Carbon Monoxide Monitor Report

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**1. Introduction.**

Carbon Monoxide or CO poisoning is a dangerous condition that can cause serious tissue damage, or even death.[[1]](#footnote-1) Many U.S. households are at risk of CO poisoning due to the use of fuel-burning appliances inside the home. This project uncovers the trends and risk factors associated with CO poisoning in U.S. households. During our analysis, we found that household income, rent, educational attainment, household heat source, and the year the household was constructed were the most significant predictors of CO monitor status.

To date, very little research has been performed on the analysis of homes at risk of CO poisoning. The U.S. Consumer Product Safety Commission (CPSC) provides several resources on the risks of CO poisoning[[2]](#footnote-2) and this report provides additional empirical analysis of the CO poisoning risk in U.S. households.

A CPSC memorandum on the risks of CO poisoning found that CO monitors reduce the risk of death in a CO poisoning incident.[[3]](#footnote-3) Conversely, households without monitors are at a much higher risk of death from CO poisoning. This report helps to prioritize constituent groups most at risk of CO poisoning which could be used for targeted policies that reduce the risk of CO poisoning.

We specifically analyze 14 predictors of CO monitor status in a U.S. household (present or not present) from the American Housing Survey. A combination of classification algorithms was used to predict the presence of a CO monitor in a U.S. household. This report contains detailed information on the dataset, data mining process, experimental setup, results, and opportunities for future research.

**2. Description of the data set.**

Our dataset is the U.S. Census Bureau’s 2017 American Housing Survey (AHS). The AHS is a housing survey that collects information on a wide range of housing subjects, including characteristics of U.S. housing inventory.[[4]](#footnote-4) The dataset contains over 66,000 responses from U.S. households and it contains features about the type of heating fuel used in a home, the presence of a CO monitor, demographic data, geographic information, and over 3000 other topics.[[5]](#footnote-5) The data itself is encoded according to a predefined data dictionary.

A subset of the full dataset was used for this analysis. 18 columns from the original dataset were used in this report and 14 of those columns were used to predict the target of CO monitor status. These 14 features are:

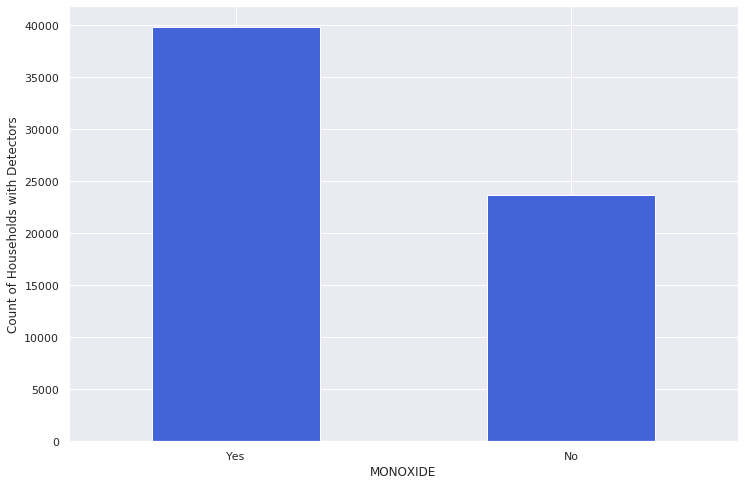
* Primary air conditioning system
* Secondary air conditioning system
* Type of heating equipment
* Fuel of heating equipment
* Hot water system
* Household income
* Homeowners association status (HOA)
* Year the household was built
* Rent payment
* Rent control status
* Marital status
* Educational attainment
* Race
* Household language

Our dataset also contained geographic location, UUID, and weighting factor of each sample which could be used in future analysis. These features were selected from the over 3000 original topics because they provide a good summary of key demographic factors and household indicators that could be associated with carbon monoxide status. The household indicators were selected because they are tied to the heating and cooling equipment in a household and gas appliances naturally produce CO as a byproduct of combustion.

**3. Algorithm Description**

Logistic regression, random forest, and support vector machine classifiers were used to analyze the dataset. This is because our labels for CO monitor status are not present or present. Initial exploration of the data found that most households have a CO monitor, but a significant portion do not have one.

**Most U.S. Households have a CO Monitor**



Our analysis found that certain features, including household income, rent status, year household was built, education level of the occupants, and the type of heating appliances are linked to the presence of a carbon monoxide monitor in U.S. household.

