Data Report

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Introduction

In collaboration with the Union of Municipalities of New Brunswick and Dr. Craig Brett of Mount Allison University, we conduct a fixed-effects two-stage least squares (or FE-2SLS) regression analysis of average tax rates on police spending in New Brunswick municipalities, using median household income as an instrumental variable to reduce simultaneity bias. We herein investigate whether police spending is a significant predictor of municipal tax rates and, if so, how specific policing providers play into this correlation. Moreover, we leverage the fact that police expenditure (as per the Provincial Police Service Agreement [PPSA] with the Royal Canadian Mounted Police [RCMP]) is largely an exogenous bill outside of municipal control to use this to approximate tax base elasticity with respect to tax rates. In addition, we consider the relationship between population and this estimated elasticity, observing that smaller municipalities tend to exhibit higher tax base elasticity than larger ones due to a variety of mobility factors.

(Note that this report is intended to be taken together with our GitHub project repository, with repeated references to specific scripts/file paths. However, it is certainly possible to peruse this document independently, as we have made every effort to ensure that all relevant information is encapsulated herein.)

Background of the Problem

Price per unit of public goods—particularly police spending, in the context of this study—varies widely across municipalities in New Brunswick. We herein aim to regress regression municipal tax rates on the costs of several different public goods. We place particular emphasis on the significant variation in per capita cost of municipal bills under the PPSA—a contract between the Government of New Brunswick [GNB] and the RCMP to provide smaller municipalities with policing services. As the RCMP provides the province with a single combined bill, the GNB charges different municipalities based on population, safety levels, and other factors, with this formula acting as an exogenous factor in the cost of policing services.

On the other hand, it is common for larger municipalities have their own direct contracts with the RCMP, further obscuring the relationship between municipal spending patterns and taxation. For instance, the Codiac Regional Policing Authority serves the municipalities of Dieppe, Moncton, and Riverview, none of which pay additional fees to the GNB under the PPSA. Others still maintain their own independent police forces like the Bathurst Police Force (although there remains a minor RCMP presence in Bathurst).

The Union of Municipalities of New Brunswick has provided us with data on municipal policing providers as of 2024 to aid in our analysis. Confounding this, however, is the 2023 New Brunswick local governance reform, which redrew a large swath of municipal boundaries, partly driven by the desire to cut down on "redundant" local service districts. Not only were several municipalities and districts merged together, but in many cases, entirely new municipalities with original names were created (Government of New Brunswick 2024).

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To make matters worse, although this was certainly the most significant reform in New Brunswick municipal governance in decades, it was not the first—our panel data reveals municipal recombination on a smaller scale transpired multiple times over the 2000–2018 period as well. Regardless, we have found a reliable way to map the 2024 data backwards to past municipal jurisdictions (this is further described in the **Methodology** section), allowing us to integrate time-invariant provider indicators into our model. In future extensions of this project, we may utilize more recent data to study the current policing system situation while collaborating with the UMNB.

Overall, this setup is of interest insofar that it allows us to study the effects of different expenditure categories with different levels of exogeneity on tax rate, as well as approximate tax base elasticity given the exogenous nature of police spending under the PPSA. The coefficient on police spending per capita shall reveal how much of a burden municipal residents bear as PPSA bills increase, while our elasticity estimates may provide insight into the revenue-raising capabilities of municipalities and justify policy changes to the current policing system in New Brunswick.

As such, we herein construct a fixed-effects two-stage least squares (FE-2SLS) regression model of the relationships described above. The *fixed-effects* (FE) aspect allows us to address time-invariant biases, controlling for unobserved heterogeneity across municipalities. However, this neglects the simultaneity bias arising from the bidirectional relationship between average tax rate (our response variable) and tax base per capita (one of our explanatory variables).

Hence, the *two-stage least squares* (2SLS) part of our model utilizes the fact that median household income (our instrumental variable) is correlated with tax base per capita but not with average tax rate. Regressing tax base on median income and using our predicted values in the second-stage fixed-effects regression allows us to isolate (to some extent) the effect of tax base on tax rate from the effect of tax rate on tax base. Both aspects of our combined FE-2SLS model are common approaches in econometrics, and we outline both more thoroughly in the **Methodology** section.

Literature Review

First off, Brett and Pinkse (2003) investigate the "determinants of municipal tax rates in British Columbia," considering population, distance from major metropolitan centers (namely Vancouver), income, and several other factors as determinants of tax rates. They do not particularly emphasize spending patterns as a potential factor in municipal taxation, but the methodology presented in their paper provide a useful framework on which to build for our project.

In a similar vein, we consider studies of how increased provincial suppoort for municipal budgets affected tax rates in New Brunswick. One of our more surprising takeaways was the finding that, in a generalized method of moments (GMM) three-stage least squares (3SLS) model with even more sophisticated instrumentation than ours, the coefficient on tax base when predicting tax rate was positive (Brett and Tardif 2008, 448–49). This concurs with findings we shall present in the **Results** section—seemingly a weird counteintuitive quirk of the NB economic system in particular. (Indeed, the methodology used in Brett and Tardif (2008) is quite similar to our own, with several refinements, and may inspire improvements on our statistical models as this project continues to develop.)

