Exploring Public Engagement and Preferences: Trends in Traffic-Calming Support Rates and Ballot Return Rates in Toronto (2015-2023)*

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March 2, 2024

This paper explores how people in Toronto get involved in city decisions through yearly surveys by the City Clerk's Office from 2015 to 2023. It looks at various topics like Front Yard Parking, Traffic Calming, Permit Parking Removal, and more, with a special focus on how support for traffic calming and ballot return rates have changed over time. While the community's support for traffic calming has been going up in a positive way, there's an unexpected decrease in the number of returned ballots, making the study more interesting. This paper aims to find out what might be causing this situation, giving insights into how the public engages with city matters and what they prefer.

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*Code and data supporting this analysis is available at: https://github.com/Brian031205/Exploring-Public-Engagement-and-Preferences

1 Introduction

In big cities like Toronto, getting people involved is crucial for shaping public policies. The City Clerk's Office is in charge of running surveys for City divisions, gathering thoughts from residents and businesses on various topics governed by City by-law (Chapter 190). The topics include Front Yard Parking, Boulevard Café, Boulevard improvement area, Traffic calming, Traffic Calming-Island, Traffic calming safety zone, Permit parking, Permit parking removal, Commercial Boulevard Parking, Appeal-Front Yard Parking, Proposed Business improvement. These surveys aim to engage the community in decision-making, tackle local concerns, and make sure rules meet the needs of Toronto residents and businesses (OpenDateToronto, 2023).

According to the "Polls Regarding Changes in a Neighborhood" on the city government's website, Toronto conducts yearly surveys to understand the views of property owners, residents, and businesses affected by neighborhood changes, like front yard parking and traffic calming (TorontoCityGovernment, 2023). Whenever there's a proposal, the city polls people in the area. For a poll to be favorable, it must meet specific requirements in by-laws or city policies. A positive result lets the proposal move forward, and final approval may come from the City Council, depending on the poll type (TorontoCityGovernment, 2023).

This paper zeroes in on trends in support for traffic calming and ballot returns, analyzing annual city polls from 2015 to 2023. It aims to give insights into the trends and preferences of public engagement using Toronto's poll data from 2015 to 2023, focusing on in-favor rates of traffic calming and return rates. Table 1 gives a 2015 sample, showing ballot preferences for topics like Front Yard Parking and Traffic Calming. Table 2, Figure 1, and Figure 2 display the in-favor rate of traffic calming ballots from 2015 to 2023, revealing a positive linear regression model for the supporting rate of traffic calming over the years. Table 3 and Figures 3 depict the situation of ballot return rates from 2015 to 2023, demonstrating a negative linear regression model for the ballot return rates over the years. Finally, I discuss the methodology and analyze the linear models of the support rate of traffic calming and the ballot return rate over the years, as well as the possible effect of the declining ballot return rate on the increasing support rate of traffic calming.

2 Data and Visulization

The data I used in this paper are obtained from the Open Data Toronto Portal, accessed through the library `opendatatoronto` (Gelfand 2022). The dataset, which covers polls conducted by the city from 2015, was first cleaned before analyzing by the open-source statistical programming language R (R Core Team 2022), using functionalities from `tidyverse` (Wickham et al. 2019), `ggplot2` (Wickham 2016), `dplyr` (Wickham et al. 2022), `readr` (Wickham, Hester, and Bryan 2022), `tibble` (Müller and Wickham 2022), `janitor` (Firke 2021) and `knitr` (Xie 2014).

2.1 Sample of Summarized Poll Data

Table 1 offers a summarized glimpse of poll data from 2015, displaying the number of ballots in favor of various topics. For "Front Yard Parking," 5 out of 9 ballots were in favor. In terms of "Traffic Calming," 2 out of the 9 ballots didn't meet the requirement. "Appeal-Front Yard Parking" got 1 ballot in favor, and "Boulevard Café" earned 1 ballot in favor. This table gives a special overview of preferences and responses for these specific topics during the 2015 poll.

