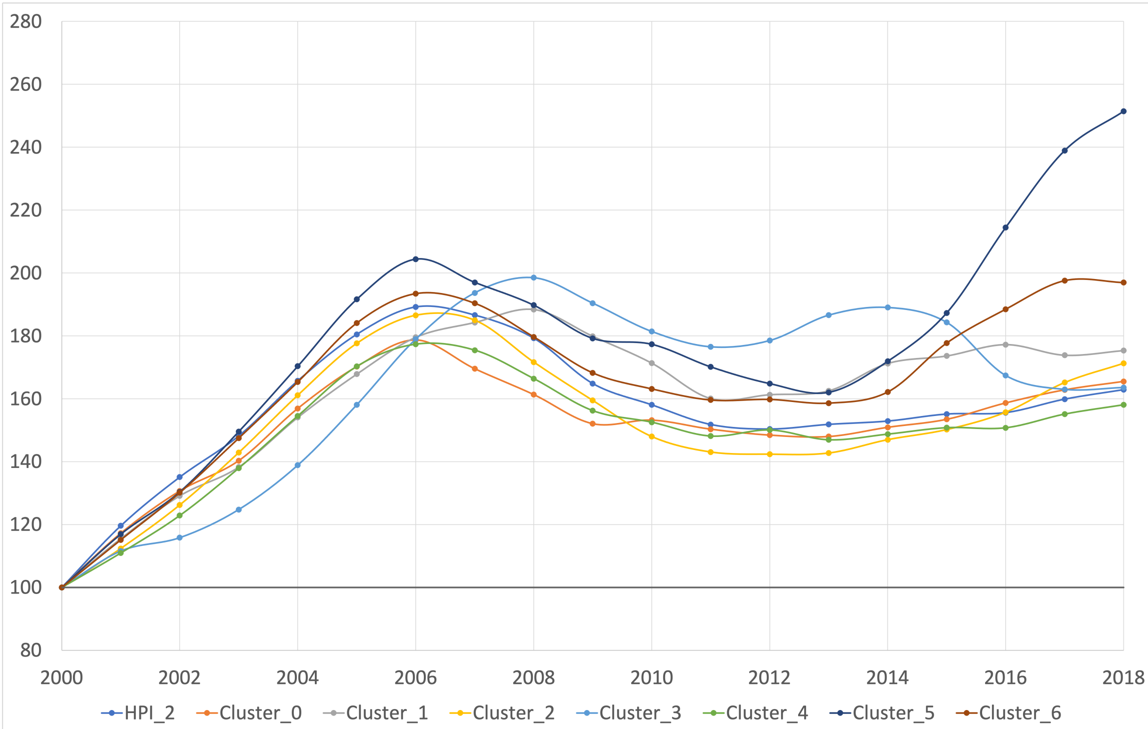


Figure A.4 – Price Index by Cluster

Clusters are determined using the k-means algorithm. HPI-2 is our preferred overall price index using a repeat sales price method with smoothing. The base year is set to 2000.

Cluster	Tax Amount	Assessed Amount	Total Rooms	Total Bedrooms	Total Bath	Building Area	Age
1	6323	216142	6.78	3.09	2.36	1849.4	43.5
2	20516	998742	10.56	4.62	4.38	4537.1	49.8
3	5500	187234	7.22	3.40	1.79	1809.6	121.7
4	53798	3661073	13.67	5.52	6.58	7693.4	44.5
5	9128	331730	8.67	4.07	2.81	2699.7	45.2
6	4280	140325	4.77	1.91	1.31	1147.6	72.7
7	4602	143559	5.96	3.12	1.42	1312.1	65.7

Table A.13 – Cluster Means

Notes: The table provides the cluster means from a k-means algorithm. The number of clusters was determined using the "elbow" method.

