

**Understanding the Effects of
Temperature on the Philadelphia
Criminal Justice System**

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I. Introduction

Recent years have seen a trend toward criminal justice reform. Ideas such as abolishing prisons, decriminalizing marijuana, and changing the bail system have grown in popularity. One of the biggest changes to the criminal justice system is the election of progressive district attorneys. In 2017, Philadelphia was one of the first cities to elect such a prosecutor in Larry Krasner, a former public defender and activist who had even sued the Philadelphia Police. With a new emphasis being placed on reforming the criminal justice system, there has also been an increased focus on using data to identify and reform the areas of the system that are most in need of improvement.

In this paper, I hope to use the data-driven criminal justice reform movement as

a basis to assess the human bias that occurs in the two initial steps of the criminal justice system: arresting and charging. Arrests occur when a police officer takes a suspect into custody with a reason to believe that the person has committed a crime. An assistant district attorney or member of the district attorney's office then decides whether to press charges against the individual and what charges to bring. Arrests can occur anywhere - from a house to a public space to the police station itself. Charging is then usually decided by a lawyer who works in an office. Using Philadelphia data, I plan to study if both arrests and charges are influenced by the temperature outside.

Though arrests can occur outdoors, charges are always filed and decided indoors. While there should be no effect of outside temperature on inside decision-making for the district attorney's office, I hope to show that all players in the criminal justice system are affected by outside

temperature, either directly or indirectly. There is existing literature that shows that crime tends to increase in the current period during good weather (Ranson 2014; Blakeslee and Fishman 2017; Horrocks and Menclova 2011) and increase in the next period when there is bad weather in the current period (Jacob, Lefgren, and Moretti 2005). Prior research also shows that decision-making, both in the criminal justice system (Heyes and Saberian 2019) and in other sectors (Busse et al. 2015; Conlin, O'Donoghue, and Vogelsang 2007), is also affected by outside temperature. Combining this existing research, it is not a big step to say that higher temperatures increase crime, change the temperament of decision-makers, and thus increase the number of arrests and charges filed in Philadelphia. As far as I have seen, there is prior research on weather impacting crime and immigration court decisions but none on arrests and charges, making this potentially the first of its kind.

I conduct my research using two data sets. The first comes from the Philadelphia District Attorney's Public Data Dashboard, a collection of daily data reports broken down by each step in the criminal justice process. I focus my efforts on the daily arrest and daily charging data from each police district, though this research could be applied to other data sets going forward. The second data set comes from the Franklin Institute, which serves as the National Weather Service's official weather collecting and recording station for Philadelphia.

The rest of this paper is laid out as follows: Section II details the existing literature related to my topic, Section III further describes the data sets that were used and cleaned, Section IV details the methodology of the regressions, Section V discusses the output and results of the models, and Section VI concludes with a summary and final discussion of the paper.

II. Literature

Economists, psychologists, and criminologists have long been interested in understanding crime. Prior research on this subject has found a correlation between temperature and crime, temperature and other areas of criminal justice, and weather and temperament. In my search, I was unable to find research connecting arrests and charges with weather patterns, in particular temperature, but these three other areas of research together form a good foundation for my proposed topic.

Several studies have examined the impact of temperature on crime patterns. Most adjust their data to use crime rates rather than total crime numbers, to include multiple weather variables, and to study patterns over time. Using a three-year panel of monthly crime and weather data across the United States, Ranson found that higher temperatures are statistically significant in causing an increase in crime rates (2014). The overall results were nonlinear and

suggested that, specifically, property crimes are only affected by temperature up to 50 °F (Ranson 2014). A study on Indian agriculture also revealed that variation in temperature impacts the incidence of both violent and property crimes (Blakeslee and Fishman 2017). Another foreign study, this time out of New Zealand, found that temperature impacts the number of violent and property crimes reported (Horrocks and Menclova 2011).

