Macalester College

The Impact of COVID-19 on Residential Property across Chicago's Neighborhoods

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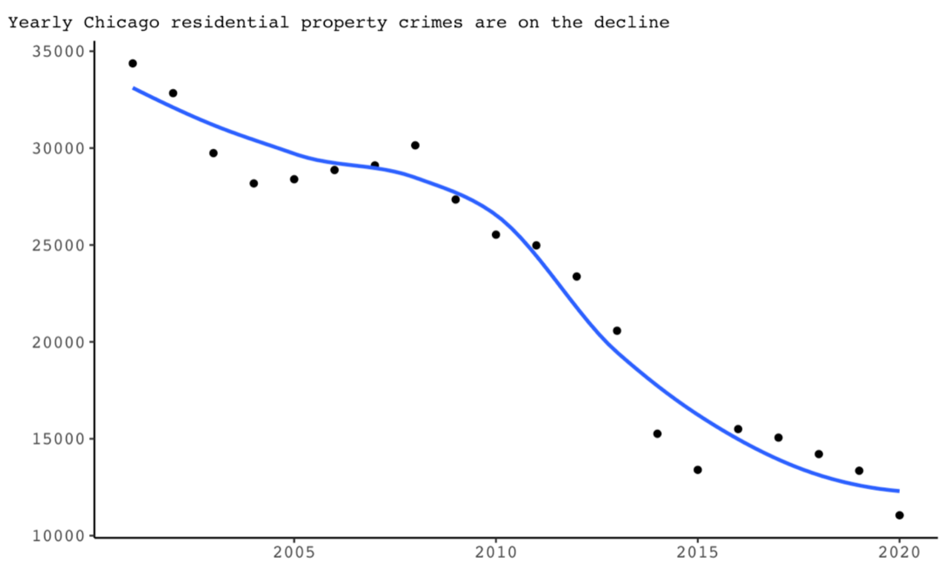
Introduction

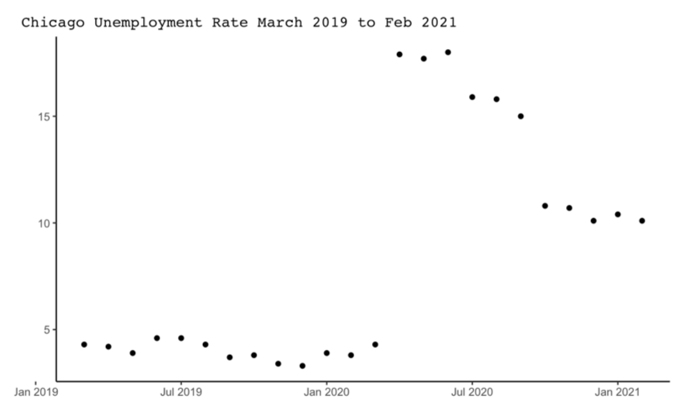
When you hear 'Chicago', what do you think of? If you've never visited the city, you may think of an unsafe community plagued by gun violence and crime. In fact, in a quiz with 58,992 responses by *The New York Times*, 53% of people selected Chicago to be ranked first nationally in murder rate while in reality the city is ranked 7th (Asher and Monkovic). While Chicago does have gun violence problems, progress in reducing other types of crime has been made. Records dating back to 2001 courtesy of the Chicago Data Portal show that residential property crime has overall been on the decline, falling from over 34,000 yearly property crimes in 2001 to under 15,000 a year since 2018. In fact, levels reached their lowest in 2020 at 11,052 recorded residential property crimes in the city limits – more than 2200 crimes fewer than 2019.



It is appropriate to ask if the drop in crime from 2019 to 2020 happened as a continuation of the overall declining trend in crimes (perhaps associated with the long-time price decline of common theft items such as TVs), the initiation of the COVID-19 pandemic, or a combination. While assigning exact weights to the causes of the crime drop would be near impossible, this paper seeks to assess if COVID-19 caused a significant decline in residential property crime rates in each of Chicago's 77 different community areas.

Literature Review

Known as the founder of economics crime literature, Gary Becker posited that the number of offenses committed by a person is a function of his probability of conviction, his punishment, and other variables, such as the income available to him, the frequency of nuisance arrests, and his willingness to commit an illegal act (Becker 1974). As a result, the Becker model should apply to residential property crimes more than any other type of crime, as they often have the goal of obtaining physical objects for wealth purposes and punishments are typically softer than assault and abusive crimes. Understanding Becker's model, we'd expect the unemployment rate to be positively associated with crime. In fact, theory predicts and empirical studies show the crime-unemployment to be the strongest for property crimes, with no real evidence of a relationship between violent crime and unemployment rate (Abrams 2021[1]). Based on this theory alone, it is expected that since the Chicago unemployment rate rose over 13% with the onset of the pandemic ("Chicago, IL Unemployment Rate") and has since remained above "normal" that we'd see increased property crime levels post March 2020. However, with this theory we do not consider two concepts. First, as a result of the high unemployment rate, much of the most financially impacted population received stimulus checks, enabling them to have some flow of income without employment. Second and more importantly, the lockdown measures implemented as a result of COVID-19 caused much of the population to be in their place of residence at incredibly high rates - thus making residential property crime more difficult. To account for these lockdown



