Freezing Fires: Toronto Firefighters were More Likely to be Injured or Killed while Battling Rapidly Spreading House Fires in the Winter between 2011 to 2019

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Abstract

This paper uses exploratory data analysis to discover the most likely causes of Toronto Fire Service (TFS) firefighter casualties between 2011 to 2019. Using Open Data Toronto's fire incident dataset, the paper exposes that the majority of firefighter casualties occured at residential fires, during the winter months, and when the fire had already spread beyond of object of origin when the first unit arrived on scene. Although the TFS is one of the few Canadian fire departments with declining firefighter causality rates, the results demonstrate where the TFS can take proactive steps and develop timely interventions to create safer operational environments and further reduce firefighter casualties.

1 Introduction

In 2019, the *Association of Workers' Compensation Board of Canada* (AWCBC) revealed a notable change in Canadian firefighter fatality and time-loss claims over a 10-year period. Consequently, the AWCBC published the report *Determinants of Injury and Death in Canadian Firefighters: A Case for a National Firefighter Wellness Surveillance System* (2019) which analyzed nationwide Canadian firefighter insurance claims between 2008 to 2017. The report revealed that there has been a 21-percent increase in overall on-duty firefighter fatalities and a 3.8-percent increase in overall firefighter time-loss claims caused by on-duty injuries. Consequently, the AWCBC's analysis strongly recommended that fire departments take proactive steps to develop timely and responsive interventions that will lead to healthier and longer lives for Canada's 100,000-plus volunteer and career firefighters (Garis 2019).

In this paper, we will analyze the number of firefighter casualties in Canada's largest municipal fire department – the Toronto Fire Service (TFS). The TFS defines "firefighter casualties" as on-duty deaths and injuries. In 2019, the TFS employed 3,233 firefighters across eighty-three fire stations and responded to 133,081 dispatch alarms (Gelfand 2020). We will study the number of TFS firefighter casualties between 2011 and 2019 and use exploratory data analysis to discover potential predictor variables including the type of dispatch call, the time-of-the-year, and the extent of the fire when the first unit arrived on scene. Unlike the majority of fire departments in Canada, the TFS did not experience an increase in firefighter casualties between 2011 to 2019. However, I learned through exploratory data analysis that firefighters were more likely to be injured or killed at residential structure fires, in the winter months, and when the fire had spread beyond the object of origin. These findings are extremely interesting and important because it identifies potential hazards related to these variables that may increase a firefighter's risk of being injured or killed. Therefore, the TFS can use this data to control for potential risks and hazards by taking precautionary measures to either reduce the chance of occurrence or the impact of the hazard.

The code and data supporting the analysis is avaliable on my GitHub repository for this project.

The remainder of this paper is structured as follows: Section 2 discusses the data and data ethics; Section 3 explores the variables: dispatch alarm type, month, and extent of fire; and finally, Section 4 discusses the study's findings and some weaknesses.

2 Data Description

2.1 The Open Data Toronto Fire Incident Dataset

The data used in this project was the Toronto Fire Incident Data (last updated January 25th, 2021) published on the Toronto Open Data Catalog. The data was published as a CSV table and was initially retrieved in May 2018. It contains incident and responding unit data pertaining to approximately 17,500 Toronto fire incidents which occurred between the years 2011 to 2019. A fire incident is defined by the TFS an incident involving smoke, heat, and/or flames, which has the *potential* to cause property damage (Services 2021). Consequently, the dataset excludes all non-fire incidents that Toronto firefighters were dispatched to, including medical emergencies, burning complaints, building inspections, vehicle collisions (unless it met the criteria for a fire incident) and alarm conditions (i.e., carbon monoxide, gas leaks, etc.). At least one of the City of Toronto's eighty-three fire stations were dispatched to the alarm.