Given that several studies have found a correlation between weather and crime in the current period, there has been subsequent research studying whether weather in the current period reduces or lags crime in future periods. Using weather from the previous period as an instrument in the current period, Jacob, Lefgren, and Moretti looked at whether poor weather reduces crime overall or if it just pushes crime to the next period (2005). The paper found that there is serious evidence for the

displacement of crime overtime. Bad weather may reduce crime now, but most of that crime will still occur but later (Jacob, Lefgren, and Moretti 2005). Knowing that temperature can be both an instrumental variable and an independent variable shows that weather can have a major impact on crime.

Aside from its correlation with crime reporting, temperature has also been studied in connection to other areas of the criminal justice system. A research paper from the American Economic Journal of Applied Economics studied whether judges, who work exclusively indoors in climate-controlled rooms with little physical activity, and their decisions are impacted by the weather outside. The paper looked at immigration court outcomes and found that a 10 °F increase in temperature reduces favorable decisions for the applicant by 6.55 percent (Heyes and Saberian 2019). The study also found a decrease in the grant rate

for parole applicants when temperatures were high (Heyes and Saberian 2019).

Overall, this research shows that outdoor temperature influences not just the occurrence of crime but also indoor decision-making in the entire criminal justice system.

Not only has the temperature been shown to impact the criminal justice system, but it has also been revealed to have an impact on decision-making. A study found that purchasing cars is largely impacted by that day's weather (Busse et al. 2015). For example, a convertible is more likely to be purchased on a day with nice weather, even if that day occurs during a typically cold period like winter (Busse et al. 2015). A similar study found that purchases from a catalog tend to be overinfluenced by the current weather. Specifically, the paper estimates that the likelihood of return a purchase increases by 3.95 percent if the temperature on the day of the purchase

declines by 30°F (Conlin, O'Donoghue, and Vogelsang 2007). Therefore, we can see that decision-making can be influenced by fluctuations in temperature.

If temperature impacts the number of crimes, the decision-making of judges and law enforcement officials, and the general decision-making ability of people, then it would stand to follow that weather, especially temperature, impacts the number of arrests and criminal charges brought forward as these are decisions made by law enforcement officials. With no prior research on this study, I hope to use the existing research cited above to draw the conclusion that decisions made by law enforcement officials are subject to the temperature outside.

III. Data

There were two types of data used in this paper: crime data and weather data. The crime data comes from the Public Data Dashboard of the Philadelphia District

Attorney's Office. Released on October 3 of this year, the Dashboard offers datasets and summaries regarding all steps of the criminal justice system in Philadelphia. This is the first time this data has been transparent and revealed to the general public, making this analysis one of the first of its kind. The data involving arrests is broken down by police district. The data also includes the date and type of offense, of which there are 18 in total, in a table that totals the number of arrests for each type of offense in every police district on each day. I also use a similar-style dataset for charging to see if there are different results for other parts of the justice system. The data is available for January 1, 2014 through the current date, and Table 1 shows a summary of the descriptive statistics for both data sets.

The weather data comes from the website of the Franklin Institute, a Philadelphia museum and research center dedicated to science, technology, and

education. The Franklin Institute has housed the National Weather Service's official weather observation station for the city of Philadelphia since 1993, but it has functioned as the weather-recording hub for the city since 1872. The publicly-available dataset offered by the Franklin Institute offers daily weather data for almost every year between 1872 and 2018. Since 1993, the data has been collected on the roof of the Franklin Institute's 20th and Benjamin Franklin Parkway building. The dataset includes the following variables: date, maximum temperature (°F), minimum temperature (°F), the amount of rain and melted snow (inches), the amount of snowfall (inches), and the depth of snow on the ground (inches).

Both the crime and weather data required cleaning in order to be used. First and foremost, the District Attorney's arrest data is broken down into 25 police districts and the charging data into 26 police districts.