Table 1: Sample of summarized poll data

Application For	Open Year	Poll Result
Front Yard Parking	2015	In Favour
Front Yard Parking	2015	In Favour
Front Yard Parking	2015	In Favour
Boulevard Cafe	2015	In Favour
Appeal - Front Yard Parking	2015	In Favour
Front Yard Parking	2015	In Favour
Front Yard Parking	2015	In Favour
Traffic Calming	2015	In Favour
Traffic Calming	2015	In Favour

2.2 Trend of In-Favor Rate of Traffic Calming

Table 2 gives us a quick look at how much people favored traffic calming from 2015 to 2023. The data shows us how community support for traffic calming measures changed over these years. Back in 2015, the in-favor rate was 0.7667, meaning a big chunk of the community was on board with these initiatives. The following years had ups and downs; 2016 saw a slight dip to 0.6351, but 2017 picked up again at 0.7157. The trend continued with some back-and-forths until it peaked in 2021, hitting an in-favor rate of 0.9322. Yet, in 2023, there was a small drop, settling at 0.7670. This table captures the lively shifts in how the community feels about traffic calming, giving us key insights into the changing public opinion over the years.

Table 2: Sample of traffic calming poll in favour rate

Year	Ballots In Favour	Ballots Returned	In Favour Rate
2015	618	806	0.77
2016	637	1003	0.64
2017	876	1224	0.72
2018	1167	1580	0.74
2019	1056	1499	0.70
2020	217	266	0.82

Year	Ballots In Favour	Ballots Returned	In Favour Rate
2021	110	118	0.93
2022	216	273	0.79
2023	135	176	0.77

Figure 1 illustrates the in-favor rates of traffic calming from 2015 to 2023 through a scatter plot, each dot representing a specific year. The vertical position of each point indicates the corresponding in-favor rate. The connected dots unveil the trend in community backing for traffic calming measures over time. A quick look suggests an overall upward trend, hinting at a potential positive linear link between the years and the in-favor rates.

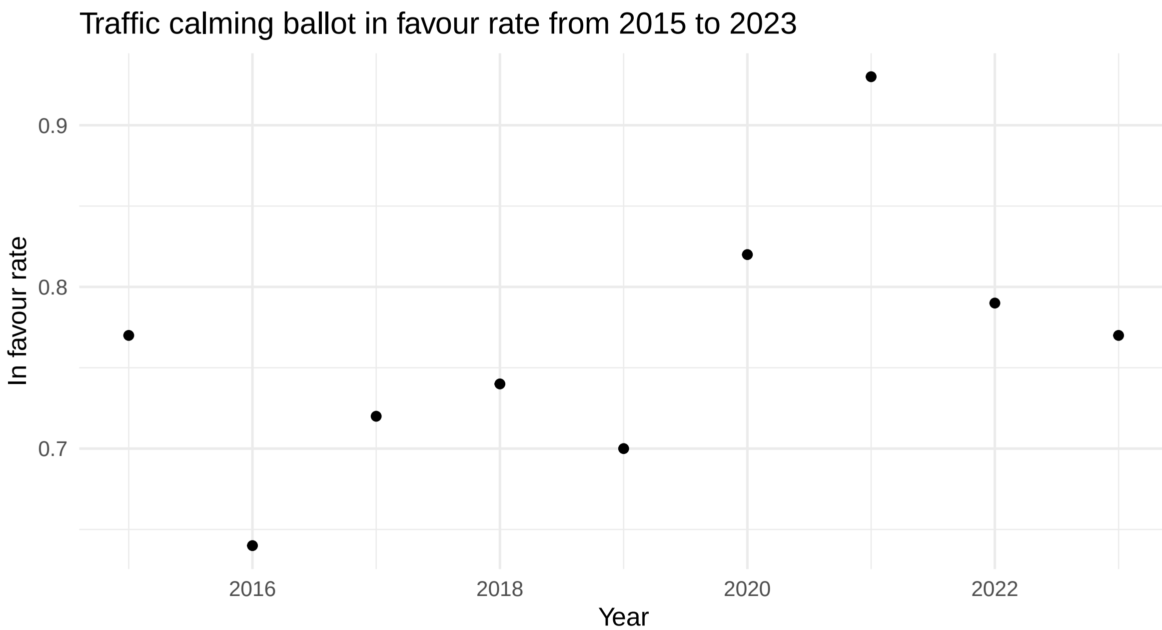

Figure 1: Traffic calming ballot in favour rate from 2015 to 2023

Figure 2 reveals the linear regression model applied to the scatter plot, showcasing the relationship between the years (independent variable) and in-favor rates of traffic calming (dependent variable). In simpler terms, the model seeks a straight line that best captures the observed trend. This suggests that as the years roll on, there's a noticeable rise in the community's support for traffic calming initiatives. While individual points may stray, the overall pattern implies a positive connection, solidifying the idea that community favor towards traffic calming has indeed grown over the studied period.