The key strengths of this dataset are:

1. It does not contain missing values for the key features (i.e., `TFS_Firefighter_Casualties`, `TFS_Alarm_Time`, `Initial_CAD_Event_Type`, `Incident_Station_Area`, etc.). The majority of data this paper needs for its analysis is available and missing values did not need to be inferred during the data pre-processing stage. Thus, this paper does not create bias or reduce the representativeness of our sample caused by filling in missing values.
2. The data is in a structured CSV file. Thus, the data is easy to implement and parse, it can be easily processed by R, and it is both human and machine readable. Consequently, the data was easy to preprocess, manipulate, visualize, and analyze.
3. The data comes from a credible source and is meaningful for this paper's analysis. The dataset was prepared by the Toronto Fire Service for the Office of the Ontario Fire Marshal, and was published on Open Data Toronto. These are all Canadian government agencies and the data was published to ensure government transparency, accountability, and accessibility. Hence, the data source is relevant to my hypothesis, legitimate, and informative.
4. The data does not have any duplicate information which prevents data inconsistencies. Therefore, the dataset does not have any inconsistencies or discrepancies caused by duplicate records.

For privacy purposes, personal information is not provided and the exact address of the incident is aggregated to the nearest intersection (Services 2021).

2.2 Data Ethics

First, the data collection process has an exclusion bias because it only collects data from on-duty firefighter casualties. The dataset only includes casualties that occurred at the fire incident itself. However, the decision to only include on-duty casualties excludes casualties that were caused by the fire incident (or multiple fire incidents) that may have occurred when the firefighter was off-duty. For instance, a firefighter could have had a heat stroke after they returned home after a structure fire, a firefighter may have a back injury after years of experience, or a firefighter may commit suicide due to PTSD symptoms. Therefore, the dataset does not include all firefighter casualties and our results will not be complete (Hao 2019).

Second, the data collection process did not specify if a firefighter casualty was a minor injury, major injury, or a fatality. Instead, the three events are grouped under one umbrella term. The decision to group all these incidents under "casualty" obscures the nuances of the data and makes each of these events appear equal. For example, the researcher may incorrectly conclude that the most dangerous month for a firefighter is January because more casualties occur in this month. However, if the data was more nuanced, the researcher may instead have learned that most minor injuries occur in January and most fatalities occur in August. Thus, the researcher may misinterpret their results and make inaccurate conclusions due to the incomplete data. Additionally, the dataset does not specify the type of injury, the cause of injury or the cause of death which could have provided deeper insights and more meaningful recommendations for preventing firefighter casualties (Hao 2019).

Table 1: Total Fire Incidents, Total Firefighter Casualties, and Averate Firefighter Casualties per Fire Incident (2011-2019)

Total Fire Incidents	Total Firefighter Casualties	Average Casualties per Incident
17536	253	0.0144275

Lastly, the data is not completely anonymized because the dataset provides multiple identifying variables that can combined to discover the identity of the firefighter(s) who were injured or killed. For example, you can use the date of the alarm and the intersection to search news articles for that specific fire incident. The news article may reveal the firefighter(s) that was injured or killed. Thus, the dataset does not protect firefighter's privacy or anonymity, and there is a high risk of re-identification (Hao 2019).

3 Descriptive Data Analysis

3.1 Total Fire Incidents, Firefighter Casualties, and Average Casualties per Incident

First, we will create a table (Table 1) to see the total number of fire incidents, the total number of firefighter casualties, and the average number of firefighter casualties per incident between 2011 and 2019.

There was no missing data because every entity had a value in the `TFS_Firefighter_Casualties` feature. We analyzed it using R (R Core Team 2020), tidyverse (Wickham et al. 2019), here (Müller 2020), and kableExtra (Zhu 2020).

The table demonstrates that the TFS responded to 17,536 fire incidents and there were 253 firefighter casualties in the same period. Although the average of 0.014 firefighter casualties per fire incident appears very low, even one casualty is too many for the TFS. Thus, we will now explore variables that may increase a firefighter's risk of being injured or killed.

3.2 Top Ten CAD Event Types with the Highest Number Firefighter Casualties

We will create a table (Table 2) that lists the number of firefighter casualties per CAD (911 dispatch system) event type. A CAD event type describes the nature of "what is happening" at an incident. Typically, each incident type is associated with a specific response plan that establishes the number and types of resources initially required for mitigating the incident and the fire engine units that must be dispatched to that event. I chose to only show the top ten CAD event types on the table because there are 115 different TFS CAD event codes to describe fire incidents alone, which will make the table too long for this report. Furthermore, the majority of CAD event types did not have one firefighter casualty between 2011 to 2019 (APCO 2012). The translations for these CAD event codes can be found on the City of Toronto's Active Fire Incidents list (TFS 2021).