[1] Empirical studies Raphael and Winter-Ebmer, 2001 and Lin, 2008

measures, we turn to two criminological theories known as "strain theory" and "opportunity theory", which predict two diverging trends for crime. Opportunity theory argues that lockdown measures have the potential to reduce the rate of criminal offenses because of restrictions on mobility and social interaction. On the other hand, strain theory maintains that socioeconomic strains that impact a large portion of the population, specifically the most vulnerable groups, have the potential to create a climate that drives individuals to create crime (UNODC 2020). In this situation, it seems reasonable to expect that opportunity theory would win out during the early lockdown phases of COVID-19 and thus property crime rates decline. As the pandemic progresses and stay at home orders end, the strain theory predicting increased crime could dominate the opportunity theory as socially and financially vulnerable groups may look toward crime to replace lost incomes and release their frustrations. Accounting for both theories, we might reasonably expect **nonresidential** property crime to be equal or higher than pre-pandemic levels as limited social mobility prevents people from inhabiting their place of work and financial and social frustrations increase the opportunity cost of theft.

Since the onset of the COVID-19 pandemic, there have been several studies analyzing the impact on crime. Matthew P. Ashby (2020) published one of the first studies as early as May 2020, less than 3 months after the pandemic hit the United States. Ashby used police-recorded open crime data to understand how the frequency of common types of crime changes in 16 large United States cities throughout the beginning of 2020. He used seasonal auto-regressive integrated moving average (SARIMA)[2] models of crime in earlier years to predict the expected 2020 crime rates if the pandemic had not occurred, and then compared these predictions to the

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[2] An ARIMA model is a highly refined curve-fitting technique that uses current and past values of the dependent variable to produce often accurate short-term forecasts of that variable. A SARIMA model is used when there is seasonality in the time series data (Studenmund 2017).

true frequencies of crime in early spring as the pandemic hit. Crime counts outside the 99% confidence interval were considered to be significantly different from the expected crime count, but only if the true count was outside the confidence interval for at least two weeks in efforts to find signal in the noise of the data. Ashby found burglary rates below the model estimate in eight cities, but only three were significant - Chicago, Los Angeles, and Memphis where rates were about half of what they were forecast. These reduced rates began in Chicago and Los Angeles during the week in which schools closed and stay at home orders were issued and they remained throughout the course of the study. Additionally, not all cities saw a decrease in residential burglary per Ashby's study. Austin, Louisville, and Minneapolis all largely had rates of burglary as predicted by the model. Ashby credited the inconsistency of how property crime across different cities reacted to the pandemic to the little amount of time having passed, as the study only used data between March and May 2020.

Gian Maria Campedelli, Serena Favin, Alberto Aziani, and Alex R. Piquero (2020) published an analysis of COVID-19's impact on crime specific to Chicago in October 2020. They used data at the level of Chicago's 77 community areas with the goal to understand how public interventions affected criminal activities at a finer spatial scale. The analysis relied on two-step methodology, with the first step estimating the community-wise causal impact of social distancing and Chicago shelter in place policies via Structural Bayesian Times-Series[3] across four crime categories (burglary, assault, narcotics-related offenses, and robbery). These models detected the direction, magnitude, and significance of the trend changes. Then, the second step of using Firth's Logistic Regression[4] to investigate the factors associated with the

[3]A more transparent time series model than ARIMA that does not rely on differencing, lags, and moving averages. This model enables users to quantify the posterior uncertainty of individual independent variables and control their variance, as well as impose prior knowledge on the model (Larsen 2016).

[4] A simple change to logistic regression that can mitigate the bias caused by rare events in a dataset (Karabon 2020).

statistically significant crime reduction was implemented. Generally, their statistical results show that changes in crime trends differ across communities and crime types. This is not surprising, as Chicago is composed of dozens of neighborhoods, many very different from one another economically, racially, and culturally. In an interview with Harvard economist Raj Chetty, Chetty emphasized this, quoting "...Chicago, despite its prosperity, is apparently also leaving a large group of people behind, confined to certain neighborhoods" (Kang 2019). Results also showed community population to be the only factor that is stably and positively correlated with significant crime reduction, and this relationship held for each of burglary, assault, narcotics-related offenses, and robbery (Campedelli, et al. 2020). Specifically, burglaries are expected to fall 3.8% when the population of the average community increases by 1000 residents and other factors are held constant at their mean. Additionally, the team of researchers found poverty as a significant variable on the 5% level and estimated if the rate of inhabitants living in poverty in an average community area increases by one percentage point, the predicted probability of a significant reduction in burglaries decreases by 12.4%. Overall, in terms of burglaries, only ten communities (12.98% of the total) experienced a statistically significant reduction during the post public intervention follow up period, and two communities experienced a significant increase in burglaries.