Python was the main tool to perform this analysis because it efficiently handles large datasets and a significant number of packages are available for data science work.

**4. Experimental setup.**

The first part of the data preprocessing was performed in R. The original AHS dataset was subset into the variables analyzed in this report. Next the file was cleaned in python by changing all responses to numerical data and encoding NA values correctly (the survey includes an NA response as a negative number that changes value depending on the question and response).

The three classifiers that we used were logistic regression, random forest, and support vector machine. We wanted to use these three techniques because they take different approaches to classification which could help increase the robustness of our results.

Due to the ease in deploying the models (CO status has two options; present or not present). We can use the classification report, accuracy, and misclassification rate to judge the performance of the models after the data is split into training and testing sets and 5-fold cross-validation.

For each classifier, the data was split into features and target:

model1target = "MONOXIDE"

X1 = df\_model1.drop(columns=[model1target]).values

y1 = df\_model1[model1target].values

The data was cross validated using a function that was included in the full scikit-learn pipeline of each classifier:

def cvf(pipe,X,y, n\_splits):

    accs = cross\_val\_score(pipe,

                       X,

                       y,

                       cv=KFold(n\_splits=n\_splits, random\_state=0))

    print('The average accuracy score of the model is ', round(accs.mean(), 3))

    print('The std deviation of the accuracy score is ', round(accs.std(), 3))

    return round(accs.mean(), 3)

Each model was also scaled and placed into the pipeline:

pipe\_logit = Pipeline([('StandardScaler', ss), ('Logistic', logit)])

pipe\_rf = Pipeline([('StandardScaler',ss), ('Random Forest', RandomForestClassifier(n\_estimators=100, max\_depth=10, min\_samples\_leaf=10, random\_state=0))])

pipe\_svm = Pipeline([('StandardScaler',ss), ('SVC', SVC(random\_state=0))])

The cross validated data models each ran, and we obtained the following accuracies:

model Logistic ...

The average accuracy score of the model is 0.806

The std deviation of the accuracy score is 0.014

CPU times: user 36.4 ms, sys: 888 µs, total: 37.3 ms

Wall time: 37.5 ms

model Random Forest ...

The average accuracy score of the model is 0.806

The std deviation of the accuracy score is 0.014

CPU times: user 1.23 s, sys: 9.54 ms, total: 1.24 s

Wall time: 1.24 s

model SVC ...

The average accuracy score of the model is 0.805

The std deviation of the accuracy score is 0.014

CPU times: user 1.71 s, sys: 147 µs, total: 1.71 s

Wall time: 1.71 s

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Accuracy - model with Kfolds=5 cross-validation

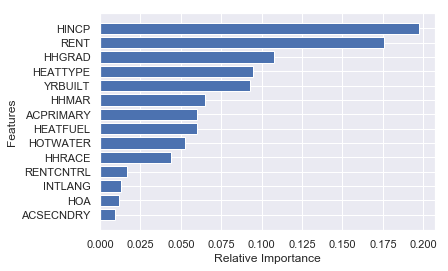
0.806 - Logistic

0.806 - Random Forest

0.805 - SVC

We then used this information to obtain the most important features associated with the random forest model (highest accuracy model).

**According to our model, the most important features are income, rent status, education level, heat type, and year built**



We also ran a classification report on the random forest model to obtain more information about the model’s performance.

precision recall f1-score support

0 0.80 1.00 0.89 1938

1 0.00 0.00 0.00 471

accuracy 0.80 2409

macro avg 0.40 0.50 0.45 2409

weighted avg 0.65 0.80 0.72 2409

Finally, we ran an ensemble of all three models combined using scikit-learn VotingClassifier (a bagging method), but the model’s accuracy did not increase.

model Vote ...

The average accuracy score of the model is 0.806

The std deviation of the accuracy score is 0.014

CPU times: user 3.13 s, sys: 6.23 ms, total: 3.14 s

Wall time: 3.14 s

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Accuracy - model with Kfolds=5 cross-validation

0.806 - Vote

We were happy with the results of the logistic regression and random forest classification models, so we continued to analyze the dataset using these classifiers.

