Building Integrity in Retrospect: Assessing the Impact of Age on 2023 Safety Evaluations*

Terry Tu, Jingyi Shen, Yaning Jin

March 13, 2024

This study harnesses a dataset from the Toronto Open Data portal, comprising 3,435 records of apartment evaluations, to analyze the correlation between building age and safety scores. Employing a linear regression model, we discovered a significant inverse relationship, highlighting that older buildings tend to have lower safety evaluations. The findings suggest a need for policy reform, particularly in the maintenance and inspection of Toronto's aging residential infrastructure. Despite the study's focus on building age, further research considering additional variables could offer a more comprehensive understanding of factors influencing building safety.

Table of contents

*Code and data supporting this analysis are available at https://github.com/TEJMaster/Toronto-Building-Safety-Analysis-2023.git

1 Introduction

In the wake of the catastrophic collapse of an aged condominium in South Florida in June 2021, which resulted in 98 casualties, a subsequent lawsuit by the bereaved families underscored the notion that routine inspections and maintenance could have forestalled the disaster(Anderson 2021). This incident precipitates our investigation into forecasting the building evaluation scores for Toronto residences in 2023 via a simple linear regression model. An analysis was conducted on the apartment building evaluation dataset obtained from the City of Toronto's open data portal to assess the relationship between the age of a property and its evaluation score assigned by the city. Our research is singularly focused on elucidating the effect of one independent variable—building age—on the dependent variable, which in this context is the building evaluation score.

Using simple linear regression analysis enables a detailed exploration of the linear relationship between the age of a building and its evaluation score. By quantifying this relationship through regression coefficients, we aim to reveal the expected change in evaluation scores for each incremental year in building age. The statistical significance of the age variable on evaluation scores will be ascertained using p-values. Provided the model satisfies the underlying assumptions, t-tests will be applied to test the hypotheses, while confidence and prediction intervals will be leveraged to quantify the effect size and enhance the accuracy of our forecasts, respectively.

2 Data

In this research, we examine apartment data sourced from the Toronto Open Data portal. The dataset encompasses 3,435 records, focusing on specific variables: the ward of each apartment, its evaluation score, and the construction year. The data covers evaluations across Toronto's 25 wards, with scores varying between a minimum of 0 and some achieving the maximum score of 100. The study includes apartments that are over three stories in height and contain at least 10 units. These apartments span a wide range of construction years, from as early as 1805 to as recent as 2023. All the apartments in this dataset adhere to the City's Apartment Building Standards bylaw, which is designed to safeguard the interests and safety of both landlords and tenants by mandating these evaluations (Toronto 2023).

2.1 Variable Description

CURRENT BUILDING EVAL SCORE: The Current Building Evaluation Score represents a measure of a building's adherence to property standards. This score is derived by summing two components: the current reactive score, which reflects the compliance based on any outstanding Orders and Notices of Violations, and the proactive building score, which is based on the most recent comprehensive evaluation of the building.

YEAR BUILT: This indicates the year when the building was initially constructed, sourced from Building Owners/Managers.

YEAR EVALUATED: This denotes the year in which the building underwent evaluation, reflecting its condition and performance.

AGE: In this research, neither YEAR BUILT nor YEAR EVALUATED was used directly, we have generated a new variable called AGE which use YEAR EVALUATED minus YEAR BUILT.

2.2 Data Analysis Tools

The data analysis was performed using R (R Core Team 2022), a powerful open-source statistical programming language. Key packages from the tidyverse collection (Wickham et al. 2019) were employed to streamline data manipulation, visualization, and analysis processes. These packages include ggplot2 (Wickham 2016) for creating advanced graphics, dplyr (Wickham et al. 2022) for data manipulation, readr (Wickham, Hester, and Bryan 2022) for its robust data reading functionality, here (Müller 2020) is used to avoid file path issue, and knitr (Xie 2014) for dynamic report generation.

