The Effects of the COVID-19 Pandemic on Crime in Chicago, IL and Houston, TX

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Introduction

The disruption caused by the COVID-19 pandemic significantly altered the lives of millions of Americans, with many spending an increased amount of time at home and less time in public places. The financial health of many Americans were also substantially threatened, as the U.S. unemployment rate soared causing many households to lose key sources of their income. While the impacts of the pandemic continue to evolve, the economic and social shocks to the daily lives of Americans creates an opportunity to analyze a significant social outcome: criminal behavior.

There are two theories of crime that are significant to understanding criminal behavior: Cohen and Felson's (1979) routine activity theory and Gary Becker's *Crime and Punishment* (1968). Cohen and Felson proposed that any disruptions to the convergence of time and space for criminal activity to occur between offenders, targets, and guardians is a primary driver of crime trends. For example, if there are less suitable targets present in a populated area such as Times Square in New York City, then there is ultimately a decrease in criminal opportunity for a motivated offender. Since the COVID-19 pandemic has caused many individuals to spend more time in their homes and less time in public spaces, this affects the spatial and temporal distribution of crime.

In economics, the most significant contribution to studying crime is Gary Becker's *Crime and Punishment* (1968). Becker uses rational choice theory to model an individual's decision to commit a crime. In this model, individuals are faced with not only weighing the marginal benefits and marginal costs of committing a crime, but the probability and severity of punishment. If the expected utility for committing a crime outweighs the perceived costs, Becker demonstrates that a rational person would commit a crime. In a study of adolescents who committed serious criminal offenses completed by Loughran et. al (2016), the findings support Gary Becker's theory at the individual level as the adolescents surveyed acted in accordance with the perceived benefits, costs, and probability of getting caught. While Gary Becker's theory has been largely upheld by economics scholars, the paper still has faced skepticism. For example, Hodgson (2012) argues that rational choice theory is too general and that Becker's theoretical application for crime relies on too many additional assumptions.

Using an expected utility approach as the framework, many economists examine the behavior of crime rates in response to exogenous shocks, such as natural disasters and economic recessions. While Zahnow et. al (2017) finds that crime rates remained stable over time following the 2011 Queensland floods in Brisbane, Australia, there were areas of the city that were more susceptible to property crime following the disaster than others. Similarly, Leitner et. al. (2011) estimates that eleven out of sixty-four Louisiana parishes have a statistically significant decrease in non-violent crimes following the natural disaster of Hurricane Katrina. This study also focuses on the four stages of natural disasters: mitigation, preparedness and planning, emergency and recovery, and reconstruction. This suggests that an effect on crime rates differs temporally which is important information when determining the effects of COVID-19 on crime over an extended period of time.

Similar to the relationship between crime and natural disasters, the impact of economic recessions on crime has been studied. Using state-level panel data over a twenty-year period, Raphael and Winter-Ebmer (2001) finds a significant effect of unemployment on property crime rates. According to the Federal Reserve Bank of Cleveland, the recession caused by COVID-19 disrupted the largest economic expansion in U.S. history and a record-breaking 3.3 million people filed unemployment insurance claims after losing their jobs to public health measures of the pandemic during the week of March 21^{st}. The unexpected losses to income and threats to livelihood faced by many Americans in a short period of time is alarming and poses a potentially significant impact on crime rates.

Cook and Zarkin (2001) attempt to explain how times of economic distress may contribute to criminal activity. The authors postulate four potential connections to criminal behavior during a recession: legitimate opportunities, criminal opportunities, use of criminogenic commodities, and the criminal justice system response to crime. They suggest that times of economic hardship may heighten one's propensity for crime. Researchers are finding that the use of criminogenic commodities, such as alcohol and drugs, increased in response to the restrictions of the pandemic. For example, a recent study conducted in China by Sun, et al. (2020) that surveys nearly 6,500 participants reveals that 18.7 percent of 331 ex-drinkers and 25.3 percent of 190 ex-smokers relapsed during the COVID-19 pandemic due to psychological distress. Furthermore, Fergusson and Horwood (2002) finds that increased alcohol abuse is linked to increases in both property and violent crime rates. Although the economic recession caused by COVID-19 is unique from other recessions, the presence of increased unemployment and substance use may produce a significant impact on crime rates.

In response to stay-at-home orders sweeping across the United States in early March 2020, many scholars attempted to estimate the effect of the pandemic on crime. One example is Ashby (2020), which uses incident-level, police-recorded data across 16 large U.S. cities and counties to observe the direction of crime rates following the announcement of stay-at-home orders. The key findings are that violent crime across the U.S. remained unchanged, but there were significant changes in property crimes. Most notably, Ashby finds that there were diverging patterns of crime across all cities. The strength of this paper is the use of incident-level data across multiple cities. In comparison to the FBI's Uniform Crime Report data, this data allows for greater control over the collection and reporting of data. Some limitations of the study are its length and failure to acknowledge other city-specific variables that may impact crime rates.

