Crime Perceptions versus Actual Crime: Evidence from Chicago

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Abstract

Despite a sharp decline in crime rates over the past three decades, public perceptions of crime have worsened. We provide and empirically test a hypothesis that may explain this discrepancy. Perceptions of crime can rise even as actual crime declines due to a "ratchet effect": while increases in crime heighten perceptions, declines do not produce a symmetric downward adjustment in perceptions. Using granular (police sector) and high-frequency (monthly) data on crime and crime perceptions in Chicago, we find that an additional homicide in a given month decreases perceived safety by 0.15 percentage points. Months with an increase in homicides relative to the previous month are associated with a statistically significant 0.38 percentage point decline in safety perceptions. In contrast, when homicides decrease relative to the previous month, perceptions improve by only half that magnitude, and the effect is not statistically significant. These results suggest that while the direction of an individual's response to changes in crime is rational, the magnitude of the response is highly asymmetric. This asymmetry can lead to divergent trajectories in perceived and actual crime over time.

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1 Introduction

Despite a substantial decline in crime rates over the past three decades, public perceptions of crime have worsened. Figure 1 shows this paradoxical relationship between 2000 and 2023.[1,2] This paradox has been widely documented, yet its underlying mechanisms remain poorly understood.

Differences between perceived and actual crime can have important behavioral and policy implications. Individuals may over-invest in self-protection, avoid welfare-enhancing activities, or support inefficient punitive policies (Koenig, 1980; Rich and Sampson, 1990; Hoffman and Hardyman, 1986). Misaligned perceptions can also affect political accountability by rewarding or punishing elected officials based on perceived rather than actual changes in public safety. This can weaken incentives for effective policymaking. Finally, such biases can generate allocative inefficiencies as public resources are diverted toward crime control even when objective conditions are improving (Tu et al., 2024).

We provide and empirically test a hypothesis that may explain this discrepancy. Specifically, we argue that perceptions of crime are subject to a *ratchet effect*: while increases in crime heighten perceptions of crime, declines do not produce a symmetric downward adjustment. This asymmetric response can lead to a growing divergence in the trajectories of perceived and actual crime over time.

To examine this phenomenon, we use high-frequency, spatially granular data from Chicago. Our primary measure of safety perception comes from the Chicago Police Sentiment Dashboard, a large-scale survey conducted between 2018 and 2023 that captures self-reported perceptions of safety (as related to crime) at the police sector level. This dataset allows us to track how safety perceptions evolve in response to changes in crime at a spatially granular and high frequency level. We combine this with administrative crime data from the Chicago Police Department, which records all reported crimes at the sector level, allowing us to measure the impact of different crime types—particularly violent crime—on public perceptions. We combine these data to create a sector-by-month panel of crime and crime

[1] Reported crime is collected from the FBI annual crime reports, while Perception of crime obtained from the Gallup Survey. The latter asks two questions to participants: "Is there more crime in the U.S. than there was a year ago, or less?" and "Is there more crime in your area than there was a year ago, or less?"

[2] Violent crime rate fell 49 percent between 1993 and 2022, while the property crime rate decreased by 59 percent See National Crime Victimization Survey collected by BJS (USA, 2024) and Pew Research Center article (Gramlich, 2024)

perceptions.

Our empirical strategy relies on panel regressions using a set of restrictive fixed effects. This accounts for unobservable differences across sectors and temporal fluctuations in crime trends. Specifically, we estimate the effect of lagged crime on safety perceptions while controlling for sector fixed effects, common time-varying factors (via month-by-year fixed effects), and sector-specific temporal trends (via sector-by-month fixed effects). To further address potential endogeneity concerns, we employ an instrumental variables (IV) approach using large-scale public events—such as sports games and concerts—that temporarily reallocate police patrols across the city. This provides exogenous variation in crime rates that allows us to better identify the causal impact of crime on safety perceptions.

Our findings indicate that perceptions of crime are particularly sensitive to homicide rates, while responses to property crimes are weaker and often statistically insignificant. An additional homicide in a given month leads to a 0.15 percentage point decrease in perceived safety, with months experiencing a rise in homicides relative to the previous month associated with a statistically significant 0.38 percentage point decline in safety perceptions. In contrast, months where homicides decline relative to the previous month see only half that magnitude of improvement, and the effect is not statistically significant. This asymmetry in response—where individuals react strongly to increases in crime but weakly (or not at all) to declines—supports the existence of a ratchet effect in crime perceptions.

