Demographic Influences on Municipal Budget Allocation and Infrastructure Development in Toronto*

Population density drive larger budget allocations meanwhile average household income drives construction projects

Aviral Bhardwaj

December 13, 2024

This study examines the relationship between population density, average household income, and budget allocations across Toronto's 25 wards and investigates their combined influence on construction activity. Using data from the city's *Capital Budget Plan*, *Ward Profiles*, and *Active Building Permits*, we analyze spending patterns in key infrastructure-related areas. Employing a causal modeling approach, our findings reveal a negative association between population density and construction activity, despite some high-density wards receiving higher budget allocations. Additionally, average household income and total budget allocations exhibit a positive correlation with the number of building permits. These results underscore potential inequities in resource distribution, highlighting the need for data-driven and equitable urban budget planning to better address community needs.

Table of contents

*Code and data are available at: https://github.com/Aviral-03/InfrastructureCausalModel-TO.

1 Introduction

In urban governance, the equitable allocation of municipal budgets is essential to meet a city's social, economic, and infrastructure needs. This challenge is especially pressing in Toronto, where 25 wards compete for limited resources amid a growing population ("Ontario's Long-Term Report on the Economy 2024" 2024). Understanding how demographic factors influence budget decisions remains under-explored. Therefore, this study seeks to answer: How do demographic factors such as population and income affect budget allocations across Toronto's wards, and can we assess their combined impact on construction activity, a key indicator of infrastructure development?

Looking back, Toronto's historical budget data have shown uneven investment, particularly in high-density, lower-income areas, leading to disparities in infrastructure and services (Ferguson, Lisa 2024). However, following 2023 Mayor election, Mayor Olivia Chow promise to prioritize housing, transit, and equity-focused initiatives (City of Toronto 2024e). The 2024 budget prioritizes significant investments in affordable housing, transportation, and community safety, while also focusing on long-term infrastructure development through a 10-year capital plan. Notable projects, such as the *Ontario Line* subway expansion, are projected to drive economic growth and urban development (Navabi 2024). Similarly, the *Sidewalks to Skylines* 10-year plan aims to create jobs and enhance residents' quality of life (City of Toronto 2024f). As these initiatives progress, ensuring equitable infrastructure investments will be crucial for Toronto's sustainable growth. With the city's population increasingly distributed across its wards, it is imperative to assess whether current budget allocations effectively align with broader development objectives amidst shifting demographic trends.

This study analyzes data from the City of Toronto's Open Data Portal, incorporating demographic information from the *2021 Ward Profiles*, budget details from the *Capital Budget & Plan By Ward (10-Year Approved) 2021-2024*, and construction data from *Building Applications and Permits*. Using a Bayesian multi-regression model guided by a causal framework, we found that both average household income and total budget allocations significantly influence the number of building permits. However, population density displayed an unexpected negative relationship with construction activity, suggesting the presence of unobserved factors affecting this link. To address this, we excluded population density as an explanatory variable and confirmed that higher-income wards receiving larger budget allocations corresponded to more construction activity. These findings highlight the importance of understanding how socioeconomic and budgetary factors shape urban development, emphasizing the need for equitable resource distribution to support balanced growth across Toronto's wards.

The paper is organized as follows: Section 2 outlines the data sources and methodology used in the analysis. Section 3 explains the Bayesian model applied to estimate the effects of demographic and economic factors, following the causal model (Figure 1). Section 4 presents key findings, including trends in budget allocations, the relationship between demographic factors and budget distribution, and the impact on construction projects. Section 5 explores the implications for urban governance and budget planning in Toronto. Finally, Section 6 addresses the study's limitations and offers recommendations for future research. Additional details, including tables, figures, and methodology, are provided in the Section A.

1.1 Estimand

Our research investigates the causal relationships between population, income, budget allocation, and active construction projects, as illustrated in Figure 1. Population and income are key confounders, influencing both budget allocation and the number of construction projects. Budget allocation serves a dual role: as a mediator connecting population and income to construction projects and as an instrumental variable, helping to estimate their effects on construction activity. The outcome variable is the number of active construction projects, while population and income are the primary predictors. Our goal is to estimate the causal effect of budget allocation on construction activity, accounting for the confounding effects of population and income.

Population is a important demographic indicator, representing the number of residents in each ward, while average household income reflects economic well-being, influencing access to resources and quality of life (Schaeffer 2021). Therefore, these two variables of interest were chosen for the analysis. For budget allocations we choose these specific categories of interest, specifically Growth-Related expenditures, State of Good Repair, and Service Improvement and Enhancement.

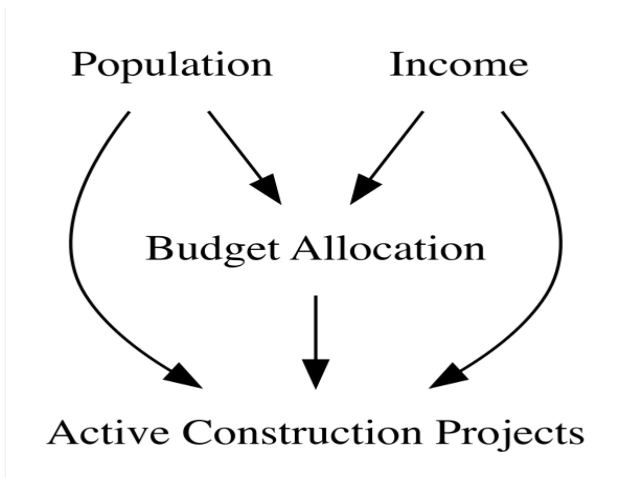


Figure 1: Causal model: Population and income influence budget allocation and construction projects

2 Data

The raw data was sourced from the City of Toronto's Open Data Portal using the `opendatatoronto` (Sharla Gelfand 2022) package. For the purpose of this analysis we used several data sets: `2023 Ward Profiles (25-Ward Model)` (City of Toronto 2024b), `Capital Budget and Plan Details from 2021-2024` (City of Toronto 2024d), `City Wards` (City of Toronto 2024c), and `Building Permits - Active Permits` (City of Toronto 2024a).

The data, provided in CSV formats, was cleaned and analyzed using R (R Core Team 2024) programming language. The `readxl` (Wickham and Bryan 2023) package was used for reading Excel files. Other R packages used includes `tidyverse` (Wickham et al. 2019), `styler` (Müller and Walthert 2024), and `dplyr` (Wickham et al. 2023) for creating tables. `ggplot2` (Wickham 2016) and `kableExtra` (Zhu 2024) were used for data visualization and table formatting. The `patchwork` (Pedersen 2024) package was used for combining multiple plots, and `sf` (Venables and Ripley 2002) for spatial data analysis. For model estimation, the `rstanarm` (Brilleman et al. 2018) package was used for Bayesian modeling, and `bayesplot` (Gabry et al. 2019) for visualizing the results. The `lintr` (Hester et al. 2024) package was used for code linting.

2.1 Ward Profiles (25-Ward Model)

The 2021 Ward Profiles (City of Toronto 2024b), based on the 25-Ward model were provided by City Planning. These profiles included census data from the 2021, 2016, and 2011 Census of Population, covering demographic, social, and economic information for each ward in Toronto. These variables were collected through methods including online responses, mailed questionnaires, the Census Help Line, and enumerators ("National Household Survey (NHS)" 2023).

These questionnaires gathered information on various topics related to residents' demographic characteristics, such as education, household income, number of dependents, employment status and etc. Participation in the survey is voluntary, and data is collected directly from residents, including their postal codes, which are used to determine their respective wards. To ensure privacy and confidentiality, the data is subsequently aggregated and anonymized (Government of Canada 2023).

This data-set was included in this analysis to provide understanding into the population and average household income for each ward, providing understanding into the city's socioeconomic landscape. 25-Ward model was used instead of the 44-Ward model as it was the most recent data available at the time of analysis and matched the Capital Budget data.

The data was stored in an Excel workbook with multiple tabs, but for this analysis, we used the first tab, `2021 Census One variable`, which contains data for all 25 wards (Ward 1, Ward 2, …, Ward 25). After cleaning, the data was saved in CSV and Parquet formats, with the following columns:

- `ward_id`: unique identifier for each ward,
- `ward`: ward name,
- `population`: total population,
- `income`: average household income.

The ward names were manually entered into the cleaned data to match with `ward_id`. A sample of the data can be seen in Table 1.

Table 1: Sample of Cleaned Toronto Ward Profile Data

Ward ID	Ward Name	Population	Income
1	Etobicoke North	115120	95200
2	Etobicoke Centre	117200	146600
3	Etobicoke-Lakeshore	139920	127200
4	Parkdale-High Park	104715	127200
5	York South-Weston	115675	88700
6	York Centre	107355	107500

2.2 Capital Budget and Plan Details

Each year, the City of Toronto publishes the Capital Budget and Plan Details dataset (City of Toronto 2024d), which outlines a 10-year capital budget and plan. This dataset breaks down the capital budget across the city's 25 wards, allocating funds for infrastructure projects, equipment purchases, and other fixed assets. This budget is developed through a collaborative process, where city staff prepare an initial draft, which is then reviewed by the Budget Committee. Input is solicited from Toronto residents and businesses, and subsequently, the Mayor presents the finalized budget proposal by February 1. City Council reviews and considers this budget within 30 days (City of Toronto 2024e).