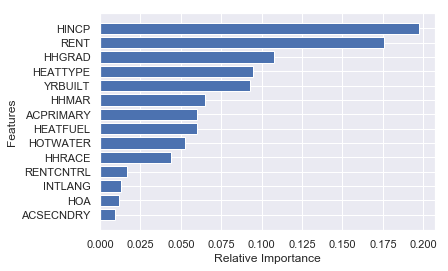
**5. Results.**

Our results reflect the three major models that we ran; logistic regression, support vector machine, and random forest. The random forest model had the highest accuracy and best classification report according to F1-score and accuracy. Even when ensembling the three models together, we did not see any significant increase in model performance. For interpretability of our results, we decided to analyze the original three models. Logistic regression also performed well, and the combination of logistic regression and random forest results provided several key insights.

Random forest models can display feature importance which is helpful for determining the most important features of our dataset according to relative importance. Logistic regression feature coefficients can also be referenced to determine how variability of the most important features affect the outcome of CO monitor status.

As referenced earlier, household income, rent, educational attainment, household heat source, and the year the household was constructed were the most significant predictors of CO monitor status.

**According to our model, the most important features are income, rent status, education level, year built, and heat type**



In fact, when running the model with household income as the only predictor, we found that accuracy was approximately 64%.

For each of these features, we ran a logistic regression to obtain the coefficients of each response option. This allows us to see how the most important features, as indicated by the random forest model, affect the likelihood of CO monitor presence in a household.

We can see how the features change the likelihood of CO monitor presence in a household below:

**YRBUILT -6.495814e-04**

**RENT -1.096360e-04**

**HHGRAD -1.443186e-05**

ACSECNDRY -4.592211e-06

HHMAR -1.519631e-06

HOTWATER -1.203310e-06

HEATFUEL -8.945706e-07

HOA -6.469158e-07

ACPRIMARY -6.423799e-07

RENTCNTRL -4.177953e-07

INTLANG -2.156112e-07

HHRACE -1.717790e-07

**HEATTYPE 3.957692e-08**

**HINCP 3.382413e-07**

Higher income, gas-fueled appliances, lower rent, older homes, and lower education levels increase the likelihood of a household with a CO monitor. Some of these results are interesting because we expected older homes, lower rent, and lower education households to be less likely to have a CO monitor because these features tend to be correlated with lower household income.[[6]](#footnote-6) This is an area that would be a good direction for future analysis

**6. Summary and conclusions.**

CO monitor status in U.S. households can be predicted from a variety of factors listed in the 2017 AHS. Our results allow us to conclude that any efforts to increase the presence of CO monitors in U.S. households should target low income households first. This is because household income is the most important feature according to our random forest classifier and lower income households are less likely than higher income households to have a CO monitor according to the logistic regression model.

We also saw some counterintuitive results in the models that we ran. For example, older homes, lower rent, and lower education households all tend to increase the likelihood of a household having a CO monitor. One possible explanation for this is that newer homes are more likely to have electric appliances instead of gas appliances due to electrification efforts across the U.S.[[7]](#footnote-7) Additionally, the lower rent and graduate status could also be features that are closely correlated with households that have gas appliances. If there is no source of gas combustion (in the case of higher rent and higher education status households), CO generation, a byproduct of gas combustion, is much less likely to occur in a home and the importance of having a CO monitor diminishes.

The 2017 AHS dataset offers many opportunities for data analysis and mining. In the future, it would be helpful to look at different models, optimize model hyperparameters, and expand the scope of features that can be used to predict the presence of a CO monitor in a U.S. household. Further research could also be performed to combine survey results with CO incidents in the U.S. The Federal Emergency Management Administration (FEMA) reports chemical release incident data for the U.S. and lists incidents according to chemical type and location.[[8]](#footnote-8) The geographic indicators in the 2017 AHS could be combined with the FEMA data to look at how CO poisoning severity links to demographic and other appliance factors as listed in the AHS dataset.

**Appendix of Computer Listings (Code for this report only, no GUI)**

# import packages

import pandas as pd

from datetime import datetime

import numpy as np

import re

import warnings

from sklearn.exceptions import DataConversionWarning

warnings.filterwarnings("ignore", category=DeprecationWarning)

warnings.filterwarnings(action='ignore', category=DataConversionWarning)

#The below file was pared down into important features from the full 2017 American Housing Survey dataset. The code for this can be found in R syntax in the Github repo.