To further investigate this asymmetry, we examine months with extreme homicide levels. We find that during periods of exceptionally high homicide rates (above the 95th percentile), perceptions of safety decline sharply, whereas months with no homicides (below the 5th percentile) have no measurable effect on improving safety perceptions. These results suggest that negative crime shocks have a lasting impact on perceptions, while periods of relative safety do little to counteract this effect. This imbalance in how individuals process crime-related information provides a compelling explanation for why perceptions of crime have continued to worsen despite declining crime rates.

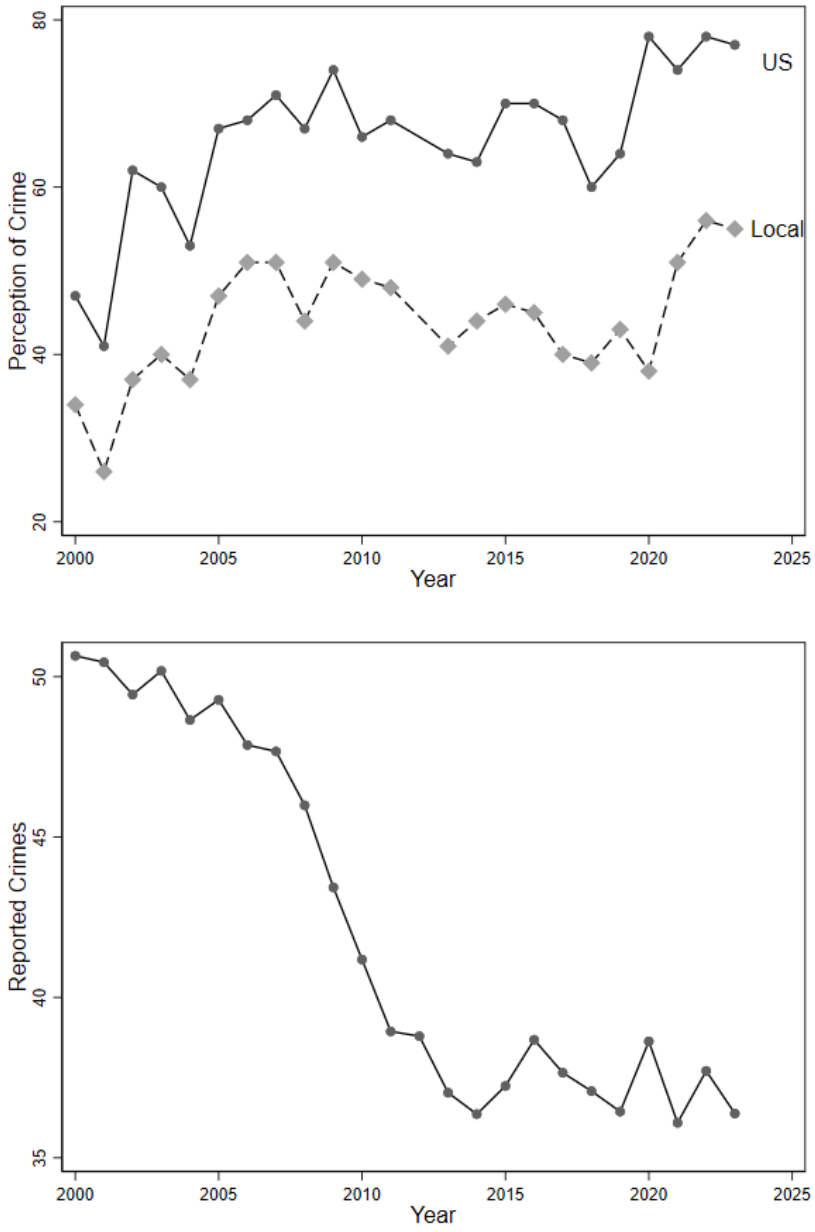
There is a large literature exploring the discrepancies between perception and reality (Ballard and Gupta, 2018; Ambrey et al., 2014; Ramírez-Álvarez, 2020; Ardanaz et al., 2014; Montolio and Planells-Struse, 2015; Ajzenman et al., 2023) . Under the context of crime and perception, previous studies have been focusing on indirect determinants of crime perception, especially the effects of media exposure (Ramírez-Álvarez (2020); Velásquez et al.