There was no missing data because every entity had a value in the `TFS_Firefighter_Casualties` and `CAD_Event_Type` columns. I could have also used the `Final_Incident_Type` feature which is the final CAD Event Type recorded by the dispatcher, but the value for every fire incident was `Fire`. Thus, the `Final_Incident_Type` feature did not provide any meaningful insights. The data was analyzed using R (R Core Team 2020), tidyverse (Wickham et al. 2019) and kableExtra (Zhu 2020).

The table reveals that about 50% of firefighter casualties $((114 + 12/253) * 100)$ occurred at residential fires and 19% of firefighter casualties $((39 + 9/253) * 100)$ occurred at commercial/industrial fires. Although these results could be due to residential and commercial/industrial fires being more common than vehicle fires, the results also suggest that the proper response to these types of fires may also put firefighters at risk. For example, residential and commercial fires require firefighters to enter the structure in order to search for and rescue civilians. While firefighters are in the structure, they are at an increased risk of being exposed to heat stress, rapid fire progress/explosions, exposure to electricity, and structural collapse (Kesler et al. 2021).

Table 2: Top Ten CAD Event Types with the Highest Number Firefighter Casualties (2011-2019)

Initial CAD Event Type	Number of Firefighter Casualties
FIR	114
FICI	39
FIHR	30
Fire - Residential	12
Fire - Commercial/Industrial	9
Alarm Highrise Residential	8
VEF	8
FACI	5
FAHR	4
FAI	3

All of these risks contribute to firefighter fatalities and injuries. This is why civilians (especially children) should never hide in inconspicuous places or re-enter the structure after they escape because this puts both firefighters and themselves at an increased safety risk (Kerber 2011).

3.3 Total Fire Incidents per Month

Next, we will explore if firefighter casualty rates increase based on the time-of-year. Previous research in Richard M. Kesler et al,'s *Effects of firefighting hood design, laundering and doffing on smoke protection, heat stress, and wearability* (2021) argues that there is a significant increase in on-duty firefighter heat-related medical emergencies in the summer months (June to September) due to the high temperatures and humid weather conditions, the heavy equipment and uniforms, and temperatures inside a burning building easily reaching several hundred degrees celsius (Kesler et al. 2021). Consequently, I will examine if the TFS experienced similar seasonal-related correlations in firefighter casualties between 2011 and 2019.

I analyzed the number of firefighter casualties per time-of-year by grouping the number of TFS fire incidents per month between 2011 and 2019 (Figure 1). I used the `TFS_Alarm_Time` feature (the timestamp of when the TFS was notified of the incident) to discover the month the fire incident took place (Services 2021).

There was no missing data because every entity had a value in the`TFS_Alarm_Time` feature. The `TFS_Alarm_Time` feature was also converted from a character vector to datetime for this analysis. The data was analyzed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), lubridate (Grolemund and Wickham 2011) and ggplot2(Wickham 2016).

The result is extremely interesting because the month that had the most fire incidents was May. The number of fire incidents starts to increase in February before peaking in May at just below 2,000 incidents. The number of fire incidents steadily decreases back towards ~1,250 by August and then plateaus during the fall and winter months.

3.4 Total Firefighter Casualties per Month

We will now compare the number of fire incidents per month to the number of fire casualties per month between 2011 and 2019 (Figure 2).

There was no missing data because every entity had a value in the `TFS_Firefighter_Casualties` and `TFS_Alarm_Time` features. The `Alarm_Time` column was also converted from a character vector to datetime for this analysis. The data was analyzed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), lubridate (Grolemund and Wickham 2011) and ggplot2(Wickham 2016).