2.3 Data Exportation

After cleaning, the modified dataset, now stored in the `cleaned_data` data frame, is written to a new CSV file named 'cleaned_building_data.csv'. This file is saved in the 'outputs/data' directory, which is again constructed using the `here` function for path management. Saving the cleaned dataset allows for a stable version of the dataset to be used for analysis or sharing, ensuring reproducibility of results.

Statistically, this script is preparing the dataset for analysis by ensuring the integrity and relevance of the data, which is foundational for any reliable statistical analysis. By creating the 'AGE' column, the script enables researchers to analyze the relationship between the age of a building and other variables of interest, such as compliance with property standards, in a quantitative manner.

3 Model

The objective of our model is dual: to discern the relationship between building age and safety evaluation scores and to quantify this relationship's strength and direction. The study utilizes a simple linear regression model to analyze the dataset obtained from the Toronto Open Data portal.

3.1 Model set-up

Let y_i represent the safety evaluation score for each building. The building's age is denoted by x_i.The model is defined as follows:

$$
\begin{aligned}
y_i &\sim \text{Normal}(\mu_i, \sigma) && (1)\\
\mu_i &= \beta_0 + \beta_1 \times \text{AGE}_i && (2)\\
\beta_0 &\sim \text{Normal}(90, 10) && (3)\\
\beta_1 &\sim \text{Normal}(-0.1, 0.05) && (4)
\end{aligned}
$$

The model is executed in R using the lm function. We select normal priors for the intercept and slope based on initial exploratory data analysis.

3.2 Model justification

A negative coefficient for AGE is anticipated, hypothesizing that older buildings may have lower safety scores due to factors such as wear and deterioration over time. We anticipate the intercept to represent the evaluation score for a newly built property, with the slope capturing the average yearly decrease in score.

4 Result

4.1 Model Coefficients Interpretation

```
              Estimate Std. Error    t value     Pr(>|t|)
(Intercept) 93.6166347 0.64804776 144.459469 0.000000e+00
AGE         -0.1007941 0.01015176  -9.928733 1.226807e-22
```

The regression model provides two key coefficients to understand the relationship between building age and the evaluation score:

Intercept (β_0)
The model estimates the intercept, β_0, to be 93.61663. This is the predicted evaluation score for a building at the time it is newly constructed, where AGE equals zero. Accompanied by a standard error of 0.64805, this coefficient's estimate signals the level of precision with which we can predict the evaluation score for new buildings. The t-value associated with the intercept is 144.459, which is highly significant, as indicated by the p-value of practically zero. This signifies a very strong statistical assurance in the intercept's estimate.

Slope (β_1)
The slope of the model, β_1, is determined to be -0.10079. This value quantifies the expected change in the building evaluation score for each additional year of age; specifically, the score is projected to decrease by about 0.10079 points annually. The standard error of 0.01015 suggests high precision in this estimation. The t-value of -9.929 reaffirms the reliability of this coefficient, with a corresponding p-value of 1.226807e-22, far below the 0.05 threshold, confirming the impact of age on evaluation scores is statistically significant.

These coefficients paint a picture of gradual decline in building quality as measured by the evaluation scores over time. The statistical significance of both coefficients assures us that the model's predictions are based on real effects and not on random fluctuations within the dataset. This analysis emphasizes the need for rigorous maintenance and periodic updates to older buildings to preserve their integrity and safety.

4.2 Model Equation

$$y_i \sim \text{Normal}(\mu_i, \sigma) \tag{5}$$
$$\mu_i = \beta_0 + \beta_1 \times \text{AGE}_i \tag{6}$$
$$\beta_0 = 93.6166 \tag{7}$$
$$\beta_1 = -0.1008 \tag{8}$$

In this model, y_i represents the predicted evaluation score for the i-th building, μ_i is the mean of the normal distribution for the i-th observation, β_0 is the intercept, and β_1 is the slope representing the change in evaluation score per year of building age.