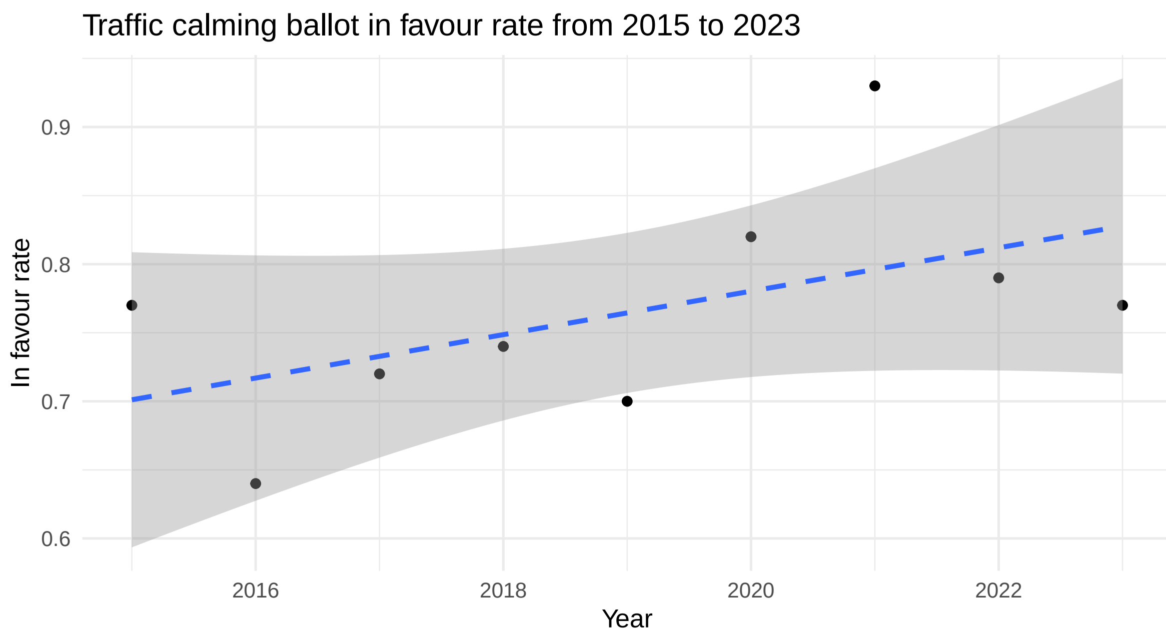

Figure 2: Traffic calming ballot in favour rate from 2015 to 2023

2.3 Trends of Ballot Return Rates

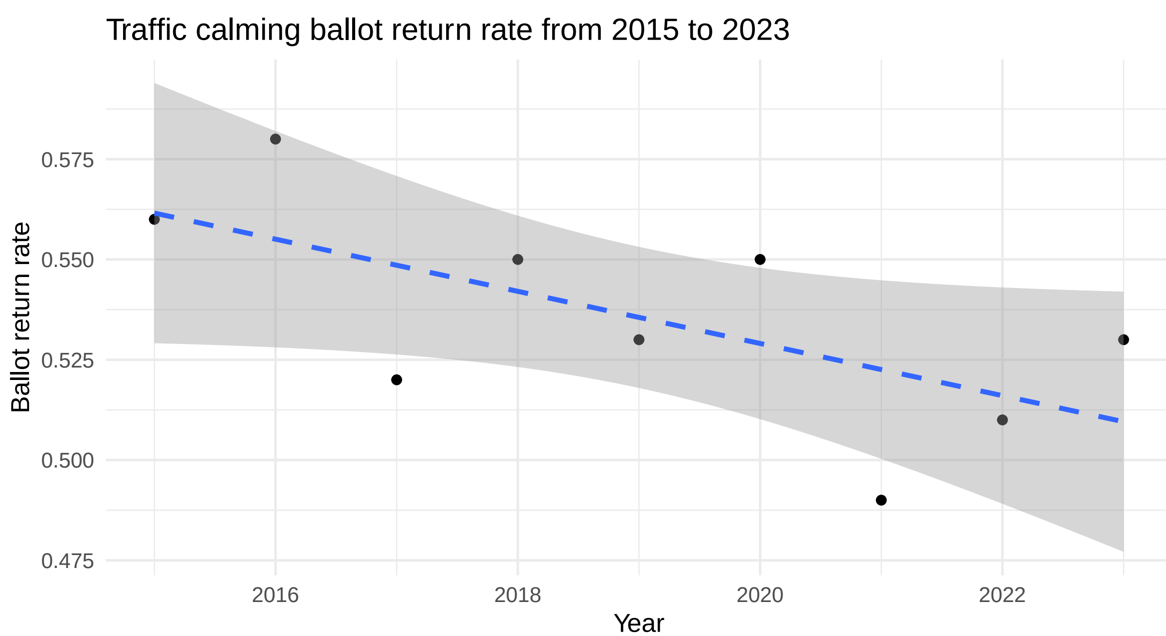

Figure 3: Traffic calming ballot return rate from 2015 to 2023

Table 3: Sample of traffic calming poll return rate

Year	Ballots Returned	Ballots Distributed	Return Rate
2015	806	1435	0.56
2016	1003	1738	0.58
2017	1224	2332	0.52
2018	1580	2855	0.55
2019	1499	2802	0.53
2020	266	481	0.55
2021	118	240	0.49
2022	273	539	0.51
2023	176	332	0.53

Table 3 presents the sample data for the return rates of traffic calming polls from 2015 to 2023. Each row corresponds to a specific year, and the associated return rate indicates the proportion of ballots returned out of the total distributed during that year. In 2015, the return rate was 0.5617, meaning that approximately 56.17% of the distributed ballots were returned. The subsequent rows show similar return rate values for each respective year. These figures provide insights into the community's engagement and participation in the traffic calming polls over the specified time period, reflecting the level of interest or responsiveness of the residents to the survey requests in different years.

Figure 3 illustrates a scatter plot based on the data presented in Table 3, depicting the relationship between the years (ranging from 2015 to 2023) and the corresponding return rates of traffic calming polls. The scatter plot visually represents each year's return rate as a data point on the graph. Additionally, a negative linear regression model has been fitted to the data points, suggesting a decreasing trend in the return rates over the specified time period.

The downward-sloping regression line indicates that as the years progress, there is a tendency for a decline in the proportion of returned ballots concerning traffic calming polls. This negative correlation suggests that, on average, the community's responsiveness to the polls has decreased over the observed years. The scatter plot, along with the fitted regression line, provides a visual representation of the statistical relationship between the temporal aspect and the return rates, offering valuable insights into the evolving dynamics of community participation in these specific polls.

3 Discussion

This research investigates the intricate relationship of community engagement in traffic calming measures, examining three pivotal elements: support rate, ballot return rate, and the linear models associated with each over the years. Table 2 illustrates a notable upward trend in the favorability of traffic calming from 2015 to 2023. However, Table 3 reveals a concerning decline in ballot return rates over the same period. These trends are vividly represented in Figures 2 and 3, showcasing positive and negative linear regression models, respectively.