For the purpose of this analysis we selected the year 2021-2024 to align with the 2022 municipal elections and the subsequent relevance to planning efforts. Furthermore, the city's budgeting process underwent significant shifts after 2020 due to the impact of the COVID-19 pandemic, which altered spending priorities and resource allocation. Focusing on the 2021–2024 timeframe allows us to analyze the post-pandemic period, avoiding the uncertainties of the pandemic and ensuring the data remains consistent and reliable.

Each budget plan includes five primary categories under *State of Good Repair*, *Growth Related*, *Health and Safety*, *Service Improvement and Enhancement*, and *Legislated*. These categories define the main areas where capital expenditures are directed. For this analysis, however, we will focus on these three variables of interest: *State of Good Repair*, *Growth Related*, and *Service Improvement and Enhancement*.

Since our analysis aims to understand how budget allocations influence construction activity and infrastructure development, we selected these three categories as they are most relevant to capital expenditures and infrastructure projects. *State of Good Repair* focuses on maintaining and preserving existing infrastructure, *Growth Related* addresses the expansion and development of new infrastructure, and *Service Improvement and Enhancement* aims to enhance public services and amenities.

Raw data includes key columns such as `Project Name`, yearly budget allocations for each year, `Ward Number`, `Ward`, `Category`, and `Total 10 Year` (Sum of Year 1 to 10), where the budget is in thousands of dollars (e.g., 10 = $10,000). Table 2 shows a sample of the cleaned data along with our variables of interest:

- `Ward ID`
- `Ward Name`
- `Category of the Capital Budget`
- `Total 10-year capital budget` allocated to each ward

Rows with `CW` (city-wide budget) were removed since they were applicable to all wards.

Table 2: Sample of Cleaned Toronto Capital Budget Data

Ward ID	Ward Name	Category	Total 10-Year Budget (in 000s)
1	Etobicoke North	Growth Related	37873.0
1	Etobicoke North	Service Improvement and Enhancement	6361.0
2	Etobicoke Centre	Growth Related	69025.0
2	Etobicoke Centre	Service Improvement and Enhancement	20116.0
2	Etobicoke Centre	State of Good Repair	5112.0
3	Etobicoke-Lakeshore	Growth Related	85358.9

2.3 City Wards

The City Wards dataset (City of Toronto 2024c), published by the City Clerk's Office and last updated on July 22, 2024, contains geographical information about each ward, including the ward ID, ward name, and ward boundary. These ward boundaries were decided as a part of *Bill 5, Better Local Government Act* in 2018, reducing the number of wards from 47 to 25 (City of Toronto 2024c).

This dataset, effective January 1, 2024, was used to map the `ward_id` to the ward name in the cleaned data. Key columns include:

- `ward_id`: unique identifier for each ward,
- `ward`: ward name,
- `ward_boundary`: geographical boundary of the ward.

The ward names were mapped to the `ward_id` and integrated with the Ward Profiles Section 2.1 and Capital Budget data sets Section 2.2 to create the final data set for analysis. This dataset was not used directly in the analysis but was essential for mapping the ward names to the ward IDs in the cleaned data.

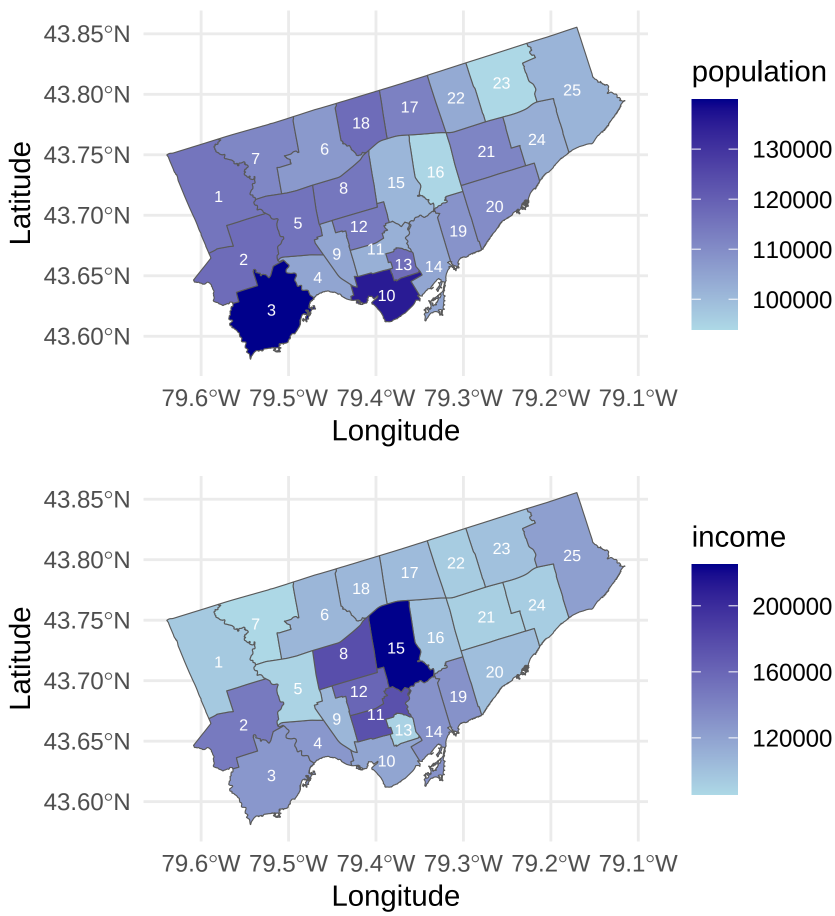


Figure 2: Map of Toronto highlighting the population and income densities by ward

2.4 Building Permits - Active Permits

The *Building Permits - Active Permits* dataset (City of Toronto 2024a), published by the City Planning Division and last updated on November 28, 2024, serves as an important record of active building permits in Toronto. A building permit is a municipally issued document, mandated by the Building Code Act and enforced by the City of Toronto, regulating the construction or demolition of physical structures (City of Toronto 2024a).

The process of obtaining a building permit involves submitting an application to the City of Toronto, including necessary drawings, documents, and other forms based on the permit type. The Building Division reviews the application, and a Toronto Building Inspector ensures compliance with the Ontario Building Code, Zoning By-law, and other applicable regulations. Once approved, the permit is issued, allowing the applicant to commence construction or demolition, and thus data is saved in the system as an active permit.

Table 3 outlines detailed information about active building permits in Toronto, including key features such as `Permit Number`, `Permit Type`, `Structure Type`, `Status`, and more.

Table 3: Sample of the raw building permits data

ID	Permit Type	Structure Type	Work	Postal Code	Status
1	Non-Residential Building Permit	Office	Addition to Existing Building	M2R	Permit Issued
2	Residential Building Permit	SFD - Semi-Detached	Addition to Existing Building	M4L	Inspection
3	Residential Building Permit	Multiple Unit Building	Alteration to Existing Building	M6R	Inspection
4	Residential Building Permit	HVAC Alt. Boiler/Furn Rplmt. or A/C	HVAC	M6K	Inspection
5	Mechanical(MS)	HVAC Alt. add on Sys. or Ductwork Alt.	Install/Alter HVAC - only	M6H	Inspection
6	Mechanical(MS)	Office	Install/Alter HVAC - only	M5C	Inspection

We selected this data-set to evaluate how our confounders, population and income, influence construction activity, and mediator, budget allocation, correlate with the number of building permits issued in each ward. The number of permits serves as a proxy for construction activity and development, highlighting the demand for infrastructure investment and capital expenditures. By examining the relationship between building permits and outlined variables, we can understand how construction activity influences resource distribution across the city's wards.

From the raw data, we selected key variables of interest: `Postal Code`, `Status`, and `Work`. The `Postal Code` was used to map building permits to their respective wards, while `Status` and `Work` were utilized to filter permits based on their current state and type of work. Table 7 lists 45 unique statuses assigned to each submitted permit. For this analysis, we focused on permits with the following statuses: `Approved`, `Application Accepted`, `Issuance Pending`, `Ready for Issuance`, `Permit Issued`, and `Permit Issued/Close File`. These statuses indicate that the permit has been approved and that construction or demolition is either underway or completed.

The cleaned data was then saved in CSV and Parquet formats with the following columns:

- **`ward_id`**: Unique identifier for each ward.
- **`total_building_permits`**: Total number of building permits issued in each ward.

Figure 3 illustrates the total number of building permits by ward, providing understanding into construction activity and development patterns across Toronto's wards.

