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20-824-983

Municipality-Level Analysis of Energy-Saving Measures in Norway

Semester Paper

Master's Degree Programme in Applied Mathematics

Swiss Federal Institute of Technology (ETH) Zurich

Supervision

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December, 2024

Abstract

This paper studies the factors that influence Norwegian households to carry out energy-saving home renovations, called "retrofits." We use a dataset spanning 2015–2022, combining socio-economic information for each municipality with data on the number of retrofits that received governmental subsidies. We transform raw counts into ratio variables (for instance, the share of single-person households or the proportion of multi-dwelling buildings) to allow for more meaningful comparisons across municipalities of varying sizes. While we use ratio transformations for many socio-economic covariates to enable cross-municipality comparison, we retain the raw count of retrofits as our outcome.

We fit an OLS model as a baseline, and then Negative Binomial model to capture the overdispersed nature of the count data. After including municipality and year fixed effects, we find that higher proportions of multi-dwelling buildings correlate with fewer retrofits, whereas higher median income and certain other socio-economic variables show mixed effects once we account for time-invariant local differences. We also observe that the number of private households in each municipality has a near-proportional relationship with retrofit counts. Overall, these insights suggest that building structure and some local characteristics strongly matter for retrofit decisions.

Acknowledgements

I would like to warmly thank Prof. Dr. Filippini for the supervision and for providing valuable advice, as well as a pleasant environment to work in. I would also like to thank Dr. Lukas Meier for the formal supervision of this paper. I would like to say "Tusen takk" to Dr. Cloe Garnache for proposing this topic and for her guidance.

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Chapter 1
Introduction

Energy efficiency and carbon reduction policies are important levers for mitigating climate change and achieving international commitments such as the Paris Agreement. In Norway, household energy consumption accounts for a large share of overall national energy use, and measures that improve residential energy efficiency can help reduce both energy expenditures and environmental impact. Consequently, understanding the social and economic factors that impact households' decisions to invest in energy-saving retrofits is relevant to environmental policy, and can also shed light on how to best allocate subsidies.

In this framework, we assembled a dataset from two sources: the Statistics Norway database (referred to as SSB) for municipality-level socio-economic variables (e.g., incomes, housing structure, wealth distribution), and ENOVA data for government-subsidized retrofits. ENOVA is a Norwegian government-owned organization that promotes the transition to a low-emission society by supporting projects and initiatives focused on energy efficiency, renewable energy, and the reduction of greenhouse gas emissions. Specifically, we obtained from ENOVA a list of individual retrofit projects across all Norwegian municipalities that received funding, together with information such as the nature of each retrofit, the amount paid, and the total cost. Examples of relevant retrofit measures include installing heat pumps, improving building insulation, upgrading windows, and deploying solar panel systems, among others. We processed the socio-economic data by converting raw counts into ratio variables (e.g., the proportion of single-person households in a municipality) to allow for comparisons across municipalities of widely different sizes. Through these transformations, we created a panel dataset (2015–2022) that captures both the yearly retrofit activities and local socio-economic conditions for each municipality.

Using this dataset, we fit several regression models to examine which factors appear to influence retrofit adoption. We use an OLS model as a baseline, then move to a Negative Binomial as it suits better the panel structure of our data. We also take into account local time-invariant traits and year-specific shocks by adding fixed effects terms to this second model. Preliminary results suggest that building characteristics—particularly the share of multi-dwelling units—tend to correlate with fewer retrofits, possibly because apartment-style living reduces individual households' direct control over renovation choices. By contrast, higher median income, once we control for the number of private households, appears to lead to a higher uptake of retrofits in simpler model specifications, though some of these effects become less pronounced when municipality and year fixed effects are introduced.

Finally, I would like to highlight that this study was performed within the restrictive framework of a master semester paper and with the primary goal of practicing scientific analysis and writing a scientific document. Thus, this paper should be seen as an explorative study and all results reported in this paper should be considered preliminary and used carefully. In its current form, the results are not suitable for citation.

Chapter 2
The Data Set

Before going into econometric analysis part, it is important to get a good understanding of the data. We have two data sets, the first one was built by merging tables from SSB and contains some socio-economic characteristic at the municipality level per year, while the second contains ENOVA data about retrofit activity at the municipality level per month (it will be aggregated at the yearly level later). This chapter consists in a quick explanation of the structure of our data set, together with some summary statistics.

2.1 Structure and transformation

Let us start by explaining the structure of our two initial data sets.

2.1.1 The Socio-Economic Data Set

This first dataset contains socio-economic variables about Norwegian municipalities, at the yearly level. It was built by extracting data from the SSB website, and ranges from 2015 to 2022 (both included). The variables are grouped into different families. The **Income Variables** represent the median income after taxes of different type of households such as individuals living alone, couples with children aged 0 to 17, or single parents with children aged 0 to 17 for instance. The **Net Wealth Variables** correspond to percentages of the population within various net wealth brackets in million Norwegian kroner (NOK). It is worth saying we did not have access to actual values of wealth, only percentage brackets. Because of this, we could not inflate/deflate the data according the costumer price index. So in order to stay consistent, all money data (the income data mentionned previously, and the subsidy and cost in part 2.1.2) in this project are nominal. Continuing with the variables, we have the **Building Types** that display the number of detached houses, houses with two dwellings, row houses or linked houses with three or more dwellings, multi-dwelling buildings, and residences for communities. Next, the **Education Levels** give us the total number of individuals aged 16 and older according to their highest educational attainment, such as secondary, tertiary, or high studies for instance. Concerning the **Household Types** we have the number of various household compositions, differing by the number of people, the presence/absence of children, and the age of the children. Lastly we have the total number of private households and the total population living within them.

To ensure comparability and interpretability across municipalities of different sizes, we transformed the raw counts (household and building composition, and education level) into ratio variables. The fractions for these ratios are detailed in the appendix A. The **Household Composition Ratios** represent the proportion of single-person households and couples without children, the share of households with children (couples or single parents); and the proportion of households consisting of two or more families. The **Building Composition Ratios** give the proportion of single-family or dual-family dwellings, and the share of multi-dwelling units. Lastly, the **Education Ratios** re presents the proportion of individuals with no or low education levels; and with high education levels.

Using ratios is advantageous for our analysis. First it neutralizes the effect of population size, thus allowing for meaningful comparisons between municipalities of different sizes. Also, we gain in interpretability, as ratios provide intuitive insights, such as the proportion of single-person households or highly educated individuals. By constructing these ratio variables, we ensure that the analyses focus on the distributional characteristics of socio-economic variables.

2.1.2 The Retrofit Data Set

This second data set was provided by ENOVA, an organization owned by the Ministry of Climate and Environment, with the main goal of contributing to a faster transition to a low-emission society. Each one of the line of the data set represents a retrofit that received a subsidy by the Norwegian government, with the month and year when the subsidy demand got accepted (ranging from 2015 to 2024), the nature of the retrofit, the subsidy amount, the total cost of the retrofit, the municipality where it happened, the municipality number (a 4 digit numbers identifying each municipality in Norway). For practical reasons we decided to use the municipality numbers to identify the municipalities. Before continuing, it is worth mentioning that the retrofit data set has two main caveats. First of all, to obtain a payback for their retrofit work, the households have to pay for it first, and subsequently send the bill in order for it to be subsidized. But sometimes, when doing this kind of works in the home, other works are done. For instance, someone will install solar panel and change the windows of the kitchen simultaneously. Thus this may inflate some costs in our data. Also, the subsidy demands need a delay of a few weeks/months to be accepted, hence a retrofit of the end of 2020 might be registered in the beginning of the year 2021. With this in mind, we can go on. To ensure a match with our previous data set we got rid of the rows from 2023 and 2024[1], updated the municipality numbers to the 2022 version[2]. We conclued this preparation by the removal of empty or non-valid rows.

We also created the variable `subsidy_share` which is simply for each row the fraction $\frac{\texttt{Subsidy}}{\texttt{Total cost}}$. Because our first data set was at the yearly and municipality level we aggregated this one at the yearly and municipality level (so that each row was associated to one municipality for one year) and created the variables `Retrofit count` and `avg_subsidy_share` that were respectively the number of retrofit for this municipality this year, and the average of the subsidy shares for this municipality this year. Additionally we created variables `avg_cost` and `avg_subsidy` that represents the average cost and subsidy for a given year. Then, we concluded the data preparation by merging the two data sets on the municipality numbers and years, in order to obtain a complete data set containing information about the retrofit activity at the yearly and municipality level, together with the socio-economic data associated with the municipality and year of the retrofit.

2.2 Summary Statistics

[1]Because our most recent socio economic data are from 2022

[2]Through the years, Norwegian government changed the number of a lot of municipalities, via merging or plain renaming, aiming to reduce the number of municipalities. See this SSB webpage

Now that the data structure and the variables are clear, we present some summary statistics.

2.2.1 Data Set Bird's Eye View

As an appetizer, let us look at the averages of some socio-economic indicators through the years in table 2.1. The indicators are respectively the median income (in NOK) average over the whole population, the proportion of the population with a net wealth below 3 M NOK, the share of buildings that are multi-dwellings (I.e. more than two), and lastly the share of one person or couple without child among households. The income and wealth variables grow steadily in opposite directions, suggesting that the population's income grows through the years, and that simultaneously the share of people with a net wealth below 3 M NOK diminishes. The share of multi-dwelling buildings and the share of small households also grow, suggesting that people live more and more in small circle (alone or in couple but without children) but in large residential buildings. In a nutshell, the Norwegian population seems to become richer, prefers to live in shared buildings and without a family. The last one may suggests that young Norwegians either leave their family to live alone more and more early, or wait longer to start their own family.

Table 2.1: Yearly Socio-Economic Indicators (Population-Weighted)

Year	**Median Inc.**	**Wealth<3M**	**Multi-Build.**	**Alone/Couple**
2015	502993	81.4%	13.6%	61.5%
2016	508274	79.6%	13.6%	61.8%
2017	519902	77.9%	13.7%	62.0%
2018	533649	77.7%	13.8%	62.5%
2019	550694	76.3%	13.9%	62.9%
2020	550729	74.8%	14.2%	63.4%
2021	572671	71.5%	14.4%	64.2%
2022	596841	69.9%	14.4%	64.7%

However, we must here highlight again that we did not deflate the money data, hence the movements of income and wealth are probably due to the increase of the CPI through the years. As discussed in part 2.1.1, we kept the money data nominal because the net wealth data were only given in percentages, and not in numerical value (I.e. we have access to let us say the percentage of the population within the 1M-3M NOK bracket, but not the average net wealth for instance). Hence for consistency we kept everything nominal. If we account for the consumer price index evolution with 2022 as a basis, we see can see in table 2.2 that the median income stays rather constant. So in the end, the idea of the Norwegian population becoming richer is caused by a caveat of our data more than anything else.