The graph for the number of TFS casualties per month does not match the graph for the number of fire incidents per month. Unlike the Figure __ where the number of fire incidents followed a gradual and inverted-U shaped relationship, the number of firefighter casualties' spikes throughout the year. First, the number of

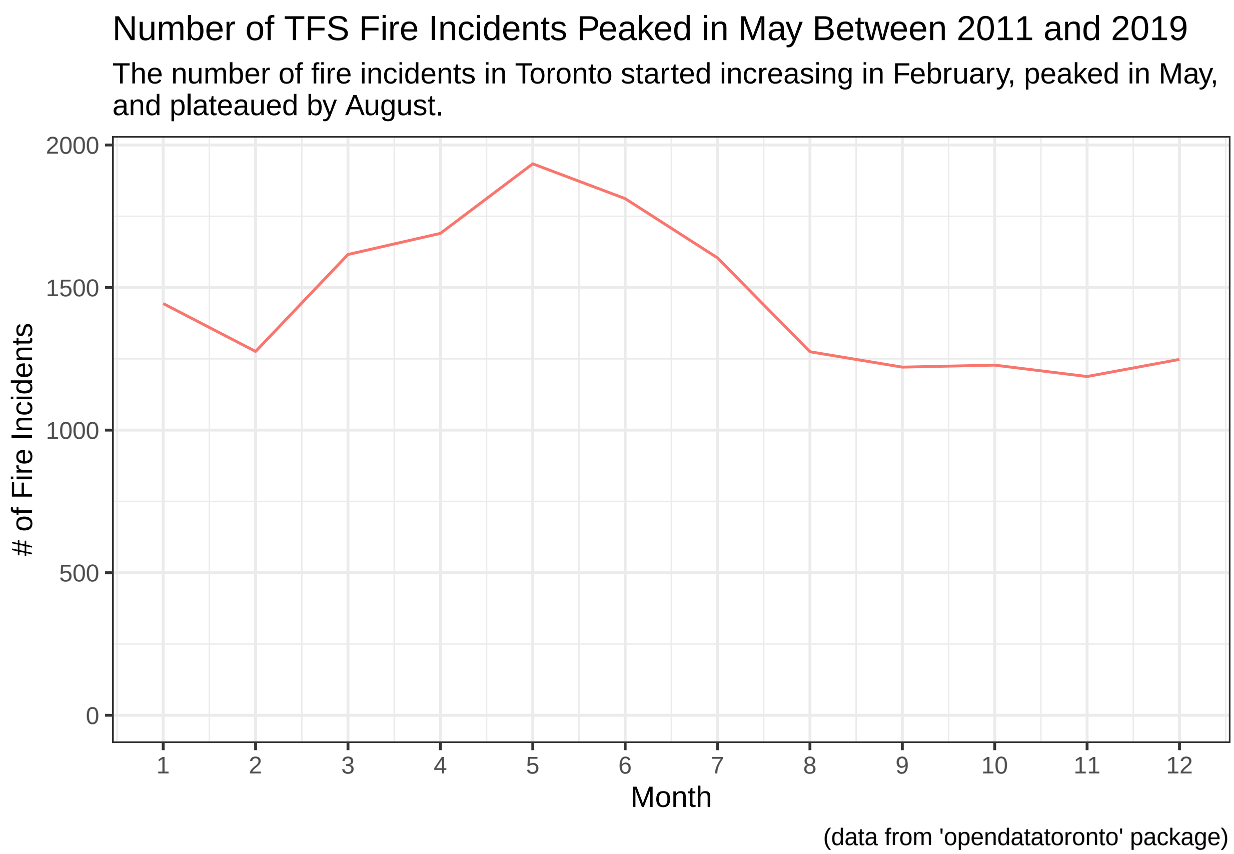

Figure 1: Total Fire Incidents per Month (2011-2019)