However, according to the Philly Police Department's website, there are only 21 police districts in the city. There are only a handful of offenses recorded for the five discrepancy districts, but I removed the 4th, 23rd, 44th, 71st, and 77th districts from the datasets in case they are former districts or were mistakenly included. A map of the remaining police districts can be seen in Figure 1. Second, the dataset begins on January 1, 2014 and is continually updated by the District Attorney's Office. The weather data does not include 2014, the first half of 2015, and the second half of 2018. As such, I have had to reduce my data points to the period between August 1, 2015 and May 31, 2018.

A third issue that required cleaning occurred because the weather data was missing or incomplete for several dates in the three-year period. Some days were fully missing from the set, while others lacked precipitation data or temperature data. Some

precipitation data was recorded as a “T,” meaning that there was a trace amount of snow or rain but not enough to get a measurement. Counting those data points as 0s would not be accurate since there was some precipitation. This discrepancy could potentially skew the data, and as such, those data points were omitted.

Merging the data was relatively simple after the two datasets were cleaned. Both datasets were available in Excel or .csv files, allowing me to just open them in Excel. I copied the weather data into the crime data sheet, making sure to match the dates as the formatting and spacing was slightly different between the two sets. After removing the discrepancy police districts, excluding the missing weather data points, and merging the two datasets together, I was left with 1,002 days of data for 21 police districts for the crime data involving arrests and criminal charges.

IV. Methodology

The crime data from the District Attorney’s Office is broken down into 18 offenses. With the daily data broken down into so many categories across multiple police districts, most entries in the data table ended up having a value of zero. To combat this outcome, past literature has run the regression model using the crimes grouped into broad categories. While the District Attorney’s Dashboard offers violent, property, and drug crimes as these umbrella groups, I chose to use violent, financial, and substance crimes as my categories. My substance grouping and the DA’s drug grouping consist of the same three crimes: drug possession, drug sales, and DUI. The following are considered violent crimes in this paper: homicide, rape, and two types of aggravated assault. Financial crimes, which have a monetary or property aspect to them, include different types of burglary, theft, and robbery. Occasionally, robbery is classified as a violent crime as violence is used, but I

chose to consider it a financial crime since the intention behind it is to take some else's possessions. The data provides a separate "All Other Offenses" category which I ignore as there is no clear definition on what crimes are included in that grouping.

Each entry in the data table is broken into a date and a district. For example, August 1, 2015, the first day in the dataset, has 21 entries - one for each police district. The model then treats the daily data from each district as separate data points. I chose to do this because some police districts are likely to have more arrests if they have a large area, house a large population, or show other characteristics that may influence crime. I had hoped to combat this by controlling for arrests or charges per X number of persons in the district. However, because police districts do not offer data on their populations and do not directly align with zip codes such that census data can be used, I needed to find another way to control

for the police district. An area for further research could be to request population metrics for each police district or to use weighted populations to convert zip codes to police districts.

A. Arrests

I estimate the following ordinary least squares model:

$$(1) Y = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + u$$

where Y is the difference in arrests from the mean for that specific type group of crimes.

Specifically, Y is calculated as:

$$(2) Y = \text{actual}_{\text{arrests}} - \text{mean}_{\text{arrests}}$$

where $\text{actual}_{\text{arrests}}$ is the number of arrests that occur on a given day and $\text{mean}_{\text{arrests}}$ is the average number of arrests per day for the entire period of study. In equation (1), x_1 is the minimum daily temperature in Philadelphia, and x_2 is the day of the week (1 = Sunday, 2 = Monday, ..., 7 = Saturday). x_3 and x_4 represent the average number of arrests per crime group subtracted from the real number of arrests in the other two crime

categories not being studied in that regression, while u is the error term. x_2 , the day of the week, is included as certain crimes may be more likely to occur on weekends as more people are out, and more mind-altering substances are consumed. x_3 and x_4 could potentially have: a negative relationship with Y as more arrests in those two categories may redirect resources from arrests in the category of study, or a positive relationship with Y as arrests above the mean in other crime types may signify a higher presence of police and thus higher arrests across the board.