Table 2.2: Median Income Inflated

Year	**Median Inc.**
2015	617675
2016	602472
2017	605156
2018	604539
2019	610336
2020	602759
2021	605719
2022	596841

Now that we have a better overview of the Norwegian population, we would like to have and idea of the retrofitting activity across the country. We can thus take a look at the top 5 municipalities with the highest number of retrofit for each year. As we can see in tables 2.3 to 2.10, the same names are often coming back each year. This is expected as those municipalities are among the most populated in Norway. We can see that Oslo is always first, each time by substantial margin except for 2018 when Bergen came very close second. Bergen is second every year except for 2015. Also, if we compare tables between them rather than the municipalities within the tables, we observe that the counts follow the trend of figure 2.1. Indeed, 2018, 2019 and 2022 are substantially above the other four years.

Table 2.3: Top 5 Municipalities, 2015

Municipality	Retrofit_Count
Oslo	268
Trondheim	177
Bergen	166
Bærum	153
Asker	101

Table 2.4: Top 5 Municipalities, 2016

Municipality	Retrofit_Count
Oslo	387
Bergen	310
Trondheim	278
Bærum	201
Stavanger	197

Table 2.5: Top 5 Municipalities, 2017

Municipality	Retrofit_Count
Oslo	561
Bergen	403
Bærum	315
Trondheim	313
Asker	204

Table 2.6: Top 5 Municipalities, 2018

Municipality	Retrofit_Count
Oslo	1071
Bergen	1027
Trondheim	557
Bærum	540
Asker	448

Table 2.7: Top 5 Municipalities, 2019

Municipality	Retrofit_Count
Oslo	1151
Bergen	766
Bærum	615
Trondheim	448
Asker	431

Table 2.8: Top 5 Municipalities, 2020

Municipality	Retrofit_Count
Oslo	489
Bergen	428
Bærum	249
Trondheim	234
Stavanger	221

Table 2.9: Top 5 Municipalities, 2021

Municipality	Retrofit_Count
Oslo	379
Bergen	319
Stavanger	258
Trondheim	224
Bærum	184

Table 2.10: Top 5 Municipalities, 2022

Municipality	Retrofit_Count
Oslo	823
Bergen	748
Kristiansand	577
Stavanger	495
Bærum	481

2.2.2 Total Retrofit Count Per Year

Since it is our main object of interest, let us take a look at the retrofit counts. In figure 2.1, we can see the total retrofit count for each year. Clearly, we see a big difference between the years 2015, 2016, 2017, 2020, 2021, and the years 2018, 2019,

2022. The latter have seen a huge number of retrofit compared to the former, with the smaller year of the high group (2019 with 16 495) being twice as large as the greater year of the low group (2020 with 8031). The years rank as follow, from highest to lowest: 2022 with 17096, 2018 with 17070, 2019 with 16495, 2020 with 8031, 2017 with 7530, 2021 with 6892, 2016 with 6154, and 2015 with 3973.

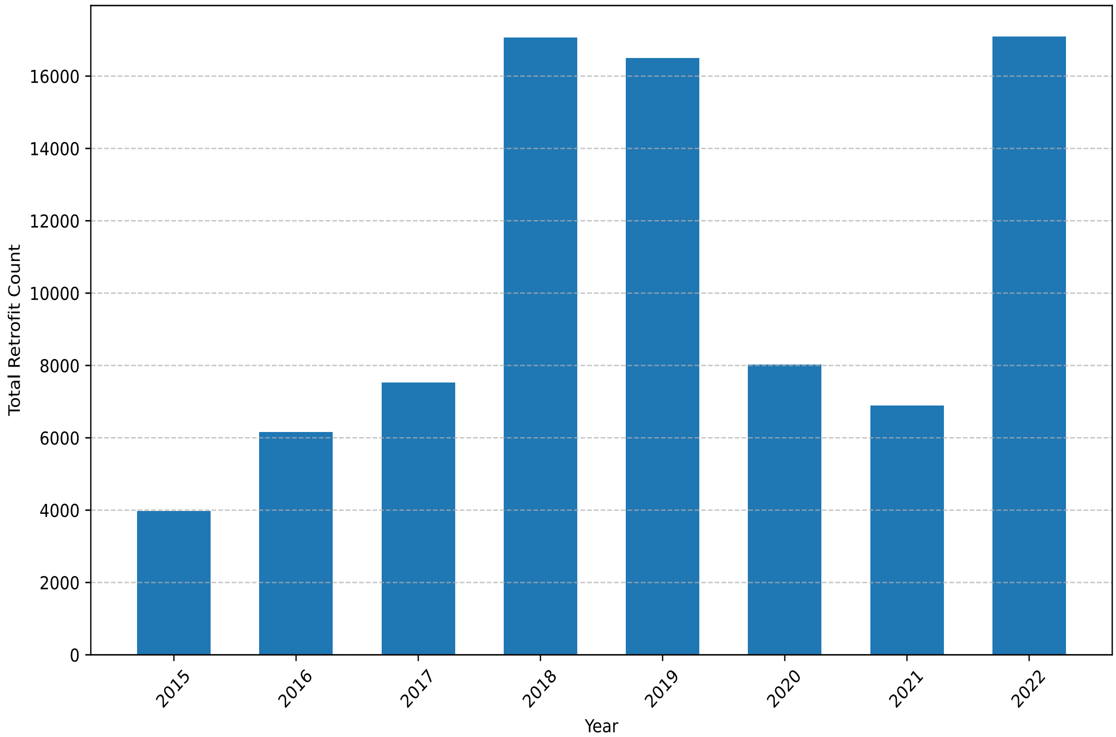

Figure 2.1: Total Retrofit Count by Year

2.2.3 Average Cost, Subsidy and Subsidy share for each Year

To gain some insight, we can furthermore look at the evolution of the the average cost, subsidy and the ratio of them through the years. The first two, namely figures 2.2 and 2.3 are do not seem to present a clear link with the retrofit count. Indeed the Cost plot has a peak in 2018, which is intriguing as this year was the second year with the biggest number of retrofit, and one would expect lower costs to drive up the number of retrofit. Similarly, the Subsidy plot does not seem to correlate a lot with the retrofit counts. Its highest point is in 2017, a low year, and its lowest in

2019, a high year for retrofit count. 2016, 2018 and 2022 are pretty similar, but the first is a low year whereas the two other are the two highest years. Only the Ratio plot seems to move a bit like the retrofit count, with the three highest year being the same in both plot, and in the same order. We also notice the same neighborhood order relationship, meaning that if a year is greater (resp. smaller) than its neighbor in one plot, then it is also greater (resp. smaller) in the other. But every order relationships are not respected, with 2020 above 2017 and 2021 above 2016 in figure 2.1, whereas we have the opposite for both relation in figure 2.4. Even

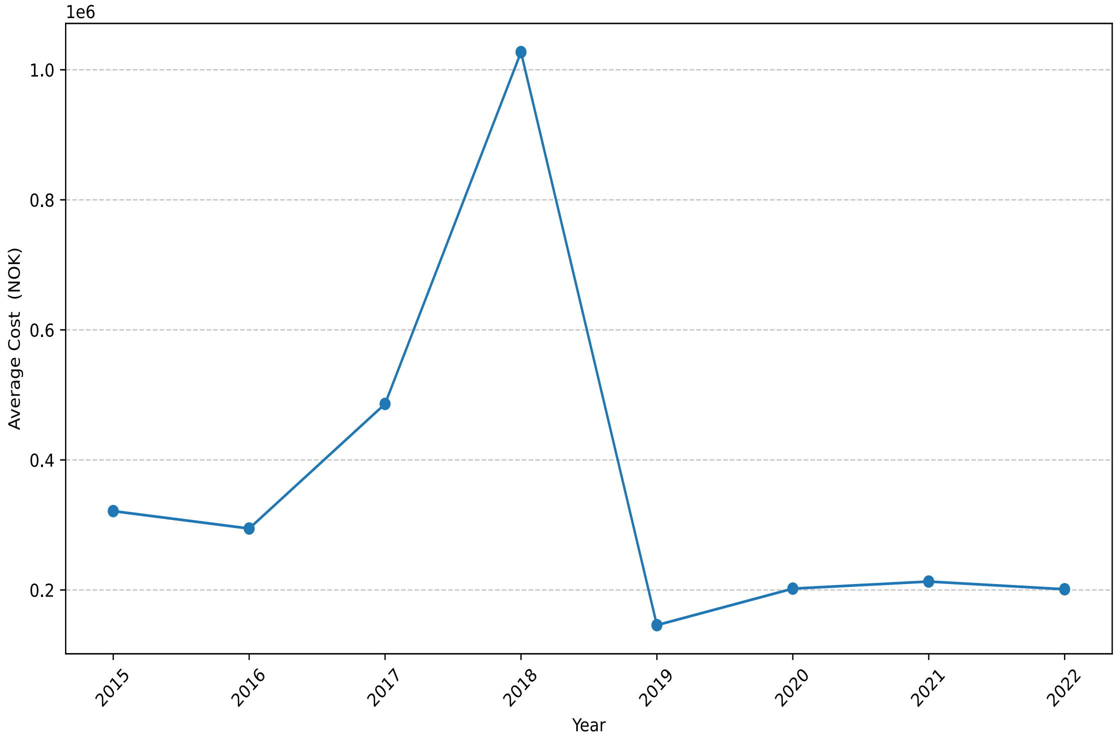

Figure 2.2: Average Retrofit Cost by Year

though 2018 and 2019 are two of the most prolific years in term of retrofit count, we notice a large discrepancy in the average subsidy and total cost, with both of them dropping substantially in 2019. To investigate this, it is interesting to look at those variables while differentiating among the different retrofits. As we can see in figure 2.6, the average costs of Removal of Oil Heater & Tank and Exhaust-Air Heat Pump experienced a very steep downfall from 2018 to 2019, coinciding with the one in figure 2.2. We can also see in figure 2.5 that those retrofits were among the most popular for those two years. The combination of those two observation explain the