COdf = pd.read\_csv("https://nickharbeck.com/wp-content/uploads/2019/11/AHSCO.csv")

#The next few lines of code set all strings as numbers.

for col in COdf[['MONOXIDE','CONTROL','HEATTYPE','HEATFUEL','HOTWATER','ACPRIMARY','ACSECNDRY','HOA','RENTCNTRL','HHMAR','HHGRAD','HHRACE','INTLANG']]:

COdf[col] = COdf[col].apply(lambda x: re.findall('[^0-9-]+([0-9-]+)', str(x)))

COdf[col] = COdf[col].str.get(0)

COdf[col] = pd.to\_numeric(COdf[col])

#Here's a clean and smaller copy of the labels hosted on my site

AHS\_LABELSNH = pd.read\_csv("https://nickharbeck.com/wp-content/uploads/2019/11/ValueLabels.csv")

AHS\_LABELSNH['Value'] = AHS\_LABELSNH['Value'].str.extract('(\d+)', expand=False)

#The cleaned dataset is a copy of the original dataset that includes complete rows

df = COdf.fillna(-10)

df = df[(df['MONOXIDE']>= 0 ) & (df['HOA']>=0) & (df['YRBUILT']>=0) & (df['RENT']>=0) & (df['RENTCNTRL']>=0) & (df['HHMAR']>=0) & (df['HHGRAD']>=0) & (df['HHRACE']>=0) & (df['INTLANG']>=0) & (df['WEIGHT']>=0) & (df['HEATTYPE'] >= 0) & (df['HEATFUEL']>= 0 ) & (df['HOTWATER']>=0) & (df['ACPRIMARY']>=0) & (df['ACPRIMARY']>=0) & (df['ACSECNDRY']>=0) & (df['HINCP']>= 0)]

print("The highest income in the dataset is $",COdf['HINCP'].max(), "per year.")

print("The lowest income in the dataset is $", df['HINCP'].min(), "per year.")

print(df.dtypes)

from sklearn.model\_selection import train\_test\_split

from sklearn.preprocessing import StandardScaler

from sklearn.preprocessing import LabelEncoder

from sklearn.pipeline import Pipeline

from sklearn.model\_selection import KFold

from sklearn.model\_selection import cross\_val\_score

from sklearn.linear\_model import LinearRegression

from sklearn.linear\_model import LogisticRegression

from sklearn.ensemble import RandomForestRegressor

from sklearn.ensemble import RandomForestClassifier

from sklearn.neighbors import KNeighborsRegressor

from sklearn.svm import SVC

from sklearn.metrics import accuracy\_score

ss = StandardScaler()

logit = LogisticRegression(random\_state=0, solver='liblinear')

import matplotlib.pyplot as plt

import seaborn as sns

def col\_histogram(df,column):

plt.figure(figsize=(12,8))

sns.set(style="darkgrid")

sns.distplot(df[column].values)

plt.tight\_layout()

plt.show()

features = ['MONOXIDE','CONTROL','HEATTYPE','HEATFUEL','HOTWATER','ACPRIMARY','ACSECNDRY','HOA','RENTCNTRL','HHMAR','HHGRAD','HHRACE','INTLANG']

for i in features:

col\_histogram(df,i)

detectorscount = COdf[(COdf['MONOXIDE']>= 0 )]

detectorscount = detectorscount.groupby('MONOXIDE').MONOXIDE.count()

# Plot of CO detector status

fig,ax = plt.subplots(figsize = (12,8))

detectorscount.plot(kind='bar', color = '#4363d8')

plt.ylabel('Count of Households with Detectors')

plt.xticks(np.arange(2),('Yes','No'), rotation = 'horizontal')

plt.show()

#The initial model will look at household income alone as a predictor of CO monitor status

HINCPModel = COdf[(COdf['MONOXIDE']>= 0 )&(COdf['HINCP']>= 0 )]

HINCPModel = HINCPModel[['MONOXIDE','HINCP']]

X = HINCPModel['HINCP'].values

y = HINCPModel['MONOXIDE'].values

le = LabelEncoder()

y = le.fit\_transform(y)

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.8, random\_state=0)

X\_train = ss.fit\_transform(X\_train.reshape(-1, 1))

X\_test = ss.transform(X\_test.reshape(-1,1))

logit\_model = logit.fit(X\_train,y\_train)

y\_predicted = logit\_model.predict(X\_test)

print(accuracy\_score(y\_test, y\_predicted))

from sklearn.metrics import confusion\_matrix

from sklearn.metrics import classification\_report

print(confusion\_matrix(y\_test, y\_predicted))

print(classification\_report(y\_test,y\_predicted))