A final paper by David S. Abrams (2021) uses data from 25 large US cities to estimate the impact of the COVID-19 pandemic on crime. This study uses a difference in difference method to compare each individual city's crime levels to its own prior to 2020. The model predicts the number of weekly crimes in a city with a dummy variable indicating if the year is 2020 or 2021, a dummy variable indicating if the week began with a stay-at-home order, a year variable, and fixed effects for week of the year and typical city crime levels. The dummy variable indicating if the week began with a stay-at-home order was found to be statistically significant at $\alpha = 0.05$ in reduction of all crimes except for drug related offenses. The study also investigated if the explanatory variables median household income, police officers as a proportion of the population, proportion of African Americans, location within the US, and share Republican showed significant relationships with crime reduction. However, none were found to. With regards to impact overall reduction in crime, results showed most property crimes to fall substantially with the onset of the pandemic, with exceptions of nonresidential burglary and car theft. Six of the 25 cities analyzed - Pittsburgh, New York City, San Francisco, Philadelphia, Washington DC and Chicago – saw overall drops in crime of over 35%. In comparison to Ashby's study, Abrams finds substantially more significant deviation in crime rates, with this difference credited to greater data availability and a different level of aggregation (Abrams 2020). An additional aspect of crime that Abrams investigated is regarding how much of the crime change is real versus as a result of less reporting at the onset of the pandemic. Abrams concluded two reasons why he believes the crime change is real. First, the proportion of crime reported by the police versus the public did not significantly change in the two cities that report this data. Second, in Philadelphia evidence showed a drop in crime that varied as a function of distance from closed bars for simple assaults, robberies, and thefts. However, there was no drop in drug crimes which are unlikely to be impacted by lockdown measures. For these reasons, Abrams believes his results of crime drops in cities including Chicago are not a function of changes in reporting but indeed due to the onset of the pandemic.

This paper adds to the existing literature by considering a greater amount of time since the onset of the pandemic as it covers nonresidential property crime in Chicago from March 2019 through February 2021. This study will build upon the Chicago crime study of community areas by using random and fixed effects modeling as well as Granger causality to assess the impact of COVID-19 on specifically residential property crime in Chicago's 77 community areas. Understanding the overall impact of COVID-19 on residential property crime as well as identifying communities where the residential property crime is significantly higher than in pre-pandemic times can help appropriately allocate additional support and policing and put Chicago on the right path to continuing the downward trend in property crime.

Research Design

As may be expected with the socioeconomic, religious, racial, and generational diversity of Chicago's neighborhoods, there is a large amount of variation in the number of residential property crimes between neighborhoods. Across the span of this study, the average neighborhood saw about 13.67 monthly residential property crimes. However, certain neighborhoods had averages below 2 monthly residential property crimes (Edison Park and O'Hare) while others had averages above 50 (Roseland and Austin). This large amount of variation between community areas would typically suggest a fixed effects modeling technique is appropriate as effects of stable characteristics within communities are controlled for, whether they are measured or not. However, this study will highlight a random effects modeling technique as it enables us to analyze the effects of variables that are time invariant over the course of the study. It is reasonable to assume these variables - such as the proportion of each neighborhood that is white or living in poverty among others - have influence on the number of residential property crimes committed in that neighborhood, thus making random effects ideal.

Ideally, this study would include every component that affects residential property crime in the form of the following equation:

(Equation 1) $(ResidentialPropCrimes)_{it} = \beta_0 + \beta_1(COVIDCaseRate)_{it} + \beta_2\,(COVIDIndicator)_t +$ $\beta_3\,(StayAtHomeOrder)_t + \beta_4(PerceptionsofPolice)_{it} + \beta_5(PolicePresence)_{it} +$ $\beta_6(QualityofEducation)_i + \beta_7(\%InPoverty)_{it} + \beta_8(\%Minority)_i + \beta_9(YoungMalePop)_i +$ $\beta_{10}(UnemploymentRate)_{it} + \beta_{11}(Month) + u_{\mathrm{it}} + \varepsilon_{\mathrm{it}}$

Where i gives the ith cross-sectional neighborhood, t the tth month, u_{it} the between entity error and $\varepsilon_{\mathrm{it}}$ the within entity error.

This equation explores the causal relationship between COVID-19 and residential property crime. Based on studies like those of David Abrams, we would expect the coefficients on β_1 and β_2 to be negative, thus signifying a decrease in residential property crime rates with the onset of COVID-19. It would additionally be reasonable to expect the coefficient on β_3 to be negative as stay-at-home orders over the course of this study occur as a result of COVID-19.

The other variables in this ideal equation are included as measures of why residential property crime levels may fluctuate between neighborhoods. We'd expect the coefficient on the population of young males to be positive as this demographic is mostly likely to commit crime and it is also a measure of the neighborhood's total population (Kelling, 2001). We are also likely to see a neighborhood's crime rates be dependent on its police perceptions and police presence. Having a variable for police presence in the model could confirm Abrams' findings that the reduction in residential property crime came not as a result of lack of reporting and patrolling but truly due to the pandemic. The model ideally also incorporates poverty and unemployment at the neighborhood monthly level to measure the change of economic hardship across time in each community, as crime tends to increase with economic hardship (Becker, 1974). The proportion of the community that is a minority is included to encompass any racial discrimination that limits economic opportunity, which is expected to result in increased crime.

Unemployment rate is incorporated to capture limited economic opportunity not as a result of racial discrimination. Similarly, an education quality variable is included to catch decreased educational opportunities in certain neighborhoods, which may push teens out of school and to the streets to commit crime. Finally, a month variable is added to control for the downward trend of residential property crime rates in Chicago.