Second, Mohler, et al. (2020) similarly compares calls for police service data post-announcement of a stay-at-home order. The main predictions of this paper are that residential burglary will decrease and domestic violence will increase as a response to more suitable targets for crime occupying their homes. The findings suggest that COVID-19 has impacted crime, but only for specific crimes. For example, reported robbery decreased in Los Angeles during the pandemic, but not in Indianapolis.

Another notable paper is Yang, et al. (2021), which uses a Seasonal-Trend decomposition using a Loess (STL) model to observe the effect of COVID-19 on crime rates in Chicago temporally. A spatial point pattern test (SPPT) using data from 2016 to 2019 compared to 2020 is used to visualize the spatial distribution of crime in Chicago. The main benefit of this model is to investigate how different events over a longer period of time affect criminal activity, such as the protests following the murder of George Floyd in June 2020 and the 2020 U.S. presidential election. A significant finding is that crime rates responded to the announcement of a stay-at-home order on March 21st by the Illinois governor, which suggests that public health policy such as social distancing and the closure of non-essential businesses had broad-reaching effects.

Background: Chicago, Illinois and Houston, Texas

The central question of my thesis is how did the COVID-19 pandemic affect criminal behavior? I test this question using data from two of the largest U.S. cities: Chicago and Houston. I selected Chicago, Illinois and Houston, Texas as the two cities to pursue in my study because of various characteristics. First, Chicago and Houston are similar in population size. In 2019, the U.S. Census Bureau estimated the population of Chicago as approximately 2.7 million and Houston as approximately 2.3 million. Second, both cities experienced large spikes in unemployment at the onset of the pandemic. The unemployment rate in Chicago and Houston in April 2020 was 16.4 percent and 14 percent, respectively. Since the pandemic did not affect all parts of the U.S. the same in terms of unemployment, selecting two cities with similar experiences will help isolate the impact of COVID-19 on crime rates. Third, median household income is comparable across Chicago and Houston. Chicago's median household in 2019 is $58,247 and Houston's median household income is $52,338 (US Census Bureau). While there are obvious cultural differences, these two cities have comparable populations, incomes and unemployment rates.

Data

The crime data set from Houston is provided by the Houston Police department and utilizes the National Incident-Based Reporting System (NIBRS) as a classification system. The NIBRS divides all reported offenses into two groups: Group A and Group B offenses. Each group is then divided into crime against person, property, or society. The Chicago incident-level data, provided by the Chicago Police Department, uses more than 350 Illinois Uniform Crime Reporting Codes (IUCR) to organize offenses. The data is further broken down into Index and Non-Index offenses. The crime data for both cities contain all recorded offenses between January 1st, 2019, and August 1st, 2021. While both crime data sources provide a wealth of information on daily crime in each city, I focus my analysis on overall crime, theft, battery, and assault in Chicago and Houston.

The COVID-19 case data for Houston is provided by the Houston Health Department and the data for Chicago is provided by the City of Chicago. Both data sets include daily case counts for COVID-19 from April 1st, 2020-August 1st, 2021. The weather data containing daily measures of maximum temperature, precipitation, and snowfall is provided by the National Centers for Environmental Information from the national Oceanic and Atmospheric Administration.

Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum
Total Crime	620.99	122.10	27	1,899
Theft	131.87	41.20	10	280
Battery	120.48	29.04	3	236

Table 1: Chicago Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum
Total Crime	645.36	64.36	338	849
Theft	70.83	36.51	0	140
Battery	111.37	20.82	56	183

Table 2: Houston Summary Statistics

Table 1 and Table 2, pictured above, show the mean, standard deviation, minimum, and maximum values of my dependent variables of total crime, theft, battery, and assault in my study. The average number of total crimes per day was slightly higher in Houston than Chicago, with the average number of crimes equal to approximately 645 per day in Houston versus 620 per day in Chicago. Given the fact that Chicago and Houston are comparable in terms of population size, unemployment, and median household income, daily total crime and violent crime averages further affirms their similarities as cities. However, the higher standard deviation values for total daily crime in Chicago compared to Houston indicates a larger dispersion of data. This shows that while Houston may experience slightly higher levels of daily crime on average, Chicago's daily crime patterns are more volatile.

Despite the higher average total crime in Houston, Chicago experienced higher daily averages of theft and battery compared to theft and assault over the time period of interest. For example, Chicago experienced nearly two times as much theft on average per day with approximately 132 theft offenses compared to approximately 70 per day in Houston.

One statistic that stands out is the minimum value of zero for theft offenses recorded on a given day in Houston as seen in Table 2. This extreme outlier may explain the disparity between daily average theft in Chicago and Houston. Additionally, the higher maximum statistics in Chicago for total crime, theft, and battery compared to Houston reveals the higher volume of offenses that occur. Although both cities are comparable in population size, this is somewhat expected as Chicago's population exceeds Houston's.

