DEVELOPING AN INDEX FOR BUILDING FIRE RISK IN PUBLIC HOUSING

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CONTEXT AND MOTIVATION

Deadly fire incidents in 2022

In early 2022, 29 people were killed in building fires at HUD-assisted, PHA-managed properties in the Bronx and Philadelphia.

HUD (and PHAs) have an obligation to provide a safe standard of housing for the country's most vulnerable residents and can likely do more to prevent catastrophic fires from occurring in the future.

In response, this project will analyze data from HUD and other external sources like FEMA to increase understanding of factors that are associated with increased risk of fire in HUD-assisted housing, and thereby increase HUD's accountability to residents.

INITIAL CONSIDERATIONS

Objective and potential benefits

Objective: Identify past fires that occurred in public housing (and eventually multifamily) buildings. Use the resulting dataset to develop an index that measures fire risk.

Potential benefits:

- Evaluate and improve inspection standards, policies, and/or regulations to reduce fire risk. Assess whether existing NSPIRE standards are well-suited to identify fire risk.
- Identify the highest risk buildings, so they can be considered for fire prevention measures like retrofitting older buildings with sprinklers. Provide evidence for/against the necessity of retrofits.
- A new factor to consider when prioritizing REAC inspections.
- Understand equity considerations that may arise if socioeconomic factors are strongly associated with fire risk.

Current/potential future data sources

HUD: Public access datasets with characteristics of public housing buildings, developments, and authorities from the HUD GIS Helpdesk.

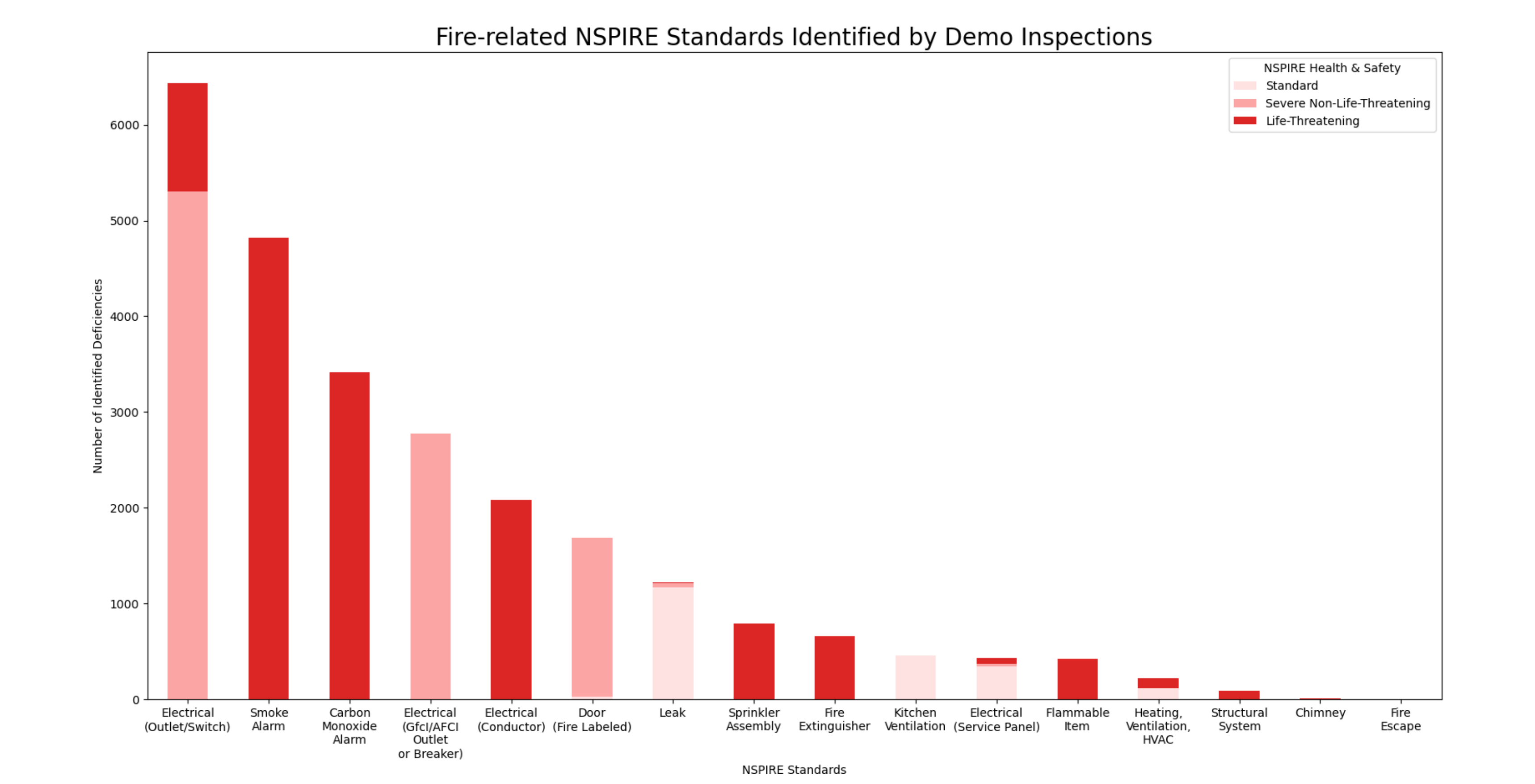
FEMA: Data from the National Fire Incident Reporting System (NFIRS). FEMA estimates that this dataset contains **70%** of the fire incidents that occur in the U.S.

NSPIRE: Deficiencies identified in a limited set of properties used to test NSPIRE. Once S&I can acquire the NSPIRE demo inspection data with building ID information, we can compare the occurrence of different deficiency types against the fire data from FEMA at the building level.

UPCS (future): Provides historically identified defects and properties, including limited fire-relevant information like data on smoke detectors, electrical hazards, etc., including detailed inspection comments.

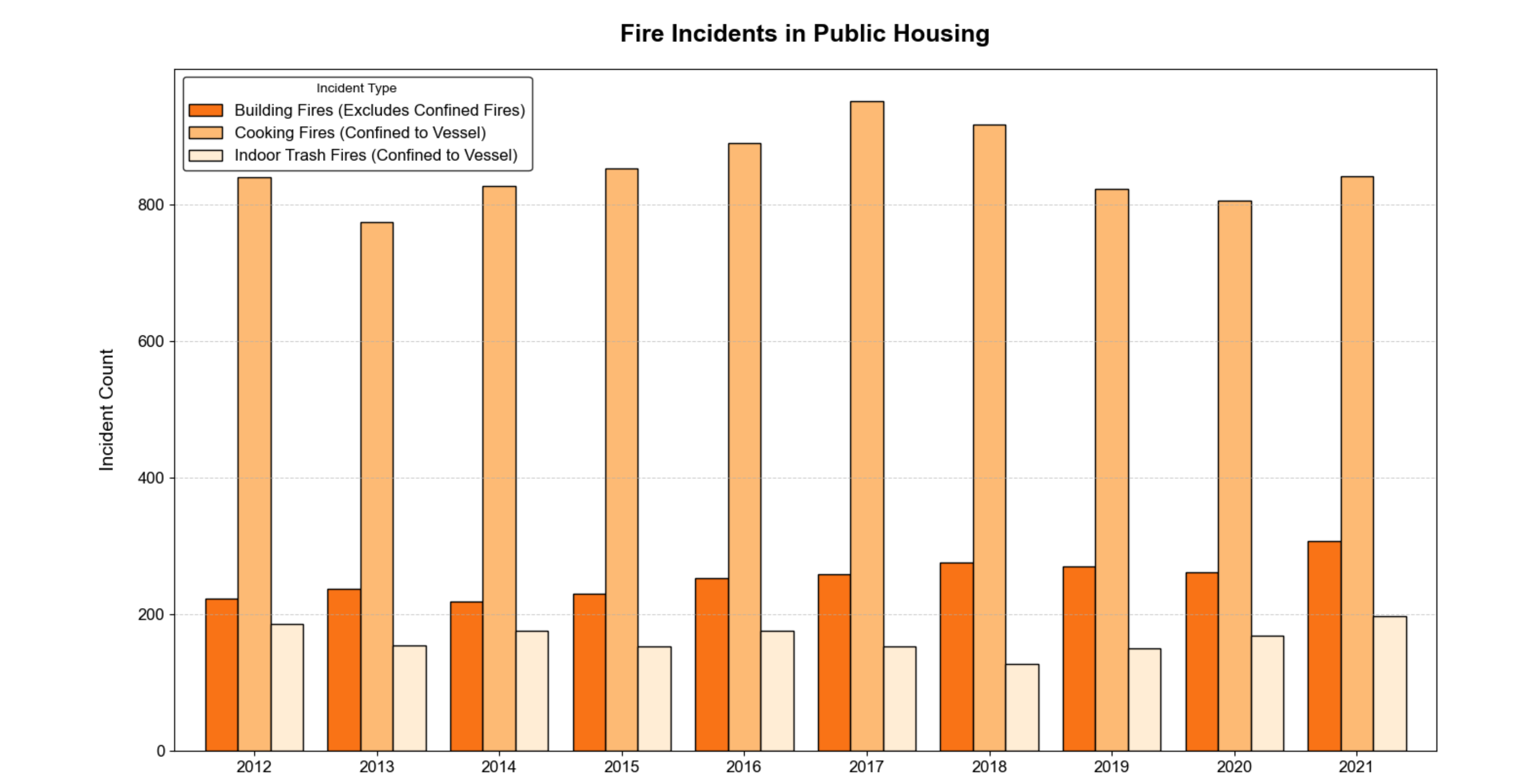
Ground Truth Observations (future): Media reports and potentially county-based reports on fire data.

Census Level Socioeconomic Data (future): American Community Survey data on demographics. (Some tract-level variables are incorporated in the public housing building characteristics dataset from HUD.)


Fire-related NSPIRE Standards Identified by Demo Inspections
NSPIRE Health & Safety
Standard
Severe Non-Life-Threatening
Life-Threatening
Number of Identified Deficiencies
0
1000
2000
3000
4000
5000
6000
Electrical (Outlet/Switch)
Smoke Alarm
Carbon Monoxide Alarm
Electrical (Gfcl/AFCI Outlet or Breaker)
Electrical (Conductor)
Door (Fire Labeled)
Leak
Sprinkler Assembly
Fire Extinguisher
Kitchen Ventilation
Electrical (Service Panel)
Flammable Item
Heating, Ventilation, HVAC
Structural System
Chimney
Fire Escape
NSPIRE Standards

Linking NFIRS and HUD data

- Link by street address. Require all components of the address, including apartment number, if present, to match. Attempt to find a match for all public housing buildings.
- If two or more buildings match the address given for a fire incident, randomly assign the fires to one of the matched buildings. Make a different random assignment for each year.
- Look for matches across 10 years of FEMA NFIRS data, from 2012 to 2021.



Fire Incidents in Public Housing
Incident Type
Building Fires (Excludes Confined Fires)
Cooking Fires (Confined to Vessel)
Indoor Trash Fires (Confined to Vessel)
Incident Count
0
200
400
600
800
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021

Average annual loss for matched fires

- On average, every year fires in public housing buildings result in about **$4,000,000** in combined property/contents loss, about **18** non-firefighter injuries, and about **1** fatality.
- The deadly 2022 fire in Philadelphia is not included, as 2022 statistics have not been released yet from NFIRS.

Two approaches for creating an index

The full range of data needed for a comprehensive analysis of fire risk was not available at this time; however, we can still make a preliminary analysis.

We will try two initial approaches for creating an index:

1. Create a decision tree classifier model to make predictions about which buildings will have fires.
   - By measuring the results, we can learn about which factors in our current dataset are associated with fire risk. We can also assign risk scores based on the resulting predictions.

2. Create an index using a weighted average methodology.
   - This is a more subjective approach. Rather than combining different factors based on the level of importance assigned by a model, we will attempt to assign our own weights.

Comparison of Building Types (Structural) Classification for Region 3 and US for MF, PH and OHP

MF

BLDG_TYPE	Region-3 (%)	USA (%)
ES	8.7	7.3
NDS	12.0	13.1
RW	34.6	30.2
SD	3.3	6.1
SF	3.5	5.0
WU	37.9	38.3

PH

BLDG_TYPE	Region-3 (%)	USA (%)
ES	2.2	1.9
NDS	7.1	8.3
RW	56.8	29
SD	15.9	34
SF	8.1	18.4
WU	10.0	8.4

OHP

BLDG_TYPE	Region-3 (%)	USA (%)
ES	45.5	30.5
NDS	17.5	21.4
RW	0	4.7
SD	0	4.4
SF	0	5.4
WU	37	33.6

ES: Elevator Structures,
NDS: No Dwelling Units,
RW: Row/Town House,
SD: Semi-Detached (Duplex),
SF: Single Family,
WU: Walk-Up (Multistory Buildings Without Elevators) .

Average defects, 2019 (MF)

Per BUILDING (AVERAGE DEFECTS)

BLDG_TYPE_CD	AVG_NO_OF_DEFECTS_PER_BLDG	NO_OF_BUILDINGS
RW	1.75	12539
ES	4.22	6094
SD	1.68	3669
SF	1.95	1740
NDS	2.02	22612
WU	2.23	19981

Per INSPECTION (AVERAGE DEFECTS)

BLDG_TYPE_CD	AVG_NO_OF_DEFECTS_PER_INSP	NO_OF_INSP
RW	7.92	2775
ES	6.52	3949
SD	8.39	734
SF	9.23	368
NDS	9.24	4958
WU	9.43	4734

Kunhi/May-18/2020

Grouping fires based on severity

You might argue that we shouldn't treat all indoor fires equally. While confined cooking fires cause some injuries, any fire that causes a death or more than $5,000 in property/contents loss is classified as an unconfined building fire.

Throughout this presentation, we will consider at two levels of severity:

1) Unconfined/Damaging Fire (More Severe)

The building had at least one unconfined building fire **OR** at least one fire that resulted in death/injury/property loss

2) Any Indoor Fire (Includes 1)

Building had at least one cooking or indoor trash fire **OR** at least one Unconfined/Damaging Fire

Correlation between fires of different severity levels

- **40%** of elevator structures (ES) had at least one recorded indoor fire between 2012 and 2021, and **15%** had at least one unconfined/damaging fire.
- Among the ES buildings with at least one unconfined/damaging fire, the rate of indoor fires per building is **8 times higher** than buildings with zero unconfined/damaging fires.