In addition to the random effects model, this analysis will test for Granger causality between the COVID-19 case rate and the residential property crime rate. Granger causality is a circumstance in which one time-series variable predictably changes before another variable, and thus enables us to analyze which variable proceeds or "leads" the other (Studenmund 2017). In this situation, we expect that COVID-19 cases to "lead" residential property crime rates rather than vice-versa. Thus, we will run the following equations:

(Equation 2) $NumCrimes_t = \beta_0 + \beta_1 NumCrimes_{t-1} + \beta_2 NumCrimes_{t-2} + \beta_3 NumCrimes_{t-3} + \beta_4 NumCrimes_{t-4} + \alpha_1 CaseRate_{t-1} + \alpha_2 CaseRate_{t-2} + \alpha_3 CaseRate_{t-3} + \alpha_4 CaseRate_{t-4} + \epsilon_t$

(Equation 3) $CaseRate_t = \beta_0 + \beta_1 CaseRate_{t-1} + \beta_2 CaseRate_{t-2} + \beta_3 CaseRate_{t-3} + \beta_4 CaseRate_{t-4} + \alpha_1 NumCrimes_{t-1} + \alpha_2 NumCrimes_{t-2} + \alpha_3 NumCrimes_{t-3} + \alpha_4 NumCrimes_{t-4} + \epsilon_t$

With Equation 2, we can test the null hypothesis that the coefficients of the lagged α jointly equal zero using the F-test. If we can reject this null hypothesis then we have evidence that the COVID-19 case rate Granger-causes residential property crimes. Additionally, we must also run the Granger test in the opposite direction and test if the coefficients of the lagged number of crimes (α) jointly equal zero. If we find the F-test significant for Equation 2 and not Equation 3, we can conclude the COVID-19 case rate Granger-causes residential property crimes.

Empirical Model and Data

Due to limited data availability, the ideal model displayed in Equation 1 is not feasible. Thus, we will use the following estimating equation:

(Equation 4) $(ResidentialPropCrimes)_{it} = \beta_0 + \beta_1(COVIDCaseRate)_{it} + \beta_2\,(COVIDIndicator)_t + \beta_3(UnemploymentRate)_t + \beta_4(HSGradRate2020)_i + \beta_5(\%InPoverty)_i + \beta_6(\%White)_i + \beta_7(\%18to24)_i + \beta_8(Month) + u_{it} + \varepsilon_{it}$

Where i gives the ith cross-sectional neighborhood, t the tth month, u_{it} the between entity error and ε_{it} the within entity error.

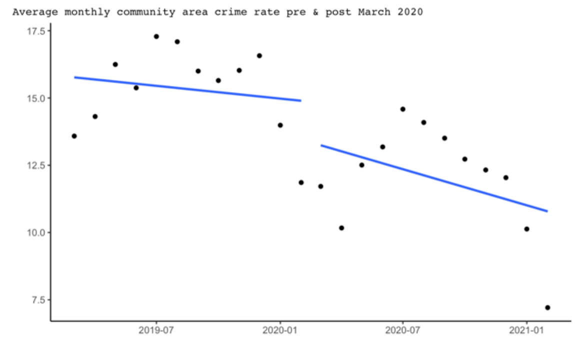
Data on police perceptions and presence on the community level basis were not available. Consistent and reliable information on Chicago's stay-at-home policies were also lacking and as a result that variable was removed from the equation. Additionally, only time-invariant information was able to be found on neighborhood level poverty rate while data on the unemployment rate could not be found at the granularity of the neighborhood. Thus, the final model uses each neighborhood's 2019 poverty rate and the overall Chicago monthly unemployment rate from March 2019 to February 2021.

The residential property crime data were collected from the Chicago Data Portal. These data were extracted from the Chicago Police Department's Citizen Law Enforcement and Reporting (CLEAR) system, and in order to protect the privacy of the victim the crime addresses are shown at the block level. Rates of crime reporting to the police may vary by neighborhood, and thus we should understand that residential property crimes may be recorded lower in certain neighborhoods than they truly are. Zip code level COVID-19 case rates were also obtained from the Chicago Data Portal on a weekly basis. A case of COVID-19 is only counted if tested and recorded by the Chicago Department of Public Health, and thus we can expect true case rates to be higher than documented. In fact, Jeffrey Shaman, an infectious disease specialist at Columbia University, has estimated the true number of active cases to be ten times the day's reported number on any given day (Aizenman, Nurith, et al., 2021).

Despite these largely unavoidable misrepresentations in the data, the Chicago Data Portal is a reliable source suitable for this analysis. I took the COVID-19 rates for each zip code and converted these rates to be monthly on the community area level using a conversion table published by Rob Paral in 2013. Finally, I obtained data on the Chicago monthly unemployment rate from *YCharts* as well as data on each community area's proportion of population that is white, proportion of population living in poverty, proportion of population 18-24, and high school graduation rate from Heartland Alliance. This rounds out the model aside from the COVID-19 indicator variable, which simply denotes months including and after March 2020 as during the pandemic and months March 2019 – February 2020 as pre-pandemic.