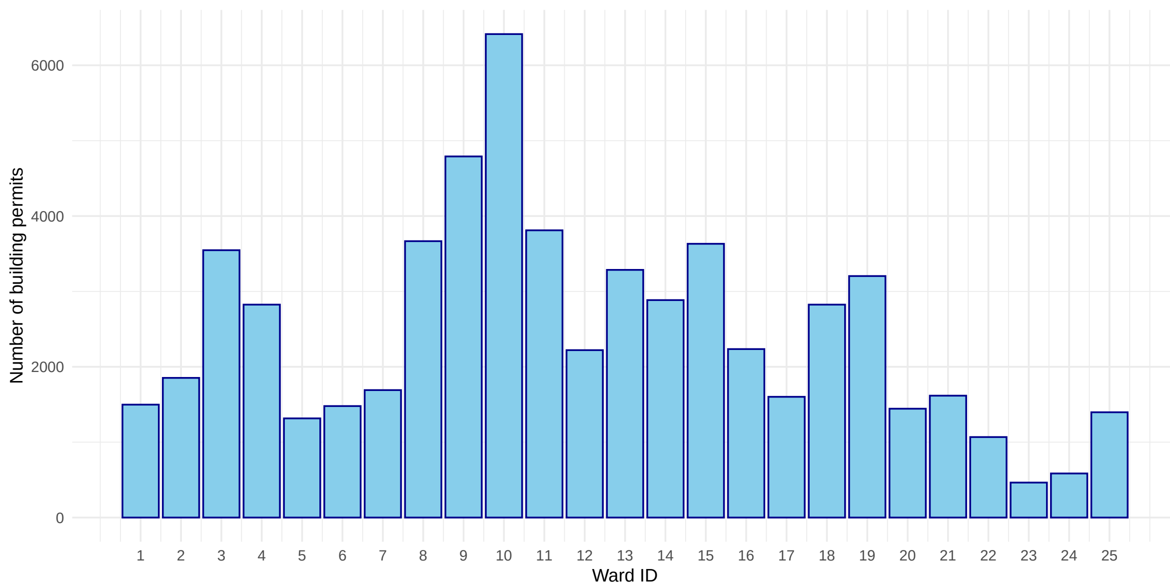
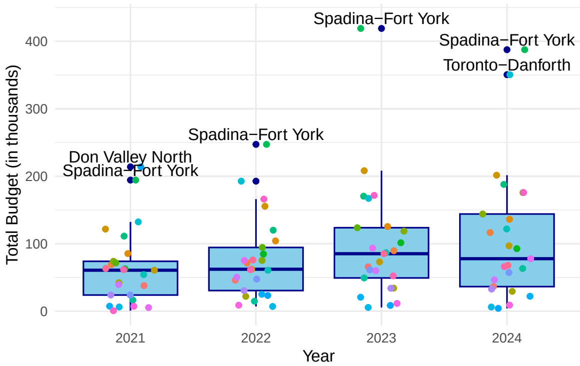


Figure 3: Total number of building permits by Ward

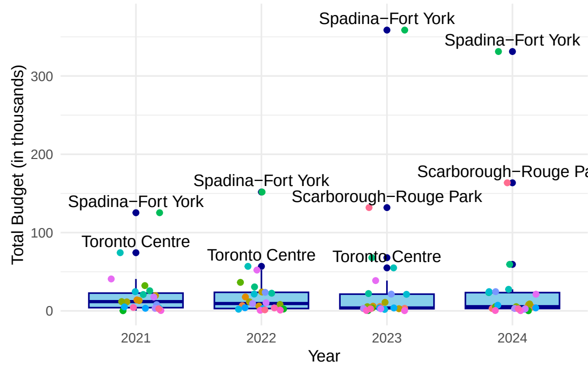
2.5 Trends in Budget Allocations (2021-2024)

The box plots in Figure 4 illustrate the trends in budget allocations across three categories—*Growth Related*, *State of Good Repair*, and *Service Improvement and Enhancement*—from 2021 to 2024. Each box plot represents the distribution of budget allocations for each year, with the median value indicated by the horizontal line inside the box. Outliers are labeled with the corresponding ward ID, highlighting wards with unusually high or low budget allocations.

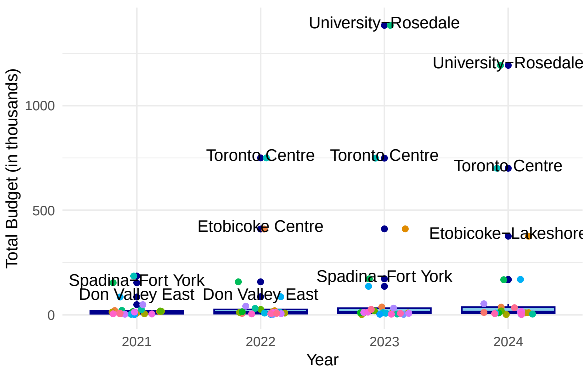
Ward 10 (Spadina-Fort York) received the highest budget allocations across both *Growth Related* and *State of Good Repair* categories, indicating significant investment in infrastructure



(a) Growth Related



(b) State of Good Repair



(c) Service Improvement and Enhancement

Figure 4: Trends in budget allocations (2021-2024) by category

development and maintenance to population-dense areas. Toronto Center, Don Valley East, and Etobicoke Center also received notable budget allocations, some of these wards have higher average household incomes as well as higher population densities. The box plots reveal that budget allocations for *Growth Related* projects have increased steadily over the years, with 75% of wards receiving higher allocations in 2024 compared to 2021. In contrast, budget allocations for *State of Good Repair* and *Service Improvement and Enhancement* projects have remained relatively consistent, with few outliers receiving higher budget allocations.

The box plots for *State of Good Repair* and *Service Improvement and Enhancement* projects however, are less varied as most of the wards received similar budget allocations across the years, with few outliers such as University-Rosedale, Toronto Centre and Don Valley West receiving higher budget allocations, who coincidentally have higher average household income.

2.6 Relationship between Variables of Interest and Budget Allocations

Our budget data spans three categories—*Growth Related*, *State of Good Repair*, and *Service Improvement and Enhancement*—for the years 2021-2024. As observed in Section 2.5, there has been a steady increase in budget allocations across these categories. To better understand the relationship between these budget categories and our variables of interest, we calculate the average budget allocation for each category across the years. The results are presented in Table 4.

Table 4: Average 10-year budget allocations by category (2021-24)

Ward ID	Ward Name	Growth Related	State of Good Repair	Service Improvement and Enhancement
1	Etobicoke North	46497.25	2565.643	7279.627
2	Etobicoke Centre	86651.25	5546.250	126011.750
3	Etobicoke-Lakeshore	112789.98	9572.525	205245.100
4	Parkdale-High Park	171717.25	8373.225	7211.932
5	York South-Weston	73226.12	12362.250	11403.250
6	York Centre	31927.25	10725.475	3865.750

2.6.1 Relationship between Predictors and Budget Allocations (Service Improvement and Enhancement)

Figure 5 illustrates the relationship between average household income, population, and the total 10-year budget allocation for Service Improvement and Enhancement projects. These projects aim to enhance the quality of services provided to residents and improve the overall infrastructure of the city (City of Toronto 2018).

Unlike Growth-Related and State of Good Repair projects, the linear regression lines for average household income and population shows a positive correlation with budget allocation for Service Improvement and Enhancement projects. Wards with higher average household incomes, such as Ward 11 (University-Rosedale) and Ward 13 (Toronto Centre), receive a larger share of the budget allocation for these projects. This suggests that higher-income areas are prioritized for service improvements and infrastructure enhancements, reflecting a targeted approach to resource allocation based on income levels.

Other wards like Ward 3 (Etobicoke-Lakeshore) and Ward 10 (Spadina-Fort York), which have high population densities, also received significant budget allocations, suggesting that these areas are priorities for service improvements and infrastructure enhancement.