CHOOSING INPUTS FOR AN INDEX

Limitations

The models mentioned in this presentation don't incorporate the following types of data, which were not available at this time:

- Most information about building construction, like building material type.
- Demographic/sociological characteristics for buildings with fewer than 10 units, which has been anonymized for PII reasons. (Mostly non-elevator structure buildings.)
- Deficiencies identified by REAC inspections.

Past occurrence of fire as a risk factor

One factor that might indicate fire risk is past occurrence of fires.

It is unlikely that having a past fire directly causes a future fire. However, if there are omitted factors that cause fire risk which are not in our dataset, those factors might be reflected in buildings that repeatedly catch fire.

These statistics should be considered in the context of the rate we would expect buildings to have repeat fires, assuming the distribution of fires was random.

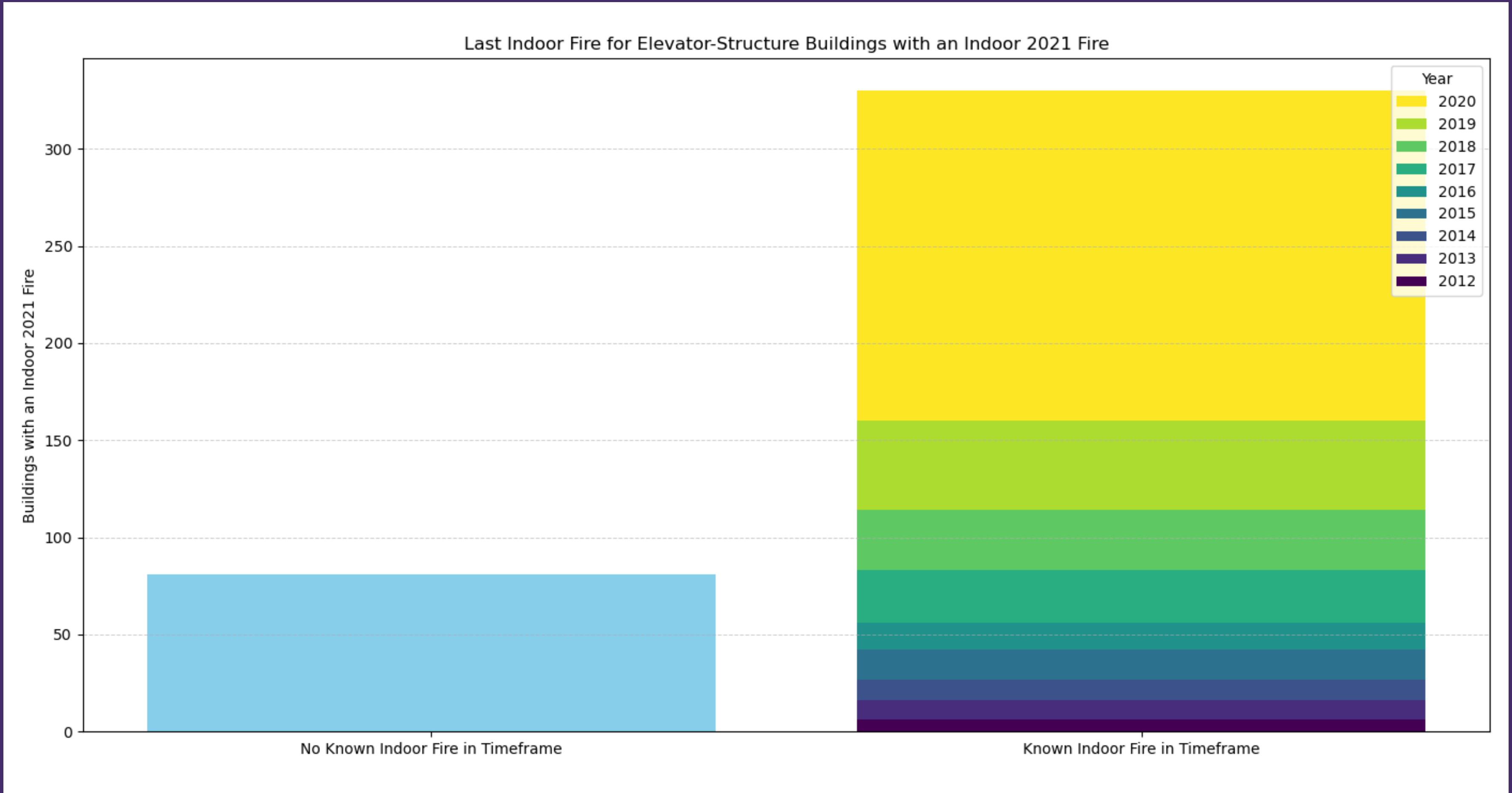
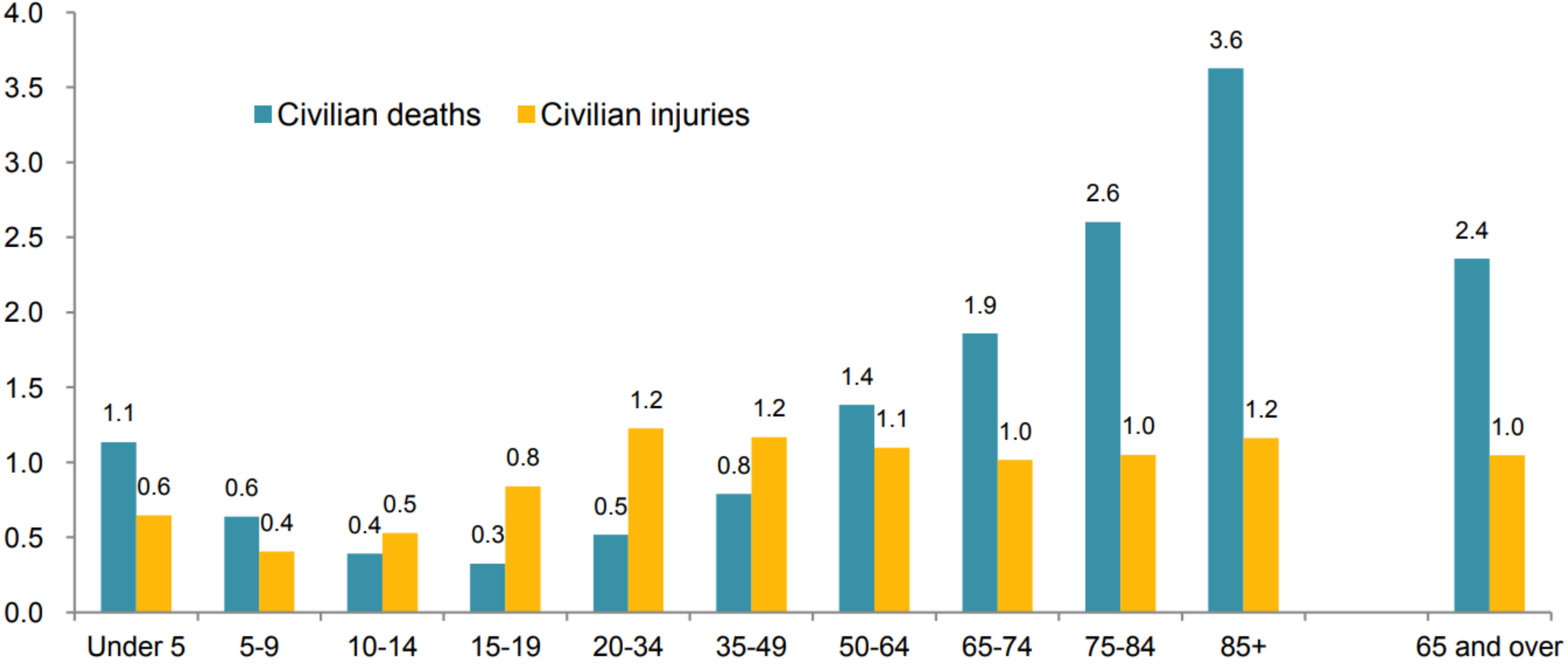

Last Indoor Fire for Elevator-Structure Buildings with an Indoor 2021 Fire
Buildings with an Indoor 2021 Fire
0
50
100
150
200
250
300
No Known Indoor Fire in Timeframe
Known Indoor Fire in Timeframe
Year
2020
2019
2018
2017
2016
2015
2014
2013
2012

Figure 8. Relative Risk of Civilian Death and Injury from Home Structure Fires, by Age Group 2007-2011



Source: National Fire Protection Association

Sociological factors that are related to fire occurrence (public housing)

	All ES Buildings	ES Buildings with >1 Indoor Fire (2012-2021)	ES Buildings with >1 Unconfined/Damaging Fire (2012-2021)
Average % of Residents Age 62 or Greater	45%	46%	51%
Average % of Residents with a Disability	45%	48%	54%
Average Total Household Income	$18,539	$17,831	$15,942

MODELING APPROACH

Types of input features considered

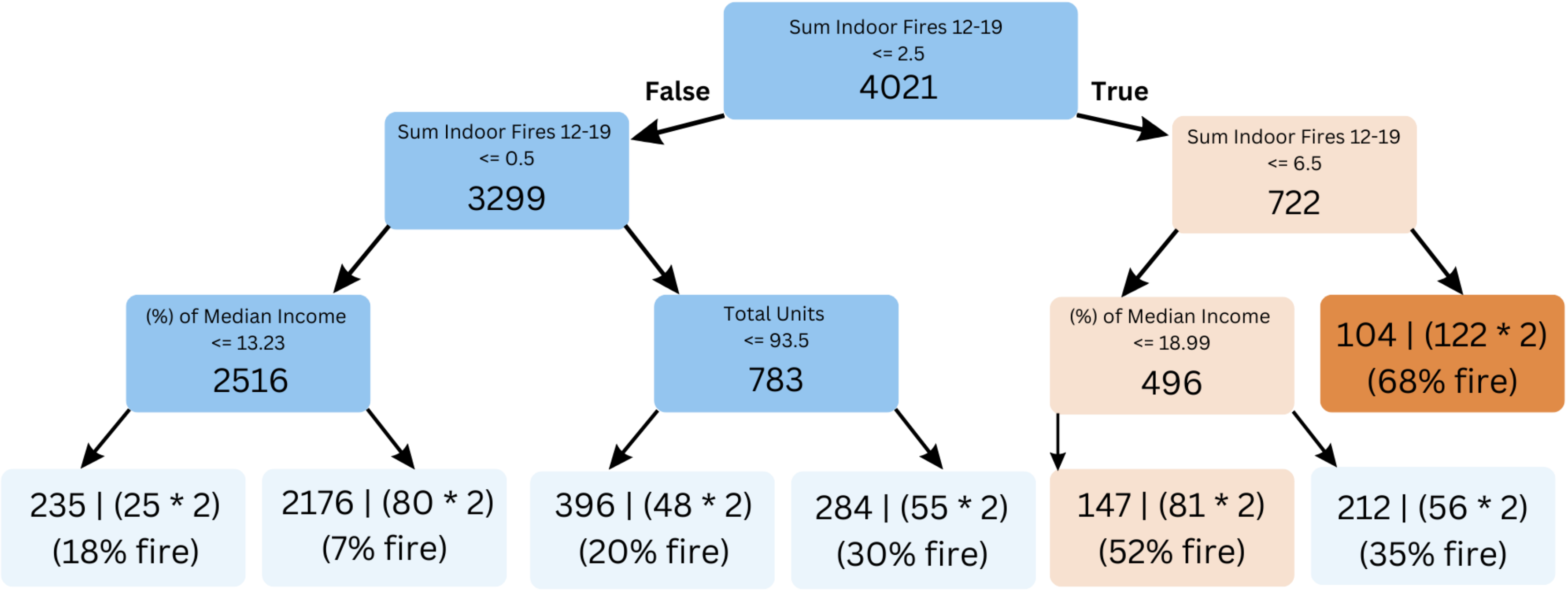
FEMA NFIRS data:

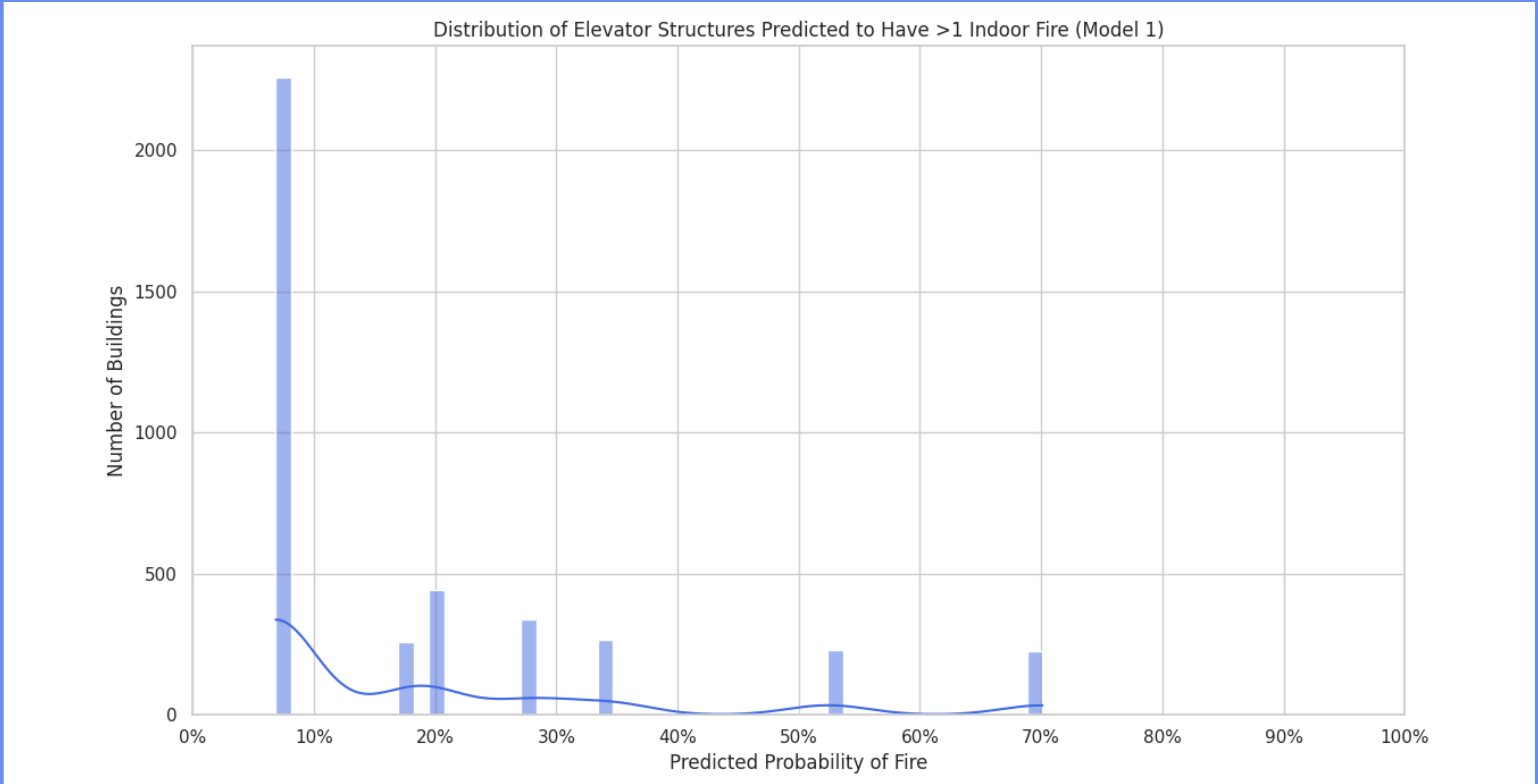
- Number of past fires (tried all indoor fires as well as only unconfined/damaging)
- Number of injuries/property loss/fire spread
- Whether smoke detectors were triggered or Automatic Extinguishing Systems were present (according to NFIRS)