We find also from Saez, Slemrod, and Giertz (2012, 29) that when tax rates change, individuals and businesses often relocate when possible, in turn affecting the tax base. This highlights the fact that the higher mobility associated with smaller localities allows for greater elasticity of the tax base with respect to tax rates. Indeed, this is a well-known phenomenon in the literature, proving key to our project's hypothesis that smaller municipalities may show higher elasticity, preventing local governments from raising tax rates to cover ever-growing PPSA bills without the erosion of their tax base.

Dahlby (2024, 1) further supports this hypothesis, finding that—particularly in recent years—climbing tax rates in Newfoundland and Labrador, Ontario, and British Columbia have resulted in altered "volume and allocation of land, labour, and capital in the economy, reducing our income and consumption opportunities." This is a clear indication that tax hikes are not a sustainably viable solution to covering rising municipal bills, as they oftentimes lead to a significant loss of tax base. Our own findings in the **Results** and **Discussion** sections below support the hypothesis that this applies in a New runswick context as well, especially when it comes to smaller municipalities.

Finally, a review of previous studies of tax rate both as a response variable (Buetter 2003, 116) and as an explanatory one (Ferede 2019, 8) reveals that the inclusion of tax base on the other side of the equation is well-known to cause simultaneity bias. While our other explanatory variables (expenditure, revenue, etc.) are fairly *exogenous* in that they are determined outside of the model, tax base per capita is an *endogenous* variable highly bicorrelated with (and thus determined by) tax rate, which creates bias in regression estimates. Findings from Auten and Carroll (1999, 689) indicate that household income is viable as an instrument to reduce this bias, being correlated with tax base (since higher income indirectly yields more taxable property) but not tax rate (since income is not an *explicit* determinant of property base). This validates the overall structure of our FE-2SLS model described in the **Methodology** section below.

Methodology

We now delineate our data collection process, data organization methods, and statistical models. We use Python (namely the polars and linearmodels/statsmodels ecosystems) to parse and clean data from Statistics Canada and the GNB. Subsequently, we run several fixed-effects and correlated random-effects regressions on the resulting data in combination with median household income as an instrumental variable to account for simultaneity bias.

Data Collection and Sources

We use an unbalanced panel of annual data from 2000–2018 on New Brunswick municipalities, received via personal correspondence with the GNB and Dr. Craig Brett of Mount Allison University; however, this data is also publicly available at (Government of New Brunswick 2000–2018), albeit in a less structured format. (The year 2005 is excluded due to missing/improperly formatted tokens, but we may coordinate further with the GNB to obtain this data in the future.) Each set of annual data contains 95 to 103 municipalities, with a total of 104 unique municipalities over all years.

This is supplemented by 2024 data on municipal policing provider agreements (Anderson 2025). We map this data backwards to municipal jurisdictions and boundaries from previous years and integrate indicators into interaction terms in our panel as described below.

Finally, the instrumental variable in the first stage of our 2SLS regression is median household income, given in census data from Statistics Canada [StatsCan]. Data is only available from 2000 (Statistics Canada 2001), 2005 (Statistics Canada 2006), 2015 (Statistics Canada 2016), and 2020 (Statistics Canada 2021); hence, linear interpolation is applied for the intervening years. The resulting income data (typically correlated with tax base but not with tax rate) is then used to reduce simultaneity bias in our fixed-effects model.

Data Cleaning and Organization

Primary Data

Primary data is cleaned in the `data_pipeline/` directory. The original Excel files extracted from `.zip` archives provided by the GNB and the UMNB are contained in the `data_raw/` subdirectory. These contain annual data from 2000–2022 on New Brunswick municipalities, as well as 2024 data on municipal policing providers. Given that some of these files are `.xls` and `.xlw` workbooks, we copy and convert them all to `.xlsx` format in the `data_xlsx/` subdirectory. The `helper_scripts/_1_raw_to_xlsx_.py` script is used for this purpose.

Files in this `data_xlsx/` subdirectory are cleaned and organized by `helper_scripts/_2_xlsx_to_clean_.py`. Finding that data from 2005 and 2019–2022 is unusable due to missing/improperly formatted tokens, our output (placed in the `data_clean/` subdirectory) excludes these time periods. No original data is discarded during this process (save for metadata and notes)—it is all simply reorganized into parseable form.

Addressing inconsistent municipality naming conventions across years/categories and concatenating all annual panels within each category (budget expenditures, budget revenues, comparative demographics, and tax bases), the `helper_scripts/_3_clean_to_final_.py` script then writes all four resulting worksheets—plus a fifth for provider data—to a single `data_final/data_master.xlsx` workbook. (The new municipal naming convention is also used to map provider data on newer, reformed 2024 municipalities and districts to past jurisdictions all the way back to 2000.)

All scripts are called and run by the main executable of the associated directory, `main.py`.