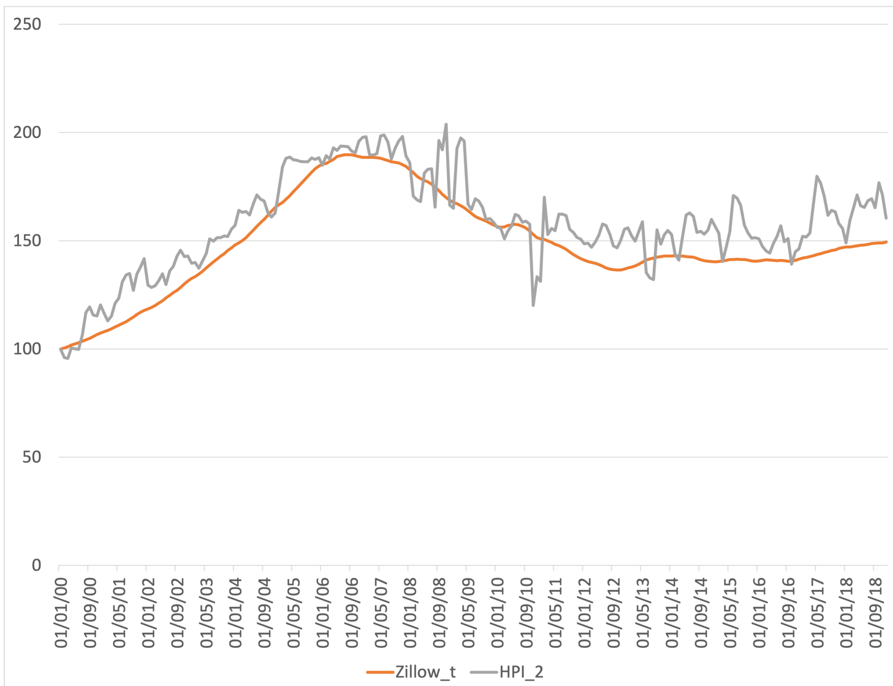


Figure A.5 – Price Index Validation

HPI-2 is our preferred overall price index using a repeat sales price method. The base year is set to 2000. The index is calculated on a monthly basis.

Appendix B:

B.7.1 Instrument Derivation

Suppose there is idiosyncratic price development, $\epsilon_{i,t,t+1}$, within a cluster, then the dynamics for house prices, $HP_{i,t+1}$, for property i is given by:

$$HP_{i,t+1} = \frac{I_{t+1}^{c(i)}}{I_t^{c(i)}}(1+\epsilon_{i,t,t+1})HP_{i,t} \tag{6}$$

where $I_{t+1}^{c(i)}$ is the index value for properties in cluster c in the year of re-assessment and $I_t^{c(i)}$ is the index value for properties in cluster c in the year of the prior re-assessment. Consider an assessment process that property values units with multiplicative noise, $w_{i,t}$. Then the assessment value, $A_{i,t}$, is given by:

$$A_{i,t} = k(1+w_{i,t})HP_{i,t} \tag{7}$$

where k is the appropriate assessment constant. This implies:

$$dlnA_{i,t+1} = ln\left(\frac{1+w_{i,t+1}}{1+w_{i,t}}\right) + dlnI_{t+1}^{c(i)} + ln(1+\epsilon_{i,t+1}) \tag{8}$$

The total assessment value, $AV_{l,t+1}$, for municipality l is then given by:

$$\begin{aligned} AV_{l,t+1} = \sum_{i=1}^{N} A_{i,t+1} &= \sum_{c\in C}\sum_{i=1}^{N_c}\left(\frac{1+w_{i,t+1}}{1+w_{i,t}}\right)\frac{I_{t+1}^{c(i)}}{I_t^{c(i)}}(1+\epsilon_{i,t+1})A_{i,t} \\ &\longrightarrow_p \sum_{c\in C}\frac{I_{t+1}^{c(i)}}{I_t^{c(i)}}N_c\bar{A}_t^c = \sum_{c\in C}\frac{I_{t+1}^{c(i)}}{I_t^{c(i)}}\hat{s}_{lt}^c AV_{lt} \end{aligned} \tag{9}$$

where s_{lt}^c is the relative share of assessment value for property cluster c in municipality l. As municipalities offset, on average, changes in the assessment value as shown in Section 5.1, tax policy can be expressed as:

$$dln\tau_{l,t+1} = -dlnAV_{l,t+1} + u_{l,t+1} = -\ln\left(\sum_{c\in C}\frac{I_{t+1}^{c(i)}}{I_t^{c(i)}}\hat{s}_{lt}^c\right) + u_{l,t+1} \tag{10}$$