The positive linear model for support rates (see Figure 2) suggests a growing support of traffic calming measures within the community. This may be attributed to an increased awareness of the positive impact of such initiatives on public safety and urban well-being. The gradual rise in support implies a satisfaction with the effectiveness of implemented traffic calming measures, meeting with the hypothesis that the public recognizes and appreciates the positive outcomes of these initiatives over time.

On the other hand, the negative linear model for ballot return rates (see Figure 3) raises concerns about the diminishing participation of the community in the polling process. This decline may stem from several factors, including potential voter fatigue, a lack of impact from individual votes, or changes in the way discussions and votes on traffic calming issues are conducted. Over time, the novelty of these discussions diminishes, and discussions and votes on the issue may gradually lose their novelty, potentially leading to less enthusiasm among community members to actively participate in the decision-making process.

The contrasting trends in support rates and ballot return rates prompt a critical examination of the potential interplay between satisfaction with implemented measures and sustained community engagement. While the public may be increasingly satisfied with the effectiveness of traffic calming measures, the declining ballot return rates suggest a need for innovative approaches to revitalize community involvement in the decision-making process. Policymakers should consider adapting communication strategies, introducing new discussion formats, or addressing issues related to voter fatigue to ensure continued active participation.

In conclusion, the research highlights a complex relationship between increasing support for traffic calming and declining ballot return rates. The satisfaction of the public with implemented measures appears to be growing, but the engagement in the polling process declines. Future studies should delve deeper into the specific variables affecting these trends and explore strategies to enhance and maintain community participation in shaping local policies. To fully understand these correlations, further investigation needs to be conducted in the future into the demographics, socio-economic factors, and local context (Butler 2007). The findings could be significant for city planning and policymaking, as they emphasize the importance of making regulatory decisions meet with community engagements. Hopefully the future urban plannings and policy makings will all prioritize community preferences and satisfaction (Ostad-Ali-Askari 2021).

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