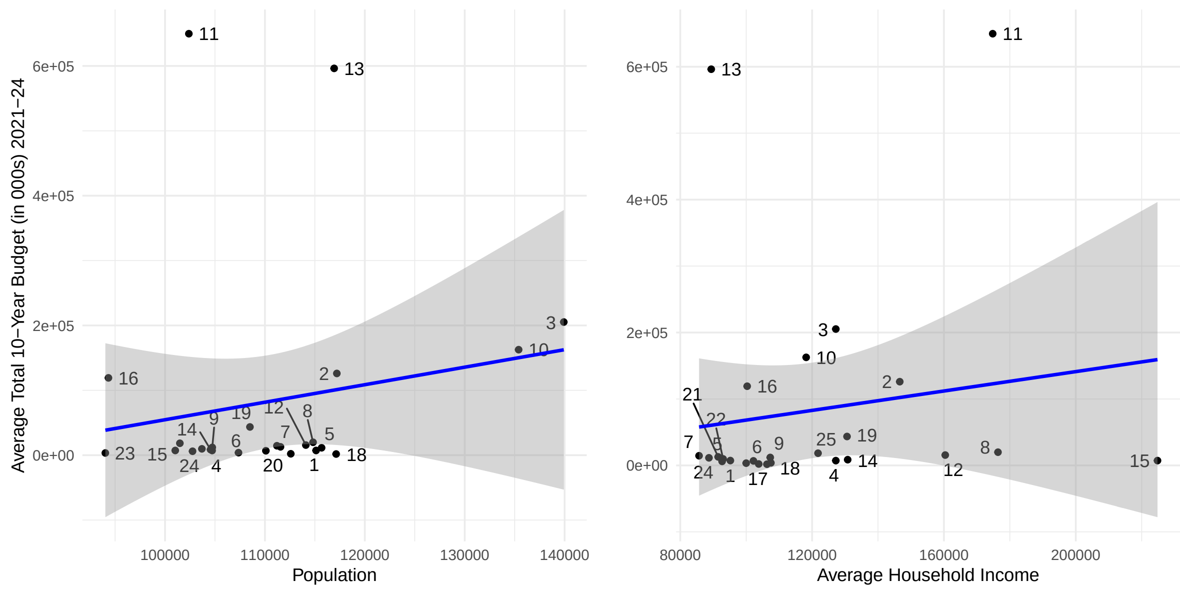


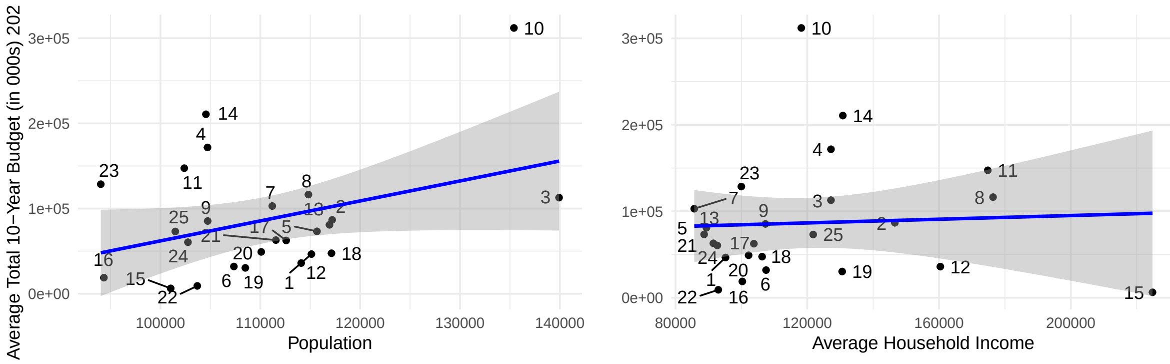
Figure 5: Service Improvement and Enhancement Budget by Ward

Despite these outliers, the majority of wards received similar budget allocations for Service Improvement and Enhancement projects, underscoring a city-wide strategy to enhance services uniformly for all residents.

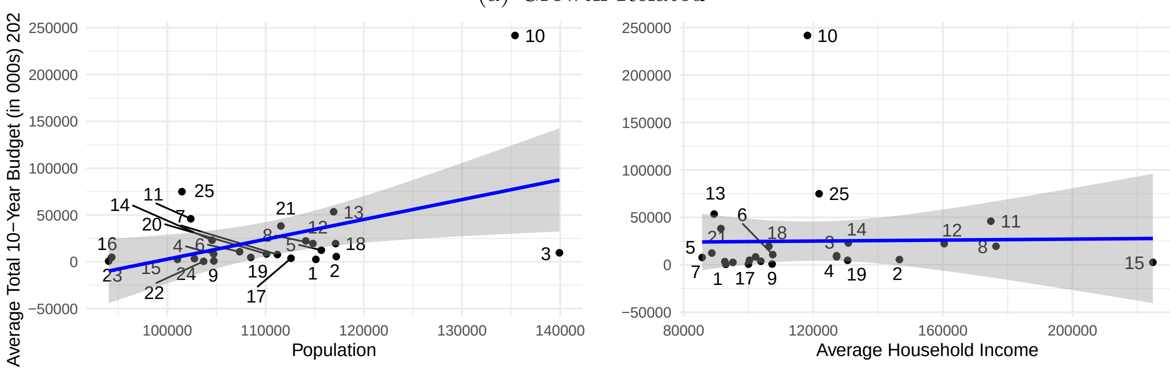
2.6.2 Relationship between Predictors and Budget Allocations (Growth-Related and State of Good Repair)

Figure 6a) illustrates the relationship between average household income, population, and the total 10-year budget allocation for Growth-Related projects. The linear regression line for average household income remains relatively flat, hovering around $100,000. This suggests that budget allocations for Growth-Related projects are not significantly influenced by income levels, indicating a more uniform distribution of funds across wards regardless of household income. A similar lack of correlation is observed in Figure 6b), where budget allocations for State of Good Repair projects also show minimal dependence on average household income.

In contrast, the linear regression line for population shows a strong positive correlation with budget allocation for Growth-Related projects. Wards with higher population densities—such as Ward 10 (Spadina-Fort York), Ward 13 (Toronto Centre), Ward 5 (York South-Weston), and Ward 2 (Etobicoke North)—receive a larger share of the Growth-Related budget. This indicates that population density plays an important role in determining funding levels for these projects, with more populous wards benefiting from increased allocations. A similar trend is observed in the budget distribution for State of Good Repair projects, where wards with higher population densities receive a proportionally larger share of the funds.



(a) Growth Related



(b) State of Good Repair

Figure 6: Growth and State of Good Repair Budget by Ward

3 Model

The purpose of this paper is to investigate the relationship between population density, average household income, and budget allocations across Toronto's 25 wards, and their potential impact on the economic well-being of each ward, as represented by the `total_building_permits` issued. To achieve this, we will first plot the data to visualize the relationships between these variables and the number of building permits issued in each ward independently. Then we will fit a Bayesian regression model with varying intercepts to estimate the effect of these variables on the number of building permits issued in each ward.

3.1 Model set-up

The particular model we used is Bayesian multiple linear regression model with varying intercepts. The model includes the following variables:

$$
\begin{aligned}
y_i|\mu_i,\sigma &\sim \text{Normal}(\mu_i,\sigma)\\
\mu_i &= \beta_0 + \beta_1 x_{\text{income}} + \beta_2 x_{\text{budget}} + \gamma_i\\
\beta_0 &\sim \text{Normal}(0, 2.5)\\
\beta_1 &\sim \text{Normal}(0, 2.5)\\
\beta_2 &\sim \text{Normal}(0, 2.5)\\
\gamma_i &\sim \text{Normal}(0, 2.5)\\
\sigma &\sim \text{Exponential}(1)
\end{aligned}
$$

In the above model:

- μ_i is the expected number of building permits issued in ward i.
- β_0 is the intercept, representing the expected number of building permits issued in a ward with average values for all other variables.
- β_1 is the coefficient for the predicted change in the number of building permits issued in a ward given a one unit increase in the average household income of the ward.
- β_2 is the coefficient for the predicted change in the number of building permits issued in a ward given a one unit increase in the total budget allocation across three categories: Growth Related, State of Good Repair, and Service Improvement and Enhancement.

The model also includes a varying intercept γ_i for each ward, accounting for the unobserved heterogeneity between wards. The varying intercepts allow the model to capture the unique characteristics of each ward that may influence the number of building permits issued.

The model was fitted using the `stan_glmer` function from the `rstanarm` package (Brilleman et al. 2018) in R (R Core Team 2024) and `modelsummary` (Arel-Bundock 2022) for model summary tables. The prior distributions for the coefficients were set to normal distributions with a mean of 0 and a standard deviation of 2.5. The model also included a prior for the intercept, which was set to a normal distribution with a mean of 0 and a standard deviation of 2.5. The standard deviation of the likelihood was set to an exponential distribution with a rate parameter of 1.

3.2 Model justification

Table 5: Mean, Median, and Standard Deviation of Each Variable

Variable	Mean	Median	Standard Deviation
Population	110451.60	110095.0	10593.872
Average Household Income	120096.00	107300.0	33980.638
Total Budget	194355.34	113992.8	226896.460

Table 5: Mean, Median, and Standard Deviation of Each Variable

Variable	Mean	Median	Standard Deviation
Total Building Permits	2454.28	2221.0	1382.892

To better understand the underlying data, Table 5 provides a summary of the mean, median, and standard deviation for each variable used in the model. The predictor variables have large values and different scales, which can cause numerical instability and convergence issues in the model. To address this, we will standardize the predictor variables by subtracting the mean and dividing by the standard deviation. This will scale the variables consistently and improve both the model's convergence and interpretability. Additionally, we did not use a Bayesian Poisson regression model or negative binomial because the number of building permits is a continuous variable, not count data. Therefore, we chose to use a Bayesian multiple linear regression model. This model allows us to estimate the effect of population density, average household income, and budget allocations on the number of building permits issued in each ward giving us a well-rounded understanding of the relationships between these variables.

The factors chosen for the model are known to influence the number of building permits issued in each ward. Population density and average household income are demographic and economic indicators that can affect construction activity. Budget allocations for Growth-Related, State of Good Repair, and Service Improvement and Enhancement projects are key drivers of infrastructure development and resource distribution. Including these variables allows for assessing their individual and combined effects on the number of building permits issued.