COVID-19 Timeline: Chicago and Houston

On March 26th, 2020, public health order No. 2020-3: Apply Governor's Stay-at-Home Executive Order was issued and effective in the City of Chicago. As a result, Chicago parks, beaches, and trails were closed to support social distancing protocols released by the CDC (Chicago.Gov). The stay-at-home order remained effective until June 3rd, 2020, when non-essential businesses began to reopen in accordance with CDC guidelines. As reflected in Figure 1, Chicago underwent a series of expansions and contractions of COVID-19 related restrictions from the early summer through the end of the year. Most notably, a Stay-at-Home advisory was issued to Chicago on November 16th, 2020, to hedge against the rising cases and hospitalizations across the city.

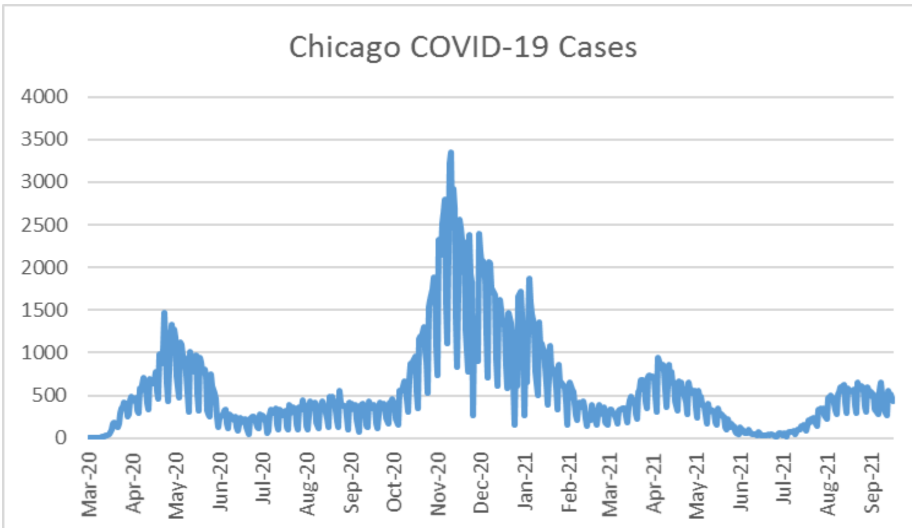

Figure 1

The City of Houston, located in Harris County, Texas, first announced a stay-at-home order for its residents on March 24th, 2020. The stay-at-home order shut down many non-essential businesses and restricted public gatherings to mitigate the spread of COVID-19. The order remained in effect until April 3rd, 2020. Similar to Chicago, Houston introduced a reopening plan categorized by different levels of COVID-19 risk. Figure 2 shows a more volatile pandemic experience for Houston compared to Chicago. This may be explained by the state-level policy decisions of Texas Governor Greg Abbot throughout the course of the pandemic. For example, Governor Abbot's decision to block mask mandates for local schools and governments in May 2021 is mirrored by the rise in cases over the summer and into the fall demonstrated in Figure 2. Although both cities have experienced different timing and length in the waves of cases throughout the duration of the pandemic, this improves the model as it helps control for any omitted variables that may alter the regression results. For example, if the severity of the pandemic worsened at the same time in both cities, the chance of excluding an independent variable that may be driving that trend increases.