4.3 Analysis of Residuals

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-69.662  -4.363   1.706   0.000   5.834  15.858
```

1. Minimum Residual: The minimum residual is -69.662, indicating that there is at least one building for which the model's predicted evaluation score was lower than the actual score by approximately 69.662 points. This could be an outlier or a building with exceptional characteristics not captured by the model.

2. First Quartile Residual: The first quartile (Q1) of the residuals is -4.364, meaning that 25% of the buildings have evaluation scores that are less than 4.364 points below the model's prediction for their age.

3. Median Residual: The median residual is 1.702, suggesting a slight positive bias in the model's predictions, as the median of the error distribution is above zero. This indicates that, on average, the model tends to slightly overestimate the evaluation scores.

4. Third Quartile Residual: The third quartile (Q3) is 5.833, indicating that 75% of the buildings have evaluation scores within 5.833 points of the model's predictions or better. This shows that the model provides reasonably accurate predictions for the majority of buildings.

5. Maximum Residual: The maximum residual is 15.859, suggesting that there is at least one building for which the model's predicted evaluation score was higher than the actual score by approximately 15.859 points. This could be another outlier or a building that performed exceptionally well.

Interpretation: The residuals provide insights into the model's fit and the distribution of errors. The presence of outliers and the distribution's slight asymmetry warrant further investigation. It's crucial to assess the model's assumptions, such as linearity, homoscedasticity, and normality of residuals, to ensure the validity of the statistical inferences made from the model. Understanding the reasons behind significant deviations can help improve the model and provide more accurate predictions.

4.4 Plot for the linear model

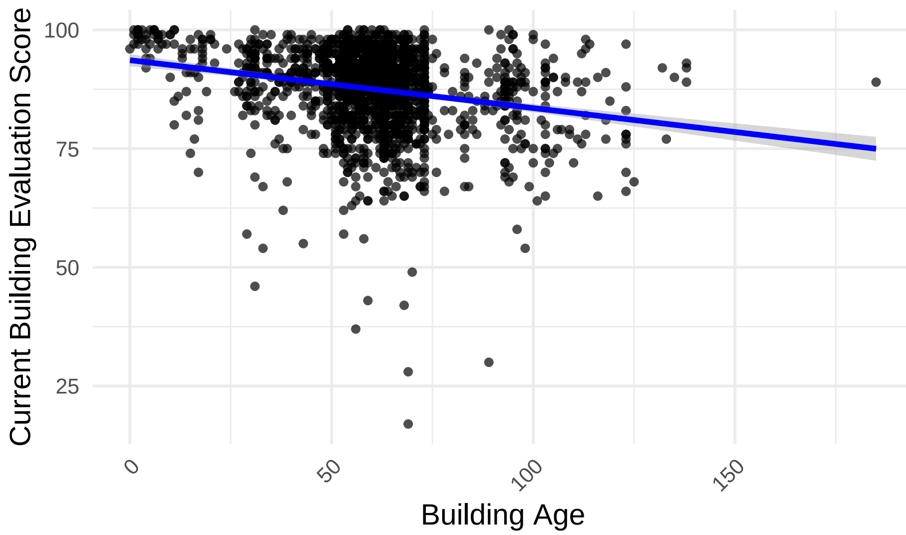

Figure 1: plot for the linear relationship between building age and evaluation score

Figure 1 provides a clear visual relationship between the age of buildings and their evaluation scores. Displayed with building age on the x-axis and evaluation score on the y-axis, the data points represent individual apartment buildings. The blue line running through the cluster of points represents the linear regression line, which captures the average effect of age on evaluation score. Noticeably, the slope of the line is downward, suggesting a negative correlation; as the buildings get older, their evaluation scores tend to decrease. This trend is consistent across the dataset, indicating a general decline in scores as building age increases, a reflection of the typical effects of wear and time on building integrity.

In statistical analysis, the significance of this downward trend is supported by a p-value much lower than the conventional threshold of 0.05, confirming the relationship between building age and evaluation score is not due to random chance. However, the plot also reveals that while younger buildings cluster more densely around higher evaluation scores, older buildings exhibit a wider spread of scores. This variation suggests that other factors may influence the condition and safety of older buildings, which are not captured solely by age. The plot does not show any clear pattern or funnel shape in the residuals, indicating that the variance of the evaluation scores is fairly consistent across the range of building ages, and the assumption of homoscedasticity is not visibly violated. Nonetheless, the model's findings imply the importance of consistent maintenance and updates to older buildings to ensure safety standards are upheld over time.

5 Discussion

5.1 Overview of the Study

This paper presented a detailed analysis using simple linear regression to investigate the impact of building age on the evaluation scores assigned by the City of Toronto. By analyzing data from the Toronto Open Data portal, the study aimed to forecast evaluation scores for Toronto residences in 2023. The analysis revealed a statistically significant inverse relationship between building age and evaluation score, suggesting that older buildings tend to have lower evaluation scores.