(2020); Ardanaz et al. (2014)) as the main mechanism causing the discrepancies between perception and reality. Other authors also try to analyze how perception of crime would be heterogenous across people and how that would matter for society (Manning et al., 2022; Ambrey et al., 2014). However, to the best knowledge of the authors, this is the first paper providing insights on a mechanism that uses actual reported crime as the main driver of individuals' perception of crime. Furthermore, this one of the first papers analyzing crime and perception under the U.S. context.

This paper also contributes to the literature on loss aversion and the psychology behind responding to positive and negative events (Levine et al., 2009; Rozin and Royzman, 2001; Taylor, 1991; Berntsen et al., 2011). Many have studied the presence of loss aversion in human decisions (Genesove and Mayer, 2001; Andersen et al., 2022; Rees-Jones, 2017; Dimmock and Kouwenberg, 2010; Sydnor, 2010; Kőszegi and Rabin, 2009; Camerer et al., 1997; Fryer et al., 2022; Drager et al., 2014; Pope and Schweitzer, 2011). However, we are the first to formalize a theoretical framework that attempts to explain how individuals perceive crime differently when conditioned on being exposed to safe and unsafe periods. We also test the model using empirical analysis to verify whether the results obtained in the model fit into the data.

The remainder of this paper is structured as follows: Section 2 describes the theoretical framework and develop the main hypothesis that generates the differences in trends between reported crimes and perception, Section 3 contains our institutional setting and data analysis, Section 4 presents our empirical design, Section 5 shows our main results and tests if the hypothesis developed in the theoretical framework section holds, and Section 6 concludes the paper.

Figure 1: Perception of Crime and Reported Crime plots



Notes: The Reported Crimes variable was obtained from FBI annual crime reports. Crime data for 2000 come from 2019 FBI report (Federal Bureau of Investigation, 2019). Crime data for 2001 and 2002 come from 2020 FBI report (Federal Bureau of Investigation, 2020). Crime data for 2003 come from 2022 FBI Report (Federal Bureau of Investigation, 2022). The remaining years use data from 2023 FBI report (Federal Bureau of Investigation, 2023). From this, it is possible to notice that the rate of victimization clearly decreases over time. On the other hand, the perception of crimes follows the opposite direction, as it is fairly increasing from 2000 to 2023, with an increase from approximately 40 percent to 79 percent at the national level and from approximately 24 percent to 58 percent at the local level.

2 Model

We propose a hypothesis that one of the potential reasons on why we observe such a behavior of diverging trend on actual crimes and perceived crimes would be due to the different weights that people would assign to positive and negative periods of violence. We define a positive period when there are fewer crimes relative to the previous period, i.e., if occurs fewer crimes, in a given area , in period t than in period t-1, in such a way that this difference would be positive. A negative period would be the opposite, i.e., if there are more crimes in t than in t-1. If people rationally react to such changes, people should update their perception proportionally for both cases, i.e, if a period is safer, then people should increase their perception of safeness at the same level that it would decrease it if there were a period of crimes.

There is an extensive psychology literature that explores the differences of individual's responses with negative and positive events. One potential explanation could simply be media exposure, as studies have shown that human beings are likely to seek and attend to negative information about others (Baumeister et al., 2001). Also, another potential explanation could be what physiologist call "biased memory effects". According to (Breslin and Safer, 2011), individuals rehearse positive events more than comparable negative events, and that this additional rehearsal increases both vividness and accuracy of memories about positive events, i.e., individuals would be more likely to forget negative events. Thus, (Mastroianni and Gilbert, 2023) argue that these two psychological effects can produce what they call an "illusion of moral decline", as it is believed that moral in society has declined, even though people's reports of the morality of their contemporaries have not declined over time.

In that sense, we propose that the intensity of a positive shock of a period of no crimes on individual's perception of safeness would be different relative to a negative shock. In other words, after a period of high volume of crimes, people's perception would be greatly affected. If such hypothesis holds to be true, then we would have that the "stock" of perception of crimes would tend to be increasing over time, as a positive period of crime would not compensate for the negative one. Another potential way of viewing such hypothesis under the "illusion of moral decline" framework, in such a way that people would believe that crime as increased due to the higher exposure to such information and due to the higher propensity of forgetting bad events from the past, resulting in greater weights in bad events in

the present. As an initial theoretical framework, we can test the law of motion of perception as follows:

$$P_{t+1} = \begin{cases} P_t + \beta \Delta C, & \text{if } \Delta C > 0 \\ P_t + \delta \Delta C, & \text{if } \Delta C \leq 0 \end{cases} \tag{1}$$

where P_{t+1} is the perception of crime in period t+1, P_t is the perception of crime in period t, while ΔC is the variation of crimes from two different periods, i.e, $\Delta C = c_t - c_{t-1}$. In this framework, if δ equals β, then we would have that people would react at the same proportion for both positive and negative periods of crimes events. However, if such coefficients are different, then this would mean that people would react differently, in such a way that this could help explaining why we observe such a difference in trends of actual crimes and perception.