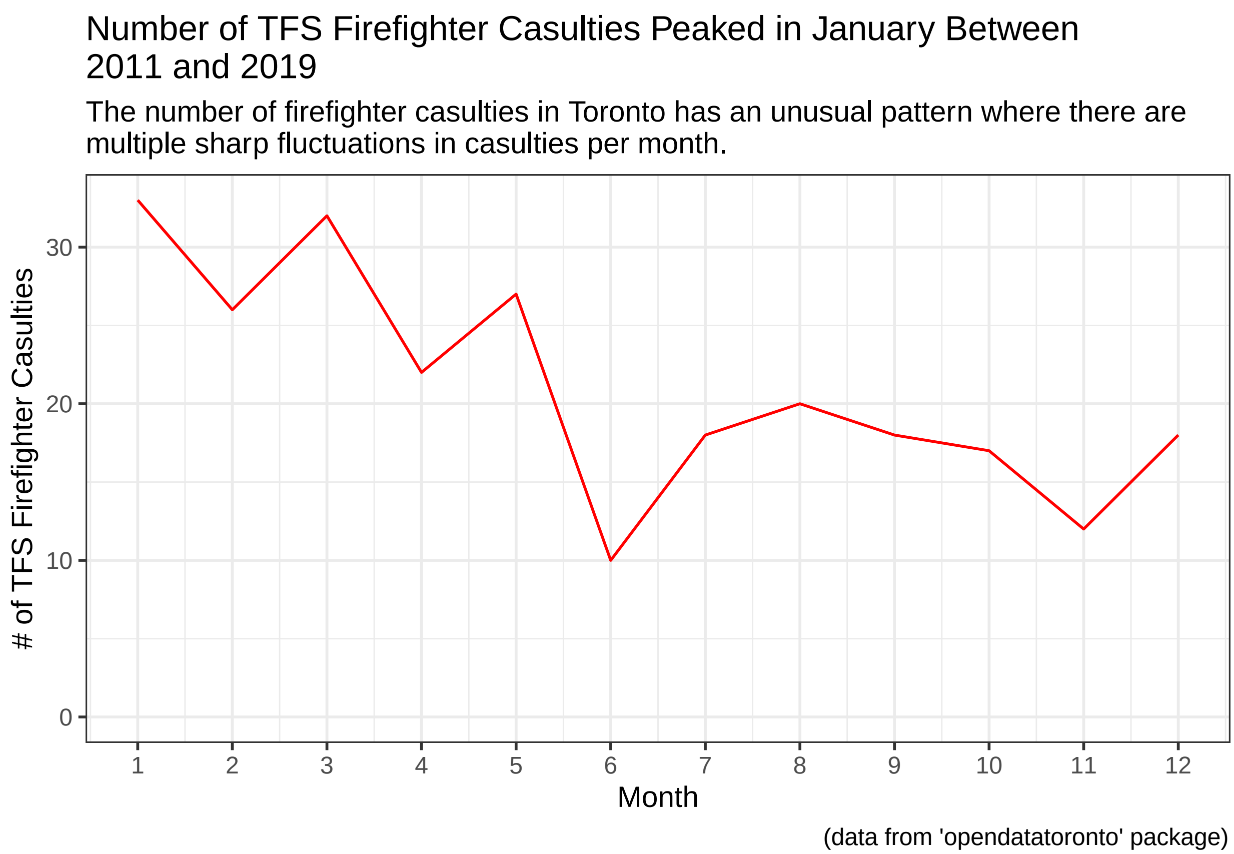

Figure 2: Line Graph for Firefighter Casualties per Month (2011-2019)

firefighter casualties gradually decrease from 33 to 10 casualties between January and June. However, the graph illustrates that there is a sharp spike in firefighter casualties in January, March and May. Secondly, the number of casualties increase again after June before plateauing around 20 casualties per month until November. Lastly, firefighter casualties sharply increase again between November and January.

Although the number of firefighter casualties do increase in the summer months as I predicted, I did expect the number of casualties to peak in January and sharply spike in March and May. The graph appears to spike when it enters a new season (i.e., spring, summer and winter). I cannot explain or find any research on this interesting phenomenon. If the data were available, we could also examine the types of casualties per month to learn what is causing these trends (Kesler et al. 2021).

3.5 Total Fire Incidents per Extent of Fire

Next, I hypothesize that the number of firefighter casualties will increase if the fire has spread beyond the object-of-origin when the first fire engine units arrive. I argue that once the fire begins to spread, it will increase the risk of casualties because the fire will be hotter, larger, and more likely to cause structural collapse.

First, we will examine the most common fire incident state when firefighters first arrive on scene. I will be using a horizontal bar graph to effectively visualize the number of fire incidents per fire extent (Figure 3).

All fire incidents that were missing `extent_of_fire` values were removed for this analysis, which removed ~6,000 fire incidents entities. The data was analyzed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and ggplot2 (Wickham 2016).