Instrumental Variable Data

Data on the instrumental income data is stored and processed in the `data_iv/` directory. There is one folder each for 2001, 2006, 2016, and 2021 (the years in which the census data were released) containing the original files downloaded from the StatsCan website. For 2016 and 2021, the downloads are straightforward, nicely formatted `.csv` files requiring no further processing. For 2001 and 2006, however, full data is only available in `.ivt` and `.xml` format; no schemas are available to parse the XML data, so we use the Government of Canada's Beyond 20/20 Browser to extract and download the data in `.csv` format. (Unfortunately, this process is not easily documentable, as the browser requires manual processing.)

With CSV files for all four years, the `main.py` executable script is finally used to clean and combine the relevant columns and rows into a single polars DataFrame. This is then saved as an `.xlsx` file in the `results/` subdirectory for immediate usage in the data analysis stage. (The aforementioned data interpolation—performed using Python's numpy library—is not applied until this stage and is thus not considered part of the data cleaning and organization pipeline.)

It is worth noting that although household income data from Canada censuses is publicly accessible for municipal-level geographic localities in 2000, 2005, 2015, and 2020, the only available source for 2010 is aggregated data from the 2011 National Household Survey. This survey refrained from providing disaggregated data at lower levels of geography, so we are unable to map it to most of the 104 municipalities in our dataset. Hence, linear interpolation is used to estimate the missing data for 2010, just as for all the other missing years. In the future, we may collaborate further with StatsCan to obtain the geographically disaggregated data, if it remains in their records.

Data Analysis and Modelling

All data analysis is performed in the `data_analysis/` directory. Our included variables are:

- **Average Tax Rate**, or **AvgTaxRate** – unitless
- **Police Spending per Capita**, or **PolExpCapita** – 10^5 CAD / person
- **Non-Police Spending per Capita**, or **OtherExpCapita** – 10^5 CAD / person
- **Non-Warrant Revenue per Capita**, or **OtherRevCapita** – 10^5 CAD / person
- **Tax Base for Rate per Capita**, or **TaxBaseCapita** – 10^5 CAD / person
- **Policing Provider** – boolean, three categories:
  - *Provincial Police Service Agreement* (excluded control variable)
  - *Municipal Police Service Agreement*, or *Provider_MPSA* (included)
  - *Municipally Owned Police Force*, or *Provider_Muni* (included)
- **Median Household Income**, or **MedHouseInc** – 10^5 CAD / person

(These scaling factors are chosen to make our regression coefficients more interpretable, but when visualizing our results in the form of plots, we switch back to % for *AvgTaxRate* and CAD / person for the remaining expenditure and revenue variables.)

Our response variable is *AvgTaxRate*, which is calculated as a weighted average of the residential and non-residential tax rates in a municipal jurisdiction. (That is—as per government formulae, non-residential rates are multiplied by a factor of 1.5 before being integrated into the calculated average. Said averages are already available in the raw data (Government of New Brunswick 2000–2018), not calculated by us; we take note of the process simply to clarify the layout of our data.) Our exogenous explanatory variables are *PolExpCapita*, *OtherExpCapita*, *OtherRevCapita*, *PolExpCapita∗Provider_MPSA*, and *PolExpCapita∗Provider_Muni*. Our sole endogenous explanatory variable is *TaxBaseCapita*, for which we control simultaneity bias using *MedHouseInc* as an instrumental variable.

Each of these variables is used throughout our FE-2SLS regression model, carried out by the `helper_scripts/allow_concurrent/_fe_2sls_.py` script. We have also included "vanilla" correlated random-effects (CRE) and fixed-effects (FE) models, run by `helper_scripts/allow_concurrent/_cre_.py` and `helper_scripts/allow_concurrent/_fe_.py`, to determine which variables are relevant and to demonstrate the need for an instrumental variable. All helper scripts are called and run by the main executable of the associated directory, `main.py`.

Our decision to integrate a panel data model with 2SLS, clearly, arose from the factors described above in our **Literature Review**, as the inclusion of *TaxBaseCapita* in the model creates simultaneity bias if unaddressed. Our ultimate choice of FE over CRE for the base panel OLS was motivated by the fact that, although statistically significant, the coefficients on the raw provider indicator variables were so low that they barely explained any variance in the response variable (more on this in the **Results** section). Meanwhile, it is clear that *TaxBaseCapita* casues simultaneity bias; the construction of a vanilla FE model was never intended as a viable alternative to our main FE-2SLS model, but rather to act as a baseline for comparison.

It is also worth noting that we chose not to use non-linear functional forms—with the most obvious candidate for a study in this particular real-world context being log transformation—as summary statistics indicate that both the *AvgTaxRate* data and explanatory variables are fairly normally distributed and do not exhibit significant skewness. (Although many economic parameters such as income and GDP indeed exhibit right-skewed distributions—hence the popularity of the log transformation—we find that our particular variables of interest do not.)

