THE UNIVERSITY OF CHICAGO

The heterogeneous effect of the COVID-19 Pandemic on theft across location categories in Chicago

By

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1 Abstract

A salient observation during the COVID-19 Pandemic is that theft has been reduced throughout the United States. The objective of this research is to determine if this reduction was heterogeneous across location categories: Nonessential and Essential businesses, Public Buildings, Transportation, Residences, and Streets. Data from the Chicago Data Portal is used to measure the amount of daily theft in the city from January 1st 2018 to November 30rd 2020.

The response variables are standardized using their respective pre-pandemic mean and standard deviations. A identical segmented regression is specified for the response variables and the Pandemic is coded as a dummy variable. The six location categories are modeled as a system using seemingly unrelated regression. A χ^2 statistic of a the Wald Test is applied pair-wise to determine if their was a statistically significant difference in coefficient estimates across restricted and unrestricted regression equations.

Overall, the all location categories experienced a decline in theft between 0.58 and 2.59 standard deviations below their mean values. The results indicate that the Pandemic was associated with a disproportionate decline in theft at both essential and nonessential businesses, where the latter had deviated from it's average by 2.59 standard deviations during the Pandemic. Residences, Public Buildings, and Streets had a similar deviation in theft. The results align with Routine Activities Theory, which predicts that the impact of the Pandemic on daily routines would disrupt the interaction between criminal and victim (or their property), resulting in fewer incidences of crime.

Further research is needed to determine if these results generalize to other cities in the United States. A clear definition of the Pandemic is needed in the literature to further identify how the Pandemic impacted criminal behavior.

2 Introduction

Chicago confirmed its first case of COVID-19 (the Pandemic) on January 24th, which was the second reported case in the United States. For the next five to six weeks, the amount of new cases slowly grew, but the daily life of Chicagoans remained unaffected, the Pandemic was a distant problem and remained in the purview of public health experts. However, the situation rapidly changed in March when the governor of Illinois issued a disaster proclamation in response to a surge in cases, the first restriction on the public was issued on March 13'th, limits to the size of gatherings.

People in Chicago anticipated more restrictions and changed their behavior accordingly, they stocked up on food and essential items, cancelled appointments, business preemptively closed, all before the governor announced a stay at home order (Zumbach et al., 2020). There was fear that the medical system would collapse and that social distancing policies would be ineffective at controlling the spread of the virus. A field hospital was set up at the McCormick Place, which is the largest convention center in North America (however, it only treated 29 patients and closed in May of 2020). Eventually, a stay at home order was announced on March 20th and became effective on the 21st for the state of Illinois.

Overall, people responded to the Pandemic and stay at home order by decreasing their level of activity. Based on cell phone data, in Cook County (where Chicago is located) there was a 50% decrease in shopping, visiting parks, working on-site, and utilizing transit stations ("COVID-19 Community Mobility Reports", 2020). Unemployment reached 17% in the Chicago metropolitan area in April, compared to 5% in March.

The stay at home order was the strictest policy issued by Illinois to control the spread of the Pandemic and it effected most aspects of daily life. The order mandated the closure of schools, nonessential businesses, and places of public amusement. Social distancing was mandatory and all gatherings were prohibited, travel was restricted and residents were required to remain at home unless engaged in essential activity. The order permitted local and state law enforcement agencies to enforce its provisions("Executive Order 2020-10", 2020).

Chicago issued its own restrictions in addition to those issued by Illinois. For example, the city extended the stay at home order for two weeks after it expired at the state level. Public parks were closed and the popular lake front was cordoned off. Two separate curfews were implemented to stop crowds from gathering, the first occurred because of large protests and the second mandated that bars and restaurants close at 9pm. Travel restrictions were imposed on visitors entering the city and required them to quarantine for two weeks. In November, a “stay at home advisory” was issued, which encouraged Chicagoans to remain at home during a surge in cases. The Chicago public school district chose not to resume in-person classes in the fall of 2020, despite Illinois permitting resumption on the state level.

A salient observation during the Pandemic was a systematic decline in theft throughout cities in the United States. In particular, theft declined by at least 18% in most major cities. Comparing the weekly incidence of theft in March of 2019 and 2020, McDonald and Balkin (2020) found a 28% decrease in New York City, 64% in San Francisco, 18% in Los Angeles, and a 24% decrease in Philadelphia. Given that the majority of crime is theft, the large decline in theft caused an overall decline in crime within the cities.

The deterrence of theft is of theoretical and practical interest to economists and policy makers (Cooter & Ulen, 2012). Hunt et al. (2017) calculated the financial cost to the judicial system of different crime types on a state and national level. They determined that taxpayers in Illinois incurred a cost of $251 (2010 dollars) for judicial and legal services per incidence of theft. This does not take into account the cost to society, which can be substantial, both in terms of tangible loss of property, cost of prevention, or negative externalities (Cooter & Ulen, 2012). Hence, a reduction in theft has financial significance to society and to the allocation of resources for crime deterrence. The disruption caused by the Pandemic is a natural experiment that can improve understanding of criminal behavior and improve theft prevention policies within cities.

2.1 Present Research

The objective of this research is to determine if the Pandemic had a heterogeneous effect on theft across location categories in Chicago, which has not been attempted in the literature. I use open source crime data provided by the Chicago Police Department to measure the number of reported thefts in the city ("Crimes - 2001 to Present", 2020). The time frame for the study is January 1, 2018 to November 30th, 2020. The empirical strategy consists of six location category equations modeled using seemingly unrelated regression and pairwise χ^2 statistic for a Wald test to determine if there's a difference in coefficients.

(rewrite)The research uses an interrupted time series framework and a segmented regression specification to estimate the level change in theft. To control for the cyclic nature of crime in Chicago (Towers et al., 2018), temporal variables (day of week, month, and temperature) are included in the models. The Pandemic is measured by an indicator variable, which takes on a value of 1 starting March 21, 2020 until the end of the study time frame. The coefficients on the Pandemic variable and a measure of percent change are used to determine if a heterogeneous effect is present.

The present research is motivated by the exogenous shock to daily life caused by the Pandemic and stay at home orders. Crime has been studied in the context of natural disasters and major sporting events, but not in the context of a global pandemic. Hence, COVID-19 and crime marks the dawn of a new literature.

The theoretical interpretation of theft will be based on the definition given by the Nolo's Plain-English Law Dictionary, which defines theft as the generic term for taking property without consent (synonymous with larceny and stealing). Theft is differentiated from similar types of property crimes and Nolo's states that "robbery (taking by force), burglary (taking after entering unlawfully), and embezzlement (stealing from an employer) are all commonly thought of as theft, [although] they are distinguished by the means and methods used, and are separately designated as specific types of crimes..." (Hill & Hill, 2009). The data includes subtypes of theft based on the classification given by the database "Crimes - 2001 to Present" (2020), which includes motor vehicle theft, identity theft, pocket-picking, and attempted theft, but the empirical analysis only considers theft on an aggregated level and makes no distinction between the different types of theft. A complete list of the subtypes is found table (7) of the Appendix D.

3 Literature Review

Is there a theoretical reason why patterns of theft in cities would change because of the Pandemic and stay at home orders? The most common explanation is given by Routine Activity Theory, which states that the occurrence of a crime is explained by the interaction between the criminal and victim as they go about their day (Cohen & Felson, 2020). The theory emphasizes the relevance of regular, routine behavior for understanding crime patterns. Routine Activity Theory has been used previously to explain changes in criminal behavior related to the Pandemic (Ashby, 2020; Campedelli, Aziani, et al., 2020; Campedelli, Favarin, et al., 2020; Yang et al., 2021).

The disruption of daily life caused by the Pandemic and stay at home order is predicted to cause a decrease in theft throughout Chicago, and that the decrease is heterogeneous across location categories. That is, theft will decrease more at locations that were impacted the most by the Pandemic, such as nonessential businesses and schools because they were required to close, compared to locations that were impacted the least, such as essential businesses, residences, and public transportation, and that this difference corresponds to changes in daily activities associated with those locations. Some have speculated that the partitioning of businesses into essential and nonessential may cause a shift in criminal behavior towards essential businesses (Stickle & Felson, 2020).

There is little to no prior research on the effects that pandemics and stay at home orders have on crime. Stay-at-home orders are rare events; to my knowledge, the last order was issued in the 1940's to control the Polio epidemic in the United States, prior to that they were implemented ubiquitously during the 1918 Flu Pandemic. The orders during the 40's were localized to specific regions and cities where outbreaks occurred, and applied to vulnerable populations like children and pregnant women. Social distancing was used to control the spread of the disease and swimming pools, churches, and schools were closed (Neely, 2020).

A contemporary case is the H1N1 Influenza of 2009; it was not as deadly, or contagious as COVID-19, but serves as the most recent example of a global pandemic. Public health experts considered using social distancing, however, no such measure was put in place. Some schools closed during localized outbreaks, but given the timing of the pandemic and geographic specificity of infections, state or nation wide closures did not occur (Jhaveri, 2020).

The public health response to COVID-19 is similar to that of the 1918 Flu Pandemic. The following strategies were used throughout the United States in 1918: social distancing, quarantining of sick individuals, mask wearing, banning gatherings, closing schools, churches, and theaters (Mineo, 2021).