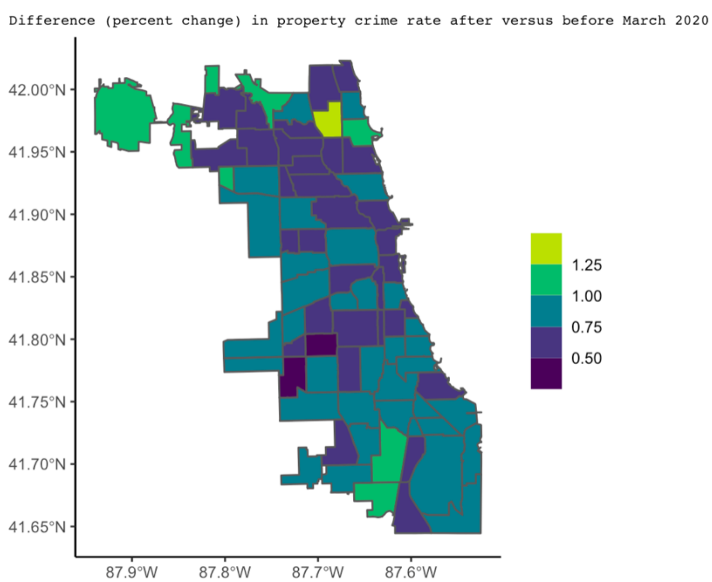
Estimation issues in this analysis include multicollinearity, largely between the month variable and the COVID-19 indicator variable. Despite its correlation with COVID-19, the month indicator variable is important as it allows us to control for the downward trend of residential property crime rates in Chicago. Thus, I ran my regressions twice, once with the month indicator variable included and once with it removed. Another potential estimation issue is serial correlation, which was found to be significant on the one percent level in each of the regressions with the Wooldridge test for serial correlation. To account for this, models were run an additional time using robust standard errors.

<u>Summary Statistics</u>



With a simple plot of the average monthly community crime rate both from March 2019 – Feb 2020 and March 2020 – Feb 2021, we see that the average monthly rate of neighborhood residential property crime dropped and declined more dramatically at the onset of the pandemic. The trend observed post March 2020 generally provides support for the opportunity theory, or that the pandemic's oppression on social mobility lowered crime rates. We do see crime rates increase in the summer months of 2020 and may jump to conclusions of the strain theory coming into play, however the Department of Justice has cited that household property crimes are highest in the summer (Lauritsen and White 2014) and thus this rise is likely seasonal.

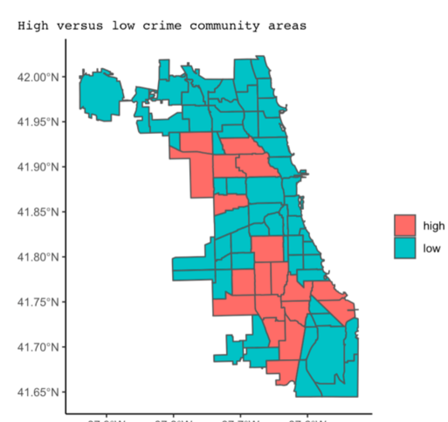
The map below shows how average residential property crime rates differed in each neighborhood, again comparing the twelve months prior to March 2020 to the period March



2020 – February 2021. As a city, Chicago saw a drop of 1180.55 monthly residential property crimes on average to 925.17 with the onset of the pandemic. Breaking our results down into community areas, we see that residential property crime only increased in eight community areas while the other 69 community areas saw decreased residential property crime rates. The exact change in crime rate for each neighborhood can be found in Table 1. Only one neighborhood (Lincoln Square) had a significant increase in crime, while 15 communities saw a significant decrease in residential property crimes. This provides strong evidence in support of COVID-19's negative impact on residential property crime rates.

Main Results

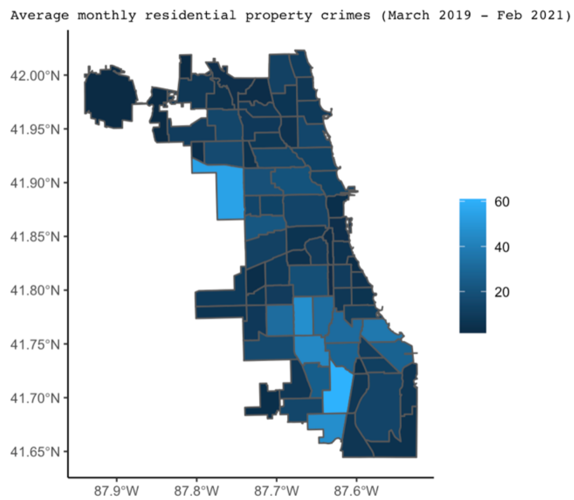
As far as the model assessing Granger causality between the COVID-19 case rate and community area crime rates go, running Equations 2 and 3 on the entirely of the data (77 community areas with 24 observations each and thus 1848 observations total) gives a significant F-test in both directions (Tables 2 and 3). These tests were run as panel data, with the entity as the neighborhoods and time component as the 24 months. Despite the significance of both tests, as seen in Table 2 the lagged coefficients for the test indicating residential property crime Granger causes the COVID-19 case rate have conflicting signs. This test also has an F-stat of 4.68, comparatively low to that of the test indicating the COVID-19 case rate Granger causes residential property crime to decrease (F-stat 15.06). The test for the COVID-19 case rate Granger causes residential property crime also has negative coefficients on all four lags, making it a more reliable result.