Finally, we also approximate tax base elasticity by multiplying the coefficient on *PolExpCapita* by the average *TaxBaseCapita* for each municipality, subsequently performing some basic algebraic manipulations. This allows us to obtain a rough estimate of how sensitive taxable income and property in a municipality is to tax hikes given increases in PPSA bils, providing key insight into potential policy changes to the current New Brunswick policing system.

We now turn to describing our instrument-free CRE and FE analyses, then proceed to more thoroughly delineate our final FE-2SLS regression model.

Correlated Random-Effects (CRE)

[TODO: Elaborate, also on how we may include instrumentation here in the future]

Fixed-Effects (FE)

After deeming the potential benefits of including the policing provider on indicators directly (not in interaction terms) insufficient to warrant [TODO: Elaborate]

Fixed-Effects Two-Stage Least Squares (FE-2SLS)

Finally, we decided on [TODO: Elaborate]

Stage 1 We begin by estimating *MedHouseInc* data for the years missing from the StatsCan census data, which we do using simple linear interpolation. (As this project continues to develop, we may investigate more sophisticated approximation approaches, but this shall do for now.) After this is done, we perform an ordinary least squares regression of *TaxBaseCapita* on *MedHouseInc* to obtain

$$TaxBaseCapita_{it} = \alpha_0 + \alpha_1 MedHouseInc_{it} + v_{it}.$$

By performing this regression before proceeding to a fixed-effects model, we manage to reduce simultaneity bias, as *MedHouseInc* is correlated with *TaxBaseCapita* but not with *AvgTaxRate*. We use these predicted $\widehat{TaxBaseCapita}_{it} = TaxBaseCapita_{it} - v_{it}$ values in the second-stage regression, where we demean all variables over municipality.

Stage 2 Our primary fixed-effects regression model is now given by

$$\begin{aligned} Avg\ddot{TaxRate}_{it} &= \beta_1 Pol\ddot{ExpCapita}_{it} + \beta_2 Other\ddot{ExpCapita} + \beta_3 Other\ddot{RevCapita} \\ &+ \beta_4 \ddot{\widehat{TaxBaseCapita}}_{it} + \beta_5 Pol\ddot{ExpCapita}_{it} * Provider\_MPSA_{it} \\ &+ \beta_6 Pol\ddot{ExpCapita}_{it} * Provider\_Muni_{it} + \ddot{u}_{it}, \end{aligned}$$

where we use the notation $\ddot{X}_{it} := X_{it} - \bar{X}_i$ to denote the difference between the value of X for municipality i in year t and the mean value of X for municipality i over all years. (Note that $\ddot{\widehat{TaxBaseCapita}}_{it}$ is not the demeaning of $TaxBaseCapita_{it}$ itself but rather the demeaned prediction from our first-stage regression.) We further opt to cluster our covariance estimator by municipality, as this is a common approach in the literature to account for unobserved heterogeneity in panel data.

Tax Base Elasticity Estimates

Given these results, we now approximate tax base elasticity with respect to tax rates by multiplying our obtained coefficient on **PolExpCapita**—one of the most exogenous expenditure categories, as previously discussed—by *TaxBaseCapita*. First, we set up the following notation:

- E for government expenditure,
- A for tax base assessed for rate,
- t for tax rate,
- $\beta := \frac{\mathrm{d}t}{\mathrm{d}E}$ for the effect of expenditure on tax rate, and
- $\eta := \frac{t}{A}\frac{\mathrm{d}A}{\mathrm{d}t}$ for tax base elasticity w.r.t. tax rate.

Given small deficits/surpluses, expenditure is approximately $E \approx tA$; hence, assuming exogeneity of the expenditure variable so that β is (relatively) free of simultaneity bias, we obtain the following:

$$\begin{aligned} \frac{\mathrm{d}E}{\mathrm{d}t} &\approx A + t\frac{\mathrm{d}A}{\mathrm{d}t} = A + A\eta = A(1+\eta) \\ \therefore 1+\eta &\approx \frac{1}{A}\frac{\mathrm{d}E}{\mathrm{d}t} \\ \therefore \frac{1}{1+\eta} &\approx A\frac{\mathrm{d}t}{\mathrm{d}E} = A\beta \\ \therefore \eta &\approx \frac{1}{A\beta} - 1 \end{aligned}$$

Clearly, the assumption of exogenous expenditure is vital to this calculus; many types of expenditure are endogenously influenced by taxation, so the (relative) exogeneity of police expenditure via the PPSA is a key factor in our approximation. Using $\hat{\beta}$ to represent the coefficient on *PolExpCapita* in our FE-2SLS regression model and TBC as shorthand for *TaxBaseCapita*, it therefore follows that for the i^{th} municipality,

$$A_i\beta \approx \overline{TBC}_i \cdot \hat{\beta},$$

since the per-capita transformations on tax base (averaged over time) and police spending cancel out. Hence, we obtain the tax base elasticity estimate

$$\widehat{\eta}_i := \frac{1}{\overline{TBC}_i \cdot \widehat{\beta}} - 1,$$

where $\widehat{\eta}_i$ the estimated tax base elasticity for municipality i over the period 2000–2018. Once finally calculated, this estimate serves as a decent (if rough) approximation of how sensitive the tax base is to changes in tax rate, given the exogenous nature of police expenditure in NB municipalities covered by the PPSA.