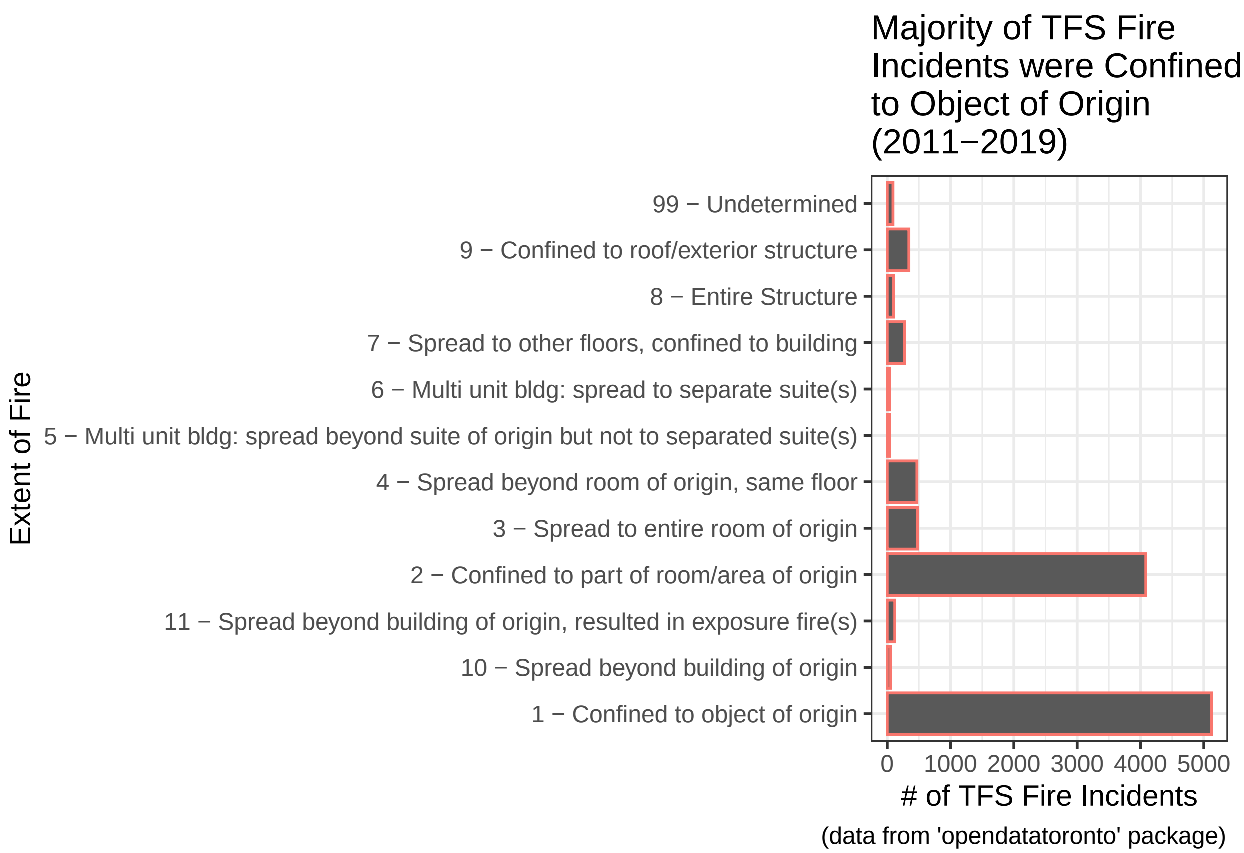

Figure 3: Bar Plot for Total Fire Incidents per Extent of Fire (2011-2019)

The bar plot reveals that the vast majority of fires (> 5,000 incidents) are still confined to their objects of origin or confined to only one part of the room (> 4,000 incidents) when firefighters first arrived on scene.

3.6 Total Firefighter Casualties per Extent of Fire

In comparison, the majority of firefighter casualties occurred when the fire was not contained to a single object or part-of-room when firefighters first arrived (Figure 4).

All fire incidents that were missing `Extent_of_Fire` values were removed for this analysis, which removed nineteen entities containing firefighter casualties data. This data was analyzed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), and ggplot2 (Wickham 2016).