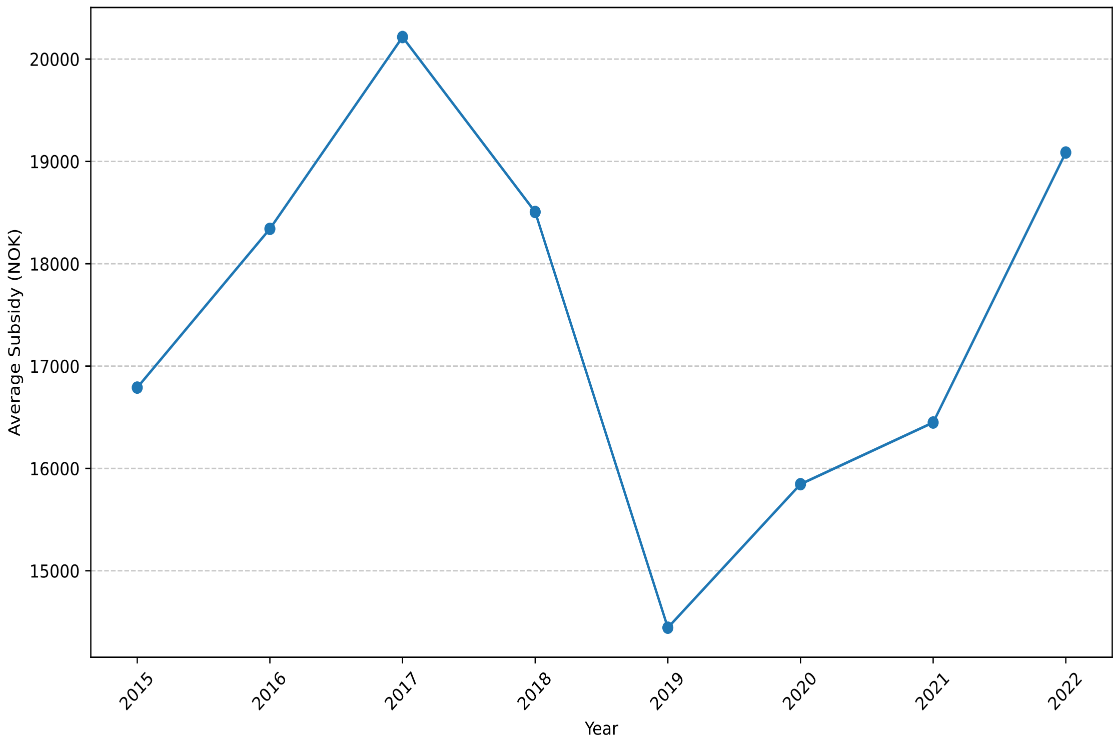

Figure 2.3: Average Subsidy by Year

2018-to-2019 drop in figure 2.2 quite clearly. Concerning the peak of Removal of Oil Heater & Tank, it might be worth saying that as of 31 December 2019, Norway phased out traditional oil heaters for household heating. This legal mandate likely explains the surge in Removal of Oil Heater & Tank retrofits just before 2020, as everyone had to remove such systems by that deadline. Furthermore, we can observe in figure 2.7 a drop from 2018 to 2019 for the average subsidies for Liquid-to-Water Heat Pump, Air-to-Water Heat Pump and Bio Boiler. In particular the two first are the most popular retrofit in 2019, and two of the three most popular of 2018 as can be seen in figure 2.5. The high counts of those for these years together with their drop in subsidy likely explains the 2019's drop in figure 2.3. Lastly, we can see in figure 2.5 the introduction of two new popular retrofits, Smart Water Heater and Price-Controlled Storage around 2022. These are automation technologies that help households take advantage of the real-time electricity prices in Norway, which surged in 2022 following the energy crisis. By shifting usage to cheaper hours, these innovations reduce energy bills.

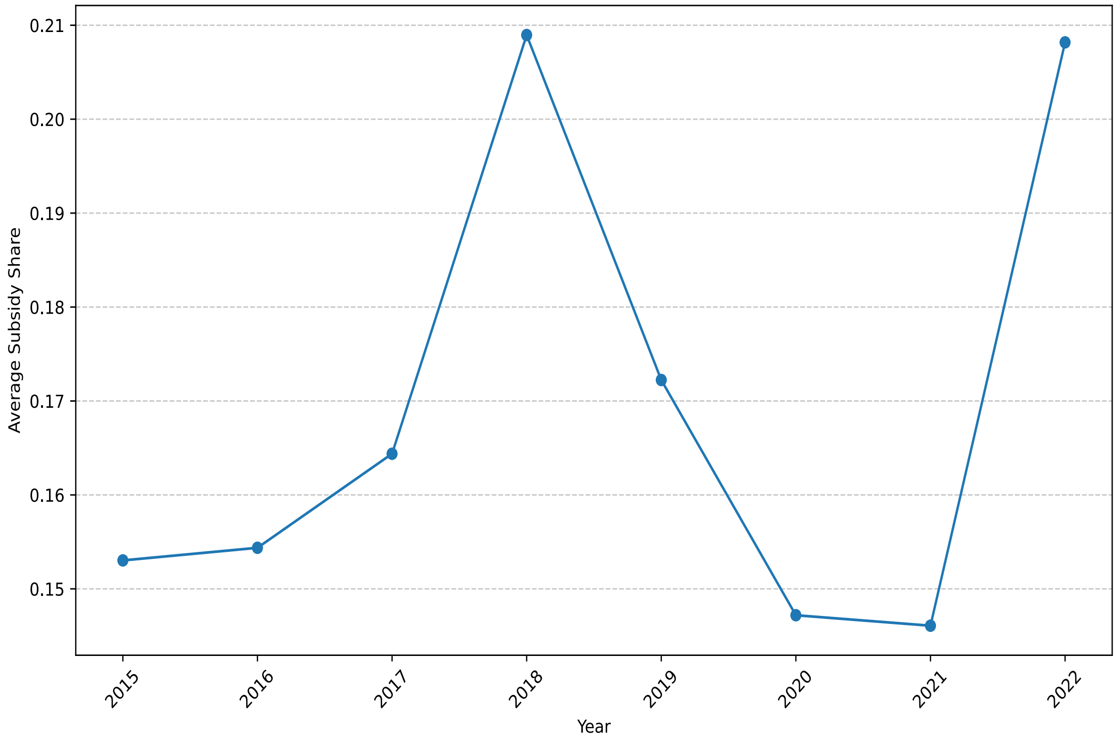

Figure 2.4: Average Ratio Subsidy/Cost by Year

Equipped with these insights from our descriptive statistics, we next turn to formal econometric modeling to quantify the socio-economic drivers of retrofit adoption.