HUD Public Housing Buildings data:

- Average income/rent, source of income
- Number of children/number of single parents
- Age/disability status/race/other demographic factors
- Number of units/beds/people total
- Year of construction
- Location/geographic variables
- Tract-level demographic variables

Training the first decision tree classifier to predict buildings with >1 indoor 2020 fire





Distribution of Elevator Structures Predicted to Have >1 Indoor Fire (Model 1)
Number of Buildings
2000
1500
1000
500
0
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
Predicted Probability of Fire

Results for the first model

The decision tree's predictions can now be measured against 2021 fires, which were not used to create the model.

In terms of predictive accuracy, the first decision tree model performs better than chance for 2021 fires, but still results in false positives.

- The model can correctly predict half of the 400 buildings that had an indoor fire in 2021.
- However, in addition to the 200 correct predictions for "Yes fire," there were 500 "Yes fire" predictions where the building did not have a fire.

Two additional models

A second decision tree classifier model was trained using only data from HUD as predictors, in an attempt to assess the relative importance of different the different features in the HUD dataset. In descending order, the most important features identified by this model were:

- Total units
- Household income as a % of local area median
- % of units with two beds
- % of single parent households
- % of disabled residents

A third model was trained to predict unconfined/damaging fires. This model was less accurate, but still better than chance. The third model used ~80 different input features and used a more complex technique called random forest classification, which combines many decision trees. The most important features identified by this model were:

- Number of past fires
- Sum of money lost to fires
- Presence of an AES system
- Income as a % of the local median
- % of disabled residents

Caveats

This methodology is insufficient to infer causality.

- We do not have a way to overcome selection bias.
- For example, it could be that buildings with a higher proportion of elderly residents are located in different areas with higher fire risk, compared to buildings with fewer elderly people.

The current dataset was not conducive to modeling non-elevator structure fires.

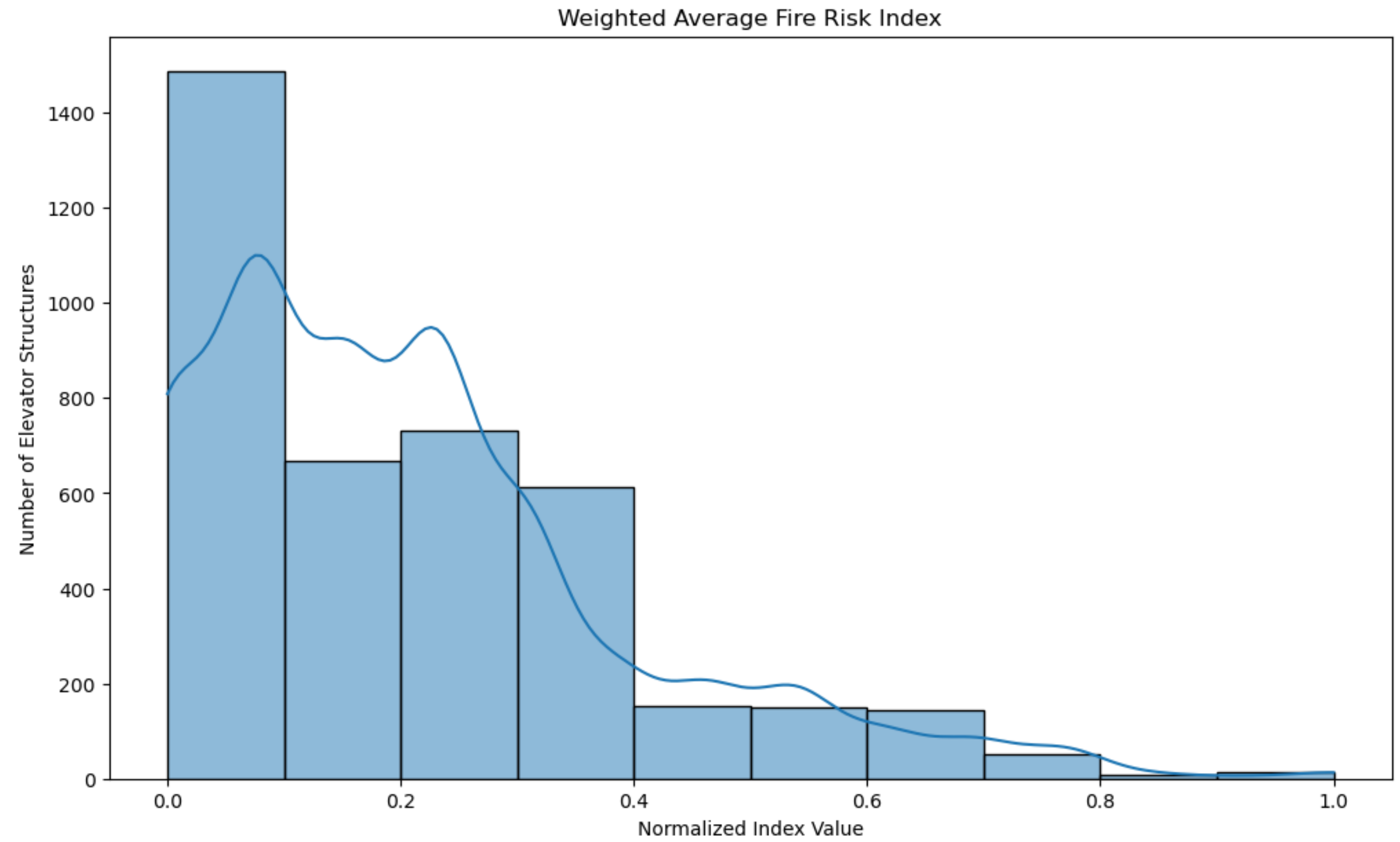
- Non-elevator structure data from HUD in the current dataset is anonymized for PII reasons.
- Non-elevator structures are more rare events, which makes predictive modeling more difficult.

WEIGHTED AVERAGE APPROACH

Formula for weighted average

- +0 for buildings with no fires
- +1 for buildings with >=1 fires
- +2 for buildings with >3 fires
- +3 for buildings with >6 fires
- +3 for buildings with an unconfined fire
- +3 for buildings with any type of fire-related injury
- +1 for buildings with average household income lower than 20% of the area median income
- +1 for buildings with >100 housing units
- +1 for buildings with >40% of residents over age 62
- +1 for buildings with >40% of residents who are disabled

Normalize the resulting value so it always falls between 0 and 1.



Weighted Average Fire Risk Index
Number of Elevator Structures
Normalized Index Value
0
200
400
600
800
1000
1200
1400
0.0
0.2
0.4
0.6
0.8
1.0

Conclusions and future work

Predicting whether an indoor fire will occur in the near future for a given elevator structure building can be done with reasonable accuracy. The most important input identified so far for this is past number of fires.

Unconfined/damaging fires, which are more severe, can also be predicted with a limited amount of accuracy, although doing so requires a more complex, less interpretable model with more inputs.

Based on the identified factors that correlate with fire occurrence, two preliminary indexes for house fire risk are presented, one based on predictions made by machine learning, and another based on a simple weighted average.

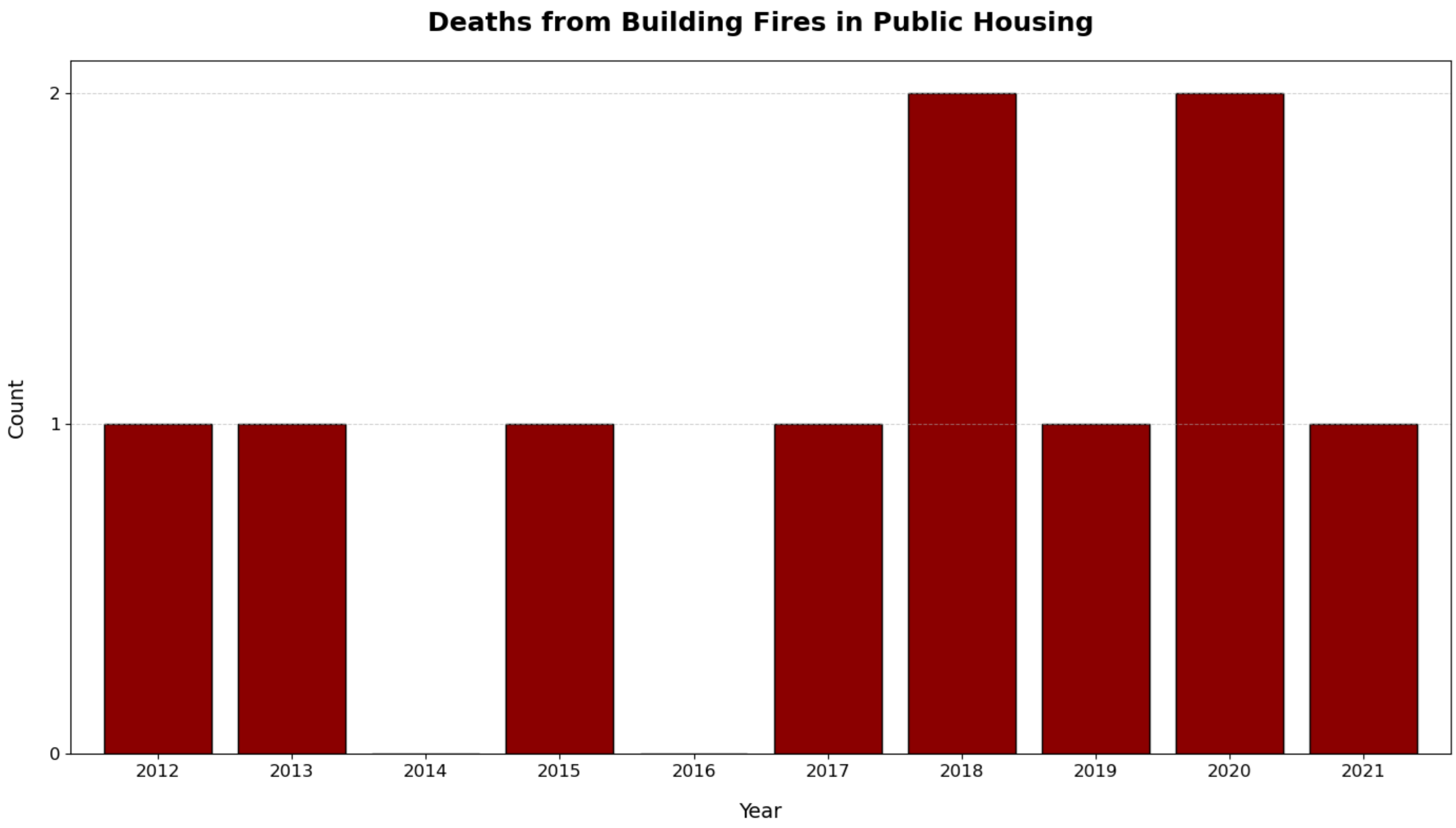
In the future:

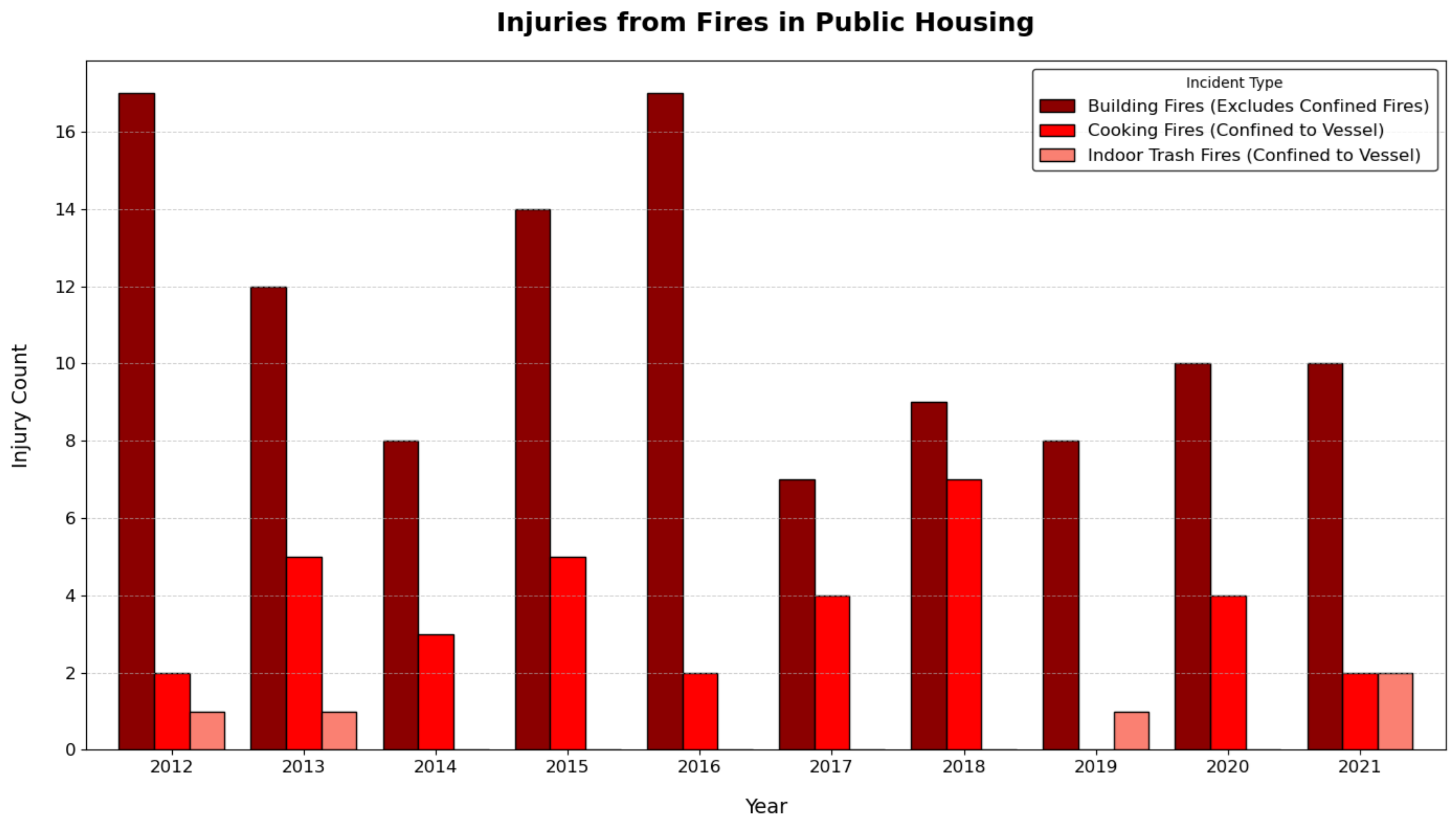
- Expand analysis to multifamily housing.
- Incorporate missing sources of data, including deficiencies identified by past inspections.
- Make predictions about the yet-to-be-released 2022 NFIRS dataset and score the results after that data is released.

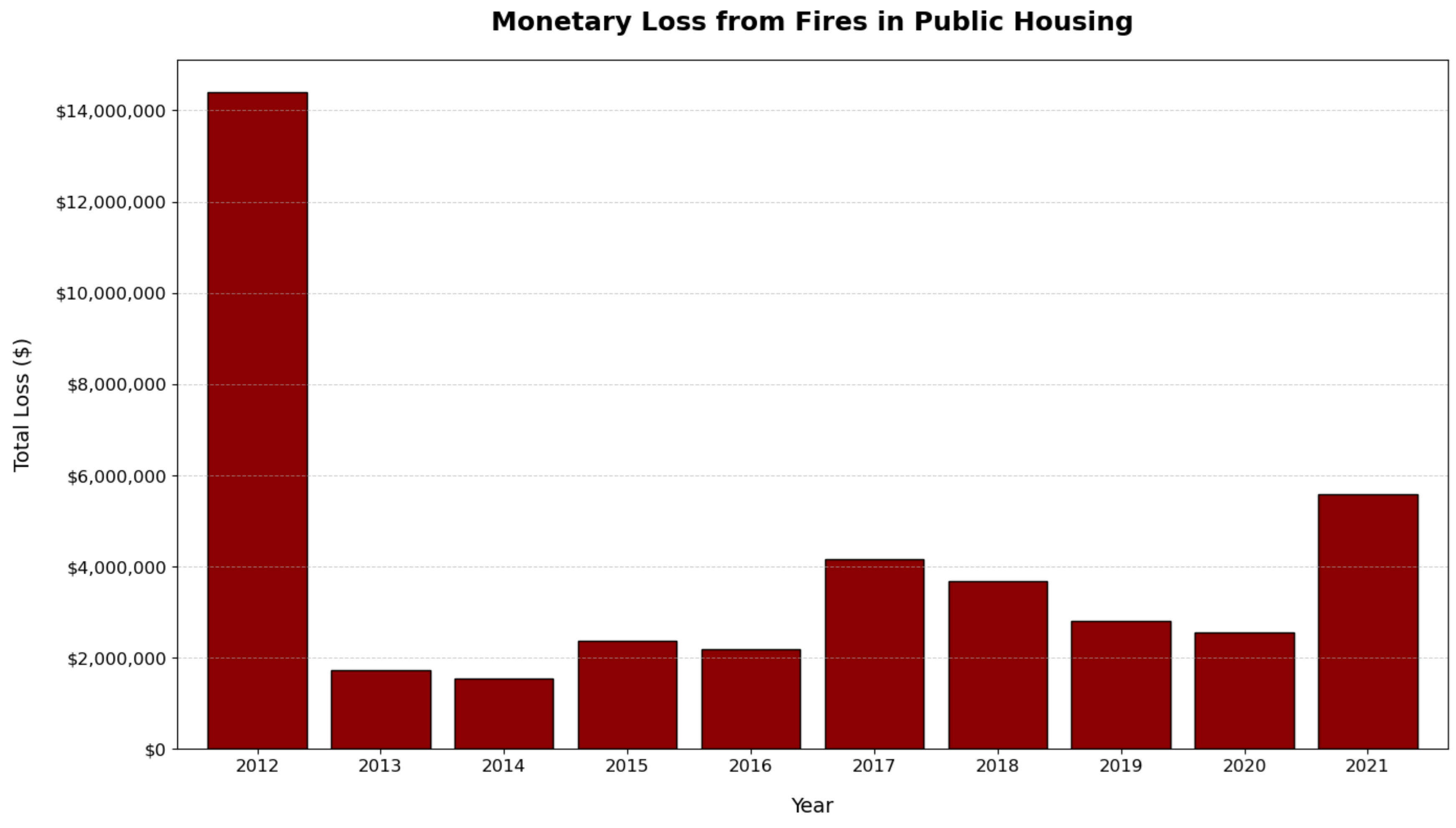
QUESTIONS?

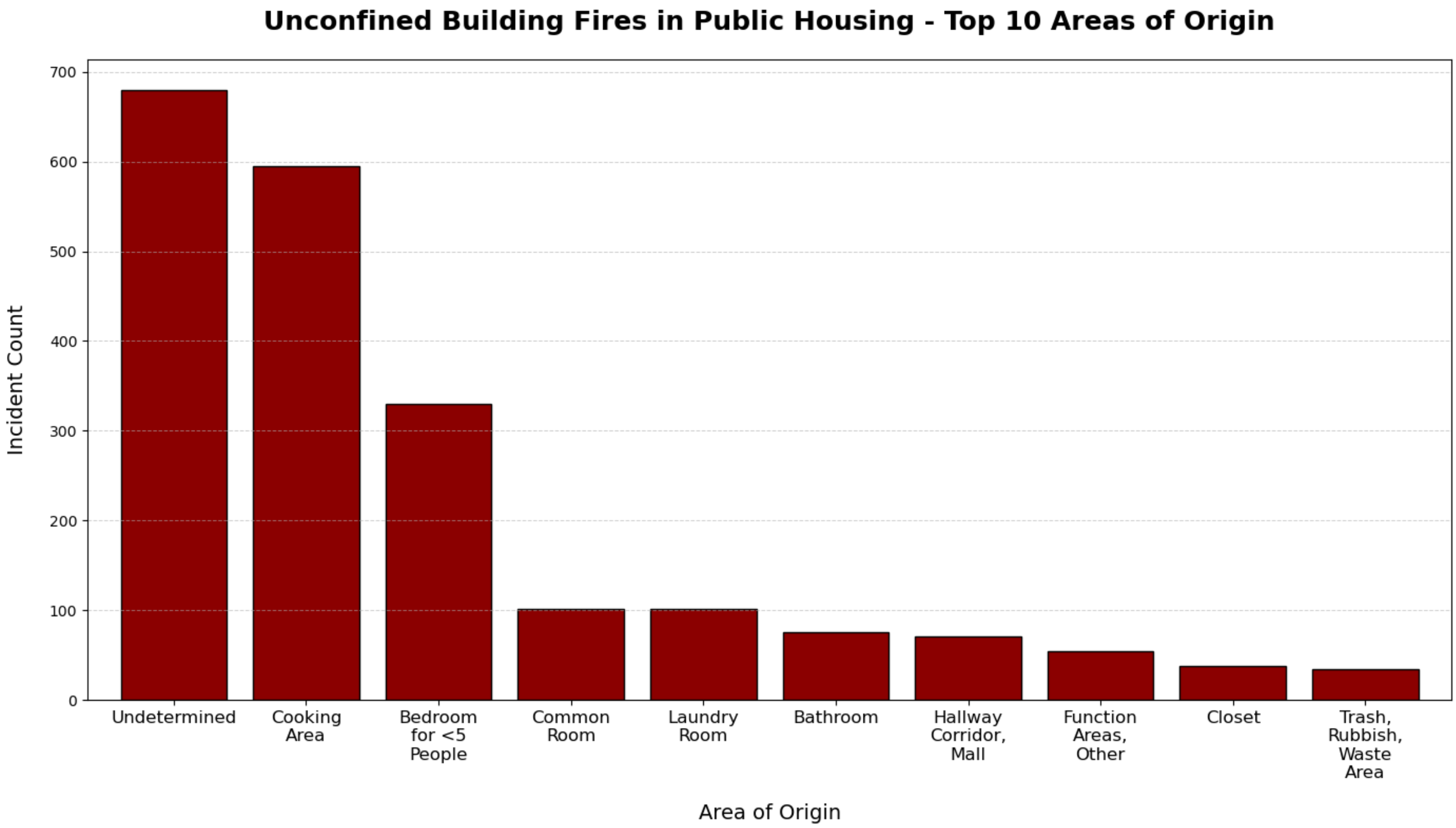
Additional Slides for Reference

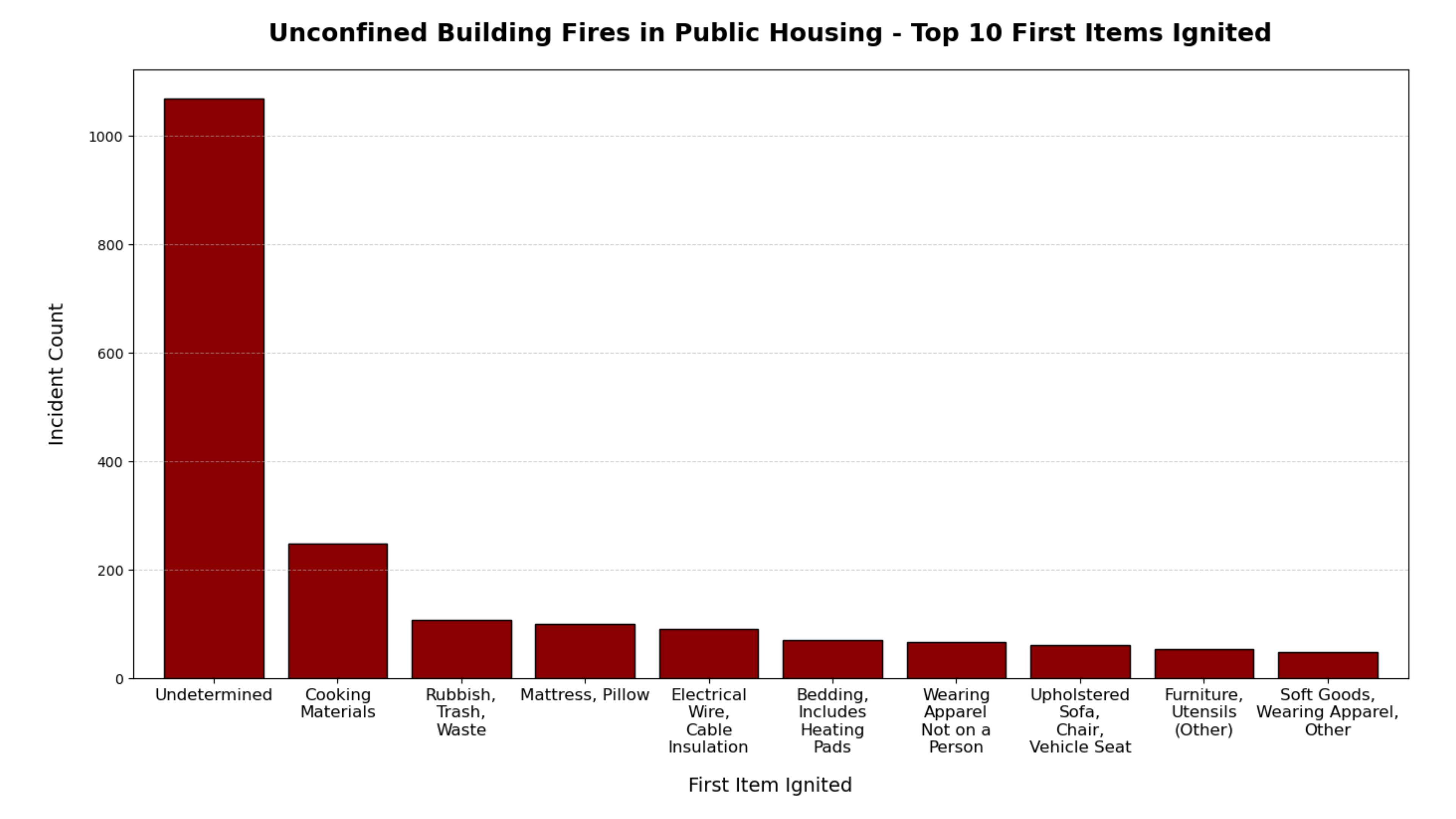
Reference: Basic Descriptive Statistics


Deaths from Building Fires in Public Housing
Count
Year
0
1
2
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021