I chose to set Y equal to the difference between that day's quantity of arrests and the mean in a specific category rather than just setting Y equal to that day's number of arrests in a specific category. For example, if the daily quantity equals the overall mean, then the model is attempting to correlate the variables with a Y of 0. If the daily quantity of arrests is less than the

mean, then the regression is predicting a negative Y value, and vice versa. The goal of this analysis is to see how temperature affects variation in arrests, and just setting Y to the total number would not give a reference point to draw conclusions. The coefficient of interest is B_1 , which tells us how the daily minimum temperature affects the difference between the actual number of arrests and the mean number of arrests for each category of crime. For example, B_1 is how the lowest temperature on a given day impacts how close that day's quantity of crime is to the daily average level of crime, holding all other variables equal.

I ran this regression three times with the following three derived models:

$$(1a) Y_{\text{substance}} = B_0 + B_1X_1 + B_2X_2 + B_3X_{\text{violent}} + B_4X_{\text{financial}} + u$$

$$(1b) Y_{\text{violent}} = B_0 + B_1X_1 + B_2X_2 + B_3X_{\text{substance}} + B_4X_{\text{financial}} + u$$

$$(1c) Y_{\text{financial}} = B_0 + B_1X_1 + B_2X_2 + B_3X_{\text{violent}} + B_4X_{\text{substance}} + u$$

Each model studies how certain variables influence the difference between the actual and the mean quantity of arrests in a day. For example, (1a) predicts the difference between the real number and the average number of substance arrests in a day based on the minimum temperature, day of the week, the difference between the actual and the mean number of violent crimes on the same day, and the difference between the actual and the average number of financial crimes on the same day.

B. Charges

After an arrest, the district attorney's office of the jurisdiction in which a crime occurred decides about whether to charge the person with the crime. The charges in a criminal case are decided by an Assistant District Attorney, as opposed to the police officer who made the arrest, based on the facts and evidence of the case. Unlike arrests, charges are decided and brought forth entirely inside of buildings, and

therefore should not be affected by the weather outside. This paper looks to study if this idea is true using the following regression models adapted from the arrest model:

$$(1a) Y_{\text{substance}} = B_0 + B_1X_1 + B_2X_2 + B_3X_{\text{violent}} + B_4X_{\text{financial}} + u$$

$$(1b) Y_{\text{violent}} = B_0 + B_1X_1 + B_2X_2 + B_3X_{\text{substance}} + B_4X_{\text{financial}} + u$$

$$(1c) Y_{\text{financial}} = B_0 + B_1X_1 + B_2X_2 + B_3X_{\text{violent}} + B_4X_{\text{substance}} + u$$

where B_1 and B_2 are the same as the arrest model, and Y , B_3 , and B_4 now represent the difference between the actual quantity of charges and the mean number of charges for each crime category per day and police district.

V. Results

A. Arrests

Charts 1-3 represent the regression outputs for substance crimes, financial crimes, and violent crimes, respectively.

Chart 1 shows the results for predicting the difference between the actual number of substance arrests each day and the mean number of substance arrests. Of our four independent variables, the coefficient on minimum temperature was the only one statistically significant at a .01 level with a p-value of .00634. The other three variables (day of the week the arrest occurred, difference in financial arrests, and difference in violent arrests) are shown to be statistically significant at a .001 level. This high level of significance in combination with high coefficients (0.213206, 0.281796, and 0.487080, respectively) is interesting to note and implies that these three variables have a positive correlation with the difference in substance arrests. The coefficient of interest, B_1 , is $-.004171$, and implies that an increase in the minimum temperature reduces the actual number of arrests for substance crimes in a day. In fact, an increasing minimum temperature moves

the number of arrests further from the mean amount of arrests. One potential problem with this model is the adjusted R-squared of only .04072.