The only known evidence of the effect of the Flu on crime was published by the Chicago Department of Public Health in 1919. By comparing the lockdown in 1918 to the same time period in 1917, they found a 38% decrease in crime throughout Chicago (Abrams, 2021). However, there does not appear to be empirical papers on the impact of previous pandemics on crime (Ashby, 2020) and research is only now emerging during COVID-19 in 2020 (Campedelli, Aziani, et al., 2020).

A systematic analysis of location categories and crime has not been found in the literature. Abrams (2021) studied how crime patterns changed around restaurants and bars in the 25 cities he studied. He found that during the pandemic, the decline in theft was less pronounced as distance from bars and restaurants increased. Borrion et al. (2020) found a a 64% reduction in retail theft during the Pandemic in a Chinese city. Yang et al. (2021) conducted a spatial temporal analysis of Chicago's community areas using STL decomposition and spatial point pattern tests. They found that the spatial patterns of theft had a statistically significant change during the Pandemic in Chicago, They postulate that there are complex patterns of crime and COVID-19 at an intra-city level, which may not be detected at more aggregated levels.

3.1 Crime within Cities

The general trend among the literature is that the onset of the stay at home orders during the pandemic caused a reduction in crime, however, this result depended on the city and crime type. The reduction was primarily caused by a decline in property crime, and violent crimes decreased little or remained unchanged. There is some evidence that some crimes actually increased in some cities, such as domestic violence in a Chinese city, and vehicle theft in Austin and Los Angeles.

Abrams (2021) looked at 25 cities in the US, including Chicago, using a panel analysis. He found that immediately following the implementation of the SAH order, there was a systematic decline in drug crimes, theft, residential burglaries, and violent crimes. Ashby (2020) analyzed 13 cities in the US, including Chicago, using SARIMA. He found diverging patterns among crime changes across the cities and crime types. Some cities experienced a reduction in residential burglary, but minimal changes in commercial burglaries and found no statistically significant change in serious assaults in public or in residences.

Campedelli, Aziani, et al. (2020) using Bayesian Structural time series, modeled crime types within Los Angeles by partitioning the pandemic into “mild” and “strict” policy time periods. They found that overall crime dropped significantly, and that overall crime dropped more during the stricter policy period. Dai et al. (2021) studied a county level city in Hubei Province, the location of Wuhan where the pandemic originated, using one-way ANOVA and an interrupted time series methodology, to study weekly calls to police. In there study, they found that “ weekly calls related to traffic, crimes, and disputes decreased significantly during the lockdown, but weekly calls related to domestic violence, public security issues, and other issues increased.” Hodgkinson and Andresen (2020) found evidence that total crime decreased in Vancouver, Canada. de la Miyar et al. (2020) found that some types of violent crimes in Mexico decreased in the weeks following the stay at home order, but no effect was found for robbery, kidnapping, and homicides. Since similar effects were seen in cities and countries, each with a different timeline for when the pandemic impacted, it is unlikely that a change in policies (e.g. a change in policing, prosecution, or reporting) could explain the change in crimes.

Mohler et al. (2020) found that "... social distancing has had a statistically significant impact on a few specific crime types." Mainly, burglary, robbery, traffic stops, but that these results were inconsistent across Los Angeles and Indianapolis. Scott and Gross (2021) researched Chicago, Baltimore, and Baton Rouge for 19 crime types and found consistent declines in total crime across all three cities immediately after the stay at home orders in each respective city were put in place. Halford et al. (2020), studying a policing district in the UK, found that by the first week of the lockdown, all recorded crimes had declined by 41% There is empirical evidence that the incidence of domestic violence increased in Chicago (Bullinger et al., 2020), Los Angeles, and Indianapolis (Mohler et al., 2020), but in general these findings weren't seen consistently from study to study.

3.2 Theft

Regarding theft, the majority of the evidence is that theft decreased significantly following the stay at home orders in cities, that theft decreased the most percentage points among crime types, and that the decrease in theft accounts for a majority of the overall drop in crime.

Campedelli, Aziani, et al. (2020) found that theft had a statistically significant reduction of 9.1 to 9.6% during the milder restriction period, and 21% to 25% during the strict period in Los Angeles. Hodgkinson and Andresen (2020) found that that theft from vehicles had a decreasing trend the week the lockdown began, and theft in general began a decreasing trend two weeks after the lockdown started in Vancouver. de la Miyar et al. (2020) found a sharp decline in vehicle theft during the 5th week onward of the lockdown in Mexico City. Mohler et al. (2020) identified a statistically significant decrease in vehicle theft in Los Angeles, Scott and Gross (2021) found a 35% decrease in larceny in Baltimore and a 15.7% decrease in theft in Baton Rouge after the stay at home orders. Halford et al. (2020) identified a 62% in shoplifting, 52% decline in theft, and a 43% decline in theft from vehicles in a Uk police district, and theorize that these changes were caused by changes in mobility, as measured by the Google COVID-19 community mobility reports.

Abrams (2021) found that across the 25 cities he studied, there was a systematic and pronounced decline in theft. Borrion et al. (2020) proposed a set of indicators and mathematical models to study retail theft, using a large Chinese city as a case study. They found an substantial drop in retail thefts in january 2020, which took several months to recover. They postulate that the cause of the reduction was not covid-19 in and of itsself, but the awareness of the outbreak, which was announced many weeks after the first cases emerged. Ashby (2020) identified a statistically significant decrease in vehicle theft in Tucson. He found in San Fransisco and Los Angeles, theft *from* motor vehicles had decreased 62% and 17%. Pietrawska et al. (2020) found that restaurant property crime dropped 34% during the first month of the stay at home order in Los Angeles.

There is some evidence that theft of vehicles remained unchanged, or actually increased during the Pandemic / stay at home orders. Hodgkinson and Andresen (2020) did not find an obvious change in theft of vehicles in Vancouver in his study. Mohler et al. (2020) found no statistically significant difference of vehicle theft in Indianapolis. Ashby (2020) actually found that vehicle theft had a statistically significant increase after the lockdown in Austin and Los Angeles. He did not find a statistically significant change in vehicle theft in Baltimore, Louisville, Memphis, Minneapolis, Montgomery County Maryland (between Baltimore and DC), Philadelphia, Phoenix, San Francisco, or Washington, DC.

3.3 Crime in Chicago

The trend in the literature is that theft significantly decreased in Chicago directly following the implementation of the stay at home order, that changes in crime patterns were not homogeneous across the city, and that the decline in theft was more pronounced in Chicago compared to other cities studied in the literature. Campedelli, Favarin, et al. (2020) analyzes the changes in crime across community areas in Chicago and across crime types using Structural Bayesian time series and Firth's logistic regression. They find that in response to the stay at home order, the effect on crime depended on the crime type and location, where the South and West side experienced a greater decrease in crime, but it depended on the crime type. Abrams (2021) identified a decline in crime of over 35% in Chicago, including a statistically significant change in the rate of property crime over time after the stay at home order. Ashby (2020) found that theft of vehicles had a statistically significant decrease in Chicago. Pietrawska et al. (2020) identified a 80% drop in restaurant property crime during March of 2020 in Chicago. Scott and Gross (2021) states that theft declined 41% in Chicago, and that most of the decline in crime was related to property and statutory crimes. Yang et al. (2021) conducted a temporal analysis of Chicago using STL decomposition and spatial point pattern tests. They found that temporal distributions on the level of days changed significantly during the pandemic, but found much smaller changes on the level of hours.

4 Data & Exploratory Analysis

4.1 Measurement of Theft

Data from the Chicago Police Department CLEAR system ("Crimes - 2001 to Present", 2020) is used to measure the amount of daily thefts in the city. The data is based on reports made to the police department and contains information on the primary and secondary description of the crime, location description, spatial location, date, if an arrest occurred, and whether the crime was domestic. The database contains crimes from 2001 to one week prior to its download, and the data is a representation of the database at the time of its download, which occurred on December 9th, 2020. For this research, the primary types of "theft" and "motor vehicle theft" are aggregated. There is no distinguishment made for what was stolen, so vehicle thefts are counted, as well as financial identity theft. Attempted thefts are included.

There are limitations to the "Crimes - 2001 to Present" (2020) data. First, the dataset does not contain unreported crimes, so it underestimates the true amount of theft in the city. We assume that the dataset is a random sample of the actual level of theft, and that changes in the samples statistical properties are representative of the true level of theft. That is, changes in the sample aren't attributable to changes in reporting. Assuming that changes in the data aren't attributable to changes in reporting or policing is not generalizable to all crime types, for instance, there was a significant decline in narcotic offenses, but this is attributable to the State's Attorney for Cook Country (where Chicago is located) choosing to halt the prosecution of narcotic offenses during the Pandemic (Hinton & Charles, 2020).

The second limitation is that the reports are based on "preliminary information supplied to the Police Department by the reporting parties that have not been verified" and third, that the "crime classifications may be changed at a later date based upon additional investigation...". It is unknown to what extend this may have an effect on a statistical model using the data. Furthermore, the Department does not guarantee the accuracy, completeness, or timeliness of the data.

Nonetheless, the "Crimes - 2001 to Present" (2020) dataset has been used previously to study crime and the Pandemic in Chicago (Ashby, 2020; Bullinger et al., 2020; Campedelli, Favarin, et al., 2020; McDonald & Balkin, 2020; Pietrawska et al., 2020; Abrams, 2021; Scott & Gross, 2021; Yang et al., 2021) and to study the temporal patterns of crime in Chicago (Towers et al., 2018).