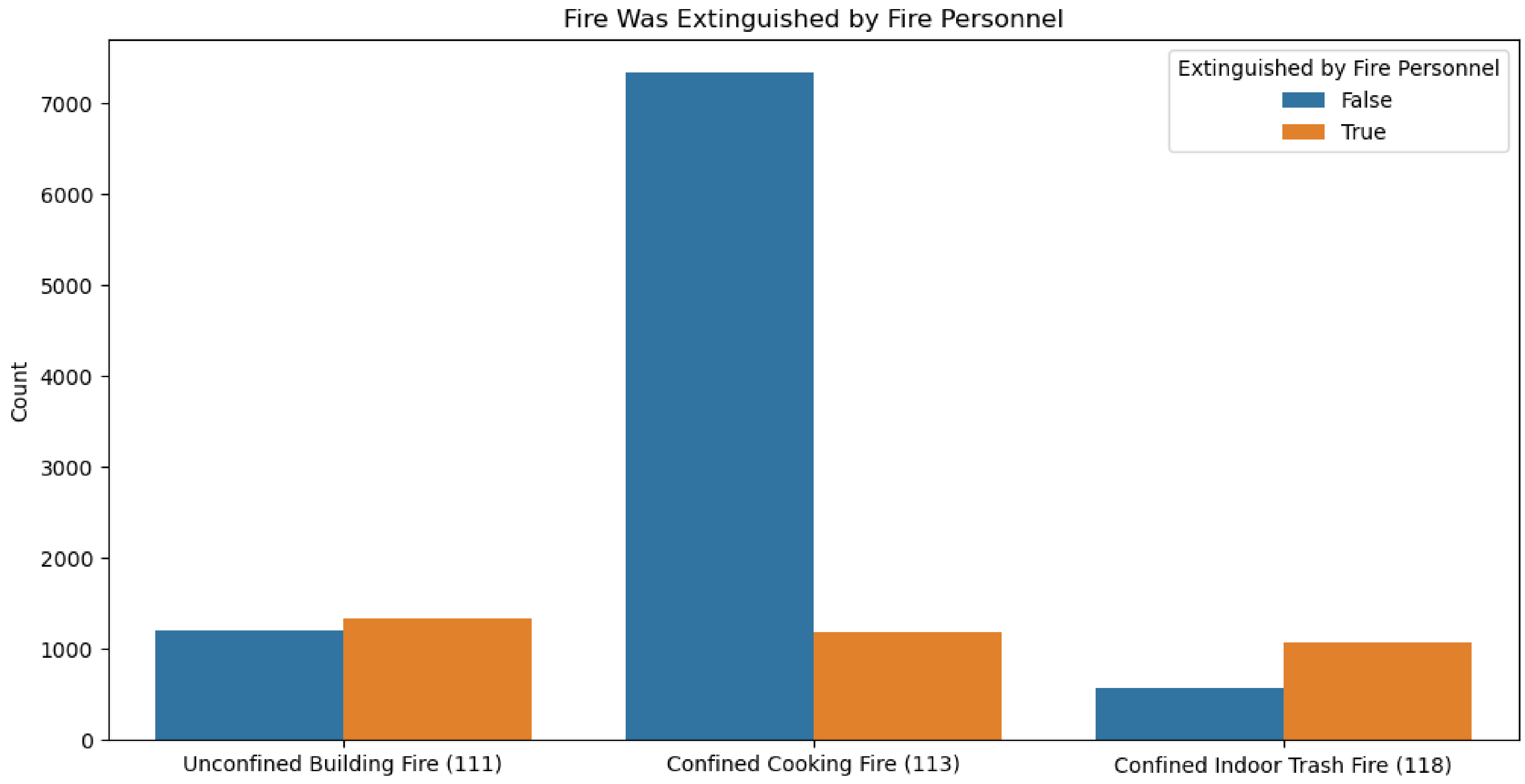

Injuries from Fires in Public Housing
Incident Type
Building Fires (Excludes Confined Fires)
Cooking Fires (Confined to Vessel)
Indoor Trash Fires (Confined to Vessel)
Injury Count
0
2
4
6
8
10
12
14
16
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
Year


Monetary Loss from Fires in Public Housing
Total Loss ($)
$14,000,000
$12,000,000
$10,000,000
$8,000,000
$6,000,000
$4,000,000
$2,000,000
$0
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
Year


Unconfined Building Fires in Public Housing - Top 10 Areas of Origin
Incident Count
0
100
200
300
400
500
600
700
Undetermined
Cooking Area
Bedroom for <5 People
Common Room
Laundry Room
Bathroom
Hallway Corridor, Mall
Function Areas, Other
Closet
Trash, Rubbish, Waste Area
Area of Origin



Unconfined Building Fires in Public Housing - Top 10 First Items Ignited
Incident Count
0
200
400
600
800
1000
Undetermined
Cooking Materials
Rubbish, Trash, Waste
Mattress, Pillow
Electrical Wire, Cable Insulation
Bedding, Includes Heating Pads
Wearing Apparel Not on a Person
Upholstered Sofa, Chair, Vehicle Seat
Furniture, Utensils (Other)
Soft Goods, Wearing Apparel, Other
First Item Ignited



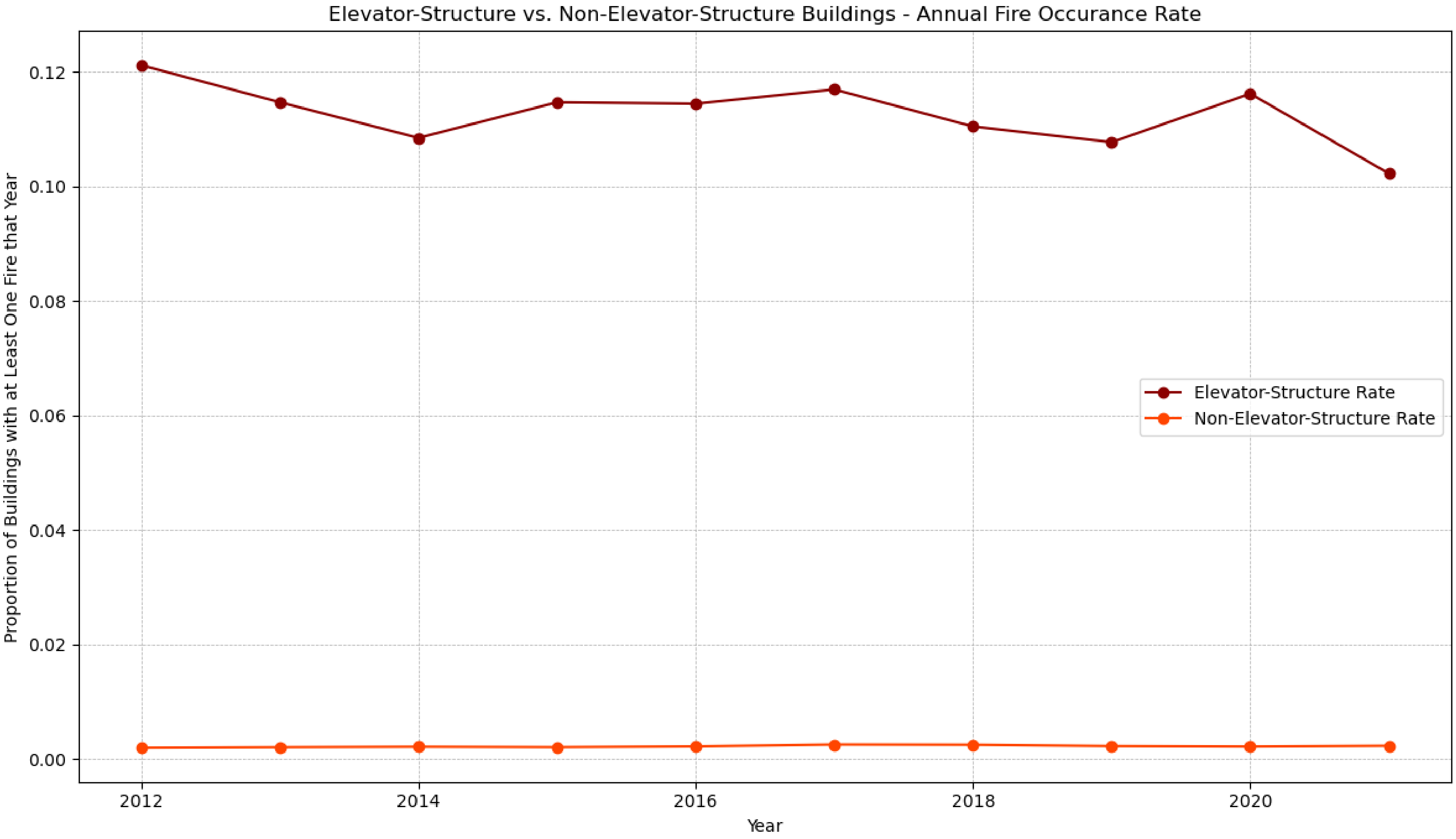
Fire Was Extinguished by Fire Personnel
Extinguished by Fire Personnel
False
True
Count
0
1000
2000
3000
4000
5000
6000
7000
Unconfined Building Fire (111)
Confined Cooking Fire (113)
Confined Indoor Trash Fire (118)

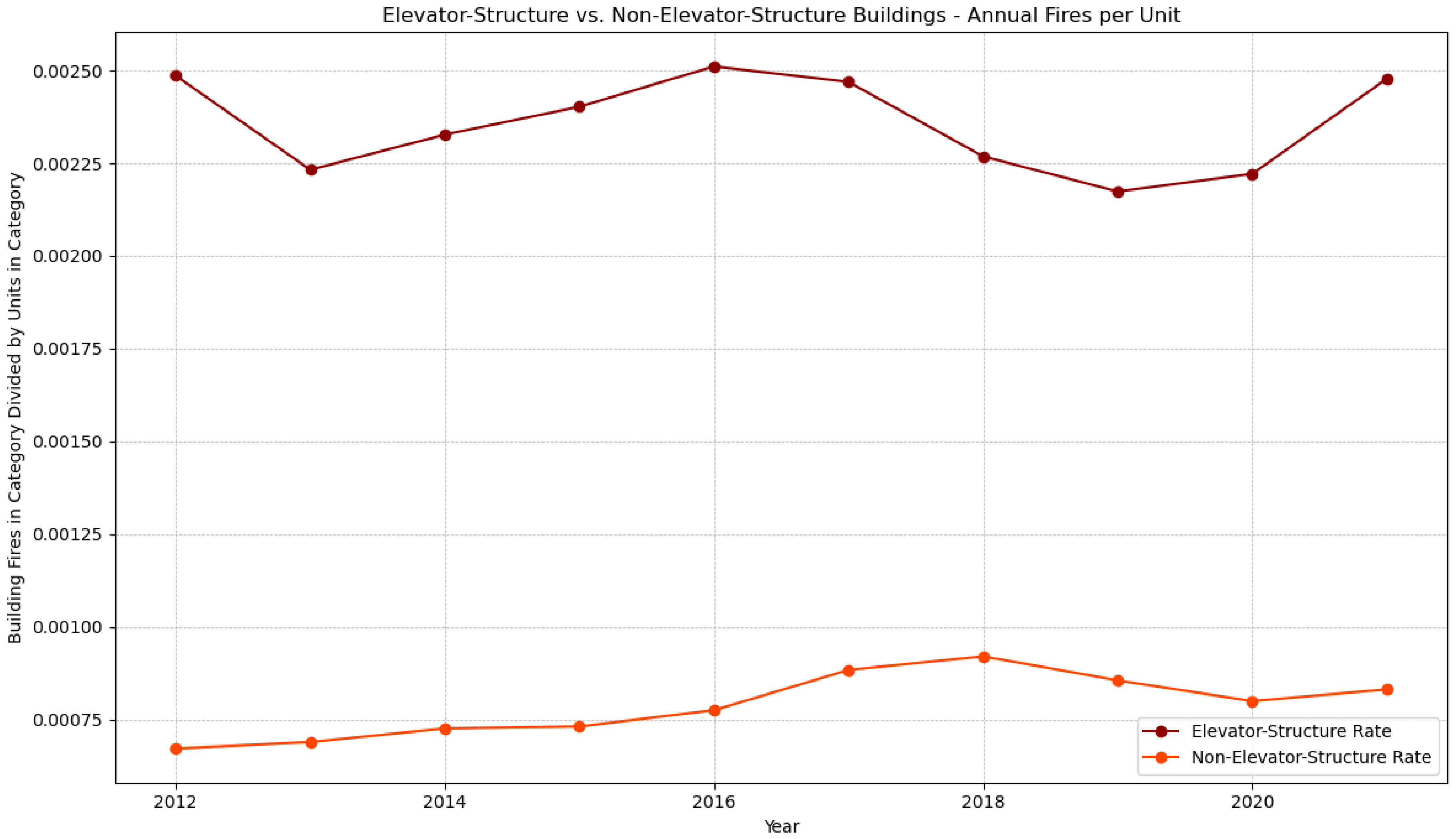
Reference: Elevator Structure vs Non-Elevator Structure