Results

We now present the numerical results of our statistical models. A more thorough discussion of the real-world implications of these findings is provided in the **Discussion** section, and raw computer output is included in the **Appendix**.

Correlated Random-Effects (CRE)

Our CRE model yielded the following results:

[TODO: Elaborate]

Fixed-Effects (FE)

Our instrument-free FE model yielded the following results:

$$\begin{aligned} Avg\ddot{Tax}Rate_{it} &= \underset{(0.0990)}{1.3092}PolExp\ddot{C}apita_{it} + \underset{(0.0914)}{0.9665}OtherE\ddot{x}pCapita - \underset{(0.0991)}{0.8964}OtherR\ddot{e}vCapita \\ &- \underset{(0.0012)}{0.0122}TaxBa\ddot{s}eCapita_{it} - \underset{(0.1951)}{0.5551}PolExp\ddot{C}apita_{it}{*}Provider\_MPSA_{it} \\ &- \underset{(0.1377)}{0.6083}PolExp\ddot{C}apita_{it}{*}Provider\_Muni_{it} + \ddot{u}_{it}, \qquad R^2 = 0.7216,\ F_{6,1708} = 66.473. \end{aligned}$$

(Note that the F-statistic provided here is robust to clustering.) On their own, these numbers are not particularly insightful—they simply serve as a baseline to which we can compare our FE-2SLS results, investigating how (the lack of) instrumentation affects our coefficients.

Fixed-Effects Two-Stage Least Squares (FE-2SLS)

We now turn to consideration of *MedHouseInc* as a potential instrumental variable to address endogeneity of *TaxBaseCapita*. As seen in the **Appendix** below, the first-stage OLS regression of *TaxBaseCapita* on *MedHouseInc* yielded the results

$$TaxBaseCapita_{it} = \underset{(0.020)}{0.668} - \underset{(2.455)}{11.2497}MedHouseInc_{it} + v_{it}, \qquad R^2 = 0.011,\ R^2_{adj} = 0.011,\ F_{1,1816} = 20.99,$$

where the F-statistic of 20.99 is far above the threshold of 10 for viable instruments. Therefore, we can safely integrate these results into the second-stage fixed-effects regression, using the (demeaned) fitted values of $Tax\widehat{Base}Capita$ from this stage. (Note that the low R^2 of 0.011 is irrelevant—we are concerned primarily with the correlation between the instrumental and endogenous variables, not with goodness-of-fit.)

Running a fixed-effects regression on the demeaned data and clustering by municipality, we obtain the following results (with full computer output once again available in the **Appendix**):

$$
\begin{aligned}
\ddot{AvgTaxRate}_{it} = \underset{(0.1371)}{0.5188}\ddot{PolExpCapita}_{it} + \underset{(0.0255)}{0.0301}\ddot{OtherExpCapita} + \underset{(0.0644)}{0.1025}\ddot{OtherRevCapita} \\
+ \underset{(0.0068)}{0.0225}\widehat{\ddot{TaxBaseCapita}}_{it} + \underset{(0.1941)}{0.0955}\ddot{PolExpCapita}_{it} * Provider\_MPSA_{it} \\
- \underset{(0.1821)}{0.2542}\ddot{PolExpCapita}_{it} * Provider\_Muni_{it} + \ddot{u}_{it}, \qquad R^2 = 0.4290,\ F_{6,1708} = 27.629.
\end{aligned}
$$

(Again, the F-statistic here is robust to clustering.) (TODO: Elaborate on the changes in coefficients post-instrumentation, citing again Brett and Tardif 2008)

In the following section, we proffer a more thorough discussion of our results and their real-world implications.

Tax Base Elasticity Estimates

[TODO: Elaborate]

Discussion

[TODO: Section intro]