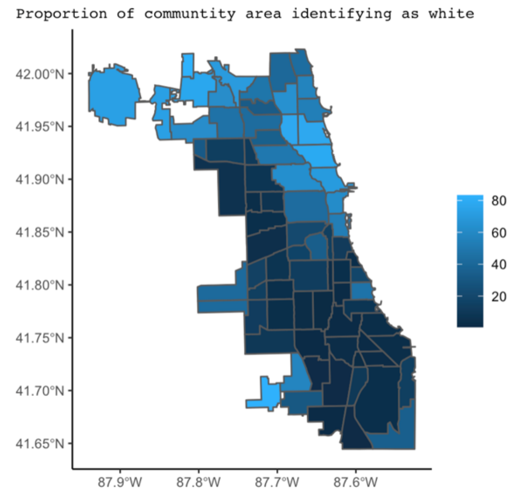


Looking for a clearer answer with Granger causality, Equations 2 and 3 were run again but this time using only community areas with an average crime rate greater than 15 monthly residential property crimes. This results in the 19 community areas shown on the right. The goal of running the Granger causality analysis with fewer neighborhoods is to understand if it was the large number of observations giving significant results in both directions. With these 19 community areas, we again see in Table 4 that the lagged coefficients for the test indicating residential property crime Granger causes the COVID-19 case rate has conflicting signs. Further, the F-stat for this test has fallen to 3.86. On the other hand, the lagged coefficients on the test of the COVID-19 case rate Granger causes residential property crime again are all negative and the F-stat stands strong at 6.68. In this situation, the fact that the lagged coefficients were all negative for one test while mixed for the other (both when using 19 and all 77 community areas) provides sufficient evidence that the COVID-19 case rate Granger causes the residential property crime rate to decrease.

We can now get more into the specifics by analyzing the results of the random effects model, which tests the underlying relationship between COVID-19 and crime rates. The results of this model are displayed in the second column of Table 6[5]; all coefficients are the expected sign except for those on high school graduation rate and the proportion of the population aged 18 to 24, which are not statistically significant. On the other hand, the COVID-19 indicator is statistically significant. Holding all other variables constant, in the pandemic months we would expect a neighborhood to have 5.697 fewer monthly residential property crimes on average in comparison to the pre-pandemic months. While the COVID-19 variable is highly significant, it isn't surprising that the case rate variable is not. Many of the strictest limits on social mobility came at the beginning of the pandemic when fear and uncertainty were high but case rates were relatively low. Other significant variables include the unemployment rate and the proportion of a community area that is white. The following figures show whiter neighborhoods tend to have much lower residential property crime rates.

[5] See column 4 of Table 6 for model with robust standard errors





As the random effects model is weighted average of the fixed effects model and between estimator, the similarity of the fixed and random effects estimates supports random effects modeling. This is further supported by a Hausman test[6]. Fixed effects help control for omitted variable bias by having neighborhoods serve as their own controls. It is encouraging that we similar results, with significance on the one percent level for the COVID-19 indicator, unemployment rate, and proportion of a community area identifying as white.

One aspect that both the random effects and fixed effects models displayed in Table 6 do not control for is time. Due to its high pairwise correlation of 0.8668 with the COVID-19 indicator variable, the monthly indicator variable was omitted for the previous pair of regressions. However, a model that includes month as an indicator variable can serve as a robustness check to prove that the downward trend in residential property crime rate comes as a result of the COVID-19 pandemic and is not simply a continuation of the trend we have seen over the past two decades of falling property crime rates. A random effects model controlling for

[6] Hausman test provided chi squared of 0.07 and pvalue of 0.9954 (for full test see Table 8)

time is displayed in the second column of Table 7[7]. The COVID-19 indicator remains significant on the one percent level, as the does the proportion of the neighborhood that is white. Unemployment is omitted from this model as it represents the monthly unemployment rate across all of Chicago, and thus its information is covered by the monthly indicator variables. However, it too remains significant in the fixed effects model shown in column 3 of Table 7.

Conclusion

With the COVID-19 indicator variable being significant in all models as well as the results of Granger causality and visualizations, there is strong evidence that a significant portion of the decrease in residential property crime following the onset of the pandemic came as a result of COVID-19. Only 28% of burglaries occur when someone is in the house (Burglary Statistics 2021), and thus it is not surprising that the amount of residential property crimes fell with the limits to social mobility brought on by the onset of the COVID-19 pandemic. As we look to the future, it can reasonably be expected for residential property crime rates to contain to remain lower than pre-pandemic levels as lifestyles have changed for many – according to the Future Workforce Report, by 2025 the number of remote workers is expected to be nearly double what it was prior to the COVID-19 pandemic (Economist Report 2021).

Future research could provide more insight into *why* residential property crime rates significantly fell in certain neighborhoods and not others. With these findings, Chicago community members and police can take proper measures to reduce residential property crime rates across *all* parts of Chicago, making the city safer for all residents.