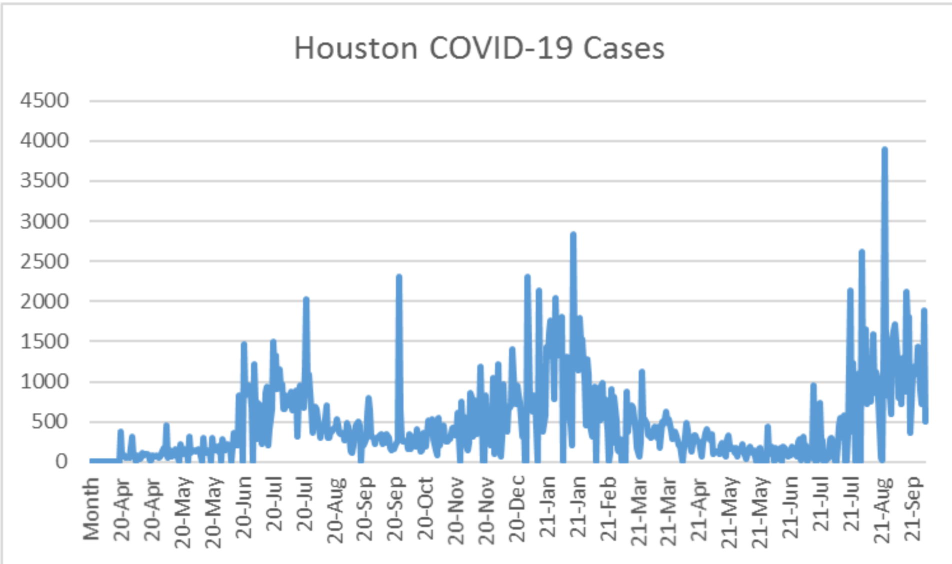

Figure 2

Methods

To estimate the impact of COVID-19 cases on crime in Chicago and Houston, I ran a series of Ordinary Least Squares (OLS) regressions using Stata. I also use White's standard errors, or robust standard errors, to account for heteroskedasticity in the model. I estimate the effects of the severity of COVID-19 cases on crime rates in Chicago and Houston by running the following regressions:

Chicago Estimates

$$\mathbf{YAnyCrime_t}=\beta0+\beta1*Cases_t+\beta2*Tue_t+\beta3*Wed_t+\beta4*Thu_t+\beta5*Fri_t+\beta6*Sat_t+\beta7*Sun_t+\beta8*m2_t+\beta9*m3_t+\beta10*m4_t+\beta11*m5_t+\beta12*m6_t+\beta13*m7_t+\beta14*m8_t+\beta15*m9_t+\beta16*m10_t+\beta17*m11_t+\beta18*m12_t+\beta19*maxtemp_t+\beta20*precipitation_t+\beta21*snowfall_t+\varepsilon_t$$

$$\mathbf{YTheft_t}=\beta0+\beta1*Cases_t+\beta2*Tue_t+\beta3*Wed_t+\beta4*Thu_t+\beta5*Fri_t+\beta6*Sat_t+\beta7*Sun_t+\beta8*m2_t+\beta9*m3_t+\beta10*m4_t+\beta11*m5_t+\beta12*m6_t+\beta13*m7_t+\beta14*m8_t+\beta15*m9_t+\beta16*m10_t+\beta17*m11_t+\beta18*m12_t+\beta19*maxtemp_t+\beta20*precipitation_t+\beta21*snowfall_t+\varepsilon_t$$

$$\mathbf{YBattery_t}=\beta0+\beta1*Cases_t+\beta2*Tue_t+\beta3*Wed_t+\beta4*Thu_t+\beta5*Fri_t+\beta6*Sat_t+\beta7*Sun_t+\beta8*m2_t+\beta9*m3_t+\beta10*m4_t+\beta11*m5_t+\beta12*m6_t+\beta13*m7_t+\beta14*m8_t+\beta15*m9_t+\beta16*m10_t+\beta17*m11_t+\beta18*m12_t+\beta19*maxtemp_t+\beta20*precipitation_t+\beta21*snowfall_t+\varepsilon_t$$

Houston Estimates

$$\mathbf{YAnyCrime_t}=\beta0+\beta1*Cases_t+\beta2*Tue_t+\beta3*Wed_t+\beta4*Thu_t+\beta5*Fri_t+\beta6*Sat_t+\beta7*Sun_t+\beta8*m2_t+\beta9*m3_t+\beta10*m4_t+\beta11*m5_t+\beta12*m6_t+\beta13*m7_t+\beta14*m8_t+\beta15*m9_t+\beta16*m10_t+\beta17*m11_t+\beta18*m12_t+\beta19*maxtemp_t+\beta20*precipitation_t+\varepsilon_t$$

$$\mathbf{YTheft_t}=\beta0+\beta1*Cases_t+\beta2*Tue_t+\beta3*Wed_t+\beta4*Thu_t+\beta5*Fri_t+\beta6*Sat_t+\beta7*Sun_t+\beta8*m2_t+\beta9*m3_t+\beta10*m4_t+\beta11*m5_t+\beta12*m6_t+\beta13*m7_t+\beta14*m8_t+\beta15*m9_t+\beta16*m10_t+\beta17*m11_t+\beta18*m12_t+\beta19*maxtemp_t+\beta20*precipitation_t+\varepsilon_t$$

$$\mathbf{YAssault_t}=\beta0+\beta1*Cases_t+\beta2*Tue_t+\beta3*Wed_t+\beta4*Thu_t+\beta5*Fri_t+\beta6*Sat_t+\beta7*Sun_t+\beta8*m2_t+\beta9*m3_t+\beta10*m4_t+\beta11*m5_t+\beta12*m6_t+\beta13*m7_t+\beta14*m8_t+\beta15*m9_t+\beta16*m10_t+\beta17*m11_t+\beta18*m12_t+\beta19*maxtemp_t+\beta20*precipitation_t+\varepsilon_t$$

Explanation of Variables

The three regressions for Chicago and Houston differ by the dependent variable, represented by Y, for total crime, property crime, and violent crime where *t* is represented by a date between January 1st, 2019, and August 1st, 2021. The variable *anycrime* aggregates the number of crimes, regardless of the category of offense, for each day in the time period of interest. The variable *theft* aggregates the daily number of theft-related offenses in each city. The variable *battery* for Chicago and the variable *assault* for Houston serve as a proxy for violent crime offenses in their respective cities. While the regressions for Chicago and Houston both include the dependent variable of total crime and theft, the cities diverge in crime classification for violent offenses related to battery and assault.