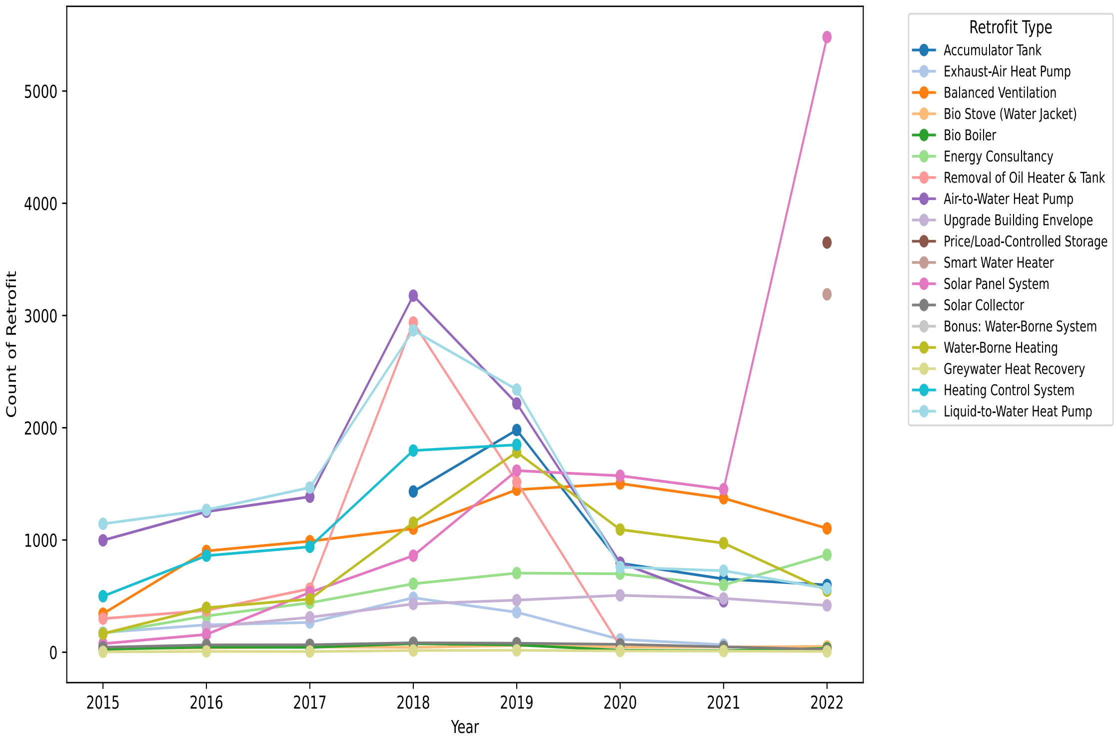

Figure 2.5: Different Types of Retrofit Counts by Year

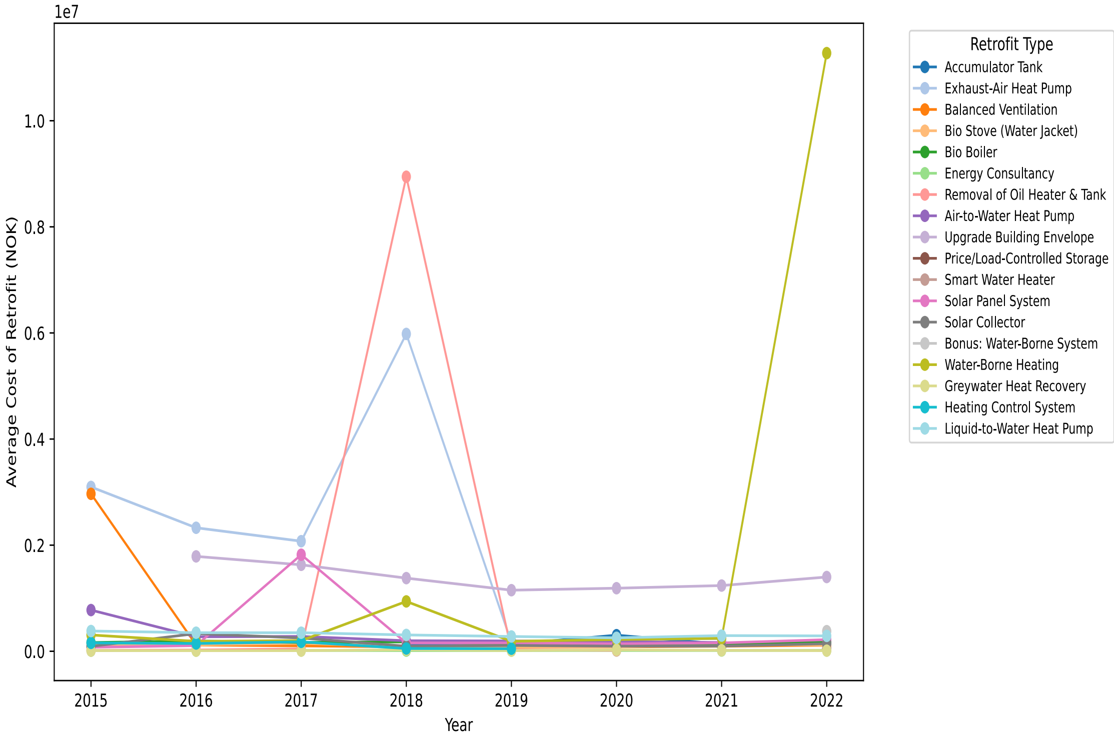

Figure 2.6: Average Cost of Different Types of Retrofit by Year

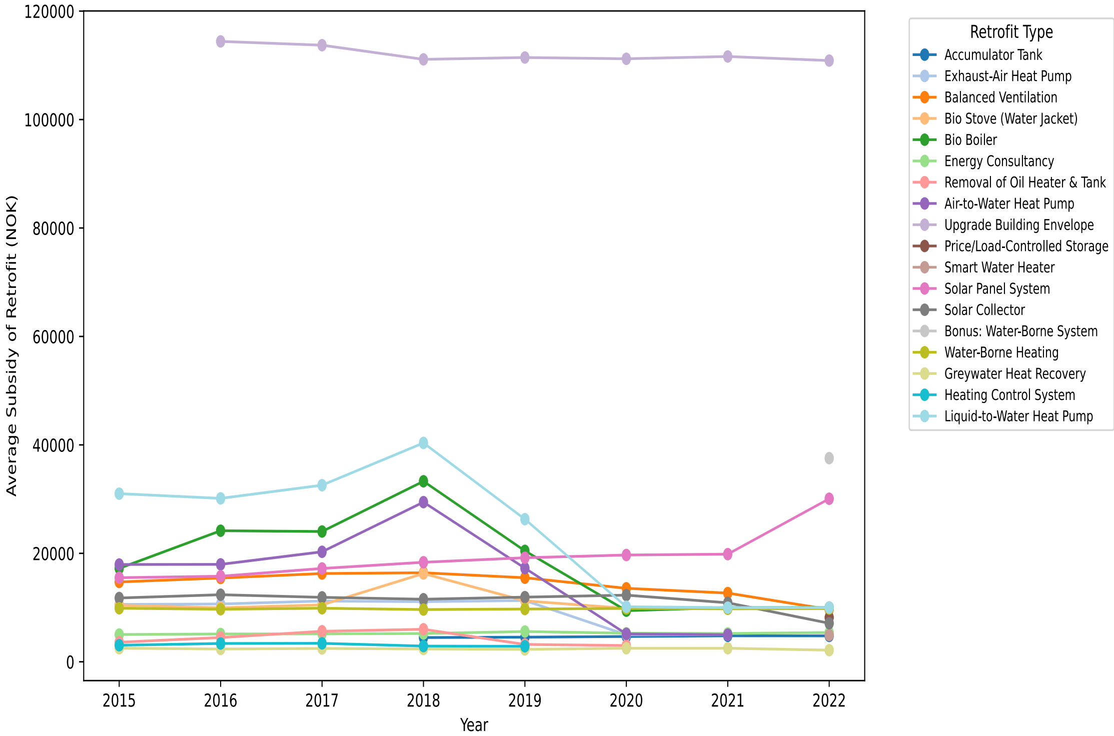

Figure 2.7: Average Subsidy of Different Types of Retrofit by Year

Chapter 3
Econometric Analysis

Now that we understand our data better, and that we have a good overview of it, we want to know which factors may influence the Norwegian population to undergo energy-saving renovation in their home. In order to do so, we fit statistical models and analyze their results. In particular, we fit an OLS model as a baseline, and then move to a Negative Binomial model with dispersion parameter α. We will discuss the rationale behind this particular choice of model, and after this jump to the analysis. Lastly, we also discuss the addition of Fixed Effects (FE) to improve the model, at the municipality and yearly level.

3.1 Baseline Model

Before looking at the model, let us discuss our choice of explanatory variables. First, we are interested in seeing wether the `subsidy_share` of a project has a real impact on the retrofit count. Next, for the ratio variables, when there were only two in the same family we only kept one (to avoid perfect multicolinearity, as the sum of both part of a ratio is 1). Hence we kept `netwealth_below3M` and `building_multi_ratio` for **Net Wealth Variables** and the **Building Types**. For the **Household Composition Ratios** we noticed that the proportion of households of two or more family was so small that the proportion of family household and small household (single person or couple without children) were essentially summing to one. We kept `small_hh_ratio`. Concerning the **Education Level**, as we only have low or high education we decided arbitrarily to keep the share of high education. As the other **Income variables** were too specific we selected `medianIncAftertaxes`. We also added `private_hh` to account for municipality sizes. We can write our baseline

OLS regression with the count outcome:

$$\text{Retrofit\_Count}_{i,t} = \beta_0 + \beta_1(\texttt{subsidy\_share}_{i,t}) + \cdots + \beta_7(\texttt{private\_hh}_{i,t}) + \varepsilon_{i,t} \quad (3.1)$$

where i is the municipality, t the year and $\epsilon_{i,t}$ the error term. We acknowledge that using our approach is similar in spirit to modeling a ratio of retrofits per household, but here the municipality size is explicitly on the right-hand side.

Table 3.1: OLS Regression

Variable	**Coef.**	**Std. Err.**	**t**	**P> $\|t\|$**	**95% C.I.**	
`const`	-149.2253	23.834	-6.261	0.000	-195.963	-102.488
`subsidy_share`	87.7020	14.851	5.905	0.000	58.580	116.824
`netwealth_below3M`	0.1253	0.083	1.517	0.129	-0.037	0.287
`building_multi_ratio`	175.5266	23.164	7.578	0.000	130.104	220.949
`medianIncAftertaxes`	0.0001	2.05e-05	5.635	0.000	7.54e-05	0.000
`small_hh_ratio`	58.8871	23.408	2.516	0.012	12.985	104.790
`edu_high_ratio`	130.4812	21.667	6.022	0.000	87.992	172.970
`private_hh`	0.0018	5.14e-05	34.839	0.000	0.002	0.002

Notes: $R^2 = 0.633$; AIC = 24840.

We see that the model's R^2 is 63.3%, indicating substantial portion of the variance in retrofit counts is explained. The `private_hh` variable is highly significant and positive, suggesting larger municipalities (in terms of number of private households) systematically have more retrofits. The other predictors are strongly significant except for `netwealth_below3M`, which has a p-value of 0.129 and hence is not statistically significant at conventional levels. In particular, the estimated coefficient on `building_multi_ratio` is about 175.5 (std. err. 23.16), indicating more multi-dwelling buildings are associated with higher retrofit counts in absolute levels. This might appear counterintuitive as shared infrastructures might mean fewer separate installations per household. Meanwhile, `edu_high_ratio`, the proportion of highly educated inhabitants, is strongly positive (130.48, p-value < 0.01), in line with the idea that higher education is linked to greater awareness or preference for energy efficiency measures. The coefficient on `subsidy_share` (the average fraction of project cost covered by the subsidy) is significantly positive at 87.70. This means that, controlling for other variables, municipalities with higher average subsidy shares seem to see more (raw) retrofits. It is worth mentioning that there is a conceptual issue:

OLS imposes that the dependent variable can be any real number, whereas here we have a nonnegative integer count. OLS can easily predict negative or fractional "retrofits." Additionally, count data often exhibit overdispersion, which violates the homoscedasticity assumption. Therefore, one might consider a Negative Binomial model. This latter directly models discrete counts, includes a dispersion parameter, and in practice often handles the high variance typical of retrofit counts better. Hence let us move to such a more appropriate model.

3.2 Negative Binomial Models

3.2.1 Rationale

As previously mentioned, our data are arranged so that each municipality is observed over multiple years. This kind of structure is called panel data. Since we are dealing with a count outcome (the number of retrofits), standard choices include Poisson or Negative Binomial regressions. But in order to model the count of retrofits, it is very important to address the issue of overdispersion. A standard Poisson regression can underestimate the standard errors and which can lead to biased inferences in the presence of overdispersion. However, the Negative Binomial model uses a dispersion parameter α to tackle this additional variability, hence it is a better choice. Also, it is clear that the count of retrofits generally depends on the number of households (`private_hh`) in the municipality. To account for this fact, we would typically include this in the model as an offset term, in order for the changes in population size to directly scale the expected count without estimating an other parameter. However, in the implementations of the Negative Binomial model that we used [1], there is no `offset` argument. So as a workaround, we incorporated log(`private_hh`) as a standard explanatory variable. Concretely, our Negative Binomial regression equation looks like

$$\log\big(\mathbb{E}[\texttt{Retrofit\_Count}_{i,t}]\big) = \beta_0 + \beta_1 X_1^{i,t} + \cdots + \gamma \log(\texttt{private\_hh}_{i,t}) \quad (3.2)$$

where i is the municipality and t the year. But instead of fixing $\gamma = 1$, we estimate it from the data. If it is close to 1 (and this will be confirmed by the results later), that suggests the model is effectively scaling counts by municipality size. This way

[1] `statsmodels.discrete.discrete_model.NegativeBinomial`

we make sure that big differences in population size among municipalities do not flaw the regression results.

3.2.2 Simple Negative Binomial Model

Here after in table 3.2 we can see the results of our basic Negative Binomial model without fixed effects.

Table 3.2: Negative Binomial with Estimated α (No FE)

Variable	Coef.	Std. Err.	z	P> $\lvert z\rvert$	95% Conf. Int.	
`const`	-45.7885	2.718	-16.845	0.000	-51.116	-40.461
`subsidy_share`	1.6524	0.279	5.930	0.000	1.106	2.198
`netwealth_below3M`	0.0006	0.001	0.440	0.660	-0.002	0.003
`log_medianIncome`	2.9179	0.194	15.041	0.000	2.538	3.298
`building_multi_ratio`	-2.1725	0.401	-5.411	0.000	-2.959	-1.386
`small_hh_ratio`	3.4104	0.408	8.365	0.000	2.611	4.210
`edu_high_ratio`	1.6419	0.353	4.656	0.000	0.951	2.333
`log_private_hh`	0.9144	0.020	46.248	0.000	0.876	0.953
α	0.4130	0.014	29.677	0.000	0.386	0.440

Notes: Pseudo $R^2 = 0.1701$; AIC = 17791.19.

The first thing that catches our eyes is the difference between the OLS's R^2 and the NegBin pseudo R^2, and both models' AIC. However, we cannot really compare the R^2 with the pseudo R^2, as the standard R^2 measures the proportion of variance explained by a linear regression, whereas the pseudo R^2 is a likelihood-based metric for count (or other non-linear) models, so they reflect different concepts of 'fit'. For the AIC, we see that the NegBin's AIC is way better than OLS's AIC. Since the AIC penalizes models for complexity (more parameters) to avoid overfitting while rewarding goodness of fit (higher likelihood), it suggests that the NegBin model has by far a better balance between fit and simplicity. We also see that `log_private_hh` has a coefficient close to 1, confirming what we said in the Rationale subsection 3.2.1. Also, the dispersion parameter $\alpha = 0.4130$ confirms the presence of overdispersion.

Socio-economic factors analysis

The coefficients of `log_medianIncome`, `subsidy_share`, and `edu_high_ratio` are all positive and highly significant, suggesting that higher median income, more generous subsidy (compared with the projects cost, i.e. greater $\frac{\texttt{subsidy}}{\texttt{cost}}$ ratios), and a larger share of inhabitants with high education all encourage more retrofits. On the other hand, `netwealth_below3M` has a small (0.0006) and statistically insignificant (large p-value of 0.660) coefficient, meaning that the share of individuals in this wealth category in a municipality does not systematically matter if we account for other variables. Concerning housing characteristics, the negative coefficient on `building_multi_ratio` (-2.1725) shows that municipalities with more (proportionally) multi-unit buildings undergo fewer retrofits, possibly because these buildings use less separated infrastructures (e.g. one central heating system for the entiere building). The variable `small_hh_ratio`, is positive at 3.4104 and highly significant, showcasing higher retrofit rates in areas where single-person and childless-couple households are more numerous, suggesting that this part of the population find it more easy/appealing to pursue renovations. Those results are to be taken with a pinch of salt, as a lot of unknown factors can also have an impact on the retrofit count.