When population density was included, for the causual model, it exhibited exclusion restriction qualities, as it showed an unexpected negative relationship with building permits, leading to its exclusion for better interpretability. The model was then refitted without population density, focusing on average household income and budget allocations as predictors.

4 Results

In this section, we visualize the relationships between population density, average household income, budget allocations with total number of building permits across Toronto's 25 wards. Additionally, we present our model results, highlighting how these variables influence the number of building permits issued in each ward.

4.1 Distribution of Average Household Income and Population Density

The City of Toronto is divided into 25 wards, and the 2021 census data highlights significant disparities in population and average household income among them. As shown in Figure 2, Spadina-Fort York (Ward 10) and Etobicoke-Lakeshore (Ward 3) have the highest population densities, with 135,400 and 139,920 residents, respectively. In contrast, Don Valley West (Ward 15) has a lower population density of 101,025 but boasts the highest average household income at $224,800.

Population distribution presents a concentration in the western part of the city and downtown areas. Notably, wards like Etobicoke Centre (Ward 2) and Etobicoke-Lakeshore (Ward 3), situated farther from downtown, have lower costs of living and correspondingly lower average household incomes, such as Etobicoke North (Ward 2) with $95,200.

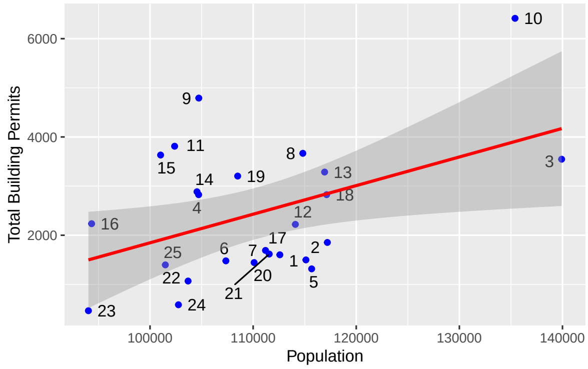
An interesting pattern emerges around Don Valley West (Ward 15), which has the highest average household income. Wards such as University-Rosedale (Ward 11), Toronto-St. Paul's (Ward 12), and Eglinton-Lawrence (Ward 8) are clustered together, indicating a geographical correlation among high-income areas. Conversely, the wards with the highest population densities do not overlap with those that have the highest average household incomes, highlighting distinct socioeconomic patterns within the city.

4.2 Relationship between Predictor Variables and Building Permits

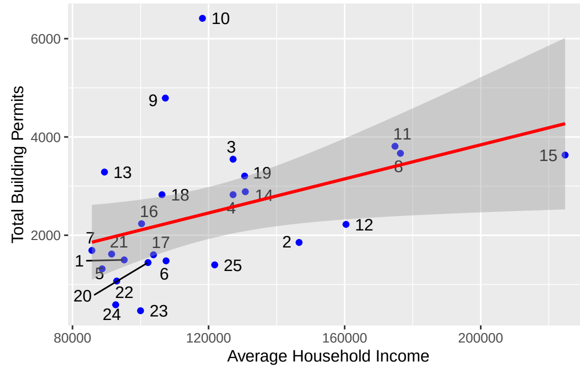
We now explore the results of independent comparisons between the outcome variable (total number of building permits in Toronto's 25 wards) and the predictor variables (population density, average household income, and budget allocations for Growth-Related, State of Good Repair, and Service Improvement and Enhancement projects). As shown in Figure 7, most predictor variables exhibit relatively flat linear regression lines, indicating a weak relationship with the total number of building permits.

For example, the relationship between population density and building permits is notably flat, suggesting that population density has minimal influence on construction activity and development across the city's wards—an unexpected result. A similar trend is observed for Growth-Related and State of Good Repair budget allocations, where flat regression lines suggest a weak relationship. This appears contradictory to earlier findings, where higher population density corresponded to increased budget allocations for these categories, which are typically associated with infrastructure development and maintenance. The same weak correlation is seen for Service Improvement and Enhancement budget allocations, as indicated by the flat regression line.

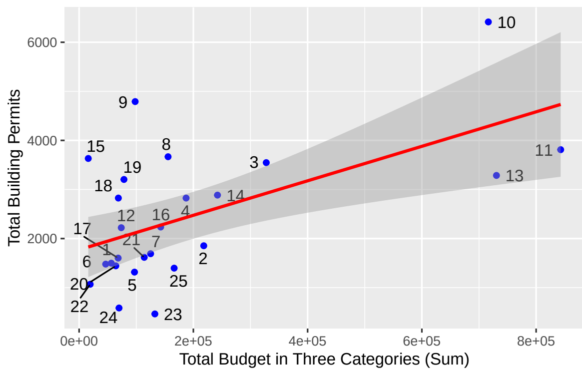
In contrast, the relationship between average household income and building permits shows a strong positive correlation. Higher-income areas tend to experience more construction activity and development. For instance, Ward 15 (Don Valley West) has the highest number of building permits, aligning with its high average household income. This suggests that higher-income areas are more likely to see increased construction and development, highlighting a clear link between income levels and building permits.



(a) Population



(b) Average Household Income



(c) Total Budget in Three Categories

Figure 7: Relationship between Variables and Total Building Permits

4.3 Model Results

The results of the Bayesian regression model, summarized in Table 6, provide important understanding into the relationship between total budget allocations, average household income, and the number of building permits issued across wards.

The model explains 59.1% of the variance in building permits, indicating a moderate level of explanatory power. The coefficients suggest that both total budget (0.530) and average household income (0.350) have a positive and significant impact on the number of building permits issued, implying that areas with higher budget allocations and income levels are more likely to see increased construction activity.

The inclusion of ward-specific random effects highlights the importance of accounting for variation between wards, suggesting that there are unobserved factors specific to each ward influencing permit issuance. Although the adjusted R^2 (0.369) indicates that the model's explanatory power is somewhat limited after accounting for the complexity of the predictors, the model still provides understanding into the role of economic factors in shaping construction activity.

Table 6: Model Results

	Model
(Intercept)	−0.009
total_budget	0.525
average_household_income	0.365
Sigma[ward_id × (Intercept),(Intercept)]	0.144
Num.Obs.	25
R2	0.594
R2 Adj.	0.359
R2 Marg.	0.459
Log.Lik.	−22.941
ELPD	−31.3
ELPD s.e.	5.0
LOOIC	62.6
LOOIC s.e.	10.0
WAIC	60.6
RMSE	0.57
r2.adjusted.marginal	0.359100614152714

With an RMSE of 0.58, the model's predictions are reasonably accurate, although there is still room for improvement.

In constructing the model, we assumed linearity and additive effects, acknowledging that these simplifications may not fully capture the interactions among variables. The model's limitations, such as the exclusion of population density due to its unexpected negative relationship, reflect a trade-off between interpretability and capturing complex dynamics. Nevertheless, the findings align with expectations that wealthier areas and those with greater budget allocations are more likely to experience construction growth, reaffirming the importance of economic resources in urban development patterns.

5 Discussion

In this section, we discuss the implications of our findings on urban development, economic well-being, and resource distribution in Toronto. We explore the role of budget allocations, average household income, and population density in shaping construction activity and infrastructure development across the city's 25 wards. Our analysis highlights the complex interplay between economic factors, demographic trends, and policy decisions, shedding light on the challenges and opportunities for equitable urban growth in Toronto.

5.1 Building Permits and Economic Well-Being

Construction plays a pivotal role in the economy, driving both job creation and economic growth (Building (CIOB) and Green 2023). One of the key indicators of construction activity is the number of building permits issued within a ward. Increased construction correlates with job opportunities, infrastructure development, and overall community well-being. For example, investment in residential and non-residential construction rose from 24.9% in 2021 to 29.5% in 2023, with projections indicating a further 1.5% increase in construction employment by 2024 (Canada and Development 2024).

As highlighted in Section 4.3 Bayesian regression model shows that average household income has a significant positive effect on the issuance of building permits. This suggests that construction activity tends to concentrate in higher-income areas, where demand for development is stronger. This finding underscores the role of income levels in driving construction and infrastructure development, emphasizing the need for targeted investments in lower-income areas to stimulate economic growth and enhance community well-being.

For potential property investors in Toronto, these understanding offer a strategic advantage. Investing in areas with higher average household incomes may be more profitable due to the increased likelihood of ongoing construction activity, which can drive property value appreciation and strengthen the local economy. While high-population-density areas are typically attractive for investment, our findings suggest that this may not always be the case.

5.2 Investing in Higher-Income Areas vs. High-Density Areas

The interplay between population density, average household income, and infrastructure investment in Toronto highlights a complex challenge in achieving equitable resource distribution. As seen in Section 2.6 high-income areas often attract more construction activity, driven by market forces and residents' ability to finance new developments. Whereas, only specific high-density areas like Ward 10 (Spadina-Fort York) and Ward 13 (Toronto Centre) receive substantial investment despite high population density, suggesting efforts to address this imbalance. Meanwhile, as discussed in Section 4.1, low-density and lower-income wards risk being underserved.