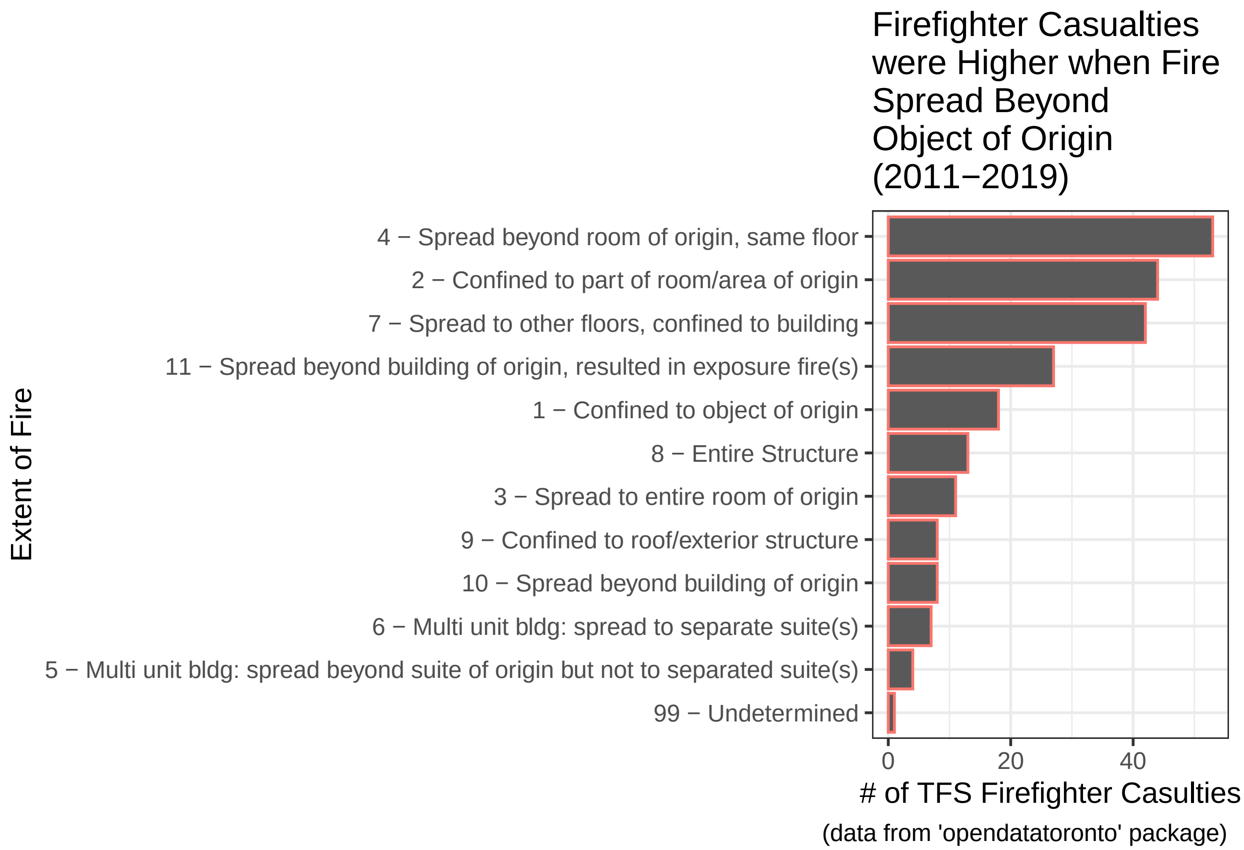

Figure 4: Bar Plot for Total Firefighter Casulties per Extent of Fire (2011-2019)

The bar plot above demonstrates that firefighter casualties are more likely to occur when the fire has spread beyond the room of origin (> 50 casualties), confined to part of the room of origin (> 40 casualties), spread to other floors (> 40 casualties), and spread beyond the building of origin (> 25 casualties). Therefore, the results reveal that firefighters are more likely to be injured to killed when the fire is no longer contained to specific object or room. The increase in casualties is likely caused by the firefighting tactics used for multi-room structural fire environments. When the fire spreads beyond the object of origin or one room, firefighters must perform search-and-rescue operations on a larger area, increased risk of heat stress because "faster fires burn hotter," higher risk of structural collapse, and other risks associated with entering a burning structure (Kerber 2011).