3.2.3 Negative Binomial with Both Municipality and Yearly FE

As previously said, a lot of hidden factors could be playing a role in the retrofit adoption. Indeed, it is clear that each year brings countrywide factors—like macroeconomic changes or a colder winter—that our socio-economic variables alone do not capture, and each municipality has certain hidden traits (e.g. housing history, political opinion trend, geography) that barely change over time. To capture those, we decided to apply Fixed Effects for both year and municipality. This lets us filter out influences that are the same across all municipalities in a given year, and also those that are unique to each municipality but remain constant over the years. Consequently, our model focuses solely on the relationships between the observed socio-economic factors and retrofit adoption, without being skewed by either year-specific national shifts or municipality-specific characteristics that do not vary. Mathematically, we can now express our model as follow:

$$\log\big(\mathbb{E}[\texttt{Retrofit\_Count}_{i,t}]\big) \;=\; \beta_0+\beta_1\,X_1^{i,t}+\cdots+\gamma\,\log(\texttt{private\_hh}_{i,t})+\delta_t+\nu_i \quad (3.3)$$

Where δ and ν are respectively the time and municipality FE terms. Table 3.3 reports the estimates for the Negative Binomial model with municipality dummies (mun_XXXX) and yearly dummies (yea_yyyy). The full list of municipality dummies was omitted for brevity, but can be found in the appendix B.1.

Table 3.3: Discrete Negative Binomial Municipality FE and Yearly FE

Variable	**Coef.**	**Std. Err.**	**z**	**P>** $\lvert z\rvert$	**95% C.I.**	
const	-15.4916	8.532	-1.816	0.069	-32.214	-1.231
subsidy_share	-0.7599	0.213	-3.570	0.000	-1.177	-0.343
netwealth_below3M	0.0009	0.002	0.375	0.707	-0.004	0.006
log_medianIncome	0.6974	0.633	1.101	0.271	-0.544	1.939
building_multi_ratio	-3.6416	1.240	-2.936	0.003	-6.072	-1.211
small_hh_ratio	1.4123	1.436	0.984	0.325	-1.402	4.226
edu_high_ratio	2.4530	2.173	1.129	0.259	-1.806	6.712
mun_XXXX	*(dummies for all municipalities omitted for brevity)*					
yea_2016	0.3526	0.043	8.208	0.000	0.268	0.437
yea_2017	0.5058	0.054	9.399	0.000	0.400	0.611
yea_2018	1.3124	0.071	18.411	0.000	1.173	1.452
yea_2019	1.2750	0.091	14.017	0.000	1.097	1.453
yea_2020	0.5367	0.104	5.185	0.000	0.334	0.740
yea_2021	0.3459	0.133	2.600	0.009	0.085	0.607
yea_2022	1.1806	0.166	7.114	0.000	0.855	1.506
log_private_hh	0.9248	0.159	5.804	0.000	0.613	1.237
α	0.0852	0.005	18.622	0.000	0.076	0.094

Notes: Pseudo $R^2 = 0.2892$; AIC = 15949.82.

When comparing the both-FE model to the no-FE model, we first notice that log_private_hh remains close to one in both specifications. This suggests that the total number of households still has a near-proportional relationship with retrofit counts, even after controlling for fixed attributes of each municipality and of each year. Next, the dispersion parameter α is smaller under the both-FE model but still significantly above zero. This means that there is still overdispersion, yet many cross-sectional and time-based differences have now been absorbed by the fixed effects.

Socio-economic factors analysis

Concerning the socio-economic variables, we can see on one hand that all coefficients but subsidy_share kept the same sign in the no-FE model, but netwealth_below3M, log_medianIncome, small_hh_ratio and edu_high_ratio (p-values of respectively 0.707, 0.271, 0.325 and 0.259) lose their statistical significance. On the other hand, building_multi_ratio continues to be significant in a negative way, indicating that more multi-unit buildings still see fewer retrofits, even when unobserved municipality-specific and year-specific factors are accounted for. This drop in significance for certain variables, together with building_multi_ratio keeping its significance, tells us that when we remove time-invariant municipal characteristics and year-specific shocks, not all socio-economic variables carry the same explanatory power they had in the simpler, no-FE setup. Only the proportion of multi-unit buildings stays significant, which makes sense as we can expect municipalities with greater shares of such buildings to have less energy-consuming entities per household because of centralized use. Finally, we notice that subsidy_share switches sign from positive to negative. This seems counter intuitive, and could be because of composition effects. Let us compare the distinct retrofit counts in figure 2.5 with the distinct subsidy shares in figure 3.1 to obtain some insights. Some of the most popular retrofit like Air-to-Water Heat Pump or Liquid-to-Water Heat Pump have a medium low subsidy share. On the other hand, Energy Consultancy really drives the subsidy share up, while not being one of the most popular retrofit at all. The popular retrofits with a low subsidy share, together with the not popular retrofits with a high subsidy share may have an impact in the negative relationship between the total average subsidy share and the total retrofit counts. In the simpler model, this composition effect was not apparent because we did not remove those underlying municipal or annual factors. By removing them now, we can see it reversing the positive link that appeared in the no-FE model.

Municipality trends

The municipality fixed effects themselves do not tell us much about why certain municipalities have higher or lower retrofit counts, because they are simply capturing each location's constant traits that our other variables do not explain. Most of their estimated coefficients fall between -2 and 1, which indicates that the majority of municipalities do not stray too far from the baseline. However, around 36% of these municipality coefficients are statistically significant at the 5% level. This shows that many municipalities truly have consistently higher or lower retrofit count, so it seems important to keep these fixed effects in the model.

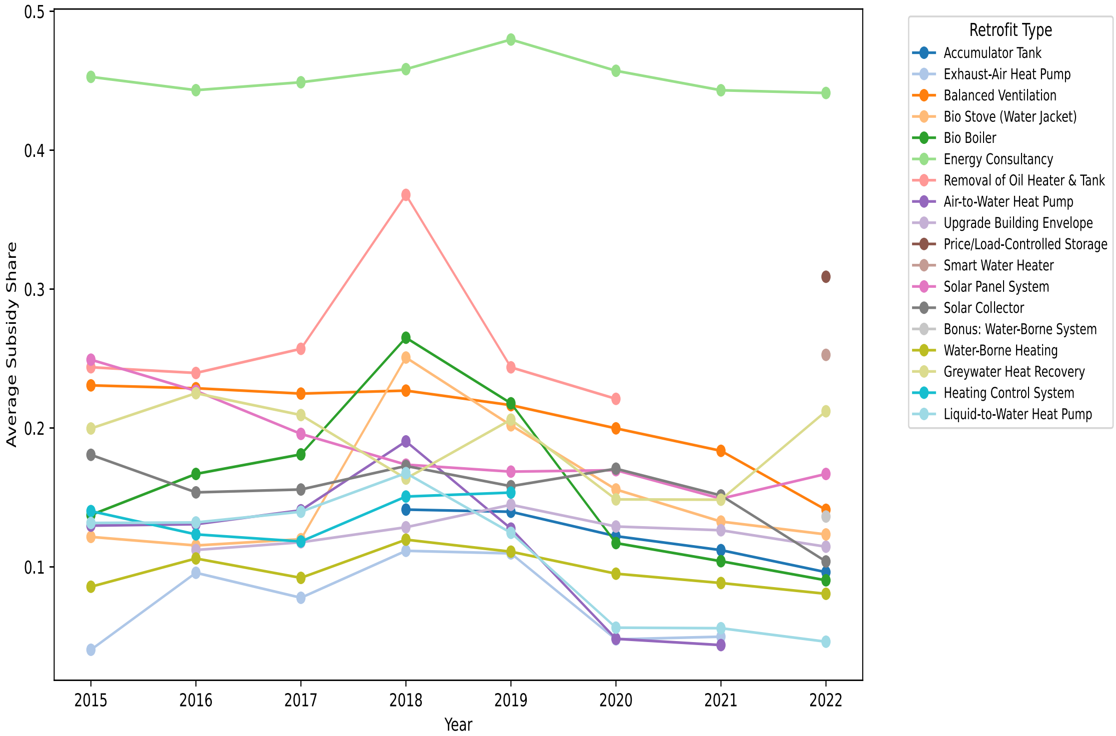

Figure 3.1: Different Types of Retrofit Subsidy Share by Year

Yearly trends

To push further our analysis we can take a look at the yearly Fixed Effects terms. First we notice that 2015 is not there, but this is normal as this our reference year to build the dummies. We can see that the year dummies of 2018, 2019, and 2022 are large and positive, whereas the other are positive but lower. This follows precisely the trend that figure 2.1 exhibits. The lows of 2020 and 2021 can potentially be explained by the COVID crisis, that lowered the overall activity and made more difficult to undergo work in the homes. Also, the high of 2022 might be explained by a surge in the Norwegian electricity prices[2], caused by an European energy crisis[3] and a colder than usual winter (hence higher demand).

[2]More expensive electricity may push Norwegian household to undergo retrofit works to lower electricity consumption

[3]The Ukraine war in the early year 2022 disrupted the gas supplies in Europe, impacting negatively the energy prices

Goodness of fit

In terms of goodness of fit, the both-FE model clearly does better than the no-FE model. Its Pseudo R^2 is significantly higher (0.2892 vs 0.1701), meaning it explains more of the variation in the data once we control for fixed features in each municipality and each year. Also, the both-FE model's AIC is the lowest of all (15949.82 vs 17791.19 vs 24840.0), which is another sign that it fits the data more effectively. Hence by adding municipality and yearly fixed effects, we remove more unexplained variation, so the model captures the factors behind retrofit counts more accurately.

Chapter 4
Conclusion

In this study, we looked into how different socio-economic factors affect the decision of Norwegian households to undertake energy-saving retrofits. We built a dataset covering 2015 to 2022, combining municipal-level socio-economic variables with information on retrofits that received public subsidies. To avoid size biases, we transformed raw counts of some socio-economic variables into ratios for household composition, building types, and net wealth levels.

We found that building characteristics, especially having many multi-dwelling units, seem to lower the likelihood of retrofits. Surprisingly, certain variables like average subsidy ratio showed a positive effect when we did not include fixed effects, but the effect turned negative once we accounted for time and location-specific influences. This can potentially be caused by composition effects.

Overall, adding municipality and year fixed effects significantly improved the model fit, indicating that stable local traits and year-to-year nationwide variations, together with the type of buildings matter when modeling retrofit counts.

Again, I would like to highlight that this study was performed within the restrictive framework of a master semester paper and with the primary goal of practicing scientific analysis and writing a scientific document. Thus, this paper should be seen as an explorative study and all results reported in this paper should be considered preliminary and used carefully. In its current form, the results are not suitable for citation.