These findings underscore the importance of equity-based budgeting, where low-density and lower-income areas should receive targeted investments to meet infrastructure needs. This approach aligns with urban development strategies that prioritize inclusivity. Notable examples include transit expansions such as the Ontario Line and Crosstown extensions (Navabi 2024).The Ontario Line is expected to connect high-density areas like Ward 10 (Spadina-Fort

York) and Ward 13 (Toronto Centre) to the broader transit network, which could stimulate further development and infrastructure investment in these wards, fostering a more balanced urban landscape and distributing population growth more evenly across the city.

For future policy, Toronto could enhance equity by expanding initiatives such as eliminating parking minimums. This policy reduces construction costs, making development in high-density areas more feasible. Such measures would promote a more balanced and sustainable urban environment, ensuring that population growth is accompanied by appropriate infrastructure investments.

5.3 Budget Allocations and Construction Activity

Our analysis shows a complex relationship between budget allocations and construction activity in Toronto's 25 wards. As discussed in Section 2.5 there has been a steady increases in budget allocations for key initiatives such as Growth-Related, State of Good Repair, and Service Improvement and Enhancement projects from 2021 to 2024, the distribution of building permits shows only a good correlation with these allocations Section 4.3. This finding suggests that budget allocations alone may not be the sole driver of construction activity, as other factors like market conditions, regulatory frameworks, and community priorities also play a significant role.

This discrepancy reflects broader challenges highlighted in Toronto's recent 10-year economic plan (Freeman 2024), which aims to tackle pressing issues such as housing, inequality, and congestion. The plan emphasizes the need for strategic investments that go beyond conventional infrastructure spending. For example, the city has committed \$35 million to cultural initiatives over the next decade, signaling a shift toward holistic urban development that prioritizes cultural and social well-being alongside physical infrastructure improvements. This shift may explain the weak correlation between budget allocations and building permits, as construction activity is influenced by a broader range of factors beyond traditional infrastructure spending.

Moreover, the Ford government's fall economic statement indicates a shrinking provincial deficit, suggesting a cautious fiscal environment that may limit how budgetary increases translate into tangible construction outputs ("2024 Fall Economic Statement" 2024). These dynamics suggest that other factors, such as regulatory frameworks, market conditions, or demographic shifts, may be playing a more significant role than budgetary allocations alone in shaping Toronto's construction landscape.

6 Weaknesses and Future Work

This analysis has several limitations that warrant consideration. As discussed in Section 2, the datasets used, sourced from the City of Toronto, provide insights into the city's demographics, budget allocations, and building permits. However, they may not fully capture the complexity of Toronto's infrastructure development and resource distribution.

For instance, in Section 2.4, all building *Work Types* were included in the analysis, which may not accurately represent construction activity in each ward. Many recorded work types, such as renovations, demolitions, and minor repairs (e.g., HVAC installations or pipework), are not indicative of significant construction projects. Future research could refine the analysis by focusing on specific types of construction projects to better reflect actual development activity.

Additionally, as noted in Section A, there are 45 unique statuses assigned to building permits, but this study analyzed only a subset of these statuses. This narrow focus may overlook important stages in the construction process. Expanding the analysis to include more permit statuses could offer a more comprehensive understanding of construction activity.

Another limitation is the lack of detailed data on specific projects within each budget category, which restricts insights into why certain wards receive more or less funding. Access to granular project-level data could provide deeper context and explanations for funding disparities.

Moreover, the analysis assumes linear relationships between population density, average household income, and budget allocations, which may oversimplify the underlying dynamics. Developing more complex models that account for non-linear relationships and interactions could yield a richer understanding of factors influencing construction activity.

Finally, the analysis assumes independence among wards, an assumption that may not hold true given shared infrastructure and resource dependencies. Future studies could incorporate spatial or network-based models to address interdependencies between wards.

6.1 Future Work

This analysis provides a foundation for future research on infrastructure development, resource distribution, and economic well-being in Toronto. Future studies could explore additional factors that influence budget allocations and building permit issuance, such as infrastructure needs, community priorities, and political considerations. By incorporating these variables into the analysis, researchers can gain a more in-depth understanding of how municipal budgets are allocated and how construction activity is distributed across the city's wards.

In terms of policy recommendations, the city should adopt equity-based budgeting to ensure underfunded, high-density wards receive adequate resources, particularly for essential services like health and safety. Toronto could also implement a baseline funding model for high-need areas and enhance public engagement in the budget process, ensuring that residents of under served wards have a voice in resource allocation. These actions would promote more transparent, balanced, and equitable urban governance.

A Appendix

A.1 Survey, Sample, and Data Collection

The relationship between income levels, population and construction outcomes is complex and influenced by diverse socioeconomic and regional factors. Current observational data, such as NHS survey to get income levels, and population of ward profiles but is inherently limited by its sample ("National Household Survey (NHS)" 2023). To better answer our research question, a more targeted survey approach is essential. This exploration outlines an idealized survey methodology designed to reduce bias, ensure representativeness, and deepen understanding.

A.1.1 Idealized Survey Design for Construction Analysis

A survey specifically designed to explore the link between income and construction outcomes would involve the following key components:

a. Defining the Survey Objectives The survey would aim to investigate how income disparities influence construction investment, access to resources, regulatory hurdles, and housing quality across different regions.

b. Sampling Methodology
To ensure a representative and unbiased dataset, the survey would employ:

- Stratified Sampling: Income levels and ward classifications (e.g., urban, suburban, rural) would be stratified to ensure proportional representation.

- Random Sampling Within Strata: Participants would be randomly selected within each stratum to enhance the validity and generalizability of the findings.

c. Sample Size and Distribution The sample size should be sufficiently large to allow for statistically significant comparisons across different income levels and geographic regions. A minimum target of several thousand participants distributed evenly across strata would be ideal.

A.1.2 Reducing Bias in Sampling and Data Collection

Bias reduction is important in survey design to ensure reliable and actionable understanding. This involves addressing various types of bias:

a. Sampling Bias Mitigation Stratified random sampling ensures that underrepresented groups, particularly those in lower income brackets or remote regions, are adequately included.

b. Non-Response Bias Mitigation Offering multiple survey delivery methods—such as online platforms, in-person interviews, and mailed surveys—enhances accessibility and participation. Additionally, providing incentives like small monetary rewards or gift cards can boost response rates among diverse groups.

c. Design Bias Mitigation To avoid influencing responses, survey questions must be neutrally worded and pilot-tested to ensure clarity. Cognitive interviews with a subset of participants can help refine the wording and structure of questions.

A.2 Building Permits Status

Table 7: Building permit statuses

STATUS
Permit Issued
Inspection
Application Withdrawn
Revised
Pending Cancellation
Application Received
Revision Issued
Order Complied
Revocation Pending
Rescheduled
Examiner's Notice Sent
Issuance Pending
Inspection Request to Cancel
Under Review
Plan Review Complete
Not Accepted
Permit Issued/Close File
Ready for Issuance
Work Suspended
Abandoned
File Closed
VIOLATION
Work Not Started
Not Started
Order Issued
Response Received

Refusal Notice
Forwarded for Issuance
Application On Hold
Application Acceptable
Follow-up Required
Consultation Completed
Extension Granted
Request Received
Active
Deficiency Notice Issued
Refused
Approved
Agreement in Progress
NA
Open
Application Accepted
Permit Revoked
Forward to Inspector
Revoked

A.3 Model Details

A.4 Posterior Predictive Check

We employ a posterior predictive check in Figure 8 to evaluate how well the model fits the data. By examining the distribution of the observed data against the simulated data, we can assess the model's predictive accuracy and identify any discrepancies. (Alexander 2024).

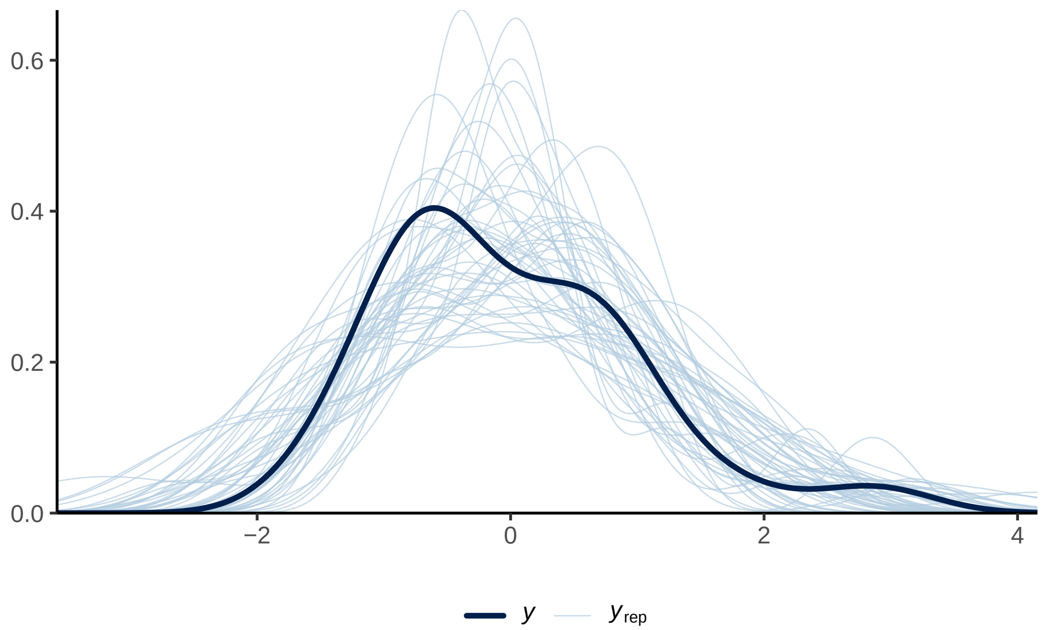


Figure 8: Examining how the model fits the data through a posterior predictive check

A.5 Comparison of the Posterior and Prior

We compare the posterior and prior in Figure 9 to examine how the estimates change once data is taken into account (Alexander 2024).