This research categorizes theft based on six location categories, each representing a subset of location descriptions that share similar characteristics. The location descriptions are grouped together based on similar to create the six categories.

The units are the daily count of theft, aggregated at the location category level. The response variables for this research are:

- Nonessential Businesses
- Public Buildings and Schools
- Public and Private Transportation
- Essential Businesses
- Residences
- Streets and Similar Locations

Table 1 displays descriptive statistics for each response variable from January 1st, 2018 to November 30th, 2020. The number of observations is $N = 1065$ and the standard deviation is based on the corrected sample variance, normalized by $N - 1$. There was a total of $193,527$ thefts reported during the study period, or 182 thefts per day. The location categories account for 94.9% of all thefts during the study period. Thefts are most common outside on the street (39% of all theft) and in residences (22%) ,and on average Essential and Non Essential Businesses experience similar amounts of theft. Public Buildings and Schools have the least amount of theft. In general, the variance of theft overall is less than the variance when theft is decomposed by location category.

4.2 Location Categories

The "Crimes - 2001 to Present" (2020) database provides a location description for each reported theft, for example: animal hospital, apartment, abandoned building, bank, street, and appliance store. To create the response variables, the locations were partitions by similarity into six distinct categories. The categories "Essential Businesses" and "Nonessential

Table 1: Descriptive Statistics for Response Variables

Variable	Mean	Std	Min	25%	50%	75%	Max	Ratio
All Theft Locations	182	41	68	151	185	212	311	1.00
Nonessential Businesses	23	10	1	17	25	30	54	0.13
Public Buildings and Schools	2	2	0	0	1	3	12	0.01
Public and Private Transportation	12	5	0	8	12	16	33	0.07
Essential Businesses	24	8	4	18	24	29	44	0.13
Residences	40	10	13	33	40	46	83	0.22
Streets and Similar Locations	72	18	32	59	70	84	164	0.39

Businesses" are based on "Executive Order 2020-10" (2020), which lists the companies that are considered essential, and succeeding orders are used that give clarifications to Order 10. Table 2 contains a subset of locations for "Essential Businesses", "Residences", and "Street and Similar Locations". Appendix B contains the full list of locations for each category.

Some locations were dropped from the analysis because the data was too sparse or they were too ambiguous. Sparsity meant there were less than 10 observations over the study period. If there was ambiguity regarding how to categorize the location, then it was dropped, for instance the location "basement" could mean a business or a residence. The dropped locations account for approximately 5% of the data.

Table 2: Examples of Locations By Category

Essential Businesses	Residences	Street and Similar Locations
animal hospital	apartment	abandoned building
appliance store	cha apartment	alley
atm (automatic teller machine)	cha breezeway	bridge
bank	cha elevator	cemetary
cleaners/laundromat	cha grounds	dumpster
cleaning store	cha hallway / stairwell / elevator	forest preserve
construction site	cha hallway/stairwell/elevator	highway/expressway

4.3 Measurement of the Pandemic

The Pandemic is interpreted as an exogenous shock to criminal behavior. It is measured using a dummy variable, with a value of 1 starting March 21st, 2020 onward. The pandemic has been measured as a dummy variable in prior research (Ashby, 2020; Campedelli, Favarin, et al., 2020; Mohler et al., 2020; Dai et al., 2021)

There are a number of limitations to measuring the Pandemic, such as controlling for contemporaneous events and specifying the start date of the Pandemic. As discussed in the methodology section, the empirical specification of an interrupted time series study requires that that other contemporaneous events are controlled for when studying a treatment effect (Bernal et al., 2019). Since the stay at home order coincided with the Pandemic, it is difficult to discern each individual effect. That is, there are empirical difficulties in determining whether a measured effect is caused by mandated behavior changes by the policies, or voluntary behavioral changes related to risk avoidance during the Pandemic. Using mobility data from Google, Apple, and SafeGraph, mobility did not return to pre-pandemic levels even after the stay at home orders were lifted. Furthermore, there are also difficulties in specifying the date of the disruptive event in empirical studies (Borrion et al., 2020).

5 Methodology

The methodology consists of two models: a seemingly unrelated regression (SUR) of the *standardized* and *unstandardized* response variables. Coefficient hypothesis testing will be applied to the model of the standardized variables, while the unstandardized model is used for ease of interpretation of the theft data. An identical regression specification is used for all equations, which models the Pandemic from a segmented approach, where a dummy variable is used to delineate pre and post-treatment periods.

For the SUR model, the response variable Y^L is standardized using the respective pre-

Pandemic mean and standard deviation. The system of equations consists of the 6 location category variables. A Wald Test, using a χ^2 statistic, is applied to all pairwise combinations of the equations of the SUR model to test if there is a statistically significant difference between the pandemic coefficient across equations. The results of the test are analyzed to identify heterogeneous patterns in the difference in the effect of the Pandemic by location. The same SUR model is specified for the unstandardized response variables, however, a separate regression is fitted using a seventh variable, "All theft" locations, which is the aggregated daily theft. Percent change is used to compare the effects of the second SUR.

The following system is estimated using SUR:

$$
\begin{aligned}
Y_t^1 &= \alpha + \beta_0^1 Period_t + \beta_1^1 Pandemic_t + \beta_2^1 Temp_t + \sum_i \beta_i^1 Day_t + \sum_j \beta_j^1 Month_t + \epsilon_t^1 \\
Y_t^2 &= \alpha + \beta_0^2 Period_t + \beta_1^2 Pandemic_t + \beta_2^2 Temp_t + \sum_i \beta_i^2 Day_t + \sum_j \beta_j^2 Month_t + \epsilon_t^2 \\
&\vdots \\
Y_t^6 &= \alpha + \beta_0^6 Period_t + \beta_1^6 Pandemic_t + \beta_2^6 Temp_t + \sum_i \beta_i^6 Day_t + \sum_j \beta_j^6 Month_t + \epsilon_t^6,
\end{aligned}
\tag{1}
$$

where Y_t^L is the standardized theft on day t of location category $L = 1, 2, \ldots 7$ on day t. Hence, Y^L is modeled identically and the coefficients of (1) are understood to be distinct for each L. Y^L is standardized using its pre-pandemic mean and standard deviation. $Pandemic_t$ is a dummy variable that takes on the value 1 onward of the stay at home order. $Temp_t$ is the average temperature in Fahrenheit on day t and is based on data from the National Oceanic and Atmospheric Administration. $Period_t$, Day_t, $Month_t$, and $Temp_t$ are included in the model because of their cyclic relationship with theft (Towers et al., 2018). Including the non-stochastic, temporal variables and controlling for temperature reduces autocorrelation and stationarizes the time series.

The SUR model of the unstandardized response variable uses the specification of (1).

Percent change is used to compare the results of β_1 and is defined as:

$$PC = 100 \cdot \left| \frac{(Avg^L + \beta_1) - Avg^L}{Avg^L} \right| = 100 \cdot \left| \frac{\beta_1}{Avg^L} \right| \tag{2}$$

and Avg^L is defined as the sample mean of Y^L during the previous two years, restricted to the months of the Pandemic:

$$Avg^L = \frac{1}{|S|} \sum_{t \in S} y_t^L \tag{3}$$

where S is the set of days between Mar 21 - Nov 30 for 2018 and 2019, and the sample size is given by $|S|$. Why use restricted sample? Hence, (2) measures the percent change of theft during the Pandemic after controlling for confounding variables.

SUR is an econometric approach to modeling a system of equations when the error terms are correlated across equations. This is indicative of a systematic relationship between the response variables and a joint estimation can increase the performance of the model by taking into account this dependency. Given that we have partitioned theft into distinct location categories, it is reasonable to assume that the errors will be correlated by unobserved variables that is common to theft The average pairwise correlation of the residuals is $\rho = 0.07$ (refer to Appendix A for the SUR results).

By estimating the system as a SUR, we can test the pairwise equality of the Pandemic coefficients across equations. The Wald Test restricts the system so that two of the equations have the same Pandemic coefficient, then calculates a χ^2 statistic by allowing the coefficients to vary across equations. Then it's determined if there is a statistically significant difference in the restricted versus unrestricted model, which indicates that the data supports the hypothesis that the coefficients are not equal.

Since the location categories have large differences in their distributions (see Table 1), directly comparing the coefficients β_1's from an unstandardized model will not reveal if a heterogeneous effect is present or not. Standardizing Y allows us to interpret the effect of the

Pandemic as a deviation from the mean, and since the distributions of the location categories differ substantially (refer to descriptive statistics in Table (1)), it standardizes the coefficients across regressions. If we do not standardize the response variable, a difference in coefficients is almost certainly because of a difference in the average level of theft at the location. The problem is the means and variances of $Y^1, Y^2, \ldots, Y^7$ vary greatly. For the sake of argument, suppose $Avg(Y^1) = 100, Avg(Y^2) = 4$, and $\hat{\beta}^1 = -25, \hat{\beta}^2 = -1$. In terms of averages, the effect is the same, but the coefficients are quite different. So a direct comparison becomes difficult if not untenable.