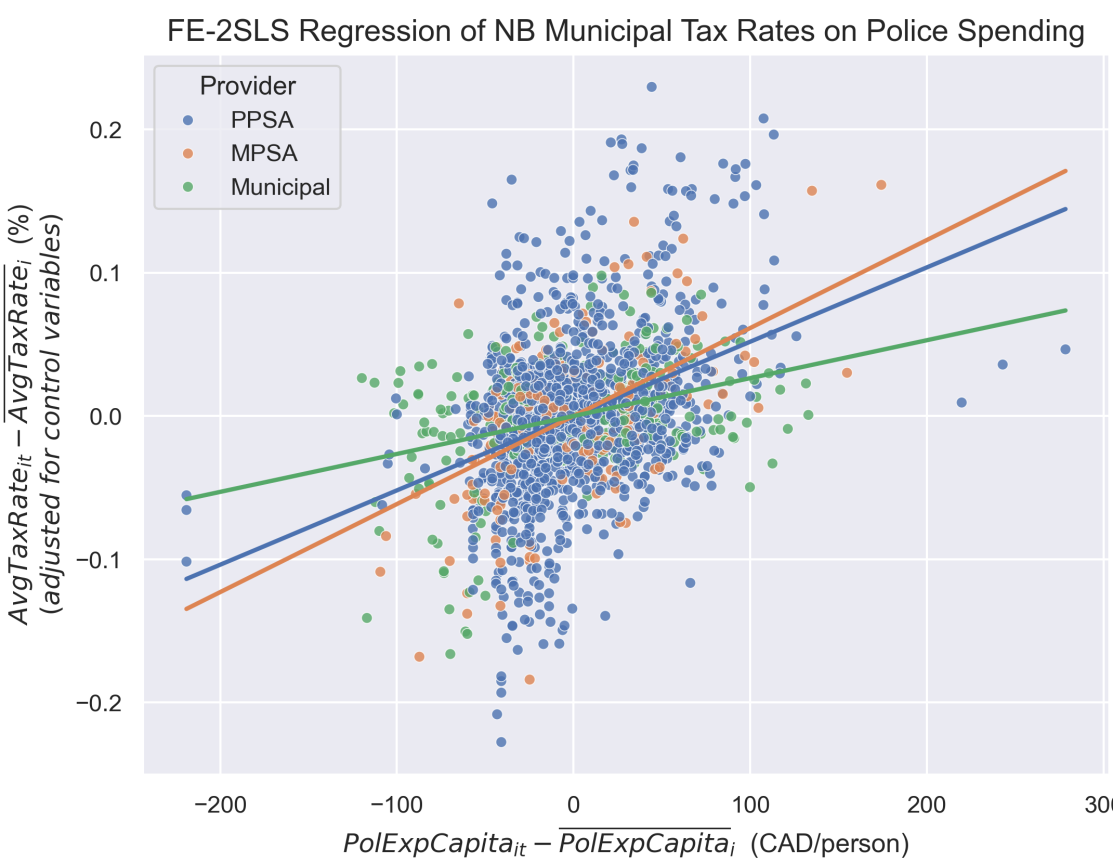

Figure 1: Lines of best fit from our FE-2SLS regression model, disaggregated by policing provider.

[TODO: Add explanation of the above figure]

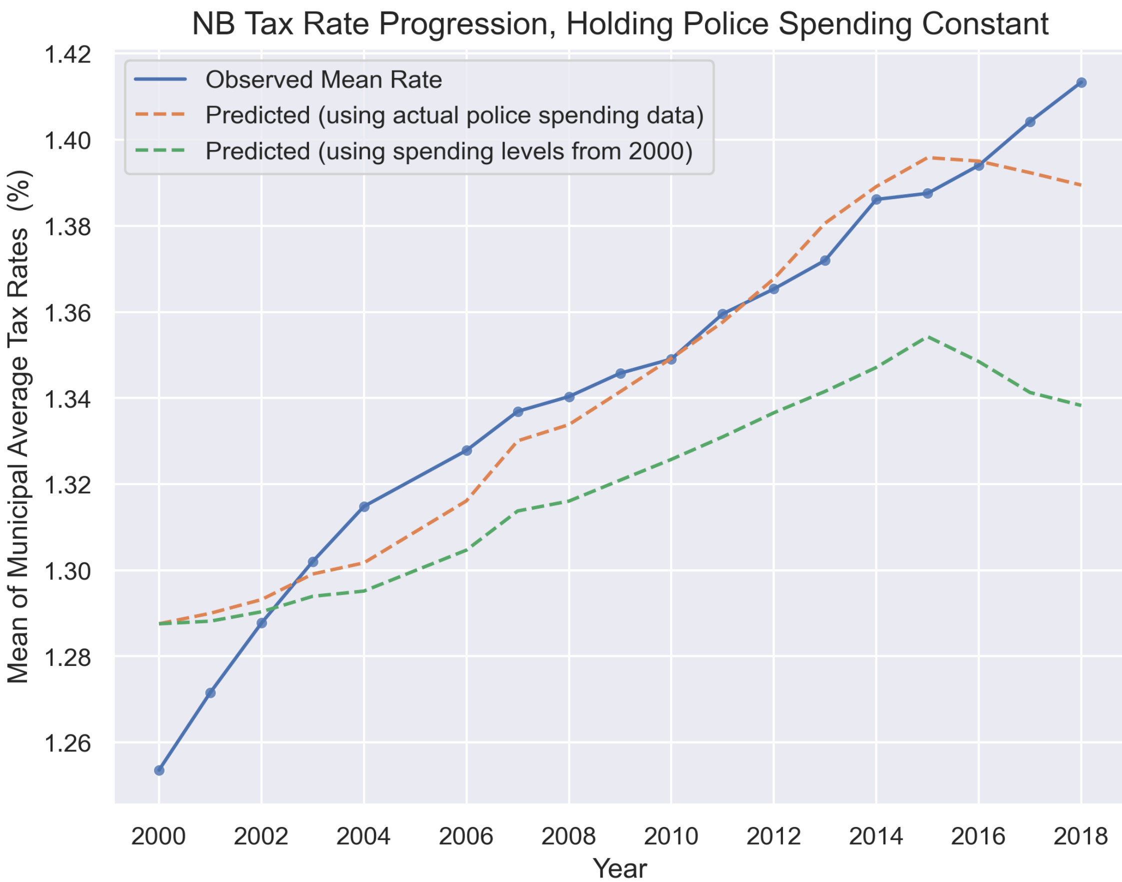

Figure 2: Counterfactual predictions of tax rates, holding police spending constant at 2000 levels.