To measure the effect of COVID-19 on crime rates, the variable *cases* capture the change in crime in response to the current day's case severity. This independent variable is critical in answering the central question of my project. Since the case data for both Chicago and Houston are daily, the model is able to best estimate this relationship as it changed frequently throughout the course of the pandemic.

To control for the impact that the weather has on crime rates, I use the following weather controls for Chicago and Houston: *maxtemp, precipitation, and snowfall*. These variables are important as Heilman and Kahn (2019) demonstrate that overall crime increased by 2.2 percent when the daily high temperature in Los Angeles exceeded 85 degrees Fahrenheit. To further isolate the relationship of interest, including weather variables account for how criminal activity is affected by changing weather. Lastly, the creation of dummy variables for each day of the week and month of the year helps control for the seasonality of crime. For example, Dodge (1988) finds that summer months attract higher levels of crime than the winter months.

Estimation Results

Chicago Results

Linear regression

Number of obs	=	943
F(21, 921)	=	65.59
Prob > F	=	0.0000
R-squared	=	0.4420
Root MSE	=	91.125

anycrime	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cases	-.249014	.0131504	-18.94	0.000	-.2748222	-.2232058
tue	-18.07184	9.445471	-1.91	0.056	-36.60899	.4653018
wed	-23.81482	9.646964	-2.47	0.014	-42.74741	-4.882242
thu	-35.66504	9.267042	-3.85	0.000	-53.85201	-17.47807
fri	8.662704	10.29859	0.84	0.400	-11.54872	28.87412
sat	-7.897868	10.06235	-0.78	0.433	-27.64565	11.84992
sun	.0528417	13.39143	0.00	0.997	-26.22842	26.3341
m2	-13.91072	12.22064	-1.14	0.255	-37.89425	10.0728
m3	-63.45057	13.80337	-4.60	0.000	-90.54028	-36.36087
m4	-52.30115	15.02262	-3.48	0.001	-81.78369	-22.81861
m5	-21.14137	22.12569	-0.96	0.340	-64.56399	22.28125
m6	-17.93699	18.57051	-0.97	0.334	-54.38241	18.50843
m7	12.84665	17.92136	0.72	0.474	-22.32478	48.01808
m8	57.70248	18.21506	3.17	0.002	21.95463	93.45032
m9	42.31898	17.46628	2.42	0.016	8.040661	76.59731
m10	26.69099	14.0778	1.90	0.058	-.9372929	54.31928
m11	-21.96426	14.50748	-1.51	0.130	-50.43581	6.507291
m12	-23.05536	13.6804	-1.69	0.092	-49.90373	3.793019
maximumtemperature	2.271224	.2751858	8.25	0.000	1.73116	2.811288
precipitation	-25.82301	9.648189	-2.68	0.008	-44.758	-6.888026
snowfall	-24.91649	3.757289	-6.63	0.000	-32.29034	-17.54265
_cons	560.2682	14.94483	37.49	0.000	530.9384	589.5981

Figure 3

Linear regression

Number of obs	=	943
F(21, 921)	=	53.99
Prob > F	=	0.0000
R-squared	=	0.4776
Root MSE	=	29.993

theft	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cases	-.0998481	.0048939	-20.40	0.000	-.1094527	-.0902436
tue	-.9646462	3.351125	-0.29	0.774	-7.541374	5.612081
wed	-3.914291	3.666372	-1.07	0.286	-11.1097	3.281122
thu	-4.387437	3.589228	-1.22	0.222	-11.43145	2.656578
fri	3.614916	3.917954	0.92	0.356	-4.074238	11.30407
sat	-7.083733	3.735869	-1.90	0.058	-14.41554	.2480701
sun	-15.6617	3.288958	-4.76	0.000	-22.11642	-9.206981
m2	.1127618	4.472055	0.03	0.980	-8.663838	8.889362
m3	-12.72319	4.236231	-3.00	0.003	-21.03698	-4.409405
m4	1.860433	4.785852	0.39	0.698	-7.532009	11.25287
m5	.9273341	5.55588	0.17	0.867	-9.97632	11.83099
m6	9.84893	6.644729	1.48	0.139	-3.191637	22.8895
m7	28.39389	6.766441	4.20	0.000	15.11446	41.67332
m8	48.73173	6.674802	7.30	0.000	35.63214	61.83132
m9	41.6448	6.451273	6.46	0.000	28.9839	54.3057
m10	25.05154	5.411697	4.63	0.000	14.43085	35.67223
m11	2.940342	5.434777	0.54	0.589	-7.725642	13.60633
m12	3.859374	6.458031	0.60	0.550	-8.81479	16.53354
maximumtemperature	.2140123	.1017805	2.10	0.036	.0142637	.4137609
precipitation	-2.786285	2.866224	-0.97	0.331	-8.411373	2.838804
snowfall	-7.973878	1.44782	-5.51	0.000	-10.81529	-5.132468
_cons	132.9528	5.292954	25.12	0.000	122.5651	143.3404