Percent change is defined in a typical way, but note that the average is restricted to only the days that correspond to the pandemic from 2019 and 2018. Theft is historically lower during the winter and spring months, while theft in the fall and summer is higher. So if averaging is done over the entire year, the percent change will be underestimated.

As discussed in the Data section, there are limitations to modeling the Pandemic in this fashion. Specifically, we are limited in the interpretation of what is meant by 'Pandemic' because it is not a homogeneous treatment across time and it does not delineate which 'part' of the pandemic is causing the effect. For example, the restrictions imposed by the government were eased and reimposed at various periods throughout the summer and fall, people may have inured to the risks of infection and began to disregard the restrictions, the rate of infection fluctuated and health system capabilities changed, there were growing political and social tensions related to both the pandemic and racial justice in the summer of 2020. The choice of treatment periods does not necessarily coincide with the start and end of the Pandemic. Therefore, the variable is a catchall for the COVID-19 pandemic, public health response, and any other result of the virus.

6 Results

Table (3) displays the results from the standardized SUR model; the full results are in Appendix A. Standard errors are in parenthesis. The Pandemic was associated with a decrease in the level of theft across all location categories. The largest decline, in terms of standard deviations, occurred at businesses and on Transportation. In particular, theft was 2.59 standard deviations below average during the Pandemic at Nonessential businesses. Theft that occurred on Streets, Public Buildings and Streets declined the least; Streets declined by 0.58 standard deviations, the least among the categories, which is still a notable decrease. The sample size of the system is 6390 and R squared is 0.53.

Table 3: SUR Results

	Pandemic Coeff	Adj. R^2
Nonessential	-2.59***	0.65
	(0.10)	
Essential	-1.82***	0.51
	(0.10)	
Transportation	-1.61***	0.53
	(0.09)	
Residences	-0.81***	0.37
	(0.09)	
PublicBuildings	-0.68***	0.36
	(0.09)	
Streets	-0.58***	0.56
	(0.08)	

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table (4) displays the χ^2 statistic of each pairwise Wald Test, insignificant results are shown in bold. The decline at Nonessential businesses was statistically different compared to all other categories. Pandemic coefficients were similar for Essential businesses and Transportation. The effect of the Pandemic on theft at Public Buildings, Residences, and Streets was similar as well. The coefficients of all other combinations were statistically different.

Figure 6 compares the results of the Pandemic effect using data from the unstandardized and standardized SUR models. The results from the standardized SUR model are shown

Table 4: Matrix of χ^2 statistic from Wald Test

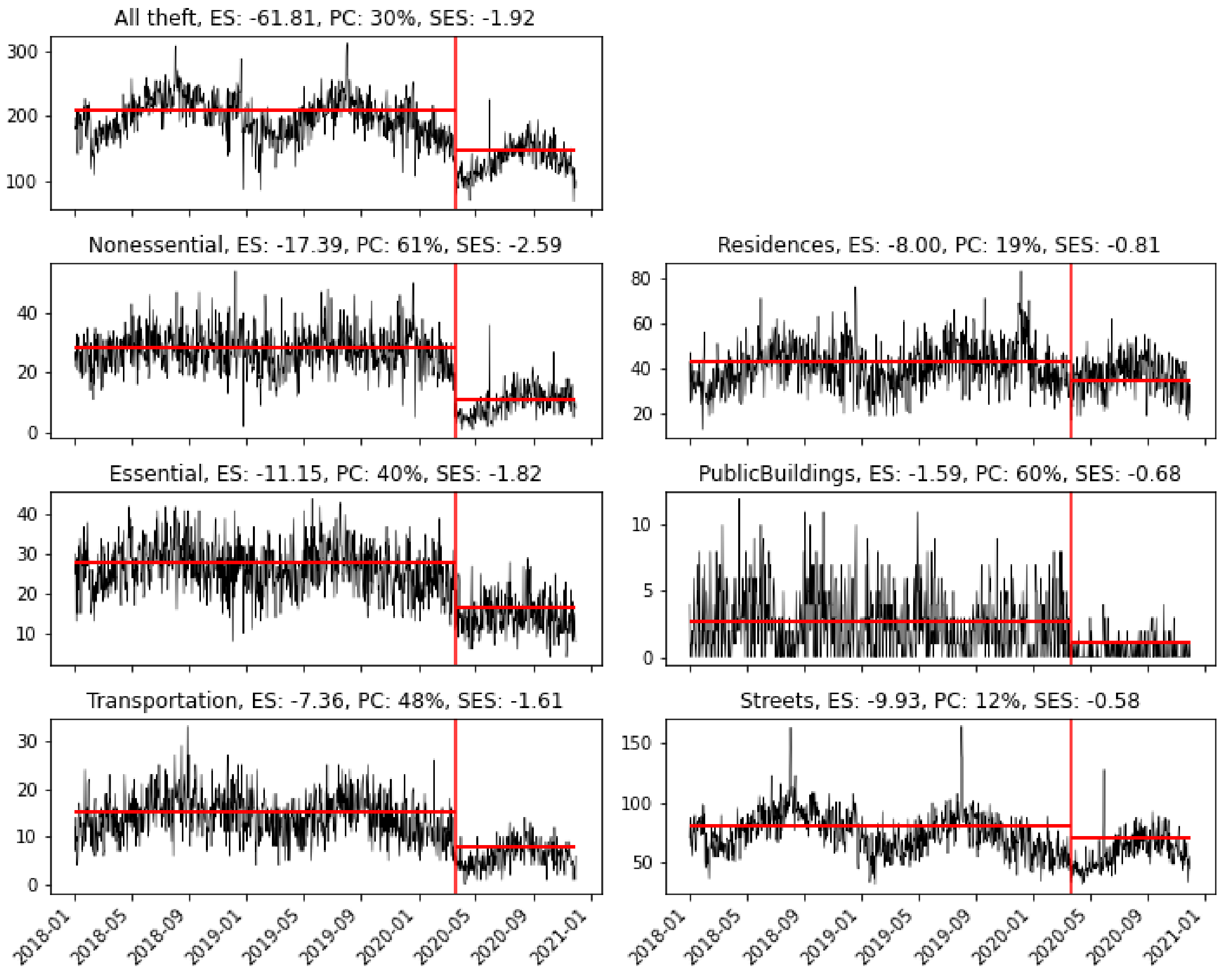
	Nonessential	Essential	Transportation	Residences	PublicBuildings	Streets
Nonessential	0.00	29.66***	52.63***	182.96***	210.73***	256.55***
Essential	29.66***	0.00	**2.43**	57.52***	73.00***	94.45***
Transportation	52.63***	**2.43**	0.00	39.17***	52.70***	71.34***
Residences	182.96***	57.52***	39.17***	0.00	**1.03**	**3.62**
PublicBuildings	210.73***	73.00***	52.70***	**1.03**	0.00	**0.70**
Streets	256.55***	94.45***	71.34***	**3.62**	**0.70**	0.00

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

in full in Appendix C. The effect size (ES) is the coefficient from the unstandardized SUR model and is used to calculate the percent change, the standardized effect size (SES) is also given. The vertical line occurs on March 21st 2020 and the horizontal line to its left is the sample mean, to its right is the sample mean plus the effect size.

A notable result is that All theft declined by 30% during the Pandemic. Nonessential businesses experienced the largest percent change of 61%. The smallest percent change occurred on Streets, which was 12%. The only notable difference between the comparison metrics is that Public Buildings had a percent change of 60%, although the fact that very few thefts occur there could inflate the percent change. Overall, the standardized and unstandardized SUR models give similar results.

Figure 1: Time Series Comparison of Results



ES = effect size, PC = percent change, SES = standardized effect size. The vertical line is at 03/21/2020. The horizontal line to the left is the sample mean, the line to the right is the sample mean plus the effect size.

7 Discussion

The literature on theft and the COVID-19 Pandemic has consistently shown that theft decreased in large US cities during the summer and fall of 2020. However, there does not appear to be any research into whether the decrease was heterogeneous across location categories, such as essential and nonessential businesses, public buildings, and streets. Therefore, the objective of this research is to determine if the impact of the Pandemic was statistically different across categories and to give possible explanations as to why some locations experienced a larger decline than others. This work contributes to the emerging body of literature on criminal behavior during pandemics and gives policy makers insights into the mechanisms that influence larceny.

The empirical analysis utilizes crime data made available by the Chicago Police Department; the time frame of the study is from January 1st, 2018 to November 30th, 2020. Theft is categorized into six response variables: Nonessential Businesses, Essential Businesses, Public and Private Transportation, Streets and Similar Locations, Public Buildings and Schools, and Residences; they are measured as an aggregate, daily count. The variables are standardized using their respective pre-pandemic means and standard deviations. Two seemingly unrelated regression are specified to model the locations as a system of equations and the Pandemic is measured by a dummy variable. A Wald Test using a χ^2 statistic is applied on the restricted and unrestricted model coefficients to determine if there is a pairwise difference in the Pandemic effect across regression equations.

7.1 Economic Explanations

Probability of being caught

If the probability of being caught stealing increased during the Pandemic, this could partially explain the decrease in theft. Consider businesses that have a surveillance system to prevent theft, for example, a security guard, cameras, or store employers. Suppose that the amount of surveillance allocated to any given patron is uniformly distributed. Based on the mobility data, there were less visits to businesses (and the amount of time spent at home increased), hence, the amount of patrons to a given business will be less at any given time. Capacity limits imposed by the government would also contribute to a lower density of patrons. Then during the Pandemic, a patron is subjected to an increased amount of surveillance, which increases his probability of being caught stealing. Therefore, this increased probability will lower the amount of theft he is willing to commit.