Chart 2 displays the results for the regression regarding the difference in arrests for financial crimes. Unlike the results for substance crimes, all four independent variables have statistical significance at the .001 level. The coefficients on the three non-interest variables are large and positive, implying a positive relationship between the difference in arrests for financial crimes and the day of the week, difference in substance arrests, and difference in violent arrests. The coefficient of interest on minimum temperature is $.0032978$ and suggests that a high minimum temperature increases our Y variable. A high enough minimum temperature may even cause the actual number of arrests to be greater than the mean, suggesting hotter weather increases the number of arrests for financially-

motivated crimes. Higher temperatures tend to drive people outdoors, making the opportunity for crimes like burglary more prevalent. However, like the substance arrests results, arrests for financial crimes have a low adjusted R-squared of 0.01863.

Chart 3 shows the results of the regression for the difference between the number of arrests and the mean number of arrests for violent crimes. In this model, our variable of interest along with the difference in substance arrests and the difference in financial arrests are statistically significant at the .001 level. The day of the week that the crime occurs is only significant at a .05 level, implying that violent crimes may not be as influenced by days when more people are out in public and when people tend to be most inebriated. Our coefficient of interest is 0.0027561 and suggests that, like with financial arrests, a higher minimum temperature increases the actual number of arrests for violent crimes. Combining this

with the significance of day of the week, we can hypothesize that violent crime occurs when more people are out of their homes, though that does not necessarily imply it will happen on weekends.

B. Charges

Charts 4-6 represent the regression outputs for substance crimes, financial crimes, and violent crimes, respectively.

Chart 4 shows the output for predicting the difference in charges for substance crimes. Day of the week, the difference in charges for violent crimes, and the difference in charges for financial crimes are all statistically significant at the .001 level and have positive coefficients. This suggests that an increase in violent or financial charges increases the number of substance charges, which could potentially be happening because those being charged with substance crimes are facing charges in other categories as well. The positive and large coefficient on day of the week implies

that more charges for substance charges are likely to be filed later in the week when people are more likely to go to bars, clubs, concerts, and other places that drugs and alcohol are popular.

In this model, minimum daily temperature is only statistically significant at the .05 level. The coefficient is also negative and much smaller than the coefficients on the other independent variables. Therefore, minimum temperature, and temperature in general, likely does not play a role in the number of charges filed for substance crimes such as DUIs, possession, and drug sales. Another potential issue that also occurred in the three arrest models is that the adjusted R-squared is very low and equals only 0.03929 in this model. While our variables have been at least somewhat statistically significant, there seems to be something missing from the analysis or models.

Chart 5 shows the regression results for the difference in charges for financial

crimes from the mean. All four independent variables are statistically significant at the .001 level. However, all the coefficients on these variables are positive yet very small. It would seem to imply that there is a positive statistical significance between the variables and the difference in charges for financial crimes. Financially motivated crimes tend to be charged more when it is later in the week, the daily minimum temperature is high, and there have been other charges filed for violent and substance crimes. As we continue to see, the adjusted R-squared for the model is very small, which casts doubt on the model.

Chart 6 represents the output for the difference in the actual number of charges for violent crimes and the average number of charges for violent crimes. For the first time in this analysis, there is a variable that has no statistical significance. The day of the week that the crime occurs does not appear to be correlated with the difference in the

number of charges filed for violent crimes. This reinforces the idea from the violent arrests model that violent crimes will occur regardless of the day, and thus the perpetrators will be arrested and charged with the same lack of consistency across time. The other three variables, however, show a statistical significance at the .001 level with positive coefficients. The coefficient on daily minimum temperature is 0.0030043 and, while very small, suggests that an increase in the lowest temperature of a day will increase the quantity of charges for violent crimes, potentially even pushing the number over the mean quantity of charges. Like the other five models, this model also has a low adjusted R-squared of 0.02013.

VI. Conclusion

In this paper, I looked to show that there was a correlation between temperature and the daily number of arrests and criminal charges brought in the Philadelphia criminal

justice system. In all six of the models, there was statistical significance at the .05 level with four of the six models offering statistical significance at the .001 level for the minimum temperature variable. Substance crimes, such as DUIs, drug possession, and drug sales, experience negative relationships with daily minimum temperature. Minimum temperature is less significant for substance crimes than for the other two groups, suggesting that temperature plays less of a role in the arrests and charges brought for substance crimes. Meanwhile, violent crimes and financially motivated crimes each saw positive relationships with the lowest daily temperature. These findings are consistent with past literature that has showed a positive correlation between reported crimes and temperature.