Figure 4

Linear regression

Number of obs	=	943
F(21, 921)	=	59.18
Prob > F	=	0.0000
R-squared	=	0.5713
Root MSE	=	19.072

battery	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cases	-.0426707	.002821	-15.13	0.000	-.0482072	-.0371343
tue	-5.412773	2.169997	-2.49	0.013	-9.671485	-1.154062
wed	-6.618273	2.230288	-2.97	0.003	-10.99531	-2.241236
thu	-7.748559	2.103548	-3.68	0.000	-11.87686	-3.620257
fri	.2335181	2.218673	0.11	0.916	-4.120724	4.58776
sat	18.38144	2.253786	8.16	0.000	13.95829	22.80459
sun	28.76258	2.367536	12.15	0.000	24.11619	33.40897
m2	1.211349	3.07994	0.39	0.694	-4.833167	7.255864
m3	-1.883959	3.548812	-0.53	0.596	-8.848655	5.080737
m4	-6.015325	3.756661	-1.60	0.110	-13.38793	1.357283
m5	1.307329	4.185761	0.31	0.755	-6.907407	9.522066
m6	3.374123	4.529701	0.74	0.457	-5.515609	12.26386
m7	4.714054	4.792133	0.98	0.326	-4.690713	14.11882
m8	6.616088	4.783121	1.38	0.167	-2.770992	16.00317
m9	4.343675	4.48644	0.97	0.333	-4.461156	13.14851
m10	-.6155284	3.708856	-0.17	0.868	-7.894319	6.663262
m11	-5.807999	3.885739	-1.49	0.135	-13.43393	1.817931
m12	-6.991059	3.896192	-1.79	0.073	-14.6375	.6553861
maximumtemperature	.7017025	.0581216	12.07	0.000	.5876364	.8157686
precipitation	-3.691203	2.24217	-1.65	0.100	-8.091558	.7091515
snowfall	-2.596956	.8793041	-2.95	0.003	-4.322628	-.871284
_cons	83.57136	3.383988	24.70	0.000	76.93014	90.21258

Figure 5

The regression results in Chicago show that overall crime, theft, and battery decrease with an increase in COVID-19 cases, and each estimate is statistically significant at $\alpha = 0.05$. For example, an increase of one COVID-19 case per day decreases overall crime by approximately -

0.25. Thefts decline by about 0.1 with each COVID-19 case, while batteries fall by -0.043. There does not appear to be a strong seasonality pattern in these results, which is evident by the lack of a clear trend of statistical significance present in daily and monthly dummy variables. On the other hand, each inch of snowfall led to a decrease in overall crime, theft, and battery in Chicago. This is expected as crime tends to decline during the winter months when the chance of snow fall is the highest.

The R-Squared variables across all three regressions for Chicago are all comparable and within a reasonable range of one another. The highest R-Squared value across all regressions is the statistic for battery, with R-Squared equal to 0.5713. The lowest R-Squared statistic across all three regressions is Chicago's total crime equal to 0.4420. A potential explanation of this is the variety of property and violent crimes that the data set contains makes it difficult for a model to account for all the variation of total crime in Chicago.

Overall, the Chicago regression results aligns with the routine activity theory proposed by Cohen and Felson (1979). The statistically significant decrease in overall crime, theft, and battery in Chicago suggests that the dispersion of people from public places and the increased occupation at home may be a potential driver of the change in crime rates, even though the economy declined precipitously during the onset of the pandemic. As the theory proposes, the absence of suitable targets due to the implementation of stay-at-home orders may have disrupted the average level of crime across the city.