A similar explanation could explain the decrease of theft at Residences and on Transportation (specifically private transportation). Since people increased their time spend at time, the relative surveillance of their property is increased compared to pre-pandemic levels. As argued previously, the increase in surveillance would lead to a high probability of being caught, and a decreased willingness to steal.

Some types of theft (i.e. pick-pocketing) rely on crowds to avoid detection. Since crowds and gatherings were prohibited, we would predict that theft on Streets would decrease since the detection avoidance mechanism is no longer present. This would lead to a thief to deterrence of crowd-reliant theft all together, or an increase in the probability of being caught would decrease the amount of theft he is willing to commit.

Search costs

Theft can be thought of as an involuntary transaction between a victim and thieve. Hence, the thieve incur a search cost, in terms of time spend looking for a victim's property and the opportunity cost of engaging in other activities, and a change in this cost would imply a change in the incidence of theft. Since there were less people in public, the search costs of theft that directly involves other people would increase. For example, the decrease in ridership of public transportation during the Pandemic would increase the search cost of theft on Transportation (busses and trains). Hence, this additional cost would make theft less attractive economically and would lead to a lower quantity of theft.

Risk of exposure to COVID-19

The increased risk of exposure to COVID-19 adds an additional cost, not otherwise taken into account before the Pandemic, into the equilibrium of the quantity of theft. Given the prevalence of theft, and the relatively low level severity of the crime, it is reasonable to believe that the general public's lower activity level to avoid exposure would apply to thieves as well. If thieves stay at home, then they do not have opportunities to steal property and the expected costs associated with becoming sick, both in terms of lost wages and health costs, would surely exceed the value of the property stolen. An argument could be made that thieves are inherently risk seeking and would discount the costs associated with COVID-19. Nonetheless, the decline in theft is argued to be best explained by thieves reducing their exposure to COVID-19.

Restricted Access to buildings

Restricting access to buildings is the most likely cause for the decrease in theft at businesses and Public Buildings. Nonessential businesses were required to shut down, pursuant to the stay at home order, restaurants were not allowed to have in door dining. Restaurants were restricted to providing pick-up or delivery only. Other essential businesses enacted polices to limit interactions. Schools went to on-line only, which removed any opportunities for students to steal while at school. Public buildings switched to online versions of their services and required appointment only access to their buildings.

Furthermore, if a thieve chose to steal from a building that restricted access to the public, their probability of being caught is significantly increased. Of course they could attempt to enter the building after hours, but this would change the crime to burglary, a much more severe (i.e. costly) type of crime to the thieve. Therefore, restricting access of the public to buildings likely played a substantial role in the decrease in theft, in particular at Nonessential businesses.

Unemployment

During the first months of the Pandemic, unemployment in the Chicago area was 17%. If a thieve becomes unemployed, there is no longer an opportunity to steal from employers or to commit theft during a commute. However, unemployment lowers the opportunity cost of theft, which could predict an increase in theft during the Pandemic.

Reduced Punishment

During the Pandemic, a prevailing problem of public safety was the prisons and jails becoming hot spots of COVID-19. A strategy that was used in Chicago (and Cook County) was to limit the amount of new inmates into the jails. This manifested by not sending arrestees to jail and by releasing inmates prematurely. Therefore, the cost associated with punishment was reduced, which could increase the prevalence of theft. Given that overall theft declined, it's not apparent to what extent reduced punishment could have increased theft.

7.2 Future Research

Even though this analysis supports the hypothesis that a heterogeneous effect is present in Chicago, further research is needed to determine if the results generalize to other cities in the United States.

Subsequent empirical models should consider a standardized measure of the Pandemic to allow for robust comparisons across studies. The measure should account for the difficulty of defining the "Pandemic" in the context of criminology. The beginning and end of the Pandemic is ambiguous, geographically dependent, and does not correspond to the timing of the stay at home orders; a distinction between the epidemiological event and public policy response is necessary. Therefore, future research is needed to define the Pandemic and delineate the phenomenon associated with the event, including but not limited to: the stay at home orders, political tension, the public's perception of the risks associated with the disease, temporal changes in attitudes towards the pandemic, and capacity of the health care system.

8 Appendix A: SUR Results

systemfit results

method: SUR

	N	DF	SSR	detRCov	OLS-R2	McElroy-R2
system	6390	6264	4004.37	0.056097	0.532452	0.471486

	N	DF	SSR	MSE	RMSE	R2	Adj R2
Nonessential	1065	1044	763.260	0.731092	0.855039	0.656695	0.650119
Essential	1065	1044	813.770	0.779474	0.882878	0.520160	0.510968
Transportation	1065	1044	692.363	0.663183	0.814360	0.541495	0.532711
Residences	1065	1044	624.542	0.598220	0.773447	0.382062	0.370224
PublicBuildings	1065	1044	618.601	0.592530	0.769759	0.371070	0.359022
Streets	1065	1044	491.836	0.471107	0.686373	0.568991	0.560734

The covariance matrix of the residuals used for estimation

	Nonessential	Essential	Transportation	Residences	PublicBuildings
Nonessential	0.73109226	0.0748039	0.0622057	0.0202293	0.00553897
Essential	0.07480387	0.7794736	0.0673131	0.0487580	0.02570960
Transportation	0.06220570	0.0673131	0.6631828	0.0474685	0.07761184
Residences	0.02022933	0.0487580	0.0474685	0.5982202	0.04425484
PublicBuildings	0.00553897	0.0257096	0.0776118	0.0442548	0.59252966
Streets	0.09075184	0.0934613	0.0509202	0.0547494	0.04821286

	Streets
Nonessential	0.0907518
Essential	0.0934613
Transportation	0.0509202

Residences	0.0547494
PublicBuildings	0.0482129
Streets	0.4711074

The covariance matrix of the residuals

	Nonessential	Essential	Transportation	Residences	PublicBuildings
Nonessential	0.73109226	0.0748039	0.0622057	0.0202293	0.00553897
Essential	0.07480387	0.7794736	0.0673131	0.0487580	0.02570960
Transportation	0.06220570	0.0673131	0.6631828	0.0474685	0.07761184
Residences	0.02022933	0.0487580	0.0474685	0.5982202	0.04425484
PublicBuildings	0.00553897	0.0257096	0.0776118	0.0442548	0.59252966
Streets	0.09075184	0.0934613	0.0509202	0.0547494	0.04821286

	Streets
Nonessential	0.0907518
Essential	0.0934613
Transportation	0.0509202
Residences	0.0547494
PublicBuildings	0.0482129
Streets	0.4711074

The correlations of the residuals

	Nonessential	Essential	Transportation	Residences	PublicBuildings
Nonessential	1.00000000	0.0990917	0.0893362	0.0305890	0.00841565
Essential	0.09909170	1.0000000	0.0936229	0.0714027	0.03783028
Transportation	0.08933619	0.0936229	1.0000000	0.0753631	0.12381016
Residences	0.03058898	0.0714027	0.0753631	1.0000000	0.07433190
PublicBuildings	0.00841565	0.0378303	0.1238102	0.0743319	1.00000000

Streets	0.15463556	0.1542309	0.0910990	0.1031308	0.09125315

	Streets
Nonessential	0.1546356
Essential	0.1542309
Transportation	0.0910990
Residences	0.1031308
PublicBuildings	0.0912531
Streets	1.0000000

SUR estimates for 'Nonessential' (equation 1)

Model Formula: Nonessential ~ Period + Temperature + Pandemic + February + March + April + May + June + July + August + September + October + November + December + Monday + Tuesday + Wednesday + Thursday + Friday + Saturday