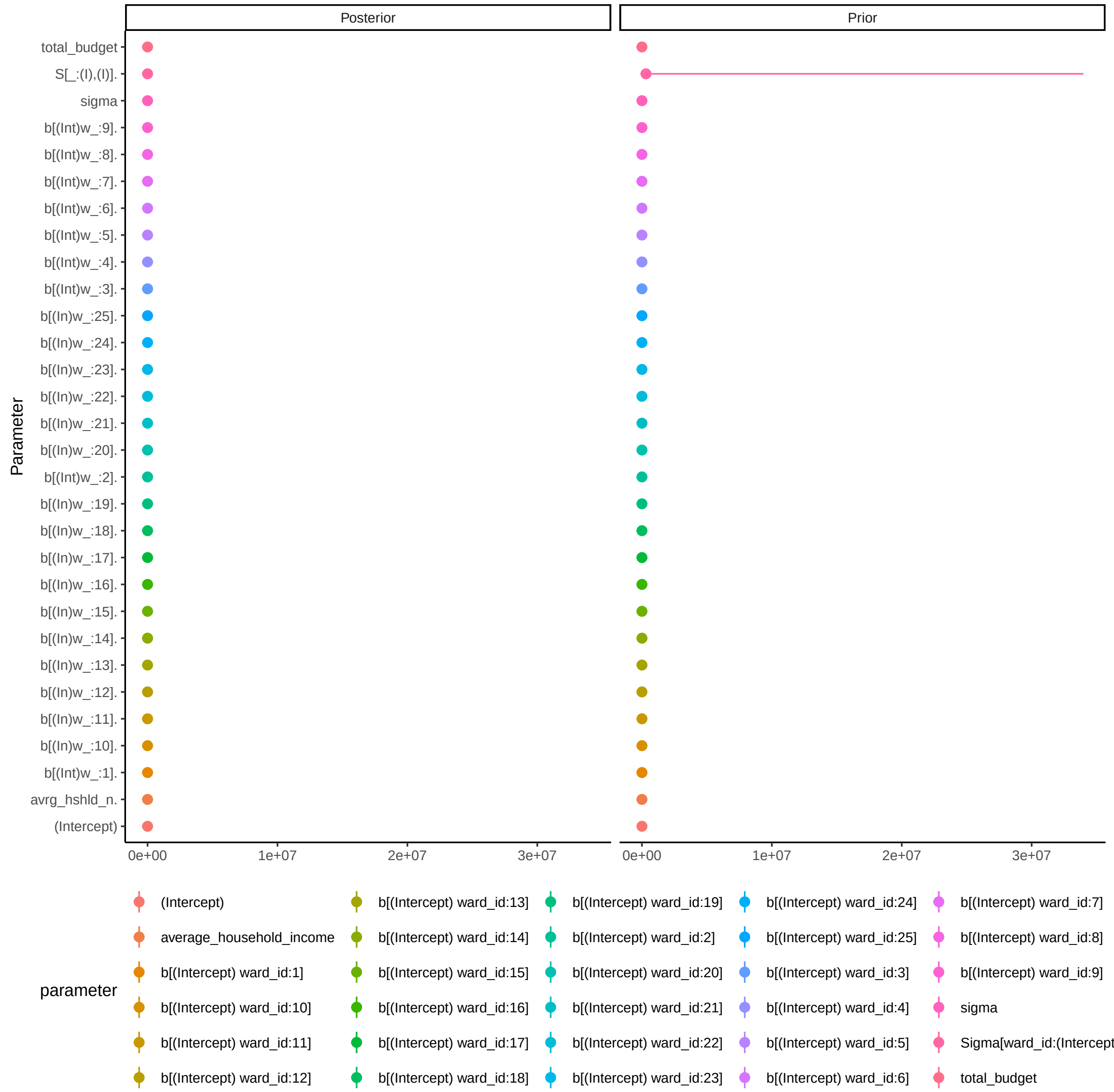
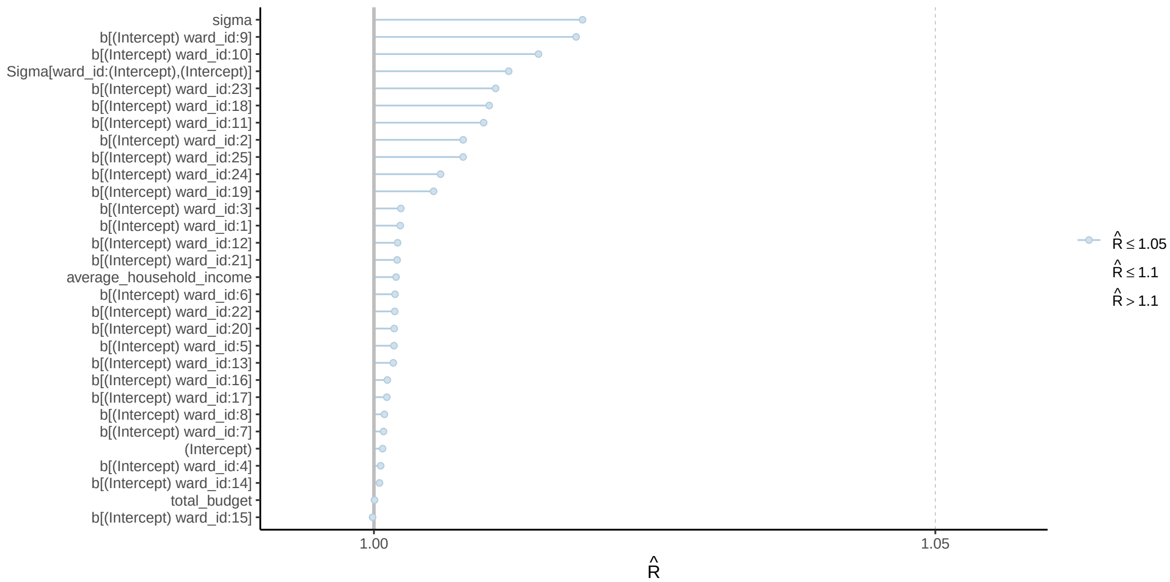


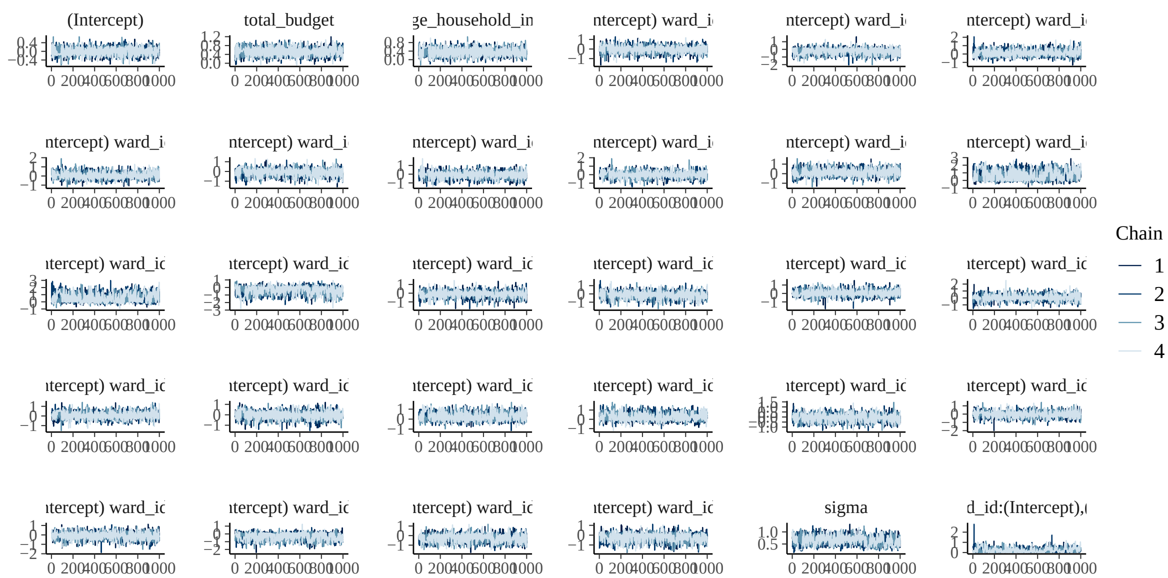
Figure 9: Examining how the model is affected by the data through a posterior-prior comparison

A.6 Markov Chain Monte Carlo Convergence

Since `rstanarm` uses the MCMC sampling algorithm (Alexander 2024), we assess whether the algorithm encountered any issues by reviewing the Rhat and trace plots, as shown in Figure 10. The Rhat plot shows no concerns, with values consistently close to 1, indicating that the algorithm converged properly (Alexander 2024). Additionally, the trace plot appears normal, as the lines remain horizontal and fluctuate as expected, further supporting the adequacy of the sampling process (Alexander 2024).