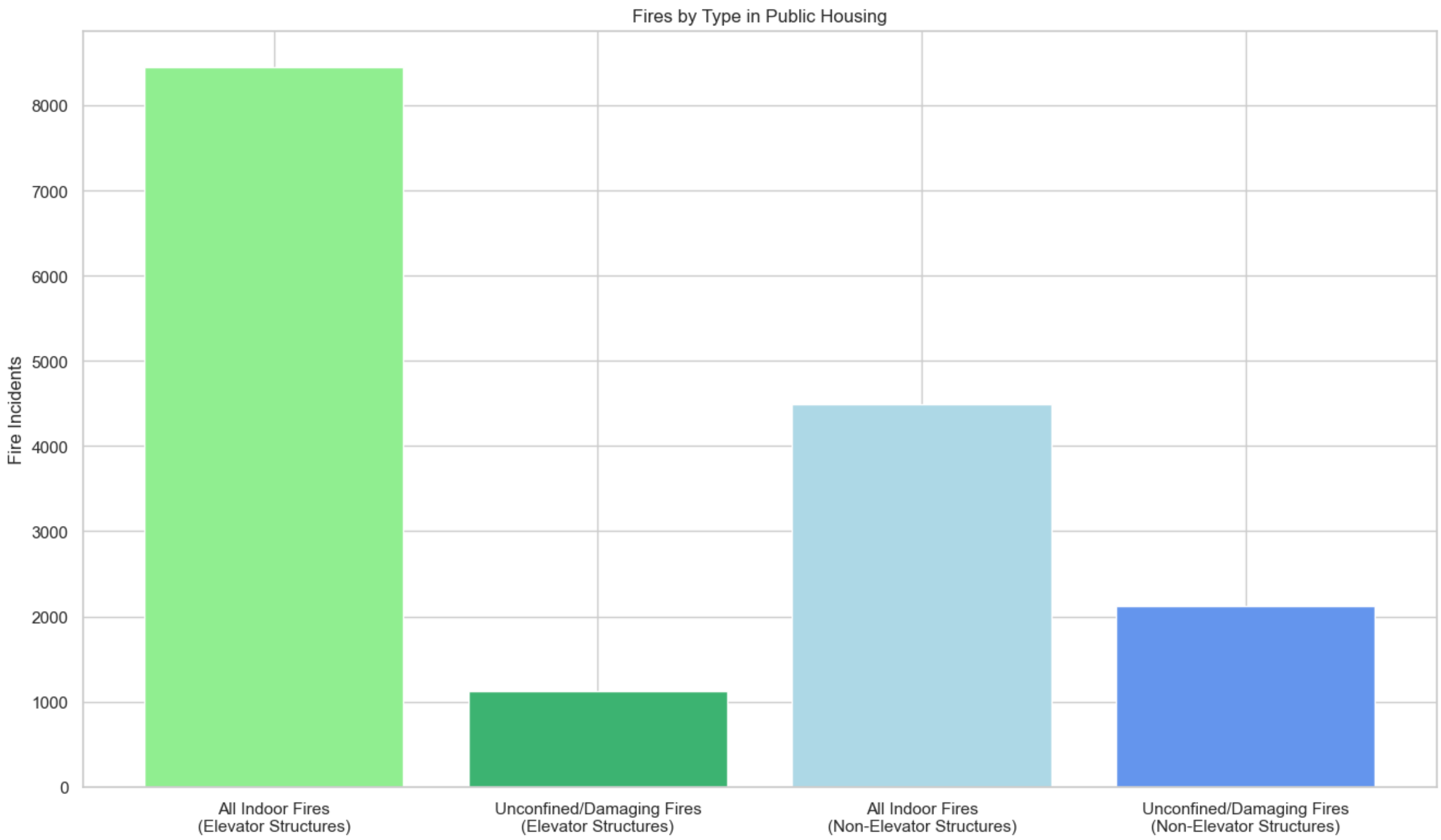
Elevator Structure vs Non-Elevator Structure Buildings

This analysis will focus on elevator-structures for the following reasons:

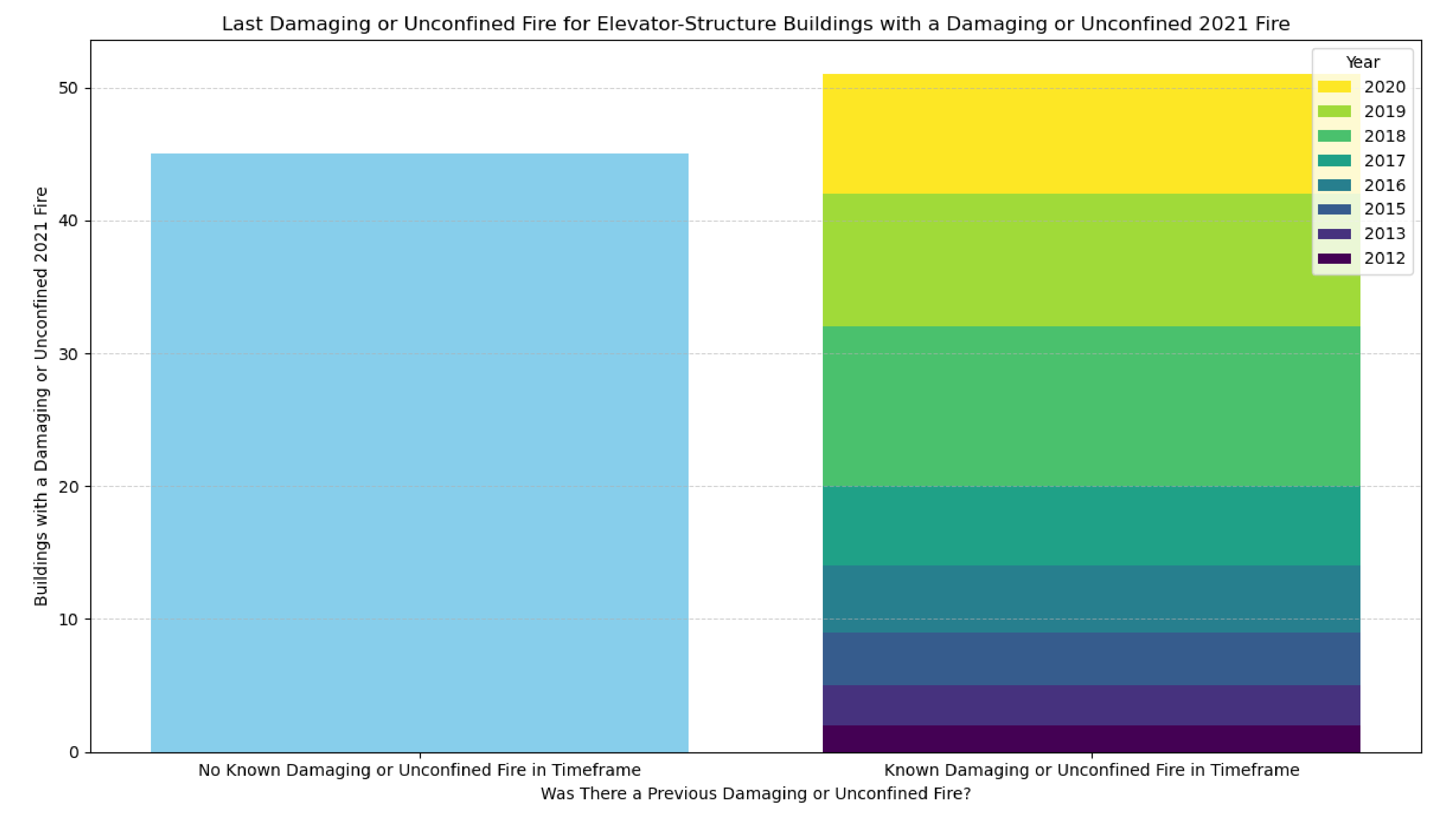
1. The rate of fires-per-building is much higher for elevator structures, and we currently only have building-level data.
2. Demographic/sociological data for buildings with fewer than 10 occupants is anonymized in the public dataset this analysis relies on.

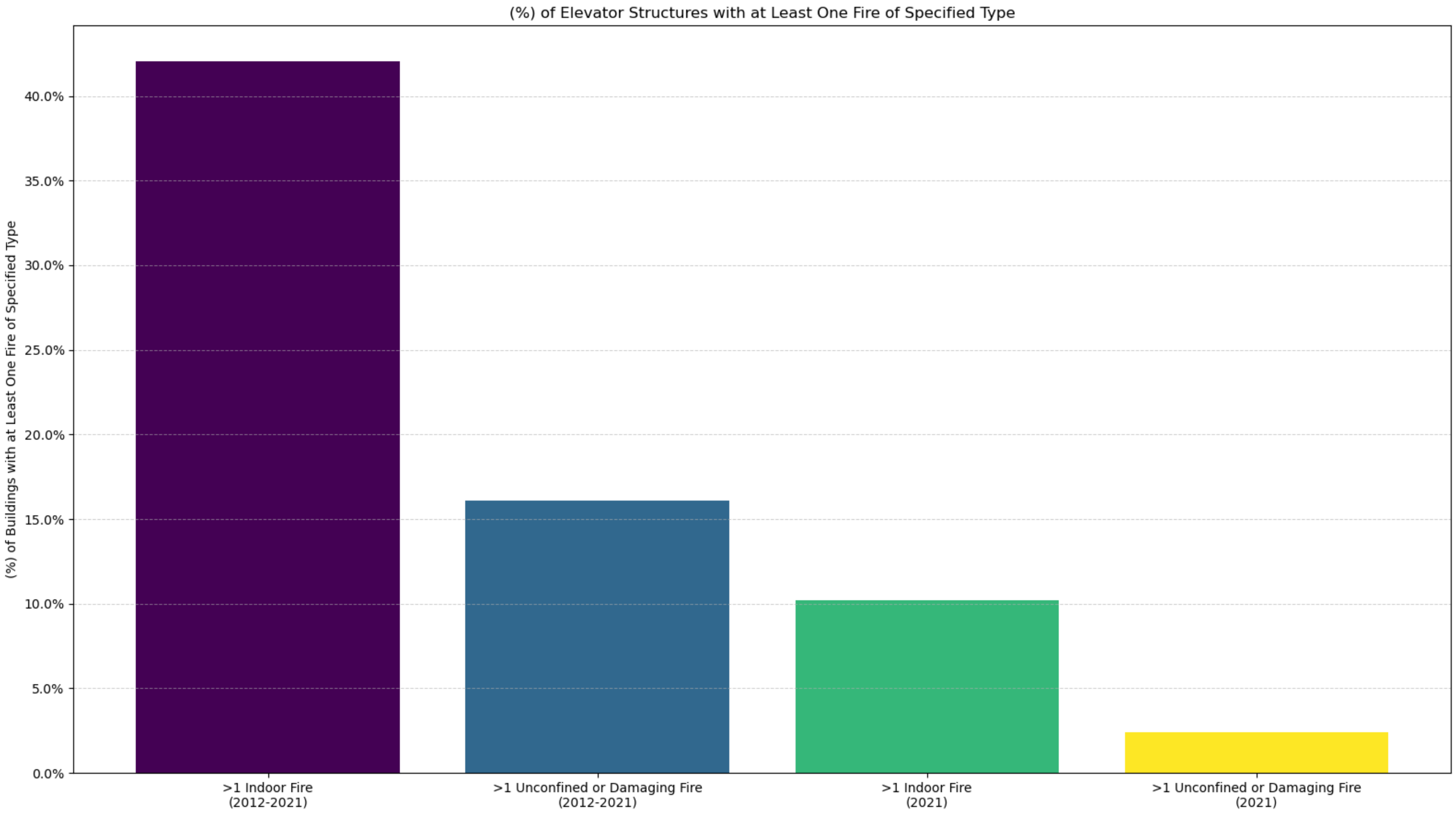

Elevator-Structure vs. Non-Elevator-Structure Buildings - Annual Fire Occurance Rate
Proportion of Buildings with at Least One Fire that Year
0.12
0.10
0.08
0.06
0.04
0.02
0.00
2012
2014
2016
2018
2020
Year
Elevator-Structure Rate
Non-Elevator-Structure Rate

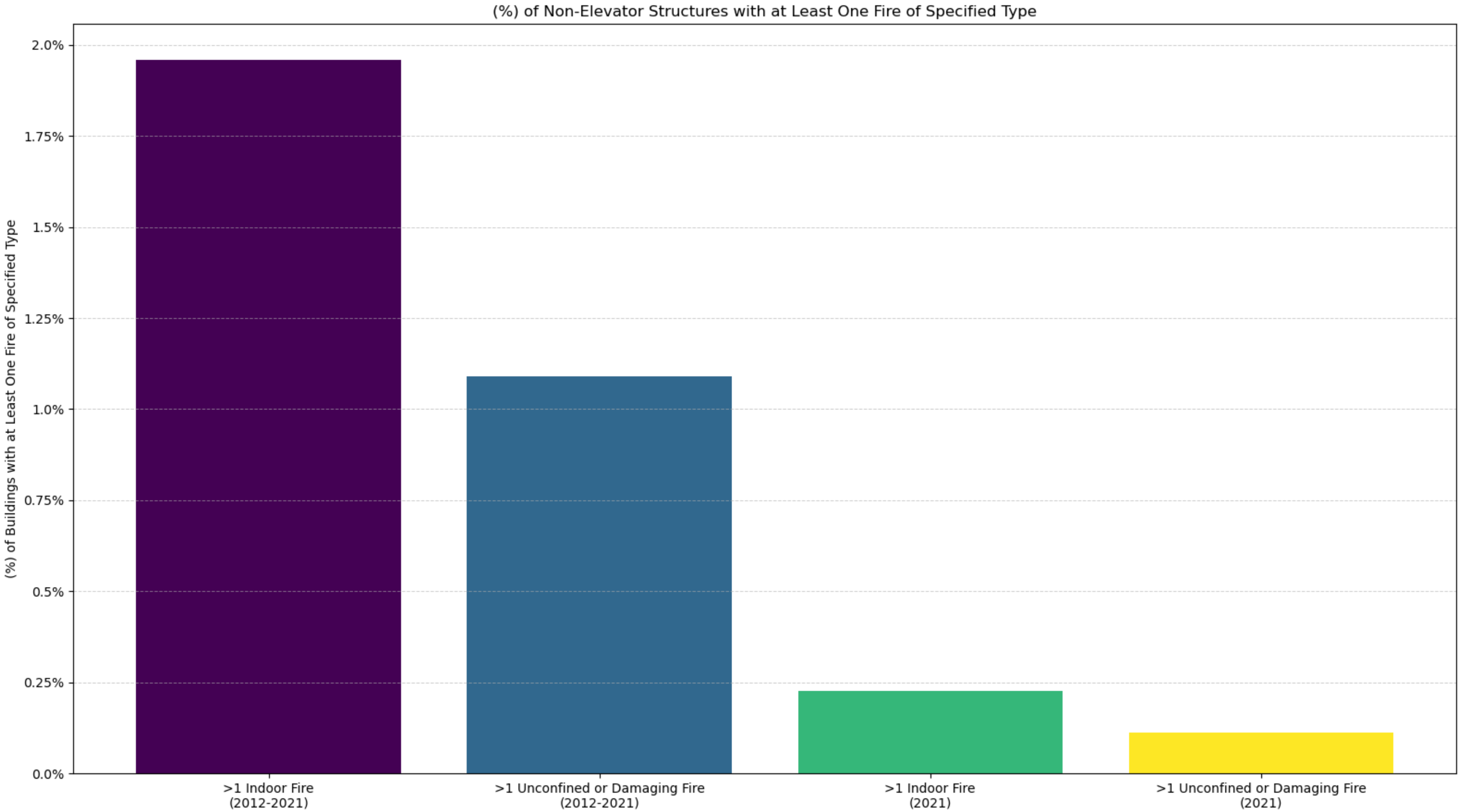

Elevator-Structure vs. Non-Elevator-Structure Buildings - Annual Fires per Unit
Building Fires in Category Divided by Units in Category
0.00250
0.00225
0.00200
0.00175
0.00150
0.00125
0.00100
0.00075
2012
2014
2016
2018
2020
Year
Elevator-Structure Rate
Non-Elevator-Structure Rate