Houston Results

Linear regression

Number of obs	=	943
F(20, 922)	=	5.42
Prob > F	=	0.0000
R-squared	=	0.0980
Root MSE	=	61.906

anycrime	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cases	.0206598	.0063019	3.28	0.001	.0082922	.0330275
tue	6.727805	8.473717	0.79	0.427	-9.902207	23.35782
wed	.798701	8.462115	0.09	0.925	-15.80854	17.40594
thu	8.61533	8.259209	1.04	0.297	-7.593701	24.82436
fri	18.05023	8.828635	2.04	0.041	.7236762	35.37678
sat	22.15601	7.853832	2.82	0.005	6.742545	37.56947
sun	4.901603	8.052113	0.61	0.543	-10.90099	20.7042
m2	-3.20213	12.70262	-0.25	0.801	-28.13153	21.72727
m3	-24.70104	12.3017	-2.01	0.045	-48.84362	-.5584629
m4	-19.09091	12.16607	-1.57	0.117	-42.96731	4.785491
m5	17.72669	13.44749	1.32	0.188	-8.66455	44.11793
m6	-.1579029	15.16941	-0.01	0.992	-29.92849	29.61268
m7	-33.47321	14.39923	-2.32	0.020	-61.73227	-5.214144
m8	-28.39149	15.07298	-1.88	0.060	-57.97282	1.189834
m9	-30.00237	14.46881	-2.07	0.038	-58.39799	-1.606745
m10	-6.528493	12.85418	-0.51	0.612	-31.75533	18.69834
m11	-5.843249	12.62953	-0.46	0.644	-30.62922	18.94272
m12	1.576742	11.53016	0.14	0.891	-21.05167	24.20515
maximumtemperature	1.311035	.4276692	3.07	0.002	.4717174	2.150353
precipitation	-5.288099	3.572467	-1.48	0.139	-12.29921	1.723011
_cons	534.5712	31.06357	17.21	0.000	473.6077	595.5348

Figure 6

Linear regression

Number of obs	=	943
F(20, 922)	=	27.98
Prob > F	=	0.0000
R-squared	=	0.2519
Root MSE	=	31.922

theft	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cases	-.0286523	.0033017	-8.68	0.000	-.035132	-.0221725
tue	2.355454	3.759576	0.63	0.531	-5.022865	9.733772
wed	1.558589	3.783405	0.41	0.680	-5.866497	8.983674
thu	1.869331	3.925764	0.48	0.634	-5.835139	9.573802
fri	3.298945	3.86687	0.85	0.394	-4.289943	10.88783
sat	6.222261	3.830818	1.62	0.105	-1.295873	13.7404
sun	-.3021803	3.763902	-0.08	0.936	-7.68899	7.084629
m2	1.877951	4.266473	0.44	0.660	-6.495174	10.25108
m3	-12.355	4.705424	-2.63	0.009	-21.58959	-3.120417
m4	-11.44625	4.840744	-2.36	0.018	-20.9464	-1.946091
m5	-7.99655	5.654846	-1.41	0.158	-19.09441	3.101313
m6	-8.472268	6.119065	-1.38	0.167	-20.48118	3.536643
m7	-.5624534	7.168142	-0.08	0.937	-14.63022	13.50531
m8	37.04656	5.622791	6.59	0.000	26.01161	48.08152
m9	21.71466	4.605705	4.71	0.000	12.67578	30.75354
m10	24.60943	3.993709	6.16	0.000	16.77162	32.44725
m11	28.75949	3.634565	7.91	0.000	21.62651	35.89247
m12	39.11941	3.807524	10.27	0.000	31.64699	46.59183
maximumtemperature	.4127561	.1402939	2.94	0.003	.1374236	.6880885
precipitation	.0186515	1.542777	0.01	0.990	-3.009111	3.046414
_cons	38.08544	10.70716	3.56	0.000	17.07221	59.09868

Figure 7

Linear regression

Number of obs	= 943
F(20, 922)	= 38.35
Prob > F	= 0.0000
R-squared	= 0.4500
Root MSE	= 15.608

assault	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
cases	.0017438	.0015212	1.15	0.252	-.0012418	.0047293
tue	-17.4855	1.96256	-8.91	0.000	-21.33711	-13.6339
wed	-21.3736	2.058066	-10.39	0.000	-25.41264	-17.33456
thu	-21.39823	1.905859	-11.23	0.000	-25.13855	-17.6579
fri	-15.01725	2.111027	-7.11	0.000	-19.16022	-10.87427
sat	-1.374618	2.201469	-0.62	0.533	-5.69509	2.945855
sun	13.13858	2.013242	6.53	0.000	9.187507	17.08965
m2	2.662095	2.53213	1.05	0.293	-2.307311	7.631501
m3	3.198941	2.541756	1.26	0.209	-1.789357	8.18724
m4	8.106811	2.596048	3.12	0.002	3.011961	13.20166
m5	13.06101	2.858267	4.57	0.000	7.45155	18.67048
m6	6.000356	2.956322	2.03	0.043	.1984548	11.80226
m7	2.112168	3.042892	0.69	0.488	-3.859631	8.083967
m8	4.541142	3.502352	1.30	0.195	-2.332365	11.41465
m9	7.289713	3.432793	2.12	0.034	.5527183	14.02671
m10	9.236183	2.903346	3.18	0.002	3.538249	14.93412
m11	5.500846	3.115088	1.77	0.078	-.6126387	11.61433
m12	8.102759	3.037676	2.67	0.008	2.141197	14.06432
maximumtemperature	.3929305	.0814245	4.83	0.000	.2331317	.5527293
precipitation	-1.969462	1.07228	-1.84	0.067	-4.073853	.1349299
_cons	82.54684	6.463295	12.77	0.000	69.86236	95.23132