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.088904650	0.198079758	0.44883	0.65364557	
Period	-0.000204755	0.000133784	-1.53049	0.12619737	
Temperature	0.000256734	0.003000181	0.08557	0.93182245	
Pandemic	-2.586081362	0.097477009	-26.53017	< 2.22e-16	***
February	-0.183240399	0.128704022	-1.42373	0.15482204	
March	-0.432215562	0.130586704	-3.30980	0.00096556	***
April	-0.124194717	0.141747823	-0.87617	0.38114099	
May	0.235155321	0.164603158	1.42862	0.15341266	
June	0.429417431	0.185144986	2.31936	0.02056789	*
July	0.448687244	0.199231559	2.25209	0.02452377	*

```
August        0.468822995  0.193659984   2.42086 0.01565372 *
September     0.440435357  0.179319092   2.45615 0.01420527 *
October       0.281291611  0.148365554   1.89594 0.05824442 .
November      0.384566538  0.134643535   2.85618 0.00437268 **
December      0.605487721  0.143636199   4.21543 2.7089e-05 ***
Monday       -0.199418084  0.097934991  -2.03623 0.04197934 *
Tuesday      -0.242912202  0.098105770  -2.47602 0.01344315 *
Wednesday    -0.182759234  0.098129934  -1.86242 0.06282454 .
Thursday     -0.229452172  0.098130338  -2.33824 0.01956290 *
Friday       -0.030859156  0.098149696  -0.31441 0.75327318
Saturday      0.570829696  0.098140510   5.81645 7.9855e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.855039 on 1044 degrees of freedom
Number of observations: 1065 Degrees of Freedom: 1044
SSR: 763.260319 MSE: 0.731092 Root MSE: 0.855039
Multiple R-Squared: 0.656695 Adjusted R-Squared: 0.650119


SUR estimates for 'Essential' (equation 2)
Model Formula: Essential ~ Period + Temperature + Pandemic + February + March +
    April + May + June + July + August + September + October +
    November + December + Monday + Tuesday + Wednesday + Thursday +
    Friday + Saturday

                Estimate   Std. Error   t value   Pr(>|t|)
```

```
(Intercept) -0.174391705  0.204528919  -0.85265 0.39404866
Period      -0.000531141  0.000138139  -3.84496 0.00012786 ***
Temperature  0.004941580  0.003097862   1.59516 0.11097951
Pandemic    -1.822995163  0.100650704 -18.11210 < 2.22e-16 ***
February    -0.064635065  0.132894420  -0.48636 0.62681117
March       -0.123292502  0.134838398  -0.91437 0.36073236
April        0.092913475  0.146362906   0.63482 0.52568769
May          0.336352601  0.169962374   1.97898 0.04808038 *
June         0.470042495  0.191173011   2.45873 0.01410444 *
July         0.570473829  0.205718220   2.77308 0.00565166 **
August       0.518336215  0.199965244   2.59213 0.00967156 **
September    0.294567732  0.185157435   1.59090 0.11193388
October      0.123992594  0.153196099   0.80937 0.41848577
November    -0.024870972  0.139027314  -0.17889 0.85805666
December     0.191777468  0.148312764   1.29306 0.19627598
Monday       0.343939673  0.101123598   3.40118 0.00069637 ***
Tuesday      0.326190408  0.101299937   3.22005 0.00132125 **
Wednesday    0.312195053  0.101324888   3.08113 0.00211618 **
Thursday     0.354046605  0.101325305   3.49416 0.00049551 ***
Friday       0.629943071  0.101345293   6.21581 7.3690e-10 ***
Saturday     0.559926723  0.101335809   5.52546 4.1493e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.882878 on 1044 degrees of freedom
Number of observations: 1065 Degrees of Freedom: 1044
SSR: 813.770487 MSE: 0.779474 Root MSE: 0.882878
```

Multiple R-Squared: 0.52016 Adjusted R-Squared: 0.510968

SUR estimates for 'Transportation' (equation 3)

Model Formula: Transportation ~ Period + Temperature + Pandemic + February + March + April + May + June + July + August + September + October + November + December + Monday + Tuesday + Wednesday + Thursday + Friday + Saturday

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.058182073	0.188656007	0.30840	0.7578372	
Period	-0.000708637	0.000127419	-5.56148	3.3975e-08	***
Temperature	0.008531892	0.002857446	2.98585	0.0028939	**
Pandemic	-1.609511847	0.092839487	-17.33650	< 2.22e-16	***
February	-0.158976318	0.122580859	-1.29691	0.1949488	
March	-0.282363214	0.124373971	-2.27028	0.0233940	*
April	-0.240905083	0.135004094	-1.78443	0.0746445	.
May	-0.123435979	0.156772074	-0.78736	0.4312502	
June	0.267206233	0.176336613	1.51532	0.1299943	
July	0.363825771	0.189753010	1.91736	0.0554642	.
August	0.693011267	0.184446506	3.75725	0.0001813	***
September	0.417170750	0.170787889	2.44262	0.0147458	*
October	0.287337805	0.141306983	2.03343	0.0422617	*
November	0.334607213	0.128237797	2.60927	0.0092033	**
December	0.305322285	0.136802629	2.23185	0.0258368	*
Monday	0.262563607	0.093275681	2.81492	0.0049707	**
Tuesday	0.189125530	0.093438335	2.02407	0.0432174	*

```
Wednesday    0.254510205  0.093461349   2.72316  0.0065739 **
Thursday     0.286988364  0.093461734   3.07065  0.0021912 **
Friday       0.418730070  0.093480171   4.47935 8.3122e-06 ***
Saturday    -0.003897865  0.093471423  -0.04170  0.9667449
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.81436 on 1044 degrees of freedom
Number of observations: 1065 Degrees of Freedom: 1044
SSR: 692.362865 MSE: 0.663183 Root MSE: 0.81436
Multiple R-Squared: 0.541495 Adjusted R-Squared: 0.532711


SUR estimates for 'Residences' (equation 4)
Model Formula: Residences ~ Period + Temperature + Pandemic + February + March +
    April + May + June + July + August + September + October +
    November + December + Monday + Tuesday + Wednesday + Thursday +
    Friday + Saturday

                Estimate   Std. Error   t value   Pr(>|t|)
(Intercept) -1.994611993  0.179177943 -11.13202 < 2.22e-16 ***
Period       0.000343171  0.000121017   2.83571 0.00466064 **
Temperature  0.009567647  0.002713888   3.52544 0.00044113 ***
Pandemic    -0.808177368  0.088175238  -9.16558 < 2.22e-16 ***
February    -0.106851526  0.116422406  -0.91779 0.35893987
March       -0.119934978  0.118125432  -1.01532 0.31018910
April        0.244143498  0.128221498   1.90408 0.05717497 .
```

```
May          0.389459958  0.148895857   2.61565 0.00903417 **
June         0.441310113  0.167477475   2.63504 0.00853732 **
July         0.686078926  0.180219833   3.80690 0.00014891 ***
August       0.649082980  0.175179927   3.70524 0.00022227 ***
September    0.422439229  0.162207518   2.60431 0.00933661 **
October      0.375893059  0.134207730   2.80083 0.00519124 **
November     0.391403296  0.121795139   3.21362 0.00135087 **
December     1.299776213  0.129929675  10.00369 < 2.22e-16 ***
Monday       0.912488889  0.088589518  10.30019 < 2.22e-16 ***
Tuesday      0.938688106  0.088744000  10.57748 < 2.22e-16 ***
Wednesday    1.011410893  0.088765858  11.39414 < 2.22e-16 ***
Thursday     0.840868942  0.088766223   9.47285 < 2.22e-16 ***
Friday       1.125555002  0.088783734  12.67749 < 2.22e-16 ***
Saturday     0.699389253  0.088775425   7.87819 8.4377e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.773447 on 1044 degrees of freedom
Number of observations: 1065 Degrees of Freedom: 1044
SSR: 624.541904 MSE: 0.59822 Root MSE: 0.773447
Multiple R-Squared: 0.382062 Adjusted R-Squared: 0.370224


SUR estimates for 'PublicBuildings' (equation 5)
Model Formula: PublicBuildings ~ Period + Temperature + Pandemic + February +
    March + April + May + June + July + August + September +
    October + November + December + Monday + Tuesday + Wednesday +
```

```
    Thursday + Friday + Saturday

                 Estimate   Std. Error  t value   Pr(>|t|)
(Intercept) -0.435861895  0.178323694 -2.44422 0.01468127 *
Period      -0.000408768  0.000120440 -3.39395 0.00071482 ***
Temperature  0.001427066  0.002700949  0.52836 0.59736370
Pandemic    -0.682100074  0.087754854 -7.77279 1.8208e-14 ***
February     0.242053985  0.115867350  2.08906 0.03694390 *
March        0.145276742  0.117562257  1.23574 0.21683207
April        0.171574220  0.127610190  1.34452 0.17907293
May          0.373990050  0.148185981  2.52379 0.01175722 *
June         0.474638894  0.166679009  2.84762 0.00449109 **
July        -0.281218185  0.179360617 -1.56789 0.11720923
August      -0.128201034  0.174344739 -0.73533 0.46230329
September    0.388105831  0.161434178  2.40411 0.01638523 *
October      0.338405206  0.133567882  2.53358 0.01143570 *
November     0.117326066  0.121214469  0.96792 0.33330785
December     0.035487950  0.129310223  0.27444 0.78380049
Monday       0.891614027  0.088167159 10.11277 < 2.22e-16 ***
Tuesday      0.929148581  0.088320904 10.52014 < 2.22e-16 ***
Wednesday    0.951774711  0.088342658 10.77367 < 2.22e-16 ***
Thursday     0.976834616  0.088343022 11.05729 < 2.22e-16 ***
Friday       0.870574868  0.088360449  9.85254 < 2.22e-16 ***
Saturday     0.123625087  0.088352180  1.39923 0.16204083
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 0.769759 on 1044 degrees of freedom

Number of observations: 1065 Degrees of Freedom: 1044

SSR: 618.600968 MSE: 0.59253 Root MSE: 0.769759

Multiple R-Squared: 0.37107 Adjusted R-Squared: 0.359022

SUR estimates for 'Streets' (equation 6)

Model Formula: Streets ~ Period + Temperature + Pandemic + February + March + April + May + June + July + August + September + October + November + December + Monday + Tuesday + Wednesday + Thursday + Friday + Saturday

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.275472088	0.159006173	1.73246	0.0834867	.
Period	-0.001259595	0.000107393	-11.72881	< 2.22e-16	***
Temperature	0.015309516	0.002408360	6.35682	3.0727e-10	***
Pandemic	-0.583974506	0.078248511	-7.46307	1.7764e-13	***
February	-0.269161401	0.103315625	-2.60523	0.0093117	**
March	-0.426982159	0.104826926	-4.07321	4.9878e-05	***
April	-0.315239999	0.113786382	-2.77045	0.0056972	**
May	-0.053390059	0.132133230	-0.40406	0.6862496	
June	0.211219782	0.148622939	1.42118	0.1555634	
July	0.487470960	0.159930768	3.04801	0.0023616	**
August	1.011792319	0.155458252	6.50845	1.1767e-10	***
September	0.640175811	0.143946271	4.44732	9.6257e-06	***
October	0.693801902	0.119098686	5.82544	7.5804e-09	***
November	0.354300728	0.108083499	3.27803	0.0010798	**