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[7] The same random effects model but with **robust standard errors** is displayed in column four of Table 7

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Appendix

TABLE 1: Monthly Residential Crime Rates by Community Area in Chicago, IL

Community Area Number	Community Area Name	Monthly Rate: March 2019 – February 2020	Monthly Rate: March 2020 – February 2021	Percent Change	T-stat
65	West Lawn	11.58	5.5	0.47	-3.23
63	Gage Park	12.92	6.33	0.49	-3.11
10	Norwood Park	9.58	5.25	0.55	-2.74
54	Riverdale	9.33	5.17	0.55	-2.74
4	Lincoln Square	5.58	8	1.43	2.62
16	Irving Park	11	6.25	0.57	-2.62
24	West Town	26.58	15.08	0.57	-2.62
62	West Elsdon	8.17	4.83	0.59	-2.5
50	Pullman	9.5	5.83	0.61	-2.38
1	Rogers Park	12.75	7.92	0.62	-2.32
22	Logan Square	19.33	11.92	0.62	-2.32
8	Near North Side	16.33	10.5	0.64	-2.19
33	Near South Side	5.17	3.33	0.65	-2.13
27	East Garfield Park	16.08	10.58	0.66	-2.07
36	Oakland	2.92	1.92	0.66	-2.07
43	South Shore	44.42	29.5	0.66	-2.07
2	West Ridge	14.67	9.92	0.68	-1.95
5	North Center	6.25	4.25	0.68	-1.95
38	Grand Boulevard	12.08	8.25	0.68	-1.95
72	Beverly	8.83	6	0.68	-1.95
32	Loop	4.5	3.08	0.69	-1.89
58	Brighton Park	10.58	7.25	0.69	-1.89
6	Lake View	17.5	12.33	0.7	-1.83
14	Albany Park	9.67	6.75	0.7	-1.83
31	Lower West Side	7.25	5.08	0.7	-1.83
37	Fuller Park	2.75	1.92	0.7	-1.83
21	Avondale	9.33	6.67	0.71	-1.77
26	West Garfield Park	17.08	12.08	0.71	-1.77
17	Dunning	11.75	8.5	0.72	-1.71
20	Hermosa	5.75	4.25	0.74	-1.58
11	Jefferson Park	6.33	4.75	0.75	-1.52
15	Portage Park	17	12.67	0.75	-1.52
34	Armour Square	3	2.25	0.75	-1.52
40	Washington Park	8.5	6.42	0.75	-1.52
41	Hyde Park	6.75	5.08	0.75	-1.52
61	New City	21.67	16.17	0.75	-1.52
67	West Englewood	53.25	39.92	0.75	-1.52
29	North Lawndale	26	19.67	0.76	-1.46
47	Burnside	4.5	3.42	0.76	-1.46
57	Archer Heights	3.5	2.67	0.76	-1.46
66	Chicago Lawn	36.5	27.75	0.76	-1.46
68	Englewood	36.83	28.17	0.76	-1.46
69	Greater Grand Crossing	36.25	27.5	0.76	-1.46
71	Auburn Gresham	49.83	37.83	0.76	-1.46
13	North Park	3.25	2.5	0.77	-1.4
60	Bridgeport	10.58	8.25	0.78	-1.34
7	Lincoln Park	15.08	11.92	0.79	-1.28
25	Austin	60.67	48.17	0.79	-1.28

30	South Lawndale	13.75	10.83	0.79	-1.28
35	Douglas	6.5	5.17	0.79	-1.28
44	Chatham	31.83	25.25	0.79	-1.28
56	Garfield Ridge	10.08	7.92	0.79	-1.28
59	McKinley Park	5.17	4.08	0.79	-1.28
46	South Chicago	30.33	24.67	0.81	-1.16
28	Near West Side	15.33	12.5	0.82	-1.1
74	Mount Greenwood	3.75	3.08	0.82	-1.1
9	Edison Park	1.5	1.75	1.17	1.04
18	Montclare	3.08	3.58	1.16	0.98
42	Woodlawn	12.5	10.5	0.84	-0.98
19	Belmont Cragin	18.08	15.33	0.85	-0.91
52	East Side	7.92	6.75	0.85	-0.91
70	Ashburn	17.92	15.25	0.85	-0.91
73	Washington Heights	27.83	23.58	0.85	-0.91
77	Edgewater	7.92	6.92	0.87	-0.79
51	South Deering	14.75	13	0.88	-0.73
12	Forest Glen	4	4.42	1.1	0.61
53	West Pullman	44.17	48.58	1.1	0.61
76	O'Hare	1.67	1.83	1.1	0.61
45	Avalon Park	10.42	9.5	0.91	-0.55
48	Calumet Heights	12.17	11.08	0.91	-0.55
64	Clearing	6.25	5.67	0.91	-0.55
23	Humboldt Park	20.58	18.92	0.92	-0.49
75	Morgan Park	15.33	14.25	0.93	-0.43
49	Roseland	59.75	62.25	1.04	0.24
3	Uptown	8.83	9.08	1.03	0.18
39	Kenwood	5.42	5.25	0.97	-0.18
55	Hegewisch	5	4.83	0.97	-0.18