Figure 8

The regression results in Houston show that while theft significantly decreased in Houston at $\alpha = 0.05$, overall crime showed a significant increase at $\alpha = 0.05$. In the regression for assault, my independent variable *cases* did not produce statistically significant results with a p-value equal to .252. Across all three regressions for Houston, the independent variable of maximum temperature was statistically significant. For example, as the daily maximum temperature increased in Houston, the overall crime count increased by approximately 1.31 offenses. Similar to Chicago when it comes to the seasonality of crime, the results do not display a distinct trend across months with a lack of statistically significant variables. However, the day of-the-week dummy variables for assault reveal a statistically significant decrease during the weekdays of Tuesday, Wednesday, Thursday, and Friday and a statistically significant increase of assaults on Sunday at $\alpha = 0.05$.

The values of R-Squared across all three models are significantly lower than Chicago's regressions, especially for total crime. Houston's R-Squared value for total crime is .0980, meaning the model does a poor job of explaining the variance of total crime in the model. The R-squared value for assault in Houston is the highest, with a value of R-Squared equal to .4500. Although the coefficient for *cases* is not statistically significant in the regression, this model performs the best in terms of accounting for the variance of a crime in Houston.

The Houston regression results aligns with both Gary Becker's economic theory of crime and Cohen and Felson's social theory of crime. The statistically significant increase in total crime in Houston as the severity of COVID-19 cases heightens demonstrates the rational choice theory Becker proposes in *Crime and Punishment* (1968). These results demonstrate that as economic conditions worsened in Houston in response to the severity of the pandemic, a rational individual's propensity of crime may have increased throughout the pandemic in response to desperation. On the other hand, the statistically significant decrease in theft in response to an increase in cases suggests potential traction of the routine activity theory. Similar to the results in Chicago, the decrease in theft suggests that Houston's population was impacted by the stay-at-home orders and may have experienced disruption to the average time and convergence of criminal opportunity across the city. Since my model did not produce statistically significant results for *cases* in the assault regression, these results suggest an omission of variables that have a substantial impact on violent crimes in my model.

Conclusion

A significant behavior that the pandemic impacted is criminal behavior, especially in urban areas that tend to serve as a hub for crime. By attempting to estimate the impact of the

COVID-19 pandemic on criminal behavior in Chicago and Houston, I have both answered and created additional questions surrounding my central research question.

While it may take a substantial number of years to estimate the true cost of the COVID-19 pandemic on our society, we can so far conclude the following after examining criminal behavior in Chicago and Houston over a 15-month period. First, as daily cases increased in Chicago, total crime, theft, and battery decreased. Moreover, the results in Chicago demonstrated a statistically significant, inverse relationship between the severity of COVID-19 cases and criminal activity. The decrease in crime suggests the validity of Cohen and Felson's (1979) proposition of the routine activity theory where criminal behavior responds to a disruption to the convergence of time and space that drive crime rates. Second, Houston's results do not demonstrate a uniform relationship between criminal behavior and the severity of the COVID-19 pandemic. In Houston, only total crime and theft produced statistically significant coefficients for the independent variable of *cases*. As cases increased and the conditions of the pandemic worsened in Houston, total crime increased whereas theft decreased. The results in Houston indicate plausibility for both economic and social theories of crime. However, the higher R-Squared value for the theft model indicates a better explanation of variation in the model in comparison to total crime.

While this study serves as a starting framework for a comparative study to estimate the impacts of the pandemic on criminal behavior, there are a few limitations and areas for further improvement. First, the low R-squared value for Houston's total crime model suggests omission of key variables that explain the dependent variable. This indicates that Houston may have additional regional or local differences that I was unable to control for, therefore impacting my regression results.

Second, the lack of daily data to adequately test Gary Becker's economic theory and Cohen and Felson's social theory of crime is a potential limitation. Since I chose to include daily crime and COVID-19 case data in my study, I sacrificed my ability to control for unemployment and measure the accuracy of the rational choice model. As the pandemic continues to progress, it may be feasible to analyze this topic in the future over a longer period of time and potentially include unemployment data.

Lastly, it would be interesting to analyze how criminal behavior responds to vaccination levels in both cities. Since vaccines are critical to mitigating the spread of the virus and decreasing the control the pandemic has over our lives, it would be interesting to see if crime rates return to pre-pandemic levels in response to higher vaccination rates. This idea for a future area of study may help us determine if the pandemic will have either temporary or lasting effects on criminal behavior in our country.

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