```
December     0.614515214  0.115302253   5.32960 1.2058e-07 ***
Monday       0.228984451  0.078616151   2.91269  0.0036596 **
Tuesday      0.102290738  0.078753241   1.29888  0.1942731
Wednesday    0.166031080  0.078772639   2.10773  0.0352927 *
Thursday     0.169381615  0.078772963   2.15025  0.0317645 *
Friday       0.541308124  0.078788503   6.87039 1.0985e-11 ***
Saturday     0.215952451  0.078781129   2.74117  0.0062266 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.686373 on 1044 degrees of freedom
Number of observations: 1065 Degrees of Freedom: 1044
SSR: 491.836169 MSE: 0.471107 Root MSE: 0.686373
Multiple R-Squared: 0.568991 Adjusted R-Squared: 0.560734
```

9 Appendix B: Location Category Composition

Table 5: Location Category Decomposition

Nonessential Businesses	Public Buildings and Schools	Public and Private Transportation
athletic club	college/university grounds	aircraft
auto/boat/rv dealership	county jail	airport building non-terminal - non-secure area
banquet hall	federal building	airport building non-terminal - secure area
bar/tavern	fire station	airport exterior - non-secure area
barber shop/beauty salon	government building/property	airport exterior - secure area
bowling alley	jail / lock-up facility	airport parking lot
car wash	police facility/veh parking lot	airport terminal lower level - non-secure area
church/synagogue/place of worship	public grammar school	airport terminal lower level - secure area
club	public high school	airport terminal mezzanine - non-secure area
department store	school - private building	airport terminal upper level - non-secure area
horse stable	school - private grounds	airport terminal upper level - secure area
kennel	school - public building	airport transportation system (ats)
library	school - public grounds	airport vending establishment
movie house/theater	school yard	airport/aircraft
pool room		auto
poolroom		boat / watercraft
retail store		boat/watercraft
small retail store		cta “l” platform
sports arena/stadium		cta bus
ymca		cta bus stop
		cta parking lot/garage/other property
		cta platform
		cta property
		cta station
		cta subway station
		cta tracks - right of way
		cta train
		other commercial transportation
		taxi cab
		taxicab
		truck
		vehicle - commercial
		vehicle - commercial - entertainment / party bus
		vehicle - commercial - trolley bus
		vehicle - delivery truck
		vehicle - other ride share service (lyft, uber,...
		vehicle non-commercial

Table 6: Location Category Decomposition Continued

Essential Businesses	Residence	Street and Similar Locations	Dropped Locations
animal hospital	apartment	abandoned building	basement
appliance store	cha apartment	alley	coach house
atm (automatic teller machine)	cha breezeway	bridge	coin operated machine
bank	cha elevator	cemetary	commercial / business office
cleaners/laundromat	cha grounds	dumpster	driveway
cleaning store	cha hallway / stairwell / elevator	forest preserve	elevator
construction site	cha hallway/stairwell/elevator	highway/expressway	gangway
convenience store	cha lobby	lagoon	garage
credit union	cha parking lot/grounds	lake	hallway
currency exchange	cha play lot	lakefront/waterfront/riverbank	livery auto
day care center	college/university residence hall	park property	livery stand office
drug store	house	parking lot	loading dock
factory/manufacturing building	nursing / retirement home	parking lot / garage (non residential)	office
farm	porch	prairie	other
funeral parlor	residence	river	stairwell
garage/auto repair	residence - garage	sewer	trailer
gas station	residence - yard (front / back)	sidewalk	trucking terminal
gas station drive/prop.	residence porch/hallway	street	vestibule
grocery food store	residential - driveway	vacant lot	
hospital building/grounds	rooming house	vacant lot / land	
hotel/motel		wooded area	
junk yard/garbage dump		yard	
liquor store			
medical/dental office			
newsstand			
other railroad property / train depot			
pawn shop			
railroad property			
restaurant			
savings and loan			
warehouse			

10 Appendix C: OLS Regression Results

Dep. Variable:	Essential Businesses	**R-squared:**	0.542
Model:	OLS	**Adj. R-squared:**	0.533
Method:	Least Squares	**F-statistic:**	57.14
Date:	Thu, 08 Apr 2021	**Prob (F-statistic):**	3.36e-148
Time:	18:34:48	**Log-Likelihood:**	-3047.3
No. Observations:	986	**AIC:**	6137.
Df Residuals:	965	**BIC:**	6239.
Df Model:	20		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	28.0473	1.642	17.083	0.000	24.825	31.269
Period	-0.0051	0.001	-4.850	0.000	-0.007	-0.003
February	1.6708	0.989	1.690	0.091	-0.270	3.611
March	0.0522	0.970	0.054	0.957	-1.852	1.957
April	0.8340	1.024	0.814	0.416	-1.176	2.844
May	2.6764	1.167	2.293	0.022	0.386	4.967
June	3.7467	1.296	2.890	0.004	1.203	6.291
July	4.5469	1.386	3.281	0.001	1.827	7.267
August	4.2365	1.344	3.151	0.002	1.598	6.875
September	2.7855	1.244	2.240	0.025	0.345	5.226
October	1.4722	1.033	1.425	0.155	-0.555	3.500
November	0.3645	0.936	0.390	0.697	-1.472	2.201
December	1.6400	0.980	1.673	0.095	-0.283	3.563
Monday	1.9901	0.641	3.106	0.002	0.733	3.247
Tuesday	1.8084	0.642	2.817	0.005	0.549	3.068
Wednesday	1.8510	0.641	2.888	0.004	0.593	3.109
Thursday	2.0573	0.641	3.210	0.001	0.800	3.315
Friday	3.7918	0.641	5.915	0.000	2.534	5.050
Saturday	3.2087	0.641	5.006	0.000	1.951	4.467
Average temperature	0.0104	0.020	0.511	0.610	-0.030	0.050
Pandemic	-10.1587	0.694	-14.642	0.000	-11.520	-8.797

Dep. Variable:	Nonessential Businesses	**R-squared:**	0.669
Model:	OLS	**Adj. R-squared:**	0.662
Method:	Least Squares	**F-statistic:**	97.49
Date:	Thu, 08 Apr 2021	**Prob (F-statistic):**	2.69e-215
Time:	18:34:49	**Log-Likelihood:**	-3120.8
No. Observations:	986	**AIC:**	6284.
Df Residuals:	965	**BIC:**	6386.
Df Model:	20		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	28.8331	1.769	16.300	0.000	25.362	32.304
Period	-0.0018	0.001	-1.626	0.104	-0.004	0.000
February	-0.4657	1.065	-0.437	0.662	-2.556	1.625
March	-3.2995	1.046	-3.156	0.002	-5.351	-1.248
April	-0.8287	1.104	-0.751	0.453	-2.995	1.337
May	1.7230	1.258	1.370	0.171	-0.745	4.191
June	3.1223	1.397	2.235	0.026	0.381	5.863
July	3.3192	1.493	2.223	0.026	0.389	6.249
August	3.4461	1.448	2.379	0.018	0.604	6.288
September	3.2173	1.340	2.401	0.017	0.588	5.847
October	2.0285	1.113	1.822	0.069	-0.156	4.213
November	2.6341	1.008	2.613	0.009	0.656	4.612
December	4.1058	1.056	3.888	0.000	2.033	6.178
Monday	-1.3245	0.690	-1.919	0.055	-2.679	0.030
Tuesday	-1.7395	0.692	-2.515	0.012	-3.097	-0.382
Wednesday	-1.3639	0.690	-1.975	0.048	-2.719	-0.009
Thursday	-1.4070	0.691	-2.038	0.042	-2.762	-0.052
Friday	-0.2582	0.691	-0.374	0.709	-1.614	1.097
Saturday	3.7770	0.691	5.469	0.000	2.422	5.132