Hence, the predicted change in the property tax amount for the individual housing unit can be expressed as:

$$dlnPT_{i,t+1} = dlnI^{c(i)}_{t+1} - \ln\left(\sum_{c\in C} \frac{I^{c(i)}_{t+1}}{I^{c(i)}_{t}} \hat{s}^{c}_{lt}\right) + \eta_{i,t,t+1} \tag{11}$$

Data Appendix

DA.7.1 Infutor-CoreLogic Panel

Matching Algorithm We match the Infutor and CoreLogic data based on an iterative matching algorithm after geocoding all Infutor address records with the Census geocoder api which is publicly available at https://geocoding.geo.census.gov/ and geomerging all CoreLogic deeds and tax records with the census tract shapefiles from the 2020 Census. This guarantees that the tract definition between the geocoder and the assigned tract in the CoreLogic data are consistent. The procedure also allows us to match on the census tract which is typically smaller than the municipality and avoids the ambiguity of municipality names which can be problematic for the merge.

The iterative procedure follows a strict matching logic. First, we check that for the match all matching keys are non-missing; we perform the match; and continue to the next step only with the residual for which either at least one matching key is missing or for which we found no match.

The unique identifier in the CoreLogic data is the APN, APN sequence number and five digit fips code which consists of the normalized two digit state fips code and the normalized three digit county fips code.

The matching priority is the following:

1. Match on: 'fipscode','census tract','housenr', 'street' and full apartment number including alphanumeric characters.

2. Match on: 'fipscode','census tract','housenr', 'street' and full apartment number including only numeric characters.

3. Match on: 'fipscode','census tract','housenr', 'street' and full apartment number including only string characters.

4. Match on: 'fipscode','census tract','housenr', 'street'

We perform a fuzzy merge on all available address details on the remainder of unmatched records using the jaro-winkler distance between strings. We performed a manual check of merges and found that matches are typically invalid.

We obtain an overall matching rate of 81%. The matching rate is better than in Qian and Tan (2020) for Connecticut; presumably because we do not match on the municipality name. Municipality names are somewhat problematic as some addresses use the name of the borough rather than that of the incorporated township.

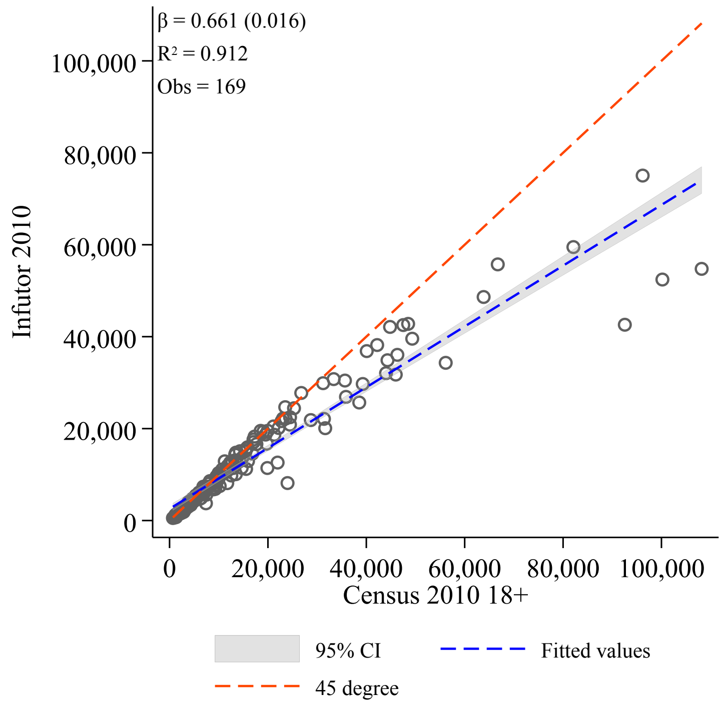


Figure DA.1 – Infutor-CoreLogic - 2010 Census

Representativeness The merge between the Infutor and CoreLogic records leads to a loss in observations. We re-evaluate the representativeness of the matched Infutor-CoreLogic panel vis-a-vis the 2010 Census. While the number of adult people that we observe in the Infutor-CoreLogic panel falls to about 0.69 per person in the 2010 Census, we capture about 0.966% of the statistical variation as shown in Figure DA.1.