3 Data

To obtain information on perception, we use the Chicago Police Sentiment Dashboard. This is a monthly survey that measures how safe Chicago residents feel and how much they trust the police through local digital ads. Despite having information on trust on police, on this project we focus on the safety score, which is measured in a scale fro 0 to 10 based on the following question: "When it comes to the threat of crime, how safe do you feel in your neighborhood?". This data set contains weekly information from 2018 to 2023, and it is available at both the district and sector level. In addition, the Chicago Police Sentiment Dashboard also contains demographic information on the people who participate on the survey, such as race, age, sex, and education level, which it can be useful to use as control variables when developing the model.

It is important mentioning that the Chicago Police Sentiment score is also collected during the same time frame for every district, in such a way that there would be no cases in which a survey is performed during a different timing in a different district. Thus, in the sentiment score data, we don't have variation on timing of the survey. Furthermore, it is valuable to add that this is not exactly a panel data, since the individuals filling the survey are not necessarily the same, but obtained randomly across the areas of Chicago. Finally, one could argue that since this is a survey, we could potentially face some selection issues on the data collection. However, the trends that are obtained from such a survey follow the same pattern as those obtained from the surveys performed by other sources, and this allow us to argue that the data set used corroborates with the general information available about perception.

In addition to this, we also use data from the Chicago Police Department to obtain information on the actual crimes that occurred over the year. In this data set, it is possible to verify every single crime registered in Chicago, by date, regardless of ending up in arrest or not. This information is available by district and beat level. From the beat level, it is also possible to obtain the information at the sector level.[3]

In this context, the actual crime data contains detailed information on the type of crime, in such a way that it is possible to see the primary type of the crime, and also some level of description of the information, along with the FBI code, in such a way that it is possible

[3]Thus, to merge both data sets in order to generate a unique data set that is possible to work with both crimes and perception, it is possible to match the districts at monthly by year level. From this, it is possible to estimate our empirical specification and test the proposed theoretical model.

to classify the crimes by type. In that sense, we can classify the crimes by category, more specifically separating in violent crimes, property crimes, and non-index crimes..[4]

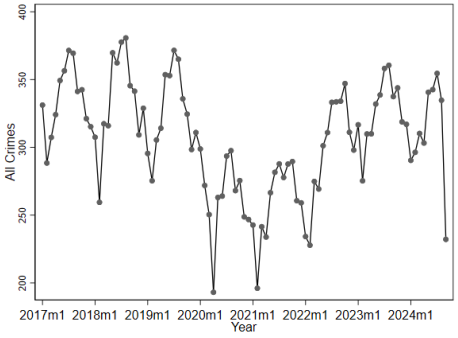
Figure 2 shows the time series of all crimes, by most relevant types. In that sense, it is possible to notice that the trends have similar variations over time, in such a way that, overall, it follows a decreasing trend. In Panel A, it is possible to visualize the rate of every reported crime and this have a similar behavior relative to property crimes, as indicated in Panel D, such that both would be decreasing. However, at Panel C, it is possible to notice that the Homicide rates are following different trends, specially between 2020 and 2022, as these would have slightly positive trends during this period, but overall it would still be fairly constant over time.

On the other hand, Figure 3 shows the time series for safety perception between 2017 and 2024. From this, it is possible to notice that up to 2022, such a trend is clearly decreasing, which would corroborate with the idea that perception and reported crimes does not follow the same trend direction. After 2022, it is possible to visualize an increase on perception of Safety, but this would also be a contradiction, as it is possible to see , still from Figure 2, that the number of crimes had actually had increased relative to 2020-2022, in such a way that it is still possible to argue that individuals are not properly responding to general level of crimes.