#Now the model will look at all of the features

df\_model1 = COdf[(COdf['MONOXIDE']>= 0 ) & (COdf['HOA']>=0) & (COdf['YRBUILT']>=0) & (COdf['RENT']>=0) & (COdf['RENTCNTRL']>=0) & (COdf['HHMAR']>=0) & (COdf['HHGRAD']>=0) & (COdf['HHRACE']>=0) & (COdf['INTLANG']>=0) & (COdf['WEIGHT']>=0) & (COdf['HEATTYPE'] >= 0) & (COdf['HEATFUEL']>= 0 ) & (COdf['HOTWATER']>=0) & (COdf['ACPRIMARY']>=0) & (COdf['ACPRIMARY']>=0) & (COdf['ACSECNDRY']>=0) & (COdf['HINCP']>= 0)]

df\_model1 = df\_model1.drop(columns = ["CONTROL", "OMB13CBSA", "WEIGHT"])

model1target = "MONOXIDE"

X1 = df\_model1.drop(columns=[model1target]).values

y1 = df\_model1[model1target].values

#Cross validation pipeline function to increase robustness of models.

def cvf(pipe,X,y, n\_splits):

accs = cross\_val\_score(pipe,

X,

y,

cv=KFold(n\_splits=n\_splits, random\_state=0))

print('The average accuracy score of the model is ', round(accs.mean(), 3))

print('The std deviation of the accuracy score is ', round(accs.std(), 3))

return round(accs.mean(), 3)

pipe\_logit = Pipeline([('StandardScaler', ss), ('Logistic', logit)])

pipe\_rf = Pipeline([('StandardScaler',ss), ('Random Forest', RandomForestClassifier(n\_estimators=100, max\_depth=10, min\_samples\_leaf=10, random\_state=0))])

pipe\_svm = Pipeline([('StandardScaler',ss), ('SVC', SVC(random\_state=0))])

# prepare python dictionary with models to test

pipe\_estimators\_model1 = {}

pipe\_estimators\_model1['Logistic'] = pipe\_logit

pipe\_estimators\_model1['Random Forest'] = pipe\_rf

pipe\_estimators\_model1['SVC'] = pipe\_svm

Kfolds = 5

scores = []

for name, pipe in pipe\_estimators\_model1.items():

print('\n model {} ...'.format(name))

#%time score = cvf(pipe, X1,y1,Kfolds)

start\_time = datetime.now()

score = cvf(pipe, X1,y1,Kfolds)

print(datetime.now()-start\_time)

scores.append((name, score))

print("\n ------------------------------")

sorted\_scores = sorted(scores, key=lambda x: x[1], reverse=True)

print("accuracy - model with Kfolds={} cross-validation".format(Kfolds))

for score in sorted\_scores:

print("{:0.3f} - {}".format(score[1], score[0]))

Model1\_dict = dict(zip(df\_model1.drop(columns=[model1target]).columns, pipe\_rf.steps[1][1].fit(X1,y1).feature\_importances\_))

SortModel1 = pd.Series(Model1\_dict).sort\_values(ascending=True)

print(SortModel1)

SortModel1 = SortModel1.reset\_index()

print('According to the random forest model, the most important features are income, rent status, education level, heat type, and year built')

plt.xlabel("Relative Importance")

plt.ylabel('Features')

plt.yticks(range(len(list(SortModel1['index']))), list(SortModel1['index']))

ax.invert\_yaxis()

importances=pd.Series(RandomForestClassifier(n\_estimators=100, max\_depth=10, min\_samples\_leaf=10, random\_state=0).fit(X1,y1).feature\_importances\_)

plt.barh(range(len(list(SortModel1['index']))), list(SortModel1[0]), align='center')

plt.show()

#We can also use logistic regression to see how the features change the likelihood of CO monitor presence in a household

Model1v2\_dict = dict(zip(df\_model1.drop(columns=[model1target]).columns, (pipe\_logit.steps[1][1].fit(X1,y1).coef\_).flat))

SortModel1v2 = pd.Series(Model1v2\_dict).sort\_values(ascending=True)

print(SortModel1v2)

print("As seen above, higher income, gas-fueled appliances, lower rent, older homes, and lower education levels increase the likelihood of a household with a CO monitor")

#Now lets see if ensembling improves the accuracy

from sklearn.ensemble import VotingClassifier

pipe\_ensemble = Pipeline([('StandardScaler', ss), ('Vote', VotingClassifier(estimators=[('Logit', pipe\_logit), ('rf', pipe\_rf), ('svc', pipe\_svm)], voting='hard'))])

pipe\_estimators\_model2 = {}

pipe\_estimators\_model2['Vote'] = pipe\_ensemble

Kfolds = 5

scores = []

for name, pipe in pipe\_estimators\_model2.items():

print('\n model {} ...'.format(name))