DA.7.2 Infutor-CoreLogic Homeownership

We obtain ownership information by using the combined Corelogic deeds and property tax record files. We then identify an owner of a property if the ownership name from the Corelogic record coincides with the resident name in the Infutor record.

DA.7.3 Effective Tax Rates

We are unaware of any comprehensive dataset that contains tax rates across the United States. We follow Amornsiripanitch (2020) and Berry (2021) and impute property taxes from the historical tax record of CoreLogic.

In particular, we match each property tax record to a municipality via a geo-merge with the municipal shapefiles as described in Appendix Section IA.3. While we can compute the statutory tax rate based on the tax amount and the assessment value from the CoreLogic records, we do not have information about the market value of the property from the CoreLogic data. Thus, we compute the mean and median tax amount at the municipal level and complement this with the Zillow Home Value Index (ZHVI) available at https://www.zillow.com/research/data/. The implicit assumption is that the mean / median tax amount correspondents to the mean / median home value, respectively. Even though we acknowledge that this is a coarse approximation, we generally found that imputed tax rates match closely the statutory tax rates as provided by the Office of Policy Management in Connecticut. Ultimately, we compute the effective tax rate as the mean / median tax amount divided by the mean / median home value.

The summary statistics by state shown in Table DA.2 and the geographical dispersion–showing the mean value at the county level–is shown in Figure DA.2.

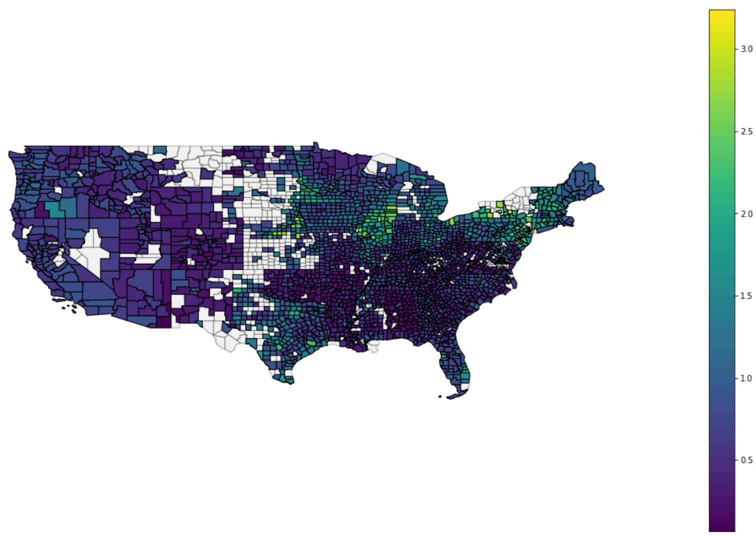


Figure DA.2 – Effective Tax Rates 2014

Notes: The effective tax rate is expressed in percent. Information on the tax amount comes from CoreLogic historical property tax data and the median house price by municipality is obtained from Zillow. The map displays the mean effective tax rate at the county level by taking the mean across all municipalities in a county.

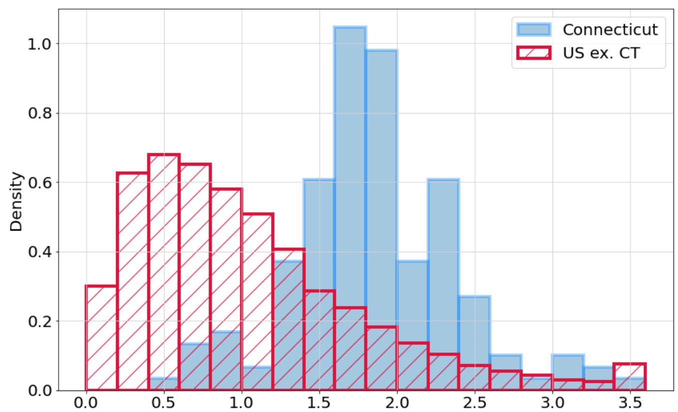


Figure DA.3 – Density - Effective Tax Rates 2014

Notes: The effective tax rate is expressed in percent. Information on the tax amount comes from CoreLogic historical property tax data and the median house price by municipality is obtained from Zillow.