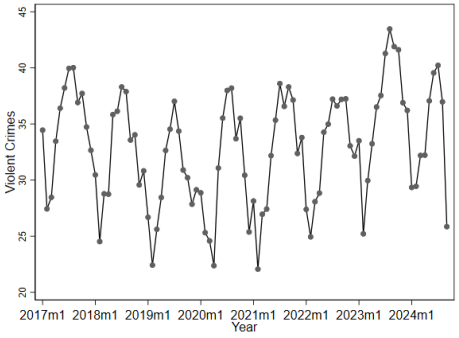
To further analyze the heterogeneity of perception across individuals, we also plot such trends disaggregated according to the level of education, race, gender, and income. From Figure 4, it is possible to visualize that perception of safety are greater of level for those with higher education, white individuals, and those with higher income. However, the trends still follows similar behavior, even differing on levels, which indicate that such a paradox of perception and actual level of crimes affects all individuals in general, despite having different levels of intensity.

[4]The violent crimes would include rape, robbery, aggravated assault, and aggravated battery, while the property crimes would include burglary, larceny, vehicle theft, and arson. Finally, the non-index crimes consists of simple assault, fraud, forgery, vandalism, illegal possession of weapon, sex abuse, disorderly, drug-related activities

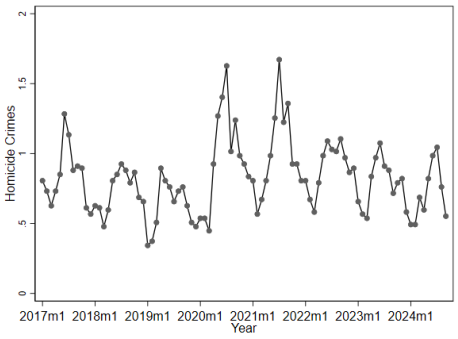
Figure 2: Time Series of Reported Crime



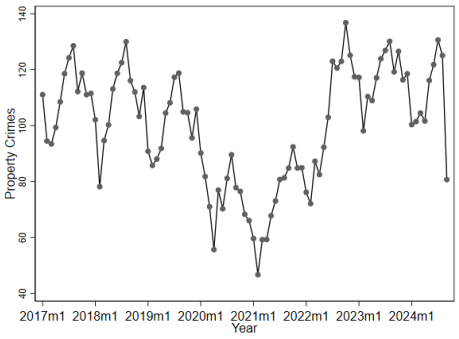
(a) Panel A



(b) Panel B



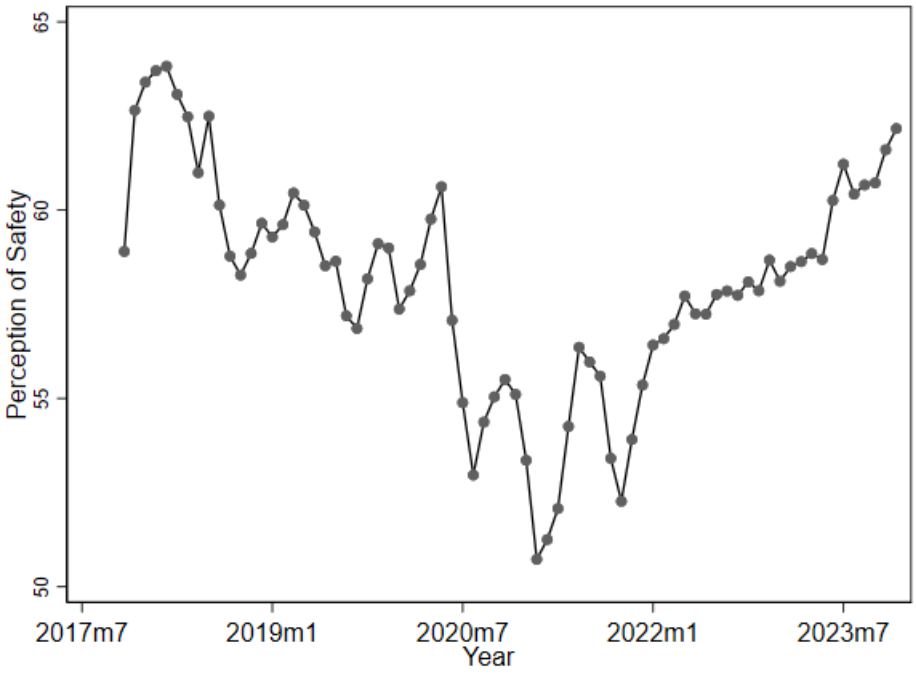
(c) Panel C



(d) Panel D

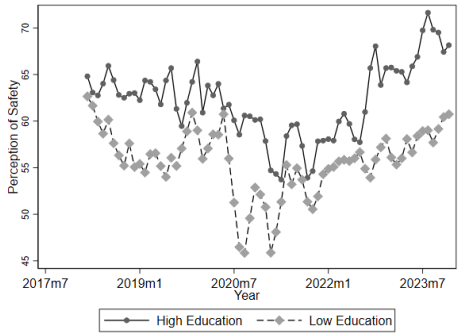
Notes: The Reported Crimes variable was obtained from FBI annual crime reports. Panel A reports the time series for all crimes. Panel B contains information on violent crimes only. Panel C describe only reported homicides, while Panel D describe property crimes. Note that for all trends the reported crimes are fairly constant over time, as the monthly variation follows similar trends every year. However, around Covid period, 2020 and 2021, it is possible to notice that all crimes and property crimes decrease on level, while homicides increases on level.

Figure 3: Time Series of Safety Perception

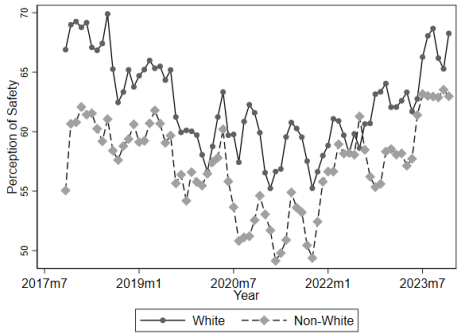


Notes: Perception data is obtained from Chicago Police Sentiment Dashboard. From this, it is possible to notice that perception of safety does not follow similar trends relative to reported crime, as trends are decreasing up to 2022, which corroborates with the idea that perceptions does not follow the actual crimes. Also, note that the increase of safety perception is also following the trends of homicide rate, as Figure A.2 shows that such a rate drastically decreases during this period.