3.7 Total Firefighter Casualties per Year

Despite this paper's grim and distressing discussion on TFS firefighter casualties, my data story has a hopeful ending. The TFS is one of the few fire departments in Canada that has not experienced growing firefighter fatalities and injuries. On the contrary, the TFS experienced a ~80% decrease in the number of firefighter casualties since 2013 (Figure 5).

There was no missing data because every entity had a value in the `TFS_Firefighter_Casualties` and `TFS_Alarm_Time` features. The `Alarm_Time` column was also converted from a character vector to datetime for this analysis. The data was analyzed using R (R Core Team 2020), tidyverse (Wickham et al. 2019), lubridate (Grolemund and Wickham 2011) and ggplot2(Wickham 2016).

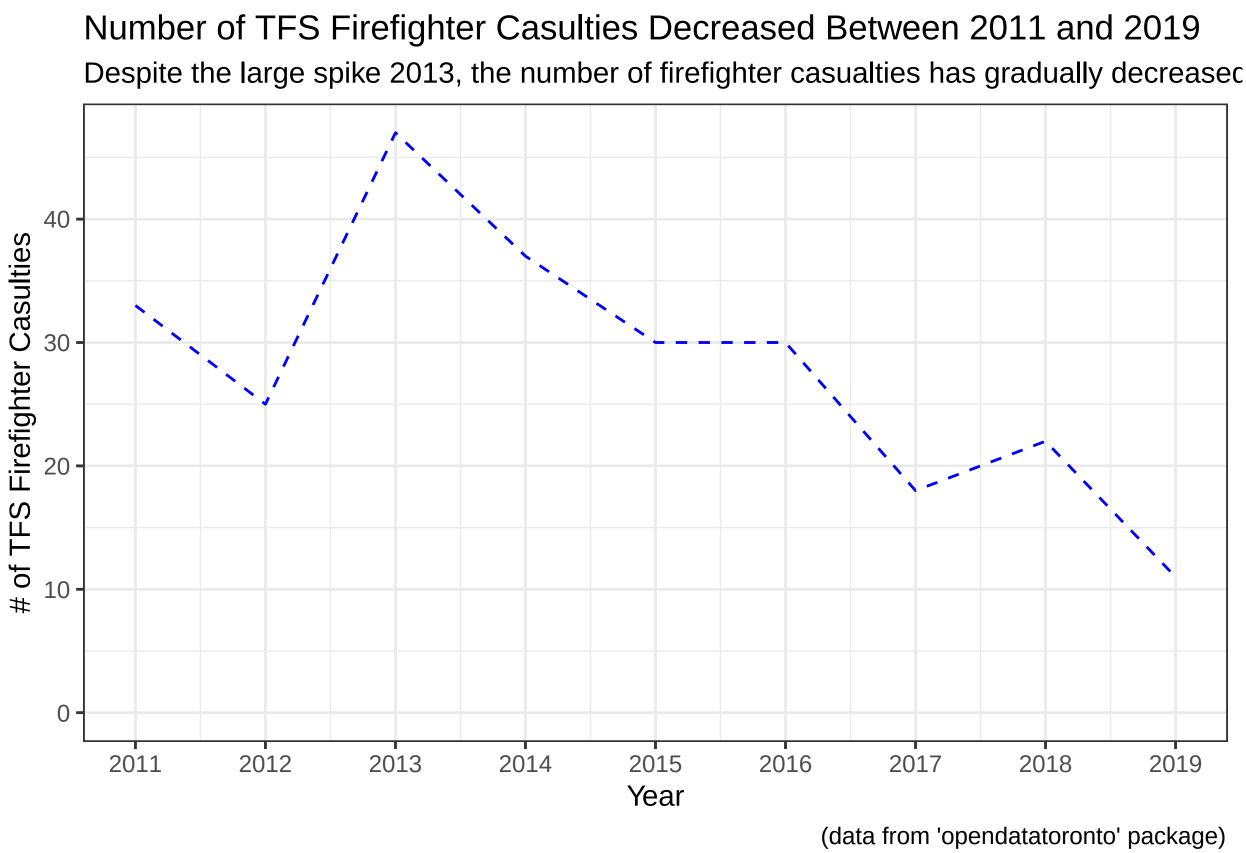

Figure 5: Line Chart for Firefighter Casulties per Year (2011-2019)

4 Discussion and Results

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