Fires by Type in Public Housing
Fire Incidents
0
1000
2000
3000
4000
5000
6000
7000
8000
All Indoor Fires
(Elevator Structures)
Unconfined/Damaging Fires
(Elevator Structures)
All Indoor Fires
(Non-Elevator Structures)
Unconfined/Damaging Fires
(Non-Elevator Structures)

Reference: Historical rate of fire occurrence


Last Damaging or Unconfined Fire for Elevator-Structure Buildings with a Damaging or Unconfined 2021 Fire
Buildings with a Damaging or Unconfined 2021 Fire
0
10
20
30
40
50
No Known Damaging or Unconfined Fire in Timeframe
Known Damaging or Unconfined Fire in Timeframe
Was There a Previous Damaging or Unconfined Fire?
Year
2020
2019
2018
2017
2016
2015
2013
2012


(%) of Elevator Structures with at Least One Fire of Specified Type
(%) of Buildings with at Least One Fire of Specified Type
40.0%
35.0%
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
>1 Indoor Fire
(2012-2021)
>1 Unconfined or Damaging Fire
(2012-2021)
>1 Indoor Fire
(2021)
>1 Unconfined or Damaging Fire
(2021)


(%) of Non-Elevator Structures with at Least One Fire of Specified Type
(%) of Buildings with at Least One Fire of Specified Type
2.0%
1.75%
1.5%
1.25%
1.0%
0.75%
0.5%
0.25%
0.0%
>1 Indoor Fire
(2012-2021)
>1 Unconfined or Damaging Fire
(2012-2021)
>1 Indoor Fire
(2021)
>1 Unconfined or Damaging Fire
(2021)

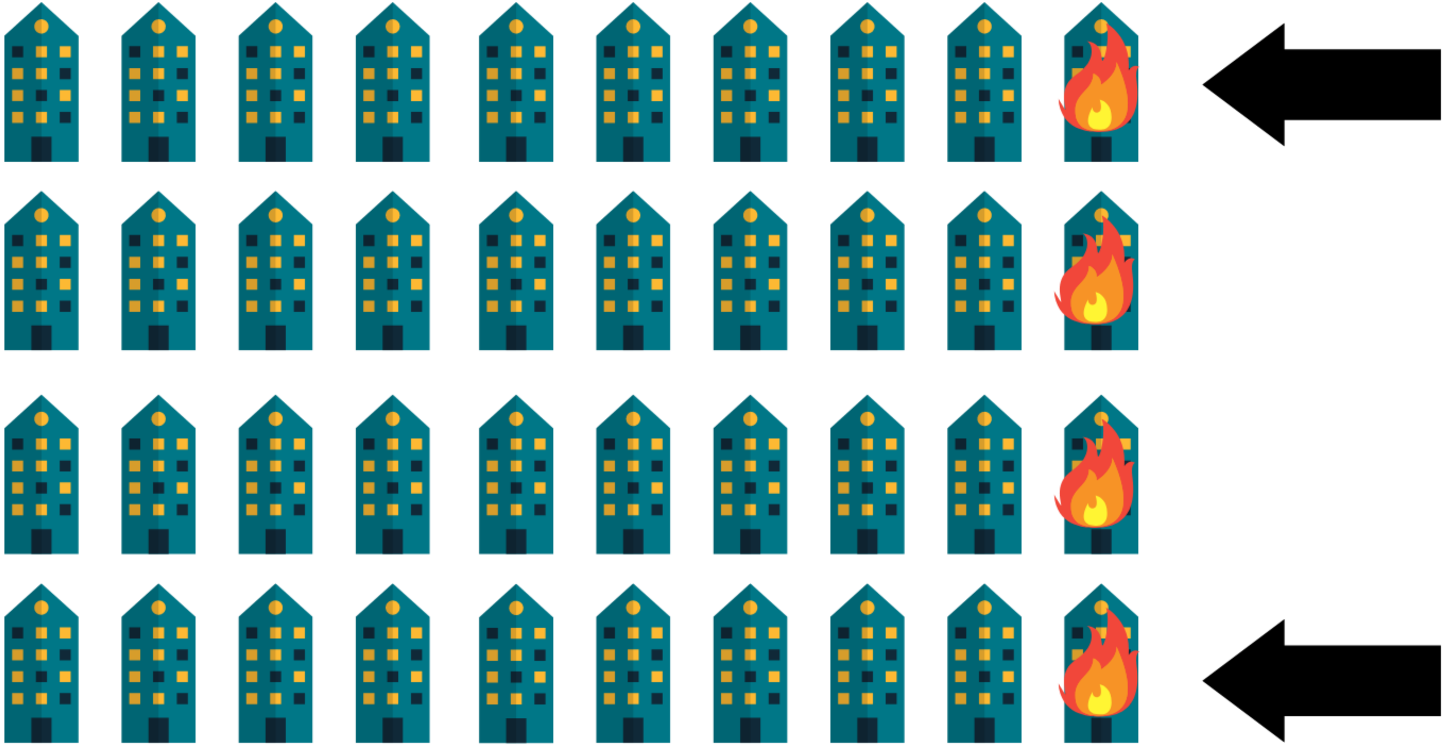
Reference: Modeling results

Results for the first model

The next few slides provide a more intuitive way of thinking about how well the first model makes predictions.

For reference, the first model's performance can be summarized numerically as follows. (The base rate is 10%.)

- ~25% recall with ~35% precision
- ~50% recall with ~29% precision
- ~75% recall with ~20% precision

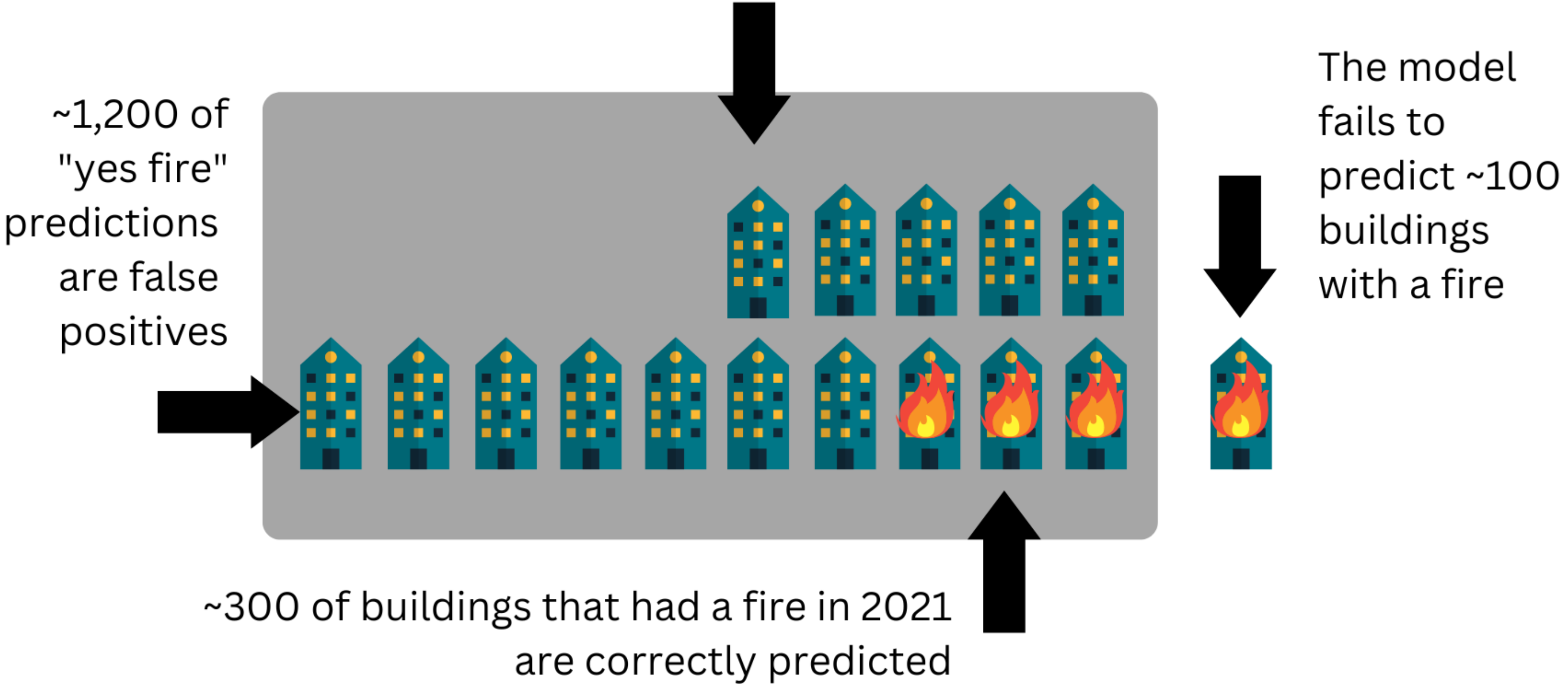


Each building represents ~100 elevator structures.

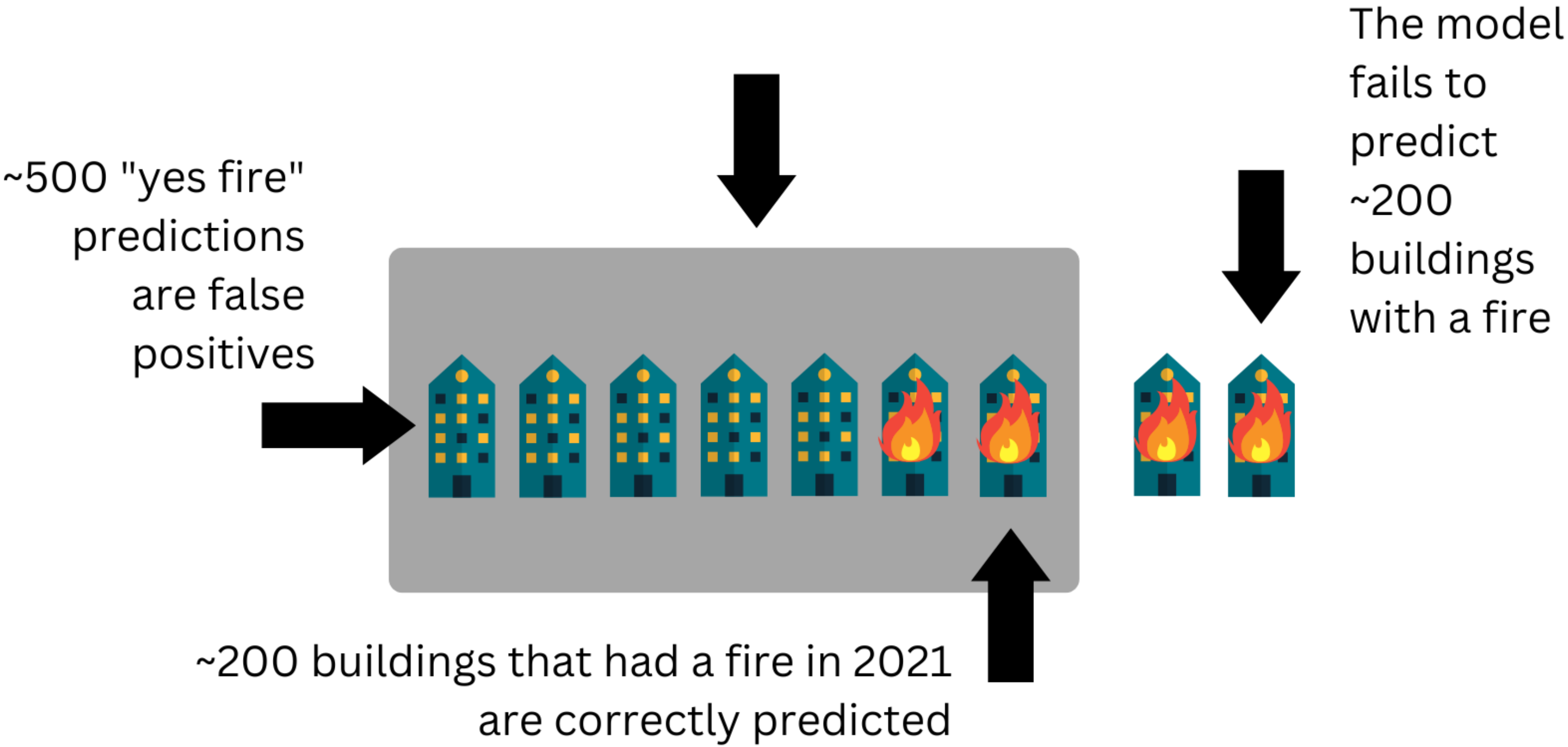
About 400 elevator structures had an indoor fire in 2021. This is ~10%.

~4,000 elevator structures in total.