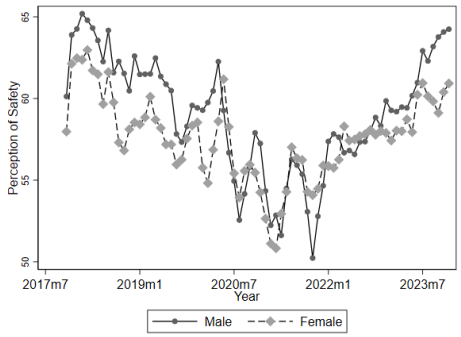
Figure 4: Time Series of Safety Perception



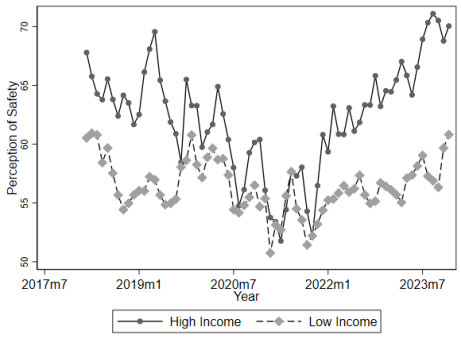
(a) Panel A



(b) Panel B



(c) Panel C



(d) Panel D

Notes: Perception data is obtained from Chicago Police Sentiment Dashboard Panel. Panel A reports the time series by level of education. Panel B contains information by race. Panel C describe perception by gender, while Panel D describe perception by income. Note that for we have significant heterogeneity according to the type of individual under study, in such a way that we must account for such observables.

4 Empirical Strategy

To obtain the correlation between crimes and perception, we rely on the 2WFE approach to solve potential endogenity issues. Because there are particularities in each sector, we include sector FE. Additionally, to control for the specificity of each period (as it is possible to visualize that months varies in similar patterns), we also include month by year FE, and an interaction sector by month fixed effect to account for the unobservable differences across districts on different periods of time. Thus, run the safety scores on lagged crimes under the following specification:

$$Y_{s,t} = \beta X_{crime_{s,t-1}} + \delta_t + \Omega_s + \delta_t * \Omega_s + \xi_{s,t} \tag{2}$$

where $Y_{s,t}$ would be the safety score at the sector s, in month t, Ω_s would be sector fixed effect, while δ_t would be month by year effect. Finally, $X_{crime_{s,t-1}}$ is the vector of specified reported crimes[5] in sector s in period t-1. Note that the crime is lagged one period, since it is reasonable to hypothesize that people would not immediately update their perception of crimes, instead they would react to a crime that occurred prior to the period they filled the survey. Here, we would be interested in obtaining β, as this would give us by how much safety perception would change with an unit increase on crimes occurring in t-1.