[TODO: Add explanation of the above figure]

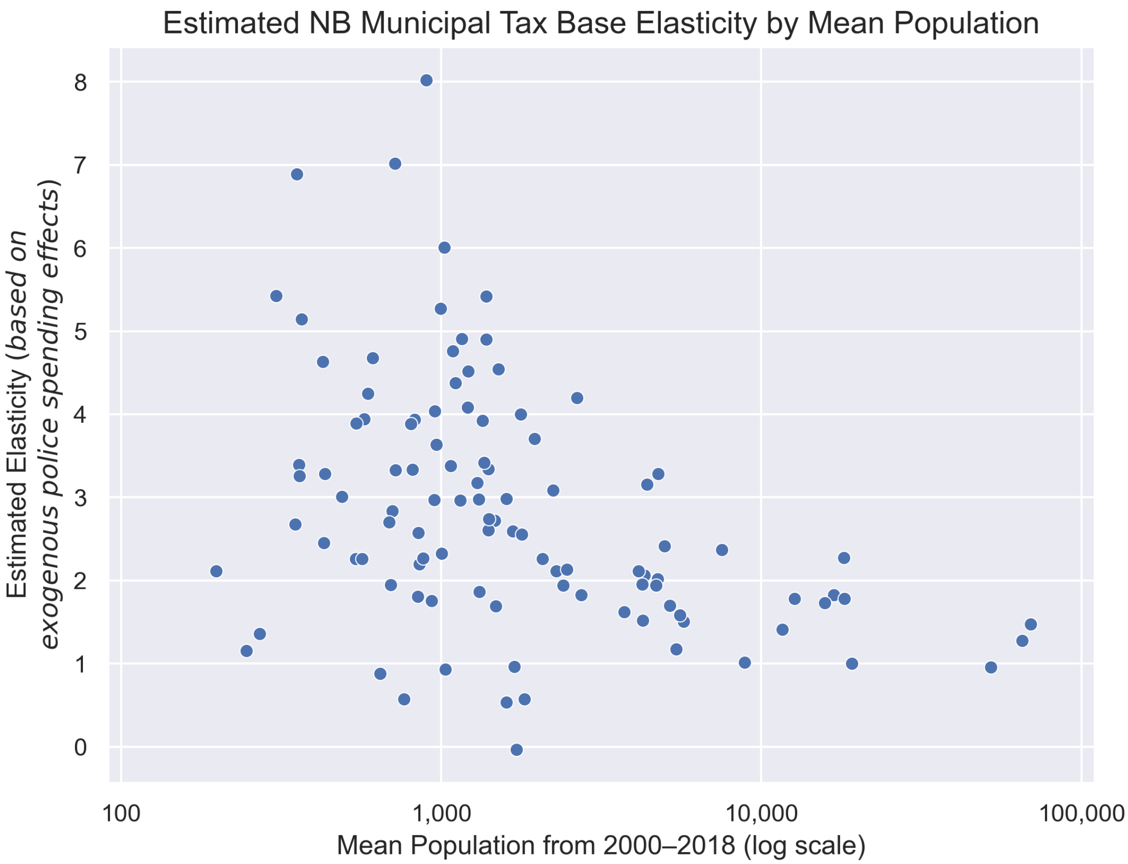

Figure 3: Tax base elasticity estimates. Smaller municipalities tend to exhibit higher asset mobility.

[TODO: Add explanation of the above figure. Potentially, also add hue by policing provider?]

Conclusion

[TODO: Elaborate]

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Appendix

We herein present raw computer output from our CRE, FE, and FE-2SLS regression models. (The original `.tex` output files are available in the `data_analysis/` directory of our GitHub repository.)

Correlated Random-Effects (CRE)

Table 1: Mixed Linear Model Regression Results

Model:	MixedLM	Dependent Variable:	AvgTaxRate
No. Observations:	1818	Method:	REML
No. Groups:	104	Scale:	0.0000
Min. group size:	6	Log-Likelihood:	11651.4921
Max. group size:	18	Converged:	Yes
Mean group size:	17.5		