Average temperature	-0.0062	0.022	-0.283	0.777	-0.049	0.037
Pandemic	-17.1056	0.748	-22.883	0.000	-18.573	-15.639

Dep. Variable:	Public and Private Transportation	**R-squared:**	0.573
Model:	OLS	**Adj. R-squared:**	0.564
Method:	Least Squares	**F-statistic:**	64.70
Date:	Thu, 08 Apr 2021	**Prob (F-statistic):**	1.66e-162
Time:	18:34:50	**Log-Likelihood:**	-2666.4
No. Observations:	986	**AIC:**	5375.
Df Residuals:	965	**BIC:**	5477.
Df Model:	20		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	17.7810	1.116	15.937	0.000	15.591	19.971
Period	-0.0050	0.001	-7.088	0.000	-0.006	-0.004
February	-0.3507	0.672	-0.522	0.602	-1.669	0.968
March	-2.2743	0.659	-3.449	0.001	-3.568	-0.980
April	-2.1321	0.696	-3.063	0.002	-3.498	-0.766
May	-1.4449	0.793	-1.822	0.069	-3.001	0.112
June	0.4596	0.881	0.522	0.602	-1.269	2.188
July	1.0001	0.942	1.062	0.289	-0.848	2.848
August	2.5445	0.914	2.785	0.005	0.752	4.337
September	1.2917	0.845	1.528	0.127	-0.367	2.950
October	0.6505	0.702	0.926	0.354	-0.727	2.028
November	0.8370	0.636	1.316	0.188	-0.411	2.085
December	0.7249	0.666	1.088	0.277	-0.582	2.032
Monday	1.0885	0.435	2.500	0.013	0.234	1.943
Tuesday	0.6552	0.436	1.502	0.133	-0.201	1.511
Wednesday	1.1383	0.435	2.614	0.009	0.284	1.993
Thursday	1.1206	0.436	2.573	0.010	0.266	1.975
Friday	1.8551	0.436	4.259	0.000	1.000	2.710
Saturday	-0.1033	0.436	-0.237	0.813	-0.958	0.752
Average temperature	0.0326	0.014	2.353	0.019	0.005	0.060
Pandemic	-6.3800	0.471	-13.532	0.000	-7.305	-5.455

Dep. Variable:	Public Buildings and Schools	**R-squared:**	0.384
Model:	OLS	**Adj. R-squared:**	0.371
Method:	Least Squares	**F-statistic:**	30.08
Date:	Thu, 08 Apr 2021	**Prob (F-statistic):**	2.31e-87
Time:	18:34:50	**Log-Likelihood:**	-1946.2
No. Observations:	986	**AIC:**	3934.
Df Residuals:	965	**BIC:**	4037.
Df Model:	20		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	2.2721	0.537	4.227	0.000	1.217	3.327
Period	-0.0013	0.000	-3.771	0.000	-0.002	-0.001
February	0.7370	0.324	2.277	0.023	0.102	1.372
March	-0.0680	0.318	-0.214	0.831	-0.691	0.555
April	0.1801	0.335	0.537	0.591	-0.478	0.838
May	0.6859	0.382	1.795	0.073	-0.064	1.436
June	0.9489	0.424	2.236	0.026	0.116	1.782
July	-0.7937	0.454	-1.749	0.081	-1.684	0.097
August	-0.4319	0.440	-0.981	0.327	-1.296	0.432
September	0.7732	0.407	1.899	0.058	-0.026	1.572
October	0.6398	0.338	1.892	0.059	-0.024	1.304
November	0.1095	0.306	0.358	0.721	-0.492	0.711
December	-0.0743	0.321	-0.232	0.817	-0.704	0.555
Monday	1.8977	0.210	9.049	0.000	1.486	2.309
Tuesday	2.1272	0.210	10.124	0.000	1.715	2.539
Wednesday	2.1369	0.210	10.187	0.000	1.725	2.549
Thursday	2.1896	0.210	10.437	0.000	1.778	2.601
Friday	2.0285	0.210	9.667	0.000	1.617	2.440
Saturday	0.2499	0.210	1.191	0.234	-0.162	0.662
Average temperature	0.0016	0.007	0.239	0.811	-0.012	0.015
Pandemic	-1.3974	0.227	-6.152	0.000	-1.843	-0.952

Dep. Variable:	Residence	**R-squared:**	0.372
Model:	OLS	**Adj. R-squared:**	0.359
Method:	Least Squares	**F-statistic:**	28.64
Date:	Thu, 08 Apr 2021	**Prob (F-statistic):**	1.38e-83
Time:	18:34:49	**Log-Likelihood:**	-3401.2
No. Observations:	986	**AIC:**	6844.
Df Residuals:	965	**BIC:**	6947.
Df Model:	20		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	21.8014	2.351	9.274	0.000	17.188	26.415
Period	0.0026	0.001	1.745	0.081	-0.000	0.006
February	0.1151	1.416	0.081	0.935	-2.663	2.893
March	-1.5893	1.389	-1.144	0.253	-4.316	1.137
April	2.1282	1.467	1.451	0.147	-0.750	5.007
May	3.4591	1.671	2.070	0.039	0.179	6.739
June	3.9147	1.856	2.109	0.035	0.272	7.557
July	6.2998	1.984	3.175	0.002	2.405	10.194
August	5.9823	1.925	3.108	0.002	2.205	9.760
September	3.8249	1.781	2.148	0.032	0.331	7.319
October	3.5254	1.479	2.383	0.017	0.622	6.429
November	3.8142	1.340	2.847	0.005	1.185	6.443
December	12.8823	1.403	9.179	0.000	10.128	15.636
Monday	9.2812	0.917	10.118	0.000	7.481	11.081
Tuesday	9.5018	0.919	10.339	0.000	7.698	11.305
Wednesday	10.3063	0.918	11.233	0.000	8.506	12.107
Thursday	8.4371	0.918	9.194	0.000	6.636	10.238
Friday	11.5088	0.918	12.539	0.000	9.708	13.310
Saturday	7.0102	0.918	7.638	0.000	5.209	8.811
Average temperature	0.1034	0.029	3.539	0.000	0.046	0.161
Pandemic	-7.5774	0.993	-7.627	0.000	-9.527	-5.628

Dep. Variable:	Street and Similar Locations	**R-squared:**	0.585
Model:	OLS	**Adj. R-squared:**	0.576
Method:	Least Squares	**F-statistic:**	68.03
Date:	Thu, 08 Apr 2021	**Prob (F-statistic):**	1.66e-168
Time:	18:34:47	**Log-Likelihood:**	-3810.5
No. Observations:	986	**AIC:**	7663.
Df Residuals:	965	**BIC:**	7766.
Df Model:	20		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	80.8086	3.561	22.695	0.000	73.821	87.796
Period	-0.0236	0.002	-10.451	0.000	-0.028	-0.019
February	1.1461	2.144	0.534	0.593	-3.062	5.354
March	-4.2853	2.105	-2.036	0.042	-8.415	-0.155
April	-3.7982	2.222	-1.710	0.088	-8.158	0.561
May	0.6362	2.531	0.251	0.802	-4.331	5.604
June	5.1235	2.811	1.822	0.069	-0.394	10.641
July	9.8653	3.006	3.282	0.001	3.967	15.764
August	18.8570	2.915	6.468	0.000	13.136	24.578
September	12.6418	2.697	4.687	0.000	7.349	17.934
October	13.7446	2.241	6.134	0.000	9.347	18.142
November	8.1068	2.029	3.995	0.000	4.125	12.089
December	12.5803	2.126	5.918	0.000	8.409	16.752
Monday	3.7758	1.389	2.718	0.007	1.049	6.502
Tuesday	1.2414	1.392	0.892	0.373	-1.490	3.973
Wednesday	2.3546	1.390	1.694	0.091	-0.373	5.082
Thursday	2.4099	1.390	1.734	0.083	-0.318	5.138
Friday	8.6446	1.390	6.219	0.000	5.917	11.373
Saturday	3.8896	1.390	2.798	0.005	1.162	6.617
Average temperature	0.2667	0.044	6.028	0.000	0.180	0.354
Pandemic	-8.8277	1.505	-5.867	0.000	-11.781	-5.875

11 Appendix D: Subtypes of Theft

Table 7: Subtypes of Theft in the Chicago CPD Database

Theft Sub Types
POCKET-PICKING
OVER $500
RETAIL THEFT
$500 AND UNDER
FROM BUILDING
AUTOMOBILE
ATTEMPT THEFT
PURSE-SNATCHING
THEFT/RECOVERY: AUTOMOBILE
TRUCK, BUS, MOTOR HOME
DELIVERY CONTAINER THEFT
ATT: AUTOMOBILE
CYCLE, SCOOTER, BIKE W-VIN
CYCLE, SCOOTER, BIKE NO VIN
ATT: TRUCK, BUS, MOTOR HOME
THEFT/RECOVERY: TRUCK,BUS,MHOME
ATTEMPT: CYCLE, SCOOTER, BIKE W-VIN
FROM COIN-OP MACHINE/DEVICE
THEFT/RECOVERY: CYCLE, SCOOTER, BIKE W-VIN
THEFT / RECOVERY - AUTOMOBILE
CYCLE, SCOOTER, BIKE WITH VIN
ATTEMPT - AUTOMOBILE
THEFT RETAIL
THEFT/RECOVERY: CYCLE, SCOOTER, BIKE NO VIN
THEFT / RECOVERY - TRUCK, BUS, MOBILE HOME
FINANCIAL ID THEFT:$300 &UNDER
FINANCIAL ID THEFT: OVER $300
AGG: FINANCIAL ID THEFT
THEFT / RECOVERY - CYCLE, SCOOTER, BIKE WITH VIN
$300 AND UNDER
OVER $300
ATTEMPT FINANCIAL IDENTITY THEFT
ATTEMPT: CYCLE, SCOOTER, BIKE NO VIN
FROM COIN-OPERATED MACHINE OR DEVICE
ATTEMPT - TRUCK, BUS, MOTOR HOME
ATTEMPT - CYCLE, SCOOTER, BIKE WITH VIN
FINANCIAL IDENTITY THEFT: OVER $300

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