Table 2: Granger Causality of crime rate as a function of COVID-19 case rate

All 77 Community Areas

Case Rate	Coefficient	Std. Error	t
L1	-0.254	0.037	-0.68
L2	-0.061	0.055	-1.1
L3	-0.083	0.06	-1.38
L4	-0.079	0.063	-1.25

F(4, 1455) = 15.06 ***
Prob > F = 0.0000

Table 3: Granger Causality of COVID-19 case rate as a function of crime rate

All 77 Community Areas

Number Crimes	Coefficient	Std. Error	t
L1	-0.053	0.0197	-2.69
L2	-0.055	0.0203	-2.7
L3	0.001	0.0205	0.07
L4	0.021	0.0204	1.03

F(4, 1455) = 4.68 ***
Prob > F = 0.0009

Table 4: Granger Causality of crime rate as a function of COVID-19 case rate

19 High Crime Rate Community Areas

Case Rate	Coefficient	Std. Error	t
L1	-0.056	0.1201	-0.47
L2	-0.1898	0.1708	-1.11
L3	-0.0338	0.1833	-0.18
L4	-0.3555	0.1831	-1.94

F(4, 353) = 6.68 ***
Prob > F = 0.0000

Table 5: Granger Causality of COVID-19 case rate as a function of crime rate

19 High Crime Rate Community Areas

Number Crimes	Coefficient	Std. Error	t
L1	-0.0365	0.0259	-1.41
L2	-0.0823	0.0266	-3.09
L3	-0.0046	0.0271	-0.17
L4	0.045	0.0269	1.68

F(4, 353) = 3.86 ***
Prob > F = 0.0044

TABLE 6: FE and RE Regression Results with no monthly indicator

Dependent variable is number of monthly neighborhood residential property crimes

VARIABLE	Numcrimes (RE model)	Numcrimes (FE model)	Numcrimes (RE model with robust std errors)
Case Rate	-0.0213	-0.00211	-0.0213
	(0.0321)	(0.0270)	(0.0283)
Covid Indicator	-5.697***	-4.848***	-5.697***
	(0.595)	(0.499)	(0.698)
Unemployment	0.195***	0.170***	0.195***
	(0.0482)	(0.0402)	(0.0468)
Proportion White	-0.191***	-	-0.191***
	(0.0736)		(0.0684)
Proportion in Poverty	0.243	-	0.243
	(0.288)		(0.317)
High School	0.0938	-	0.0938
Graduation Rate 2020	(0.160)		(0.131)
Proportion 18 to 24	-0.861	-	-0.861*
	(0.620)		(0.456)
Constant	20.36	14.65***	20.36**
	(12.83)	(0.229)	(10.29)
Observations	1440	1848	1440
Number of community areas	60	77	60
r2_o	0.191	0.0163	0.191
r2_b	0.2	0.00711	0.2
r2_w	0.146	0.113	0.146
chi2	248.8	.	88.85
rho	0.836	0.866	0.836

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Time fixed effects: NO

TABLE 7: FE and RE Regression Results with a monthly indicator

Dependent variable is number of monthly neighborhood residential property crimes

Months 5-24 omitted from table to conserve space

VARIABLE	Numcrimes (RE model)	Numcrimes (FE model)	Numcrimes (RE model with robust std errors)
Case Rate	0.0550	0.0376	0.0550
	(0.0646)	(0.0573)	(0.0719)
Covid Indicator	-7.616***	-59.52***	-7.616***
	(0.932)	(15.81)	(1.039)
Feb 2019	1.233	1.641**	1.233
	(0.897)	(0.800)	(0.752)
March 2019	2.850***	6.317***	2.850***
	(0.897)	(1.309)	0.905
April 2019	2.033***	-0.949	2.033***
	(0.897)	(1.101)	(0.849)
Unemployment	-	9.137***	-
		(2.676)	
Proportion White	-0.190***	-	-0.190***
	(0.0736)		(0.0691)
Proportion in Poverty	0.254	-	0.254
	(0.288)		(0.322)
High school graduation	0.0934	-	0.0934
rate 2020	(0.160)		(0.132)
Proportion 8 to 24	-0.868	-	-0.868*
	(0.620)		(0.462)
Constant	18.98	-25.70**	18.98*
	(12.85)	(11.52)	(10.39)
Observations	1440	1848	1440
Number of community areas	60	77	60
r2_o	0.210	0.0312	0.210
r2_b	0.199	0.00711	0.199
r2_w	0.266	0.220	0.266
chi2	504.9	.	298.7
rho	0.854	0.879	0.854

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Time fixed effects: YES

Table 8: Hausman test between random and fixed effects model

VARIABLE	b (fixed)	B (random)	(b-B) Difference	Sqrt(diag(V_b-V_B) S.E.
Caserate	-0.021	-0.0213	0.002486	0.009562
Covidindicator	-5.699	-5.697	-0.0023299	0.0151737
Unemployment	0.1947	0.1946	0.0000566	0.001157

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg
Test: Ho: difference in coefficients not systematic
chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
=0.07
Prob > chi2 = 0.9954