State	mean	std	p25	p50	p75	count
Alabama	0.2360	0.1726	0.1215	0.1865	0.2934	397
Alaska	0.5770	0.3733	0.2969	0.4098	0.8109	19
Arizona	0.4881	0.2520	0.3191	0.4660	0.6169	80
Arkansas	0.3262	0.1914	0.1645	0.3013	0.4481	392
California	0.7446	0.2670	0.6095	0.7094	0.8298	477
Colorado	0.3971	0.3027	0.2624	0.3678	0.4825	201
Connecticut	1.8530	0.5275	1.5528	1.8168	2.1714	148
Delaware	0.2874	0.1645	0.1787	0.2166	0.3243	42
District of Columbia	0.4362	NaN	0.4362	0.4362	0.4362	1
Florida	0.8831	0.5533	0.5718	0.7989	1.0636	351
Georgia	0.5651	0.2881	0.3648	0.5381	0.6997	512
Hawaii	0.2338	NaN	0.2338	0.2338	0.2338	1
Idaho	0.5521	0.2481	0.3728	0.5495	0.7209	155
Illinois	1.6461	0.8795	1.0041	1.6410	2.2240	2,233
Indiana	0.6506	0.3403	0.4077	0.6062	0.8401	1,343
Iowa	0.9189	0.4165	0.6226	0.9523	1.2201	709
Kansas	0.9508	0.4324	0.6569	0.9432	1.1833	577
Kentucky	0.6240	0.3254	0.4112	0.5760	0.7526	272
Louisiana	0.4172	0.2449	0.2623	0.3791	0.5180	228
Maine	1.0067	0.4390	0.7098	0.9781	1.2306	406
Maryland	1.0032	0.3530	0.7252	0.9968	1.1832	116
Massachusetts	1.1502	0.3371	0.9733	1.2012	1.3724	325
Michigan	1.1683	0.5067	0.8711	1.1171	1.3989	1,317
Minnesota	1.0132	0.6888	0.5537	0.8732	1.2173	2,399
Mississippi	0.4979	0.2799	0.3021	0.4520	0.6560	193
Missouri	0.6487	0.5242	0.3126	0.5120	0.7941	771
Montana	0.5773	0.2565	0.4215	0.5217	0.6957	60
Nebraska	1.9367	1.1029	1.0297	1.6238	3.0170	379
Nevada	0.6528	0.1618	0.5795	0.6349	0.6432	19
New Hampshire	1.7497	0.5880	1.3212	1.8490	2.1368	205
New Jersey	2.2141	0.7704	1.7620	2.1565	2.7764	527
New Mexico	0.4086	0.2644	0.2209	0.3396	0.5565	65
New York	2.1094	0.7668	1.5846	2.0647	2.6381	618
North Carolina	0.6459	0.3260	0.4026	0.6016	0.8410	493
North Dakota	0.5982	0.4383	0.2942	0.5005	0.8164	528
Ohio	1.0476	0.6569	0.5888	0.9814	1.3257	1,990
Oklahoma	0.3385	0.2731	0.1484	0.2834	0.4614	427
Oregon	0.8416	0.3088	0.6044	0.8741	1.0720	207
Pennsylvania	1.3989	0.5959	0.9764	1.3158	1.7414	2,268
Rhode Island	1.5410	0.5913	1.2253	1.5008	1.8488	39
South Carolina	0.4944	0.3050	0.2940	0.4396	0.6309	244
South Dakota	1.1654	0.5246	0.8697	1.1601	1.4178	264
Tennessee	0.5635	0.2483	0.3869	0.5459	0.7020	335
Texas	1.1501	0.6970	0.6329	1.0556	1.5782	1,053
Utah	0.5077	0.2260	0.3951	0.5003	0.6286	202
Vermont	1.7344	0.3942	1.5076	1.7220	1.9553	272
Virginia	0.4542	0.2337	0.3121	0.4133	0.5620	193
Washington	0.7455	0.3103	0.5686	0.7714	0.9406	258
West Virginia	0.4744	0.2146	0.3195	0.4851	0.6305	163
Wisconsin	0.9809	0.6693	0.4063	0.8032	1.4897	1,820
Wyoming	0.3681	0.1647	0.2384	0.4197	0.4851	66

Table DA.1 – Effective Tax Rates by State 2014 - Summary Statistics

Notes: The effective tax rate is expressed in percent. Information on the tax amount comes from CoreLogic historical property tax data and the median house price by municipality is obtained from Zillow.