It is interesting to note that temperature was statistically significant with both arrests and charges considering how the

two are different from each other. Arrests are almost always conducted by police officers in public or outdoor settings, while charges are always decided by those who work in a district attorney's office, which is an indoor setting. The findings were stronger for arrests but the presence of statistical significance for charges suggests that those who work indoors are also influenced by outdoor temperature. This has been confirmed by past literature (Heyes and Saberian 2019).

Despite my general findings, there are a few potential limitations of this research. First, I was unable to find the population and demographic breakdown for each police district in the data set. To control for this, I treated each date at each police district as a separate data point. Going forward, it would be beneficial to instead control for population size and other factors such as poverty rate and racial breakdown in each police district. Second, I had to use

only one weather point for all police districts, which may have skewed the results. For example, the 8th police district, which has its headquarters about 12.5 miles from the weather collecting station, is studied using the same temperature as the 9th police district in which the weather station is located. Finding more localized weather stations could be a potential fix to this problem going forward. Third, the definition of violent crime is not the same across entities. Had I included robbery as a violent crime like the Philadelphia District Attorney's Office suggested, I may have gotten different results. However, my definitions of the three crime groups look at intent, which I believe to be the best measure since I am studying whether temperature impacts decision-making.

Fourth and final, the six models produced low adjusted R-squared. In each of the six regressions, the adjusted R-squared was less than 0.05, meaning that less than 5

percent of variation in the number of arrests and charges can be explained by the temperature. Therefore, the model is likely missing variables that can best explain the variation in arrests and charges from their means. On the other hand, the relatively low adjusted R-squared could suggest that the number of arrests and charges is difficult to predict because these measures rely so heavily on police officers and those who commit crime, both of whom can be unpredictable groups. Regardless, there is likely a gap in the model. Further research should be used to determine if there are

other variables are at play as well, especially regarding other weather measures.

Overall, there is some connection between temperature and the criminal justice system. Both indoors and outdoors workers in this system seem to be affected by the weather outside. Finding a way to avoid or at least mitigate these biases should be a goal of the agency making these decisions as the lives and freedom of everyday citizens depend on a fair, unbiased system that includes 'justice' in its name for a reason.

Appendix

Table 1: Descriptive Statistics for the Crime Data

Crime Group		Mean	Median	Standard Deviation
Substance <i>Drug Possession, Drug Sales, DUI</i>	Arrests	1.906	1	3.734
	Charges	1.870	1	3.724
Financial <i>Robbery (Gun), Robbery (Other), Burglary (Residential), Burglary (Commercial), Theft (Motor Vehicle Tag), Theft (From Person), Theft (From Auto), Theft (Retail), Theft, Theft (Auto)</i>	Arrests	0.955	1	1.363
	Charges	1.034	1	1.606
Violent <i>Homicide, Rape, Aggravated Assault (Gun), Aggravated Assault (Other)</i>	Arrests	0.536	0	0.929
	Charges	0.550	0	0.998

Figure 1: Map of the 21 Philadelphia Police Districts (courtesy of the Philadelphia PD)