Chapter A
Fractions for Ratio Variables

Net Wealth Ratios:

$\texttt{netwealth\_below3M} =$

$$\frac{\begin{array}{r}\texttt{netwealth\_below0,25M} + \texttt{netwealth\_between0,25M-0,5M}+\\ \texttt{netwealth\_between0,5M-1M} + \texttt{netwealth\_between1M-2M}+\\ \texttt{netwealth\_between2M-3M}\end{array}}{\texttt{total\_netwealth}}$$

$\texttt{netwealth\_above3M} =$

$$\frac{\texttt{netwealth\_between3M-4M} + \texttt{netwealth\_above4M}}{\texttt{total\_netwealth}}$$

Building Composition Ratios:

$\texttt{building\_single\_ratio} =$

$$\frac{\texttt{build\_detached\_house} + \texttt{build\_house\_with\_2\_dwellings}}{\texttt{total\_buildings}}$$

$\texttt{building\_multi\_ratio} =$

$$\frac{\begin{array}{r}\texttt{build\_rowhouse\_linkedhouse\_house\_with\_3\_dwellings\_or\_more}+\\ \texttt{build\_multidwelling} + \texttt{build\_residenceforcommunities}\end{array}}{\texttt{total\_buildings}}$$

Household Composition Ratios:

$\texttt{small\_hh\_ratio} =$

$$\frac{\texttt{hh\_alone} + \texttt{hh\_couple\_without\_children}}{\texttt{total\_hh}}$$

$\texttt{hh\_ratio\_family} =$

$$\frac{\begin{array}{r}\texttt{hh\_couple\_with\_children0-5y} + \texttt{hh\_couple\_with\_children6-17y}+\\ \texttt{hh\_single\_with\_children0-5y} + \texttt{hh\_single\_with\_children6-17y}+\\ \texttt{hh\_family\_with\_children\_above18y}\end{array}}{\texttt{total\_hh}}$$

$\texttt{hh\_ratio\_twoormorefamilies} =$

$$\frac{\begin{array}{r}\texttt{hh\_twoormorefamilies\_without\_children0-17y}+\\ \texttt{hh\_twoormorefamilies\_with\_children0-5y} + \texttt{hh\_twoormorefamilies\_with\_children6-17y}\end{array}}{\texttt{total\_hh}}$$

Education Ratios:

$\texttt{edu\_low\_ratio} =$

$$\frac{\begin{array}{r}\texttt{edu\_basic\_school\_level} + \texttt{edu\_unknown\_or\_noncompleted}+\\ \texttt{edu\_upper\_secondary} + \texttt{edu\_tertiary\_vocational}\end{array}}{\texttt{edu\_total}}$$

$\texttt{edu\_high\_ratio} =$

$$\frac{\texttt{edu\_short\_higher} + \texttt{edu\_long\_higher}}{\texttt{edu\_total}}$$

Chapter B
Full Table for Negative Binomial with Municipality and Yearly FE

Table B.1: Negative Binomial Municipality FE and Yearly FE

Variable	Coef.	Std. Err.	z	P> $\|z\|$	95% C.I.	
const	-15.4916	8.532	-1.816	0.069	-32.214	-1.231
subsidy_share	-0.7599	0.213	-3.570	0.000	-1.177	-0.343
netwealth_below3M	0.0009	0.002	0.375	0.707	-0.004	0.006
log_medianIncome	0.6974	0.633	1.101	0.271	-0.544	1.939
building_multi_ratio	-3.6416	1.240	-2.936	0.003	-6.072	-1.211
small_hh_ratio	1.4123	1.436	0.984	0.325	-1.402	4.226
edu_high_ratio	2.4530	2.173	1.129	0.259	-1.806	6.712
mun_1103	-0.4288	0.343	-1.251	0.211	-1.101	0.243
mun_1106	-0.5468	0.250	-2.186	0.029	-1.037	-0.057
mun_1108	0.0036	0.283	0.013	0.990	-0.552	0.559
mun_1111	0.0423	0.260	0.163	0.871	-0.467	0.551
mun_1112	-0.3332	0.281	-1.188	0.235	-0.883	0.217
mun_1114	-0.5397	0.344	-1.570	0.117	-1.214	0.134
mun_1119	-0.1900	0.201	-0.945	0.345	-0.584	0.204
mun_1120	-0.0397	0.219	-0.182	0.856	-0.468	0.389
mun_1121	-0.1098	0.248	-0.442	0.659	-0.597	0.377
mun_1122	-0.0797	0.260	-0.307	0.759	-0.589	0.429

Continued on next page

Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_1124	-0.3288	0.325	-1.012	0.312	-0.966	0.308
mun_1127	-0.4399	0.306	-1.436	0.151	-1.040	0.161
mun_1130	-0.4935	0.196	-2.524	0.012	-0.877	-0.110
mun_1133	-0.7831	0.390	-2.007	0.045	-1.548	-0.018
mun_1134	-0.3330	0.319	-1.044	0.297	-0.958	0.292
mun_1135	-0.9251	0.287	-3.219	0.001	-1.488	-0.362
mun_1144	-0.7200	0.684	-1.053	0.292	-2.060	0.620
mun_1145	-1.5241	0.717	-2.127	0.033	-2.929	-0.120
mun_1146	-0.1765	0.218	-0.810	0.418	-0.603	0.250
mun_1149	-0.1420	0.236	-0.601	0.548	-0.605	0.321
mun_1151	0.2337	0.922	0.254	0.800	-1.573	2.040
mun_1160	-0.0754	0.192	-0.392	0.695	-0.453	0.302
mun_1505	-0.7376	0.294	-2.506	0.012	-1.314	-0.161
mun_1506	-0.7516	0.248	-3.028	0.002	-1.238	-0.265
mun_1507	-0.2780	0.238	-1.170	0.242	-0.744	0.188
mun_1511	-0.6943	0.297	-2.339	0.019	-1.276	-0.113
mun_1514	-0.6253	0.335	-1.867	0.062	-1.282	0.031
mun_1515	-0.7156	0.197	-3.631	0.000	-1.102	-0.329
mun_1516	-0.3194	0.326	-0.981	0.327	-0.958	0.319
mun_1517	-0.7909	0.273	-2.901	0.004	-1.325	-0.257
mun_1520	-0.5049	0.209	-2.411	0.016	-0.915	-0.094
mun_1525	-0.3407	0.267	-1.277	0.202	-0.864	0.182
mun_1528	-0.8452	0.237	-3.567	0.000	-1.310	-0.381
mun_1531	-0.6764	0.265	-2.549	0.011	-1.196	-0.156
mun_1532	-0.3240	0.292	-1.108	0.268	-0.897	0.249
mun_1535	-0.4134	0.214	-1.929	0.054	-0.833	0.007
mun_1539	-0.6563	0.262	-2.504	0.012	-1.170	-0.143
mun_1547	-1.1433	0.360	-3.172	0.002	-1.850	-0.437
mun_1554	-0.8550	0.243	-3.520	0.000	-1.331	-0.379
mun_1557	-0.6002	0.342	-1.755	0.079	-1.271	0.070
mun_1560	-0.6343	0.345	-1.838	0.066	-1.311	0.042
mun_1563	-0.4475	0.277	-1.616	0.106	-0.990	0.095

Continued on next page

Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_1566	-0.5792	0.233	-2.489	0.013	-1.035	-0.123
mun_1573	-0.9561	0.409	-2.338	0.019	-1.758	-0.155
mun_1576	-0.5696	0.293	-1.944	0.052	-1.144	0.005
mun_1577	-0.6022	0.390	-1.543	0.123	-1.367	0.163
mun_1578	-0.7125	0.357	-1.995	0.046	-1.413	-0.012
mun_1579	-0.8035	0.190	-4.229	0.000	-1.176	-0.431
mun_1804	-0.8609	0.296	-2.910	0.004	-1.441	-0.281
mun_1806	-1.0828	0.220	-4.930	0.000	-1.513	-0.652
mun_1811	-1.8033	0.699	-2.581	0.010	-3.173	-0.434
mun_1812	-0.6753	0.402	-1.679	0.093	-1.464	0.113
mun_1813	-0.6347	0.233	-2.721	0.007	-1.092	-0.178
mun_1815	-1.2140	0.585	-2.077	0.038	-2.360	-0.068
mun_1818	-1.4269	0.456	-3.128	0.002	-2.321	-0.533
mun_1820	-1.0461	0.295	-3.544	0.000	-1.625	-0.468
mun_1822	-1.3135	0.406	-3.237	0.001	-2.109	-0.518
mun_1824	-0.5919	0.201	-2.946	0.003	-0.986	-0.198
mun_1825	-0.3285	0.419	-0.784	0.433	-1.149	0.492
mun_1826	-0.9165	0.506	-1.811	0.070	-1.908	0.075
mun_1827	-1.0420	0.556	-1.873	0.061	-2.133	0.049
mun_1828	-1.4572	0.577	-2.527	0.012	-2.588	-0.327
mun_1832	-0.5912	0.269	-2.200	0.028	-1.118	-0.065
mun_1833	-0.2506	0.190	-1.320	0.187	-0.623	0.121
mun_1834	-1.1815	0.411	-2.874	0.004	-1.987	-0.376
mun_1836	-1.2908	0.527	-2.448	0.014	-2.324	-0.257
mun_1837	-1.4884	0.255	-5.843	0.000	-1.988	-0.989
mun_1838	-1.0751	0.437	-2.459	0.014	-1.932	-0.218
mun_1839	-0.7194	0.529	-1.361	0.174	-1.756	0.317
mun_1840	-1.0212	0.282	-3.623	0.000	-1.574	-0.469
mun_1841	-1.0788	0.235	-4.600	0.000	-1.538	-0.619
mun_1845	-1.4716	0.449	-3.280	0.001	-2.351	-0.592
mun_1848	-1.7454	0.422	-4.139	0.000	-2.572	-0.919
mun_1851	-2.3581	0.632	-3.733	0.000	-3.596	-1.120

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Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_1853	-0.5486	0.557	-0.985	0.325	-1.640	0.543
mun_1856	-0.9930	1.148	-0.865	0.387	-3.243	1.257
mun_1857	0.1868	0.589	0.317	0.751	-0.968	1.342
mun_1859	-1.1849	0.537	-2.206	0.027	-2.238	-0.132
mun_1860	-0.9180	0.206	-4.463	0.000	-1.321	-0.515
mun_1865	-0.6230	0.232	-2.684	0.007	-1.078	-0.168
mun_1866	-1.0751	0.253	-4.256	0.000	-1.570	-0.580
mun_1867	-1.4857	0.428	-3.468	0.001	-2.325	-0.646
mun_1868	-1.3442	0.346	-3.882	0.000	-2.023	-0.666
mun_1870	-0.9169	0.214	-4.286	0.000	-1.336	-0.498
mun_1871	-0.6436	0.280	-2.303	0.021	-1.191	-0.096
mun_1874	-0.6487	0.515	-1.260	0.208	-1.658	0.360
mun_1875	-1.8805	0.527	-3.570	0.000	-2.913	-0.848
mun_3001	-0.2406	0.210	-1.147	0.251	-0.652	0.170
mun_3002	0.2586	0.242	1.069	0.285	-0.216	0.733
mun_3003	-0.0358	0.264	-0.136	0.892	-0.553	0.482
mun_3004	-0.0019	0.257	-0.008	0.994	-0.505	0.502
mun_3005	-0.3268	0.269	-1.216	0.224	-0.854	0.200
mun_3006	-0.2834	0.308	-0.920	0.358	-0.887	0.321
mun_3007	-0.4482	0.210	-2.136	0.033	-0.859	-0.037
mun_301	-0.2797	0.555	-0.504	0.614	-1.368	0.808
mun_3011	0.3918	0.350	1.121	0.262	-0.294	1.077
mun_3012	-0.3044	0.406	-0.749	0.454	-1.101	0.492
mun_3013	0.5081	0.280	1.817	0.069	-0.040	1.056
mun_3014	0.1270	0.255	0.499	0.618	-0.372	0.626
mun_3015	-0.2974	0.281	-1.058	0.290	-0.848	0.253
mun_3016	0.3414	0.208	1.641	0.101	-0.066	0.749
mun_3017	-0.2737	0.248	-1.106	0.269	-0.759	0.211
mun_3019	0.2310	0.306	0.755	0.450	-0.369	0.831
mun_3020	0.3330	0.410	0.812	0.417	-0.470	1.136
mun_3021	-0.3587	0.453	-0.791	0.429	-1.247	0.530
mun_3022	-0.4783	0.342	-1.397	0.163	-1.149	0.193