Additionally, we also hypothesize a theoretical framework in which individuals would react differently depending if the period has more or less crimes than the past, i.e., that people would respond in a higher magnitude to bad events (occurrence of violent crimes) in comparison to good events (no violent crimes). To properly test this, we can do as follows:

$$Safety_{s,t} = \alpha_s + \beta Safety_{s,t-1} + \gamma \Delta C_{s,t} + \rho D_{s,t} \Delta C_{s,t} + u_{st} \tag{3}$$

[5]Here we would run models specifying different classification of crimes. We follow both more general and more specific approaches when considering the types of crime. For instance, we analyze general classifications as index and non-index crimes, violent crimes, and property crimes, but we focus on specifically in Homicide scenarios in the main specification

where D is an indicator of whether district s in period t had an increase in crimes relative to the previous period, $\Delta C_{s,t}$ would indicate by how much district s in period t changes. Our main coefficient of interest would in such a framework would be to obtain ρ and γ, in such a way that if our hypothesis holds true, then we should have that ρ is larger than γ, as this would imply that individuals would put more weights on violent periods, relative to non-violent periods.

Additionally, to address potential endogeneity issues that would not be perfectly solved by using the TWFE specification, we create an instrument to identify the effects of crimes on perception. We use large attendance events[6] as instruments with the idea that large events would result in temporary reallocation of police patrols to the hosting the event. The main hypothesis is that such a movement across sectors would generate an impact on crime without affecting individuals perception of crime, especially for those located farther from the venues, such that both relevance condition and the exclusion restriction would hold.

To build the instrument we account for the distance of the sector to the venue, and the average attendance of each event, as this would affect the number of police patrols being reallocated. In that sense, the instrument is defined as follows:

$$Z = \sum_{v=1,e=1}^{v=4,e=n} \frac{N_{v,e} Attendance_e}{Distance_v} \tag{4}$$

where $N_{v,e}$ is the number of events type,[7] e, in a given month t in a specific venue v, such that we account for attendance[8] in such event type, and the distance to the specific venue. In that sense, for every specification, Cragg-Donald Wald F statistic is above 10, which indicates that the instrument is strong, i.e., we tend to not have bias generated by weak instruments. The results will be discussed in the next section.

[6]Events (Including Sports and Concerts) occurring in the four main venues in Chicago: United Center, Soldier Field, Wrigley Field, and Rate Field

[7]Event type is classfied according to the sport category and to the concert

[8]For sports, attendance is calculated using the mean of yearly attendance for a given club, while for concerts we use the stadium capacity, as it is assume that by allocating a concert in a specific venue, it is expected full capacity

5 Results

From the main specification, we obtain that individuals would properly react to homicide, but they would not react to property crimes. In Table 1, we can observe the estimates of the regression of safety perception in period t on actual crimes that occurred in period t-1 , but expanding all the different types of index crimes, as classified by the FBI definition. In column 1, we obtain that people would be negatively perceiving crimes related to aggravated battery, robbery, homicides, and burglary, in such a way that homicide would have a stronger magnitude in comparison to any other crime. This would corroborates with the hypothesis that people would negatively react to more serious crimes, and not that much for the extreme ones.

However, with less restrictive fixed effects, we obtain that individuals would positively react to larceny. Despite obtaining, in column 2, that such an effect would dissipate when controlling sector trends FE, to investigate that further we expand the type of larceny by subdividing in crimes involving less than 500 dollars and crimes involving more than 500 dollars. The estimates can be observed from columns 3 and 4, such that only larceny cases involving "small values" would be statistically significant, i.e., the positive estimates in column 1 would be driven by the smaller crimes, in which people could tend to not feel unsafe due to the relatively low valuation of the goods involved. When controlling for sector trends, in column 5, we can observe that there is no effect for both types of larceny. Finally, in both columns 2 and 4, we can also notice that, when controlling for sector trends, only homicide is statistically significant, at 10 percent level of significance. Considering that the specification from column 2 and 4 would be the closest to obtain a causal inference among these initial specifications (although there is the possibility of having endogeneity if we have unobservables at the district-month level) , this would indicate that people would clearly react to more extreme crimes, such as those involving homicide, as such a coefficient is very strong in magnitude, and still statistically significant, despite the small sample size, but such an effect would not be so clear for less serious cases.