The Model Predicts the Buildings in the Gray Box Will Have a Fire Next Year



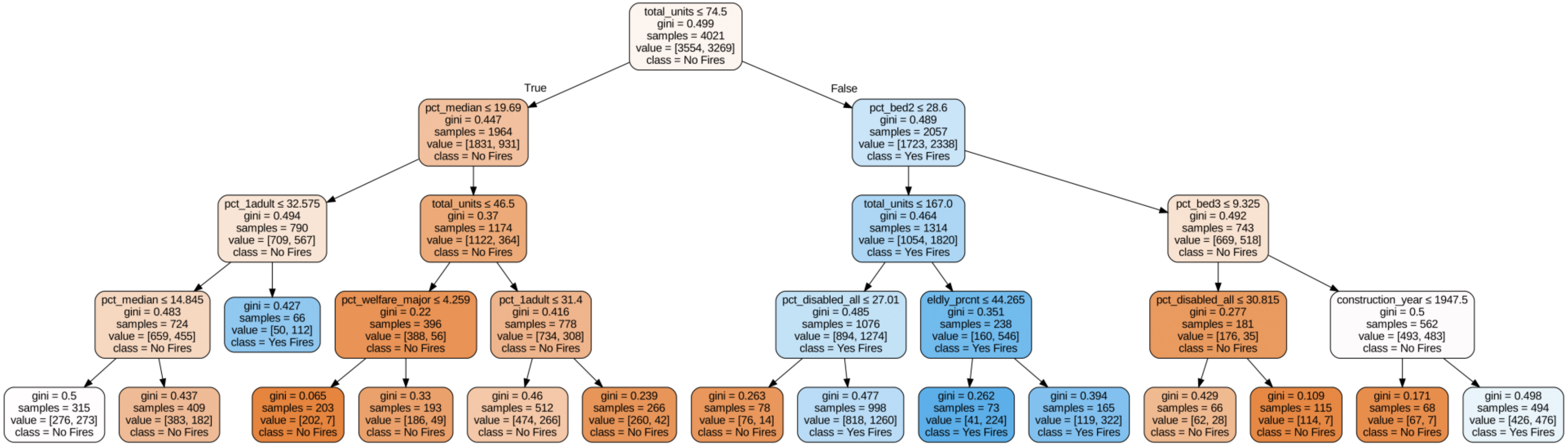
The Model Predicts the Buildings in the Gray Box Will Have a Fire Next Year



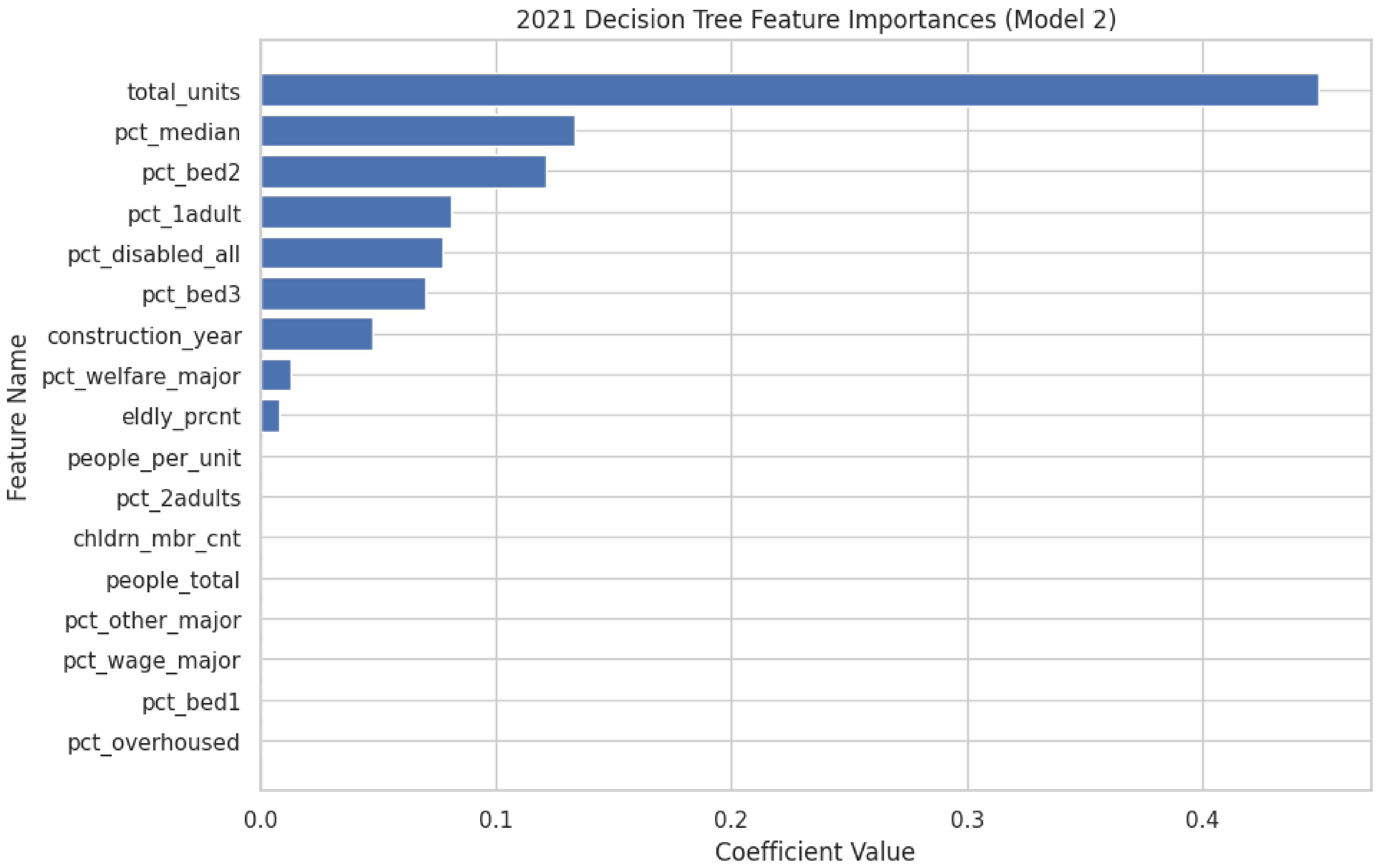
Second attempt, tree model with only HUD building data

As we saw earlier, the data on past fires was doing most of the work in the first model.

However, the HUD building data also has some limited predictive power. To see this, let’s train a second decision tree classifier model, using only HUD building characteristics as inputs. This will allow us to see the most important HUD features, and what direction they are contributing in.



total_units ≤ 74.5
gini = 0.499
samples = 4021
value = [3554, 3269]
class = No Fires
True
False
pct_median ≤ 19.69
gini = 0.447
samples = 1964
value = [1831, 931]
class = No Fires
pct_bed2 ≤ 28.6
gini = 0.489
samples = 2057
value = [1723, 2338]
class = Yes Fires
pct_1adult ≤ 32.575
gini = 0.494
samples = 790
value = [709, 567]
class = No Fires
total_units ≤ 46.5
gini = 0.37
samples = 1174
value = [1122, 364]
class = No Fires
total_units ≤ 167.0
gini = 0.464
samples = 1314
value = [1054, 1820]
class = Yes Fires
pct_bed3 ≤ 9.325
gini = 0.492
samples = 743
value = [669, 518]
class = No Fires
pct_median ≤ 14.845
gini = 0.483
samples = 724
value = [659, 455]
class = No Fires
gini = 0.427
samples = 66
value = [50, 112]
class = Yes Fires
pct_welfare_major ≤ 4.259
gini = 0.22
samples = 396
value = [388, 56]
class = No Fires
pct_1adult ≤ 31.4
gini = 0.416
samples = 778
value = [734, 308]
class = No Fires
pct_disabled_all ≤ 27.01
gini = 0.485
samples = 1076
value = [894, 1274]
class = Yes Fires
eldly_prcnt ≤ 44.265
gini = 0.351
samples = 238
value = [160, 546]
class = Yes Fires
pct_disabled_all ≤ 30.815
gini = 0.277
samples = 181
value = [176, 35]
class = No Fires
construction_year ≤ 1947.5
gini = 0.5
samples = 562
value = [493, 483]
class = No Fires
gini = 0.5
samples = 315
value = [276, 273]
class = No Fires
gini = 0.437
samples = 409
value = [383, 182]
class = No Fires
gini = 0.065
samples = 203
value = [202, 7]
class = No Fires
gini = 0.33
samples = 193
value = [186, 49]
class = No Fires
gini = 0.46
samples = 512
value = [474, 266]
class = No Fires
gini = 0.239
samples = 266
value = [260, 42]
class = No Fires
gini = 0.263
samples = 78
value = [76, 14]
class = No Fires
gini = 0.477
samples = 998
value = [818, 1260]
class = Yes Fires
gini = 0.262
samples = 73
value = [41, 224]
class = Yes Fires
gini = 0.394
samples = 165
value = [119, 322]
class = Yes Fires
gini = 0.429
samples = 66
value = [62, 28]
class = No Fires
gini = 0.109
samples = 115
value = [114, 7]
class = No Fires
gini = 0.171
samples = 68
value = [67, 7]
class = No Fires
gini = 0.498
samples = 494
value = [426, 476]
class = Yes Fires


2021 Decision Tree Feature Importances (Model 2)
total_units
pct_median
pct_bed2
pct_1adult
pct_disabled_all
pct_bed3
construction_year
pct_welfare_major
eldly_prcnt
people_per_unit
pct_2adults
chldrn_mbr_cnt
people_total
pct_other_major
pct_wage_major
pct_bed1
pct_overhoused
Feature Name
0.0
0.1
0.2
0.3
0.4
Coefficient Value

Results for second tree model

This model performs better than random chance, but still substantially worse than the first model using FEMA and HUD data.

In technical terms, here are some of the precision/recall metrics for the second model (the base rate is 10%):

- ~25% recall with ~25% precision
- ~50% recall with ~20% precision
- ~75% recall with ~15% precision

Adjusted approach for third model

Because of unconfined/damaging fires occur less frequently, this third model was trained on combined 2018-2019 fires, and attempted to predict whether an unconfined/damaging fire occurred in either 2020 or 2021.

Rather than a decision tree, this model is a random forest, which aggregates the results from many decision trees. Unfortunately, random forest doesn’t give us the same simplicity as a decision tree, but in this case a simple decision tree was not performing well.

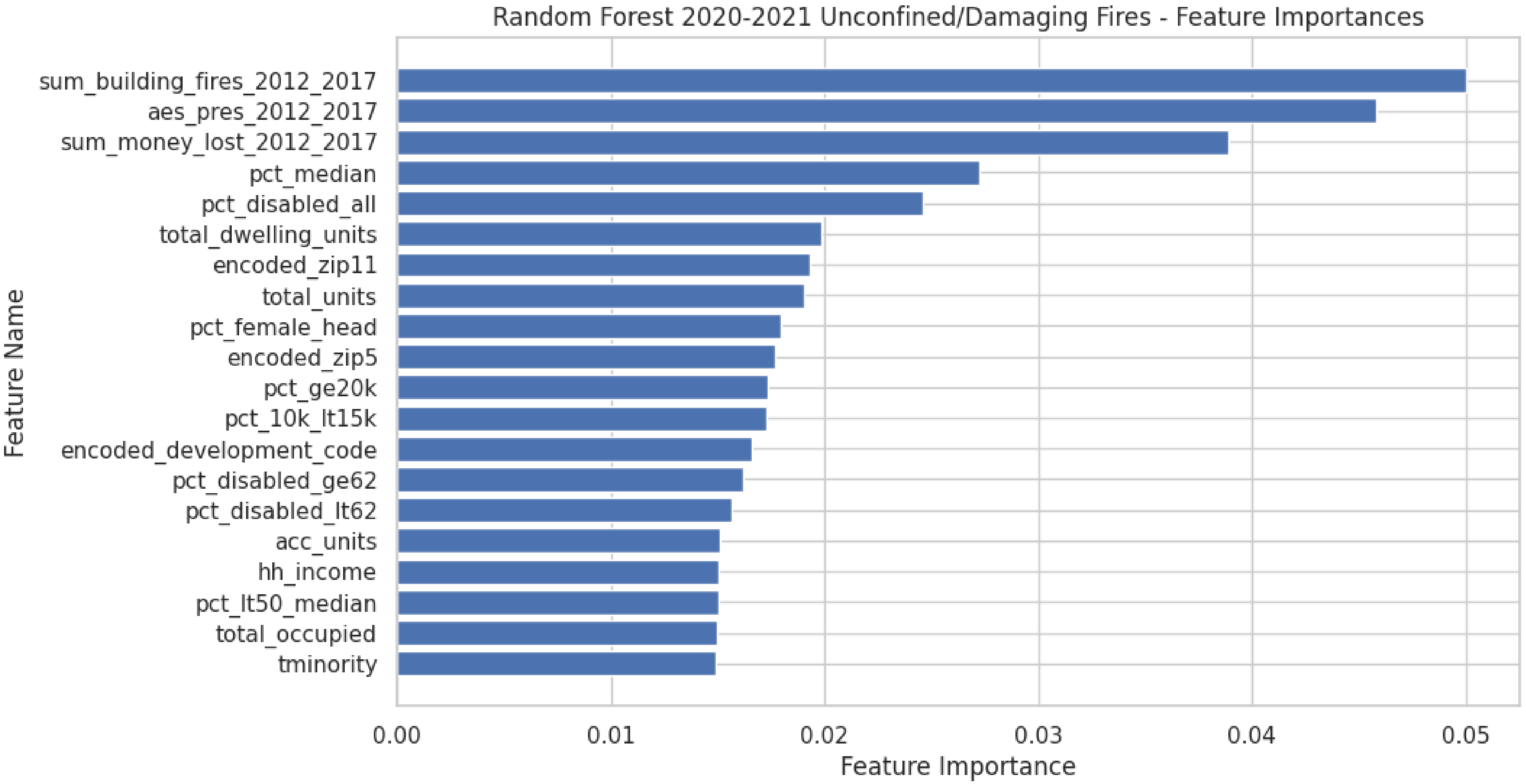
The random forest model is trained on 82 input feature, most of which are HUD building characteristics.

Results for third model

The third model, which attempts to predict unconfined/damaging fires, performed reasonably well. Keep in mind, this model, unlike the first two models, is predicting across a two-year window.

In technical terms, here are some of the precision/recall metrics for the third model (the base rate is 5%):

- ~25% recall with ~25% precision
- ~50% recall with ~20% precision
- ~75% recall with ~10% precision


Random Forest 2020-2021 Unconfined/Damaging Fires - Feature Importances
sum_building_fires_2012_2017
aes_pres_2012_2017
sum_money_lost_2012_2017
pct_median
pct_disabled_all
total_dwelling_units
encoded_zip11
total_units
pct_female_head
encoded_zip5
pct_ge20k
pct_10k_lt15k
encoded_development_code
pct_disabled_ge62
pct_disabled_lt62
acc_units
hh_income
pct_lt50_median
total_occupied
tminority
Feature Name
0.00
0.01
0.02
0.03
0.04
0.05
Feature Importance