Continued on next page

Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_3023	-0.2173	0.534	-0.407	0.684	-1.264	0.829
mun_3024	0.0747	0.532	0.140	0.888	-0.968	1.117
mun_3025	0.0119	0.378	0.031	0.975	-0.729	0.753
mun_3026	-0.1191	0.203	-0.586	0.558	-0.517	0.279
mun_3027	0.1596	0.321	0.498	0.619	-0.469	0.788
mun_3028	-0.2353	0.227	-1.038	0.299	-0.679	0.209
mun_3029	-0.0477	0.341	-0.140	0.889	-0.716	0.621
mun_3030	0.0575	0.294	0.195	0.845	-0.519	0.634
mun_3031	0.3505	0.390	0.898	0.369	-0.414	1.115
mun_3032	-0.1405	0.354	-0.397	0.692	-0.835	0.554
mun_3033	-0.0340	0.247	-0.138	0.890	-0.517	0.449
mun_3034	-0.0115	0.193	-0.060	0.952	-0.390	0.367
mun_3035	-0.4061	0.183	-2.217	0.027	-0.765	-0.047
mun_3036	-0.1715	0.200	-0.857	0.391	-0.564	0.221
mun_3037	-0.8049	0.325	-2.476	0.013	-1.442	-0.168
mun_3038	-0.3104	0.462	-0.671	0.502	-1.217	0.596
mun_3039	0.2652	0.445	0.597	0.551	-0.606	1.137
mun_3040	-0.4755	0.314	-1.515	0.130	-1.090	0.140
mun_3041	-0.2884	0.291	-0.992	0.321	-0.858	0.282
mun_3042	-0.1748	0.457	-0.382	0.702	-1.071	0.721
mun_3043	-0.4697	0.304	-1.546	0.122	-1.065	0.126
mun_3044	-0.1300	0.298	-0.437	0.662	-0.714	0.454
mun_3045	0.3033	0.254	1.194	0.232	-0.195	0.801
mun_3046	-0.2721	0.355	-0.766	0.444	-0.968	0.424
mun_3047	-0.6861	0.199	-3.445	0.001	-1.076	-0.296
mun_3048	-0.2949	0.176	-1.679	0.093	-0.639	0.049
mun_3049	-0.1038	0.287	-0.361	0.718	-0.667	0.459
mun_3050	0.2660	0.295	0.902	0.367	-0.312	0.844
mun_3051	-0.4753	0.464	-1.025	0.306	-1.385	0.434
mun_3052	-0.5781	0.331	-1.748	0.080	-1.226	0.070
mun_3053	-0.5548	0.224	-2.479	0.013	-0.994	-0.116
mun_3054	-0.4924	0.209	-2.361	0.018	-0.901	-0.084

Continued on next page

Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_3401	0.0896	0.255	0.352	0.725	-0.410	0.589
mun_3403	0.1589	0.316	0.503	0.615	-0.460	0.778
mun_3405	-0.3450	0.360	-0.960	0.337	-1.050	0.360
mun_3407	-0.3805	0.222	-1.712	0.087	-0.816	0.055
mun_3411	-0.0786	0.212	-0.371	0.711	-0.494	0.337
mun_3412	-0.3259	0.208	-1.568	0.117	-0.733	0.081
mun_3413	-0.1219	0.192	-0.634	0.526	-0.499	0.255
mun_3414	-0.8146	0.268	-3.041	0.002	-1.340	-0.290
mun_3415	-0.1058	0.196	-0.540	0.589	-0.490	0.278
mun_3416	-0.2160	0.273	-0.792	0.428	-0.751	0.319
mun_3417	-0.6844	0.314	-2.181	0.029	-1.300	-0.069
mun_3418	-0.5087	0.265	-1.916	0.055	-1.029	0.012
mun_3419	0.0850	0.299	0.284	0.776	-0.502	0.672
mun_3420	-0.2269	0.216	-1.051	0.293	-0.650	0.196
mun_3421	-0.3810	0.253	-1.506	0.132	-0.877	0.115
mun_3422	-0.5124	0.313	-1.638	0.101	-1.125	0.101
mun_3423	-0.4393	0.433	-1.015	0.310	-1.287	0.409
mun_3424	-1.2766	0.465	-2.743	0.006	-2.189	-0.364
mun_3425	-0.9305	0.505	-1.844	0.065	-1.919	0.058
mun_3426	0.2052	0.537	0.382	0.703	-0.848	1.258
mun_3427	0.1511	0.309	0.489	0.625	-0.455	0.758
mun_3428	0.0005	0.339	0.001	0.999	-0.663	0.664
mun_3429	0.5848	0.435	1.343	0.179	-0.269	1.438
mun_3430	-0.3870	0.429	-0.901	0.367	-1.228	0.454
mun_3431	-1.8699	0.420	-4.454	0.000	-2.693	-1.047
mun_3432	-0.8497	0.411	-2.066	0.039	-1.656	-0.043
mun_3433	-0.2546	0.349	-0.729	0.466	-0.939	0.430
mun_3434	-0.9730	0.385	-2.524	0.012	-1.729	-0.217
mun_3435	-0.7134	0.295	-2.422	0.015	-1.291	-0.136
mun_3436	-0.9725	0.266	-3.650	0.000	-1.495	-0.450
mun_3437	-1.1946	0.265	-4.511	0.000	-1.714	-0.676
mun_3438	-0.9015	0.323	-2.791	0.005	-1.535	-0.268

Continued on next page

Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_3439	-0.4477	0.269	-1.664	0.096	-0.975	0.080
mun_3440	-0.0373	0.275	-0.136	0.892	-0.576	0.502
mun_3441	-0.3933	0.225	-1.750	0.080	-0.834	0.047
mun_3442	-0.4374	0.186	-2.355	0.019	-0.801	-0.073
mun_3443	-0.6398	0.199	-3.223	0.001	-1.029	-0.251
mun_3446	-0.1258	0.179	-0.703	0.482	-0.477	0.225
mun_3447	-1.2192	0.276	-4.414	0.000	-1.761	-0.678
mun_3448	-0.6088	0.248	-2.452	0.014	-1.095	-0.122
mun_3449	0.0713	0.320	0.223	0.824	-0.557	0.699
mun_3450	-0.2701	0.462	-0.585	0.559	-1.175	0.635
mun_3451	-0.3633	0.258	-1.408	0.159	-0.869	0.143
mun_3452	-0.0766	0.356	-0.215	0.830	-0.774	0.621
mun_3453	-0.2230	0.331	-0.673	0.501	-0.873	0.427
mun_3454	-0.0446	0.459	-0.097	0.923	-0.945	0.856
mun_3801	-0.3606	0.227	-1.590	0.112	-0.805	0.084
mun_3802	0.1689	0.206	0.819	0.413	-0.235	0.573
mun_3803	-0.4337	0.201	-2.162	0.031	-0.827	-0.041
mun_3804	-0.1554	0.245	-0.633	0.527	-0.637	0.326
mun_3805	-0.4157	0.222	-1.869	0.062	-0.852	0.020
mun_3806	-0.4545	0.218	-2.089	0.037	-0.881	-0.028
mun_3807	-0.7347	0.232	-3.167	0.002	-1.189	-0.280
mun_3808	-0.8155	0.220	-3.712	0.000	-1.246	-0.385
mun_3811	-0.2481	0.296	-0.839	0.401	-0.827	0.331
mun_3812	-0.6555	0.393	-1.667	0.095	-1.426	0.115
mun_3813	-0.5882	0.179	-3.292	0.001	-0.938	-0.238
mun_3814	-0.7038	0.236	-2.979	0.003	-1.167	-0.241
mun_3815	-0.5352	0.267	-2.006	0.045	-1.058	-0.012
mun_3816	-0.8149	0.244	-3.343	0.001	-1.293	-0.337
mun_3817	-0.3874	0.292	-1.327	0.184	-0.959	0.185
mun_3818	-0.6534	0.284	-2.297	0.022	-1.211	-0.096
mun_3819	-0.3218	0.392	-0.822	0.411	-1.089	0.446
mun_3820	-0.2024	0.358	-0.565	0.572	-0.904	0.499

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Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_3821	-0.1877	0.405	-0.463	0.643	-0.982	0.607
mun_3822	-0.1401	0.446	-0.314	0.753	-1.015	0.734
mun_3823	-0.6679	0.519	-1.288	0.198	-1.685	0.349
mun_3824	-0.9472	0.418	-2.267	0.023	-1.766	-0.128
mun_3825	0.0301	0.335	0.090	0.929	-0.627	0.687
mun_4201	-0.4846	0.285	-1.700	0.089	-1.043	0.074
mun_4202	-0.3466	0.251	-1.379	0.168	-0.839	0.146
mun_4203	-0.2804	0.214	-1.312	0.189	-0.699	0.138
mun_4204	0.0361	0.286	0.126	0.900	-0.525	0.597
mun_4205	-0.0835	0.179	-0.467	0.641	-0.434	0.267
mun_4206	0.4305	0.181	2.373	0.018	0.075	0.786
mun_4207	0.1441	0.215	0.670	0.503	-0.277	0.565
mun_4211	-0.5561	0.326	-1.706	0.088	-1.195	0.083
mun_4212	-1.0997	0.446	-2.467	0.014	-1.973	-0.226
mun_4213	-0.7998	0.279	-2.867	0.004	-1.347	-0.253
mun_4214	-0.6002	0.236	-2.539	0.011	-1.064	-0.137
mun_4215	-0.1293	0.303	-0.426	0.670	-0.724	0.465
mun_4216	-0.0351	0.261	-0.135	0.893	-0.546	0.476
mun_4217	-0.4861	0.395	-1.230	0.219	-1.261	0.288
mun_4218	-0.1578	0.419	-0.376	0.707	-0.980	0.664
mun_4219	-0.3845	0.306	-1.257	0.209	-0.984	0.215
mun_4220	-0.3207	0.524	-0.611	0.541	-1.349	0.707
mun_4221	-0.0362	0.492	-0.074	0.941	-1.001	0.929
mun_4222	0.0290	0.637	0.046	0.964	-1.219	1.277
mun_4223	-0.1122	0.201	-0.559	0.576	-0.506	0.282
mun_4224	0.2703	0.445	0.607	0.544	-0.603	1.143
mun_4225	0.1584	0.189	0.837	0.403	-0.213	0.529
mun_4226	0.4066	0.370	1.099	0.272	-0.319	1.132
mun_4227	0.2766	0.207	1.335	0.182	-0.129	0.683
mun_4228	0.2933	0.423	0.694	0.488	-0.535	1.122
mun_4601	0.2510	0.435	0.578	0.564	-0.601	1.103
mun_4602	-0.3959	0.184	-2.156	0.031	-0.756	-0.036