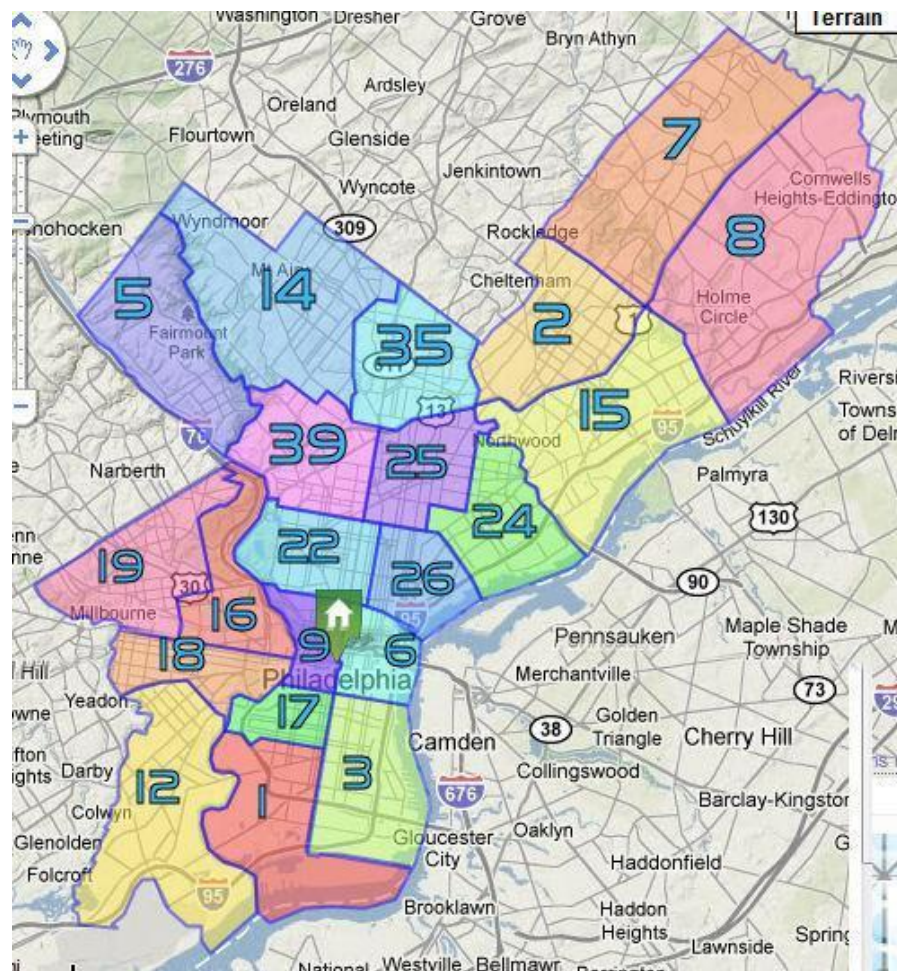


Chart 1: Arrests for Substance Crimes

```
Call:
lm(formula = sub_Dif ~ Min_Temp + Day_of_week + Fin_Dif + Vio_Dif,
    data = group)

Residuals:
    Min     1Q  Median     3Q    Max
-8.869 -1.691 -0.940  0.258 73.786

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.426399   0.092684  -4.601 4.24e-06 ***
Min_Temp     -0.004171   0.001528  -2.730 0.00634 **
Day_of_week   0.213206   0.012584  16.943 < 2e-16 ***
Fin_Dif       0.281796   0.018572  15.173 < 2e-16 ***
Vio_Dif      0.487080   0.027241  17.880 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.658 on 21037 degrees of freedom
Multiple R-squared:  0.0409,    Adjusted R-squared:  0.04072
F-statistic: 224.3 on 4 and 21037 DF,  p-value: < 2.2e-16
```

Chart 2: Arrests for Financial Crimes

```
Call:
lm(formula = Fin_Dif ~ Min_Temp + Day_of_week + Sub_Dif + Vio_Dif,
    data = group)

Residuals:
    Min     1Q  Median     3Q    Max
-2.5009 -0.8945 -0.2136  0.2328 31.2641

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.1035926   0.0342309  -3.026 0.002479 **
Min_Temp     0.0032978   0.0005637   5.850 5.00e-09 ***
Day_of_week   0.0159475   0.0046766   3.410 0.000651 ***
Sub_Dif       0.0384163   0.0025318  15.173 < 2e-16 ***
Vio_Dif      0.0827014   0.0101183   8.173 3.16e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.351 on 21037 degrees of freedom
Multiple R-squared:  0.01881,    Adjusted R-squared:  0.01863
F-statistic: 100.8 on 4 and 21037 DF,  p-value: < 2.2e-16
```