#%time score = cvf(pipe, X1,y1,Kfolds)

start\_time=datetime.now()

score = cvf(pipe, X1,y1,Kfolds)

print(datetime.now() - start\_time)

scores.append((name, score))

print("\n ------------------------------")

sorted\_scores = sorted(scores, key=lambda x: x[1], reverse=True)

print("accuracy - model with Kfolds={} cross-validation".format(Kfolds))

for score in sorted\_scores:

print("{:0.3f} - {}".format(score[1], score[0]))

df\_model2 = COdf[(COdf['MONOXIDE']>= 0 ) & (COdf['HOA']>=0) & (COdf['YRBUILT']>=0) & (COdf['RENT']>=0) & (COdf['RENTCNTRL']>=0) & (COdf['HHMAR']>=0) & (COdf['HHGRAD']>=0) & (COdf['HHRACE']>=0) & (COdf['INTLANG']>=0) & (COdf['WEIGHT']>=0) & (COdf['HEATTYPE'] >= 0) & (COdf['HEATFUEL']>= 0 ) & (COdf['HOTWATER']>=0) & (COdf['ACPRIMARY']>=0) & (COdf['ACPRIMARY']>=0) & (COdf['ACSECNDRY']>=0) & (COdf['HINCP']>= 0)]

df\_model2 = df\_model2.drop(columns = ["CONTROL", "OMB13CBSA", "WEIGHT"])

model2target = "MONOXIDE"

X1 = df\_model2[['HOA','YRBUILT','RENT','RENTCNTRL','HHMAR','HHGRAD','HHRACE','INTLANG','HEATTYPE','HEATFUEL','HOTWATER','ACPRIMARY','ACSECNDRY','HINCP']].values

y1 = df\_model2['MONOXIDE'].values

y1 = le.fit\_transform(y1)

X1\_train, X1\_test, y1\_train, y1\_test = train\_test\_split(X1, y1, test\_size=0.8, random\_state=0)

LogitModel1 = logit.fit(X1\_train,y1\_train)

y1\_predicted = logit.predict(X1\_test)

print(confusion\_matrix(y1\_test, y1\_predicted))

print(classification\_report(y1\_test,y1\_predicted))

1. Carbon monoxide poisoning. 2019. Mayo Clinic. Accessed from <https://www.mayoclinic.org/diseases-conditions/carbon-monoxide/symptoms-causes/syc-20370642> [↑](#footnote-ref-1)
2. Carbon Monoxide Information Center. 2019. United States Consumer Product Safety Commission. Accessed from <https://www.cpsc.gov/Safety-Education/Safety-Education-Centers/Carbon-Monoxide-Information-Center> [↑](#footnote-ref-2)
3. Ault, Kimberly. Estimates of Non-fire Carbon Monoxide Poisoning Deaths and Injuries. 1997. Accessed from <https://www.cpsc.gov/s3fs-public/pdfs/foia_3512c1f.pdf> [↑](#footnote-ref-3)
4. About this Survey. 2019. American Housing Survey (AHS). U.S. Census Bureau. Accessed from <https://www.census.gov/programs-surveys/ahs/about.html> [↑](#footnote-ref-4)
5. The full 2017 AHS dataset can be accessed at <https://www.census.gov/programs-surveys/ahs/data/2017/ahs-2017-public-use-file--puf-/ahs-2017-national-public-use-file--puf-.html> [↑](#footnote-ref-5)
6. Douglas-Hall, Ayana and Chau, Michelle. 2007. Parents’ Low Education Leads to Low Income, Despite Full-Time Employment. Accessed from <http://www.nccp.org/publications/pub_786.html> [↑](#footnote-ref-6)
7. Tsao, Jeffrey Y. Et. al. 2018. The electrification of energy: Long-term trends and opportunities. DOI: <https://doi.org/10.1557/mre.2018.6> Accessed from <https://www.cambridge.org/core/journals/mrs-energy-and-sustainability/article/electrification-of-energy-longterm-trends-and-opportunities/10440EBB31859DBE848C28AC70AAE8FB>. [↑](#footnote-ref-7)
8. National Fire Incident Reporting System. Accessed from <https://www.nfirs.fema.gov/> [↑](#footnote-ref-8)