(a) Rhat plot



(b) Trace plot

Figure 10: Checking the convergence of the MCMC algorithm

A.7 Credibility Intervals

Lastly, we employ a 95% credibility interval as showcased in Figure 11, to gain a better understanding of the probability distribution of our coefficients.

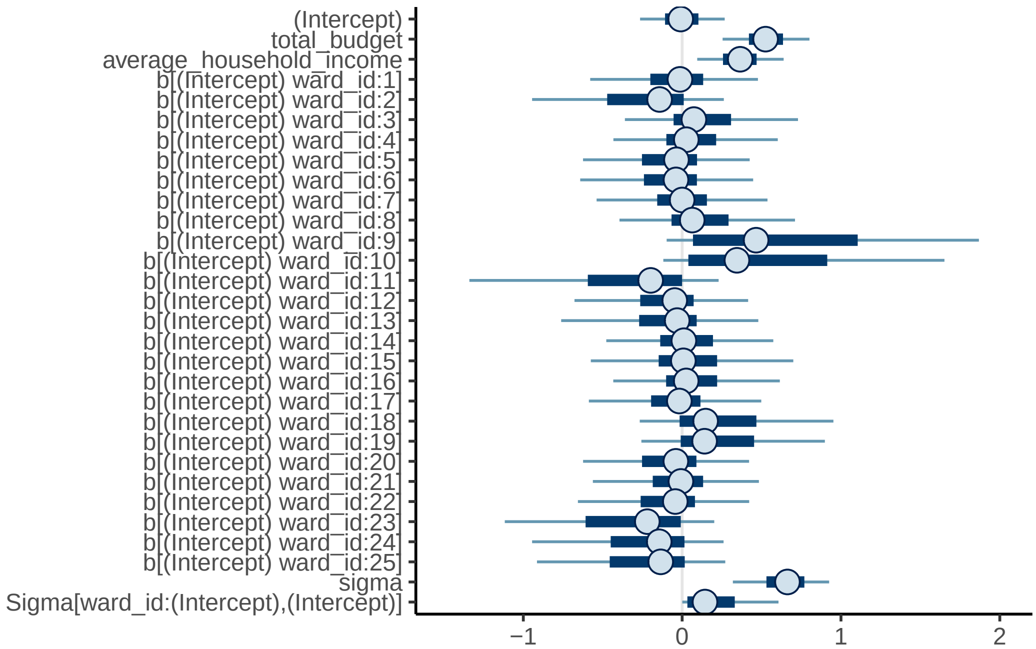


Figure 11: Credible intervals

References

"2024 Fall Economic Statement." 2024. https://news.ontario.ca/en/release/1005246/building-ontario-for-you.

Alexander, Rohan. 2024. *Telling Stories with Data*. "University of Toronto". https://www.tellingstorieswithdata.com.

Arel-Bundock, Vincent. 2022. "modelsummary: Data and Model Summaries in R." *Journal of Statistical Software* 103 (1): 1–23. https://doi.org/10.18637/jss.v103.i01.

Brilleman, SL, MJ Crowther, M Moreno-Betancur, J Buros Novik, and R Wolfe. 2018. "Joint Longitudinal and Time-to-Event Models via Stan." https://github.com/stan-dev/stancon_talks/.

Building (CIOB), Chartered Institute of, and Brian Green. 2023. "Socio-Economic Impact of Construction." CIOB. www.ciob.org/industry/policy-research/policy-positions/socio-economic-impact-construction.

Canada, Employment, and Social Development. 2024. "Construction: Ontario 2023-2025 - Job Bank." Employment; Social Development Canada, Government of Canada / Gouvernement Du Canada. www.jobbank.gc.ca/trend-analysis/job-market-reports/ontario/sectoral-profile-construction.

City of Toronto. 2018. "Neighbourhood Improvements." www.toronto.ca/services-payments/streets-parking-transportation/enhancing-our-streets-and-public-realm/neighbourhood-improvements/.

———. 2024a. "Building Permits - Active Permits." Data Set. City of Toronto Open Data Portal. https://open.toronto.ca/dataset/building-permits-active-permits/.

———. 2024b. "Ward Profiles (25-Ward Model)." Data Set. City of Toronto Open Data Portal. open.toronto.ca/dataset/ward-profiles-25-ward-model/.

———. 2024c. "Open Data Dataset." open.toronto.ca. open.toronto.ca/dataset/city-wards/.

———. 2024d. "Budget - Capital Budget Plan by Ward (10-Yr Approved)." Data Set. City of Toronto Open Data Portal. open.toronto.ca/dataset/budget-capital-budget-plan-by-ward-10-yr-approved/.

———. 2024e. "2024 City Budget." *City of Toronto*, May. www.toronto.ca/city-government/budget-finances/city-budget/.

———. 2024f. "Sidewalks to Skylines: A 10-Year Action Plan for Toronto's Economy." www.toronto.ca/city-government/accountability-operations-customer-service/long-term-vision-plans-and-strategies/action-plan-toronto-economy/.

Ferguson, Lisa. 2024. "Compromised Budget Delivers Historic New Investment Turning the Corner on a City in Decline, While Also Allocating Millions More to the Police." *Social Planning Toronto*, February. www.socialplanningtoronto.org/budget_results.

Freeman, Joshua. 2024. "Toronto's 10-Year Economic Plan." *CP24*, October. https://www.cp24.com/politics/toronto-city-hall/2024/10/16/torontos-10-year-economic-plan-calls-for-city-to-tackle-congestion-inequality-housing/.

Gabry, Jonah, Daniel Simpson, Aki Vehtari, Michael Betancourt, and Andrew Gelman. 2019. "Visualization in Bayesian Workflow." *J. R. Stat. Soc. A* 182: 389–402. https://doi.org/

10.1111/rssa.12378.

Government of Canada, Statistics Canada. 2023. "National Household Survey (NHS)." Surveys; Statistical Programs.

Hester, Jim, Florent Angly, Russ Hyde, Michael Chirico, Kun Ren, Alexander Rosenstock, and Indrajeet Patil. 2024. *Lintr: A 'Linter' for r Code*. https://CRAN.R-project.org/package=lintr.

Müller, Kirill, and Lorenz Walthert. 2024. *Styler: Non-Invasive Pretty Printing of r Code*. https://CRAN.R-project.org/package=styler.

"National Household Survey (NHS)." 2023. Surveys; Statistical Programs.

Navabi, Ash. 2024. "How Toronto Is Responding as the Fastest Growing City in North America." *UrbanToronto*. https://urbantoronto.ca/news/2024/06/how-toronto-responding-fastest-growing-city-north-america.56316#:~:text=From%20July%201%2C%202021%20to,204%2C000%20residents%20during%20this%20time.

"Ontario's Long-Term Report on the Economy 2024." 2024. The Government of Ontario. www.ontario.ca/document/ontarios-long-term-report-economy-2024/chapter-1-demographic-trends-and-projections-2024.

Pedersen, Thomas Lin. 2024. *Patchwork: The Composer of Plots*. https://CRAN.R-project.org/package=patchwork.

R Core Team. 2024. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Schaeffer, Katherine. 2021. "'What's the Difference Between Income and Wealth?' And Other Common Questions about Economic Concepts." *Decoded*. Pew Research Center. https://www.pewresearch.org/decoded/2021/07/23/whats-the-difference-between-income-and-wealth-and-other-common-questions-about-economic-concepts/.

Sharla Gelfand. 2022. *Opendatatoronto: Access the City of Toronto Open Data Portal*. https://CRAN.R-project.org/package=opendatatoronto.

Venables, W. N., and B. D. Ripley. 2002. *Modern Applied Statistics with s*. Fourth. New York: Springer. https://www.stats.ox.ac.uk/pub/MASS4/.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wickham, Hadley, and Jennifer Bryan. 2023. *Readxl: Read Excel Files*. https://CRAN.R-project.org/package=readxl.

Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Zhu, Hao. 2024. *kableExtra: Construct Complex Table with 'Kable' and Pipe Syntax*. https://CRAN.R-project.org/package=kableExtra.