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Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_4611	-0.1062	0.279	-0.381	0.703	-0.653	0.440
mun_4612	-0.4485	0.267	-1.679	0.093	-0.972	0.075
mun_4613	-0.5401	0.199	-2.717	0.007	-0.930	-0.151
mun_4614	-0.5959	0.235	-2.532	0.011	-1.057	-0.135
mun_4615	-0.6032	0.330	-1.829	0.067	-1.250	0.043
mun_4616	-0.6203	0.334	-1.859	0.063	-1.274	0.034
mun_4617	-0.4685	0.186	-2.512	0.012	-0.834	-0.103
mun_4618	-0.5067	0.246	-2.058	0.040	-0.989	-0.024
mun_4619	-0.4036	0.564	-0.715	0.474	-1.510	0.702
mun_4620	-0.3053	0.572	-0.534	0.593	-1.426	0.815
mun_4621	-0.2526	0.214	-1.179	0.238	-0.672	0.167
mun_4622	0.2776	0.239	1.162	0.245	-0.191	0.746
mun_4623	-0.4787	0.358	-1.337	0.181	-1.181	0.223
mun_4624	-0.1672	0.213	-0.787	0.432	-0.584	0.249
mun_4625	0.0867	0.283	0.306	0.760	-0.469	0.642
mun_4626	0.1685	0.241	0.698	0.485	-0.304	0.641
mun_4627	-0.0204	0.253	-0.080	0.936	-0.517	0.476
mun_4628	-0.5392	0.285	-1.891	0.059	-1.098	0.020
mun_4629	-0.2096	0.879	-0.238	0.812	-1.933	1.514
mun_4630	-0.2475	0.201	-1.228	0.219	-0.642	0.147
mun_4631	-0.2985	0.212	-1.411	0.158	-0.713	0.116
mun_4632	-0.4959	0.304	-1.630	0.103	-1.092	0.100
mun_4633	0.1581	0.598	0.265	0.791	-1.013	1.330
mun_4634	-0.3515	0.374	-0.940	0.347	-1.084	0.381
mun_4635	-0.1396	0.347	-0.402	0.688	-0.820	0.541
mun_4636	-0.5715	0.553	-1.034	0.301	-1.655	0.511
mun_4637	-0.3299	0.462	-0.714	0.475	-1.236	0.576
mun_4638	-0.7385	0.302	-2.449	0.014	-1.330	-0.147
mun_4639	-0.1318	0.339	-0.389	0.697	-0.797	0.533
mun_4640	-0.5301	0.402	-1.318	0.187	-1.318	0.258
mun_4641	-0.8918	0.499	-1.786	0.074	-1.871	0.087
mun_4642	-1.3854	0.497	-2.789	0.005	-2.359	-0.412

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Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_4643	-1.7124	0.320	-5.355	0.000	-2.339	-1.086
mun_4644	-0.6498	0.310	-2.095	0.036	-1.258	-0.042
mun_4645	-0.6008	0.332	-1.811	0.070	-1.251	0.049
mun_4646	0.2392	0.397	0.603	0.546	-0.538	1.017
mun_4647	0.2035	0.265	0.767	0.443	-0.316	0.723
mun_4648	-0.6104	0.294	-2.079	0.038	-1.186	-0.035
mun_4649	-0.3556	0.222	-1.602	0.109	-0.791	0.079
mun_4650	-0.1419	0.345	-0.411	0.681	-0.818	0.534
mun_4651	-0.1622	0.244	-0.664	0.506	-0.641	0.316
mun_5001	-0.4887	0.383	-1.277	0.202	-1.239	0.262
mun_5006	-0.0523	0.213	-0.246	0.806	-0.470	0.365
mun_5007	-0.8625	0.257	-3.358	0.001	-1.366	-0.359
mun_5014	-1.2255	0.293	-4.185	0.000	-1.799	-0.652
mun_5020	-0.9430	0.500	-1.886	0.059	-1.923	0.037
mun_5021	-0.1465	0.232	-0.632	0.527	-0.601	0.308
mun_5022	-0.3542	0.317	-1.118	0.264	-0.975	0.267
mun_5025	-0.2224	0.314	-0.709	0.478	-0.837	0.392
mun_5026	0.0104	0.343	0.030	0.976	-0.661	0.682
mun_5027	0.1847	0.216	0.856	0.392	-0.238	0.608
mun_5028	-0.1999	0.184	-1.089	0.276	-0.560	0.160
mun_5029	-0.2784	0.308	-0.903	0.367	-0.883	0.326
mun_5031	-0.3134	0.351	-0.893	0.372	-1.001	0.375
mun_5032	-0.6646	0.272	-2.439	0.015	-1.199	-0.131
mun_5033	-0.4961	0.527	-0.941	0.347	-1.530	0.538
mun_5034	-0.5425	0.371	-1.461	0.144	-1.270	0.185
mun_5035	-0.1428	0.213	-0.669	0.504	-0.561	0.276
mun_5036	-0.5402	0.348	-1.551	0.121	-1.223	0.142
mun_5037	0.0205	0.281	0.073	0.942	-0.530	0.571
mun_5038	0.0292	0.204	0.143	0.886	-0.371	0.430
mun_5041	-0.0516	0.428	-0.121	0.904	-0.891	0.788
mun_5043	-0.1133	0.679	-0.167	0.867	-1.444	1.217
mun_5044	-0.9312	0.618	-1.506	0.132	-2.143	0.281

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Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_5045	-0.4593	0.414	-1.109	0.267	-1.271	0.352
mun_5046	0.1865	0.501	0.372	0.710	-0.796	1.169
mun_5047	-0.2986	0.337	-0.886	0.375	-0.959	0.362
mun_5049	0.0918	0.513	0.179	0.858	-0.913	1.097
mun_5052	-0.7124	0.693	-1.027	0.304	-2.072	0.647
mun_5053	0.1553	0.313	0.497	0.619	-0.457	0.768
mun_5054	0.1333	0.203	0.656	0.512	-0.265	0.531
mun_5055	-0.8991	0.233	-3.853	0.000	-1.356	-0.442
mun_5056	-0.7479	0.277	-2.704	0.007	-1.290	-0.206
mun_5057	-0.1710	0.224	-0.762	0.446	-0.611	0.269
mun_5058	-0.1415	0.252	-0.562	0.574	-0.635	0.352
mun_5059	-0.5650	0.195	-2.894	0.004	-0.948	-0.182
mun_5060	-0.7998	0.226	-3.543	0.000	-1.242	-0.357
mun_5061	-0.0842	0.350	-0.240	0.810	-0.771	0.602
mun_5401	-1.4806	0.327	-4.523	0.000	-2.122	-0.839
mun_5402	-1.9114	0.301	-6.355	0.000	-2.501	-1.322
mun_5403	-1.1670	0.247	-4.730	0.000	-1.651	-0.683
mun_5404	-1.5802	0.727	-2.174	0.030	-3.005	-0.156
mun_5405	-1.3092	0.363	-3.606	0.000	-2.021	-0.598
mun_5406	-1.3406	0.395	-3.393	0.001	-2.115	-0.566
mun_5411	-2.1895	0.627	-3.492	0.000	-3.418	-0.960
mun_5412	-1.2116	0.352	-3.444	0.001	-1.901	-0.522
mun_5413	-0.5280	0.495	-1.067	0.286	-1.498	0.442
mun_5414	-1.0317	0.556	-1.856	0.063	-2.121	0.058
mun_5415	-0.4959	0.702	-0.707	0.480	-1.871	0.879
mun_5416	-0.9987	0.377	-2.647	0.008	-1.738	-0.259
mun_5417	-1.1953	0.437	-2.737	0.006	-2.051	-0.339
mun_5418	-1.3052	0.275	-4.743	0.000	-1.845	-0.766
mun_5419	-1.1509	0.336	-3.424	0.001	-1.810	-0.492
mun_5420	-0.7530	0.530	-1.421	0.155	-1.792	0.286
mun_5421	-1.2682	0.214	-5.923	0.000	-1.688	-0.849
mun_5422	-1.5288	0.280	-5.467	0.000	-2.077	-0.981

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Table B.1 (continued)

Variable	Coef.	Std. Err.	z	P>—z—	95% C.I.	
mun_5423	-1.7512	0.673	-2.603	0.009	-3.070	-0.433
mun_5424	-1.3326	0.371	-3.590	0.000	-2.060	-0.605
mun_5425	-1.0575	0.432	-2.448	0.014	-1.904	-0.211
mun_5427	-1.2307	0.362	-3.397	0.001	-1.941	-0.521
mun_5429	-1.2531	0.517	-2.425	0.015	-2.266	-0.240
mun_5430	-2.0577	0.592	-3.476	0.001	-3.218	-0.898
mun_5433	-1.2592	0.852	-1.478	0.139	-2.929	0.410
mun_5434	-1.9411	1.101	-1.763	0.078	-4.099	0.217
mun_5435	-1.1391	0.410	-2.776	0.005	-1.943	-0.335
mun_5436	-1.1201	0.343	-3.262	0.001	-1.793	-0.447
mun_5437	-1.4166	0.528	-2.685	0.007	-2.451	-0.382
mun_5438	-2.0568	0.833	-2.468	0.014	-3.690	-0.424
mun_5439	-1.1888	0.881	-1.350	0.177	-2.915	0.537
mun_5440	-1.8307	1.117	-1.638	0.101	-4.021	0.359
mun_5441	-1.6677	0.391	-4.266	0.000	-2.434	-0.901
mun_5442	-0.5804	0.613	-0.946	0.344	-1.782	0.622
mun_5443	-0.7304	0.467	-1.564	0.118	-1.646	0.185
mun_5444	-1.7801	0.344	-5.177	0.000	-2.454	-1.106
yea_2016	0.3526	0.043	8.208	0.000	0.268	0.437
yea_2017	0.5058	0.054	9.399	0.000	0.400	0.611
yea_2018	1.3124	0.071	18.411	0.000	1.173	1.452
yea_2019	1.2750	0.091	14.017	0.000	1.097	1.453
yea_2020	0.5367	0.104	5.185	0.000	0.334	0.740
yea_2021	0.3459	0.133	2.600	0.009	0.085	0.607
yea_2022	1.1806	0.166	7.114	0.000	0.855	1.506
log_private_hh	0.9248	0.159	5.804	0.000	0.613	1.237
α	0.0852	0.005	18.622	0.000	0.076	0.094

Notes: Pseudo $R^2 = 0.2892$; AIC = 15949.82.

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