Since the effects are more evident on homicides, we will focus on these cases instead of general crimes. In that sense, in Table 2, we consider a scenarios of extreme months, i.e., considering a high-level of homicides indicator that equals 1 if the mean of homicides in a given period was above the 95th percentile , otherwise, it would be 0. This allows us to capture periods of extreme violence. We also use a similar indicator for cases in

which the percentile is below the 5th percentile, which would capture a period with no homicides. From columns 1 and 2, it is possible to see that the extreme negative months have statistically significant estimate, in such a way that a high homicide period would decrease the safety perception in 71.1 percent when not using control variables or sector trends FE, while by including the sector trends FE such a magnitude would be only 41.5 decrease, being statistically significant only at the 10 percent level of significancy. By including the control variables, in columns 3 and 4, we obtain similar results to columns 1 and 2, but with smaller magnitudes for respective cases. On the other hand, when we look on periods with no homicides in a period, there is no statistically significant change in perception in safer months for any of the specifications.

This may imply that people respond differently to positive and negative months, in such a way that when months of violent crimes are experienced the perception on crimes is heavily affected, while the safer months are not enough to compensate for such negative effects. Thus, this could lead, over time, to what has been observed in surveys, i.e., that despite crimes has been decreasing over time, people feel less safe. It is valuable to add that such an estimation is also important to bring some level of exogeneity on the treatment level, since these months are extremes, and this is somewhat random, in the sense of the timing of those more extreme crimes, this would tend be less prone to endogeneity issues, and this is still result in the same conclusion that people would negatively respond to homicides.[9]

We also test the theoretical framework proposed in section 2. In that sense, Table 3 contains the specification from Equation 3, and it is possible to verify that individuals would feel safer if the safety score from the previous period is higher, i.e., if safety perception in t-1 increases one unit safety perception would increase by 43 percent in t. Additionally, there is positive but not statistically significant effects, at 5 percent significance level, for differences on homicides rates on perception if we have a period less crimes relative to the previous period. However, if the number of homicides in the current period is greater than in the previous period (i.e., if D equals 1), then we have that the perception of safety would decrease and such effect would be statistically significant, and in a much higher magnitude relative to cases in which D equals zero. Finally, if there is a period of no homicide, as it is possible to see from column 3, there is no effect on safety perception. This corroborates

[9]In table 5 (from appendix) columns 3 and 4 includes the same specification as above, but now including non-index crimes as control, in such a way that we obtain similar results as in Table 2, which indicates that including non-index crimes would not influence the estimates.

with the hypothesis that people would respond differently to periods with no homicides relative to period of high number of homicides, more specifically, individuals would have greater negative reactions to periods of violence than positive reaction in periods with no violence.[10]

As an additional specification, in order to verify that the TWFE is correctly specified, we also implement an IV approach, using sports and concerts events as instruments. Tables 4 and 5 shows the estimates of such a specification and we obtain consistent results relative to the TWFE, with crimes affecting crimes perception way more relevantly in violent crimes rather than property crimes. Moreover, we also obtain that the negative effects of a period with high homicide volume are greater than the positive effects of periods with low homicide volume.

Therefore, the estimates from the empirical strategy and the theoretical model test indicate that people respond to homicides, but in different levels depending on whether the periods of homicides are safer or violent, in such a way that people could be rational in some sense (if we consider that they are responding to crimes), but the negative levels of responses to crimes eventually result in a decreasing safety index (which would mean higher crime perception) over time, even if the levels of crimes decrease on average, as observed in the data.[11]

[10] We also simulate a scenario in which we would have a lagged safety perception of 1, and we would still observe a similar pattern, i.e., even in a case of people feeling perfectly safe in the t-1, a period in which there are no homicides would positively , and not statistically significantly impact on the safety perception, but a period of higher crime rate than in the previous period would negatively impact, in a much larger magnitude their safety perception.

[11] We also run additional specifications available in the appendix, disaggregating for index and non-index crimes, in Table A.1 and by different types of crimes A.2, in such a way that we obtain similar behaviors as the main specification, as it is possible to notice that homicide would be the most significant effects, specially when disaggregating for periods in the high percentile of homicides rates and periods in the low percentile of homicide rates.

Table 1: Safety Perception on Actual Crimes

	(1