	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
Intercept	0.012	0.000	52.256	0.000	0.012	0.013
PolExpCapita	1.306	0.038	34.329	0.000	1.231	1.380
OtherExpCapita	0.966	0.022	44.659	0.000	0.924	1.008
OtherRevCapita	-0.896	0.026	-34.670	0.000	-0.947	-0.845
TaxBaseCapita	-0.012	0.000	-43.716	0.000	-0.013	-0.012
PolExpCapita__mean	0.568	0.160	3.550	0.000	0.254	0.881
OtherExpCapita__mean	0.287	0.081	3.524	0.000	0.127	0.447
OtherRevCapita__mean	-0.312	0.104	-3.012	0.003	-0.516	-0.109
TaxBaseCapita__mean	-0.004	0.001	-4.955	0.000	-0.006	-0.003
PolExpCapita:Provider__MPSA	-0.555	0.062	-8.924	0.000	-0.677	-0.433
PolExpCapita:Provider__Muni	-0.597	0.047	-12.644	0.000	-0.690	-0.505
Provider__MPSA	0.001	0.000	3.742	0.000	0.000	0.001
Provider__Muni	0.001	0.000	4.121	0.000	0.000	0.001
Group Var	0.000	0.000				

Fixed-Effects (FE)

Dep. Variable:	AvgTaxRate	**R-squared:**	0.7216
Estimator:	PanelOLS	**R-squared (Between):**	0.1325
No. Observations:	1818	**R-squared (Within):**	0.7216
Date:	Tue, Apr 08 2025	**R-squared (Overall):**	0.1356
Time:	21:29:06	**Log-likelihood**	1.196e+04
Cov. Estimator:	Clustered		
		F-statistic:	738.02
Entities:	104	**P-value**	0.0000
Avg Obs:	17.481	**Distribution:**	F(6,1708)
Min Obs:	6.0000		
Max Obs:	18.000	**F-statistic (robust):**	66.473
		P-value	0.0000
Time periods:	18	**Distribution:**	F(6,1708)
Avg Obs:	101.00		
Min Obs:	95.000		
Max Obs:	103.00		

	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
PolExpCapita	1.3092	0.0990	13.222	0.0000	1.1150	1.5034
OtherExpCapita	0.9665	0.0914	10.575	0.0000	0.7872	1.1458
OtherRevCapita	-0.8964	0.0991	-9.0486	0.0000	-1.0907	-0.7021
TaxBaseCapita	-0.0122	0.0012	-10.440	0.0000	-0.0145	-0.0099
PolExpCapita:Provider__MPSA	-0.5551	0.1951	-2.8459	0.0045	-0.9377	-0.1725
PolExpCapita:Provider__Muni	-0.6083	0.1377	-4.4162	0.0000	-0.8784	-0.3381

F-test for Poolability: 51.098

P-value: 0.0000

Distribution: F(103,1708)

Included effects: Entity

Fixed-Effects Two-Stage Least Squares (FE-2SLS)

Stage 1

Dep. Variable:	TaxBaseCapita	**R-squared:**	0.011
Model:	OLS	**Adj. R-squared:**	0.011
Method:	Least Squares	**F-statistic:**	20.99
Date:	Tue, 08 Apr 2025	**Prob (F-statistic):**	4.93e-06
Time:	21:29:06	**Log-Likelihood:**	-363.29
No. Observations:	1818	**AIC:**	730.6
Df Residuals:	1816	**BIC:**	741.6
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	0.6668	0.020	33.737	0.000	0.628	0.706
MedHouseInc	-11.2497	2.455	-4.582	0.000	-16.066	-6.434

Omnibus:	920.376	**Durbin-Watson:**	1.434
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	8236.943
Skew:	2.196	**Prob(JB):**	0.00
Kurtosis:	12.458	**Cond. No.**	354.

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Stage 2

Dep. Variable:	AvgTaxRate	**R-squared:**	0.4290
Estimator:	PanelOLS	**R-squared (Between):**	0.9794
No. Observations:	1818	**R-squared (Within):**	0.4290
Date:	Tue, Apr 08 2025	**R-squared (Overall):**	0.9783
Time:	21:29:06	**Log-likelihood**	1.131e+04
Cov. Estimator:	Clustered		
		F-statistic:	213.84
Entities:	104	**P-value**	0.0000
Avg Obs:	17.481	**Distribution:**	F(6,1708)
Min Obs:	6.0000		
Max Obs:	18.000	**F-statistic (robust):**	27.629
		P-value	0.0000
Time periods:	18	**Distribution:**	F(6,1708)
Avg Obs:	101.00		
Min Obs:	95.000		
Max Obs:	103.00		

	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
PolExpCapita	0.5188	0.1371	3.7845	0.0002	0.2499	0.7877
OtherExpCapita	0.0301	0.0255	1.1801	0.2381	-0.0199	0.0802
OtherRevCapita	0.1025	0.0644	1.5912	0.1117	-0.0238	0.2288
TaxBaseCapita	0.0225	0.0068	3.2987	0.0010	0.0091	0.0359
PolExpCapita:Provider__MPSA	0.0955	0.1941	0.4923	0.6226	-0.2851	0.4762
PolExpCapita:Provider__Muni	-0.2542	0.1821	-1.3962	0.1628	-0.6113	0.1029

F-test for Poolability: 115.50

P-value: 0.0000

Distribution: F(103,1708)

Included effects: Entity