Chart 3: Arrests for Violent Crimes

```

Call:
lm(formula = Vio_Dif ~ Min_Temp + Day_of_Week + Sub_Dif + Fin_Dif,
    data = group)

Residuals:
    Min       1Q   Median       3Q      Max
-2.8041 -0.5237 -0.4450  0.4606 12.4511

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0359859  0.0232917  -1.545  0.1224
Min_Temp     0.0027561  0.0003834   7.189 6.74e-13 ***
Day_of_Week  -0.0077179  0.0031820  -2.425  0.0153 *
Sub_Dif       0.0307332  0.0017188  17.880 < 2e-16 ***
Fin_Dif       0.0382772  0.0046831   8.173 3.16e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9188 on 21037 degrees of freedom
Multiple R-squared:  0.02228, Adjusted R-squared:  0.02209
F-statistic: 119.8 on 4 and 21037 DF, p-value: < 2.2e-16

```

Chart 4: Charges for Substance Crimes

```

Call:
lm(formula = Sub_Dif ~ Min_Temp + Day_of_Week + Vio_Dif + Fin_Dif,
    data = charges)

Residuals:
    Min       1Q   Median       3Q      Max
-12.786 -1.674 -0.955  0.233  70.632

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.745950  0.092684  -8.048 8.83e-16 ***
Min_Temp     -0.003286  0.001524  -2.156  0.0311 *
Day_of_Week   0.227109  0.012567  18.072 < 2e-16 ***
Vio_Dif       0.453858  0.025282  17.952 < 2e-16 ***
Fin_Dif       0.196133  0.015712  12.483 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.65 on 21037 degrees of freedom
(1 observation deleted due to missingness)
Multiple R-squared:  0.03948, Adjusted R-squared:  0.03929
F-statistic: 216.1 on 4 and 21037 DF, p-value: < 2.2e-16

```

Chart 5: Charges for Financial Crimes

```

Call:
lm(formula = Fin_Dif ~ Min_Temp + Day_of_Week + Vio_Dif + Sub_Dif,
    data = charges)

Residuals:
    Min       1Q   Median       3Q      Max
-2.443 -0.981 -0.275  0.241  59.179

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.2647179  0.0405411  -6.530 6.74e-11 ***
Min_Temp     0.0027812  0.0006661   4.176 2.98e-05 ***
Day_of_Week  0.0314592  0.0055324   5.686 1.31e-08 ***
Vio_Dif      0.0608096  0.0111292   5.464 4.71e-08 ***
Sub_Dif      0.0374870  0.0030031  12.483 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.596 on 21037 degrees of freedom
(1 observation deleted due to missingness)
Multiple R-squared:  0.01335, Adjusted R-squared:  0.01316
F-statistic: 71.15 on 4 and 21037 DF, p-value: < 2.2e-16

```

Chart 6: Charges for Violent Crimes

```

Call:
lm(formula = Vio_Dif ~ Min_Temp + Day_of_Week + Sub_Dif + Fin_Dif,
    data = charges)

Residuals:
    Min       1Q   Median       3Q      Max
-2.8413 -0.5401 -0.4608  0.4433 15.5721

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.1502645  0.0251016  -5.985 1.12e-09 ***
Min_Temp     0.0030043  0.0004120   7.288 1.12e-13 ***
Day_of_Week  0.0001118  0.0034275   0.032 0.9740000
Sub_Dif      0.0332446  0.0018519  17.737 1.12e-34 ***
Fin_Dif      0.0233047  0.0042652   5.464 4.71e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9879 on 21037 degrees of freedom
(1 observation deleted due to missingness)
Multiple R-squared:  0.02032, Adjusted R-squared:  0.02016
F-statistic: 109.1 on 4 and 21037 DF, p-value: < 2.2e-16

```

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