5.2 Insights into Urban Development and Maintenance

One key insight from this study is the importance of building age in the overall health and safety of urban residential environments. The findings underscore the potential risks associated with older buildings, which may not meet modern standards or may have deteriorated over time. This knowledge emphasizes the need for regular inspections, maintenance, and upgrades to older buildings to ensure they remain safe and habitable. Additionally, the study highlights the value of continuous monitoring and evaluation by urban authorities to maintain and improve housing standards across the city.

5.3 Policy Implications and Housing Quality

Another significant insight relates to the policy implications for housing quality and safety standards. The correlation between building age and lower evaluation scores may prompt policymakers to reconsider regulations surrounding building inspections, maintenance schedules, and renovation requirements. It suggests an opportunity for targeted interventions in older buildings to prevent potential hazards and improve living conditions for residents. Moreover, these findings could guide urban planning strategies, prioritizing the revitalization of aging housing stock and ensuring equitable access to safe and quality housing.

5.4 Limitations of the Study

Despite its contributions, this study has several limitations. Firstly, the model accounts for only a small fraction of the variability in evaluation scores, indicating that other factors besides building age significantly influence these scores. The exclusion of variables such as building materials, design, maintenance history, and location may limit the comprehensiveness of the findings. Additionally, the model's assumptions (e.g., linearity and homoscedasticity) and the presence of outliers suggest caution in generalizing the results without further investigation.

5.5 Future Directions

Given the limitations and the insights gained, future research should aim to incorporate additional variables that could affect building evaluation scores. A more comprehensive model including factors like renovation history, compliance with current building codes, and socio-economic characteristics of the neighborhood could provide a deeper understanding of what influences building evaluation scores. Longitudinal studies could also shed light on the trends over time, offering insights into the effectiveness of policy interventions and maintenance practices. Moreover, comparative analyses across different cities or countries could highlight unique challenges and best practices in building maintenance and safety standards.

In conclusion, while this study has provided valuable insights into the impact of building age on evaluation scores, it also opens the door for further research to explore the multifaceted nature of building quality and safety. Addressing these questions is crucial for developing effective strategies to improve urban living conditions and ensure the longevity and safety of the housing stock.

6 Appendix

References

Anderson, Curt. 2021. "Lawsuit Claims Surfside Condo Collapse Triggered by Building Work." *NBC 6 South Florida*. NBC 6 South Florida. http://www.nbcmiami.com/news/local/lawsuit-claims-surfside-condo-collapse-triggered-by-building-w ork/2622574/.

Müller, Kirill. 2020. *Here: A Simpler Way to Find Your Files*. https://CRAN.R-project.org/package=here.

R Core Team. 2022. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Toronto, City of. 2023. "Open Data." *City of Toronto*. https://www.toronto.ca/city-government/data-research-maps/open-data/.

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, Romain François, Lionel Henry, and Kirill Müller. 2022. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Wickham, Hadley, Jim Hester, and Jennifer Bryan. 2022. *Readr: Read Rectangular Text Data*. https://CRAN.R-project.org/package=readr.

Xie, Yihui. 2014. "Knitr: A Comprehensive Tool for Reproducible Research in R." In *Implementing Reproducible Computational Research*, edited by Victoria Stodden, Friedrich

Leisch, and Roger D. Peng. Chapman; Hall/CRC. http://www.crcpress.com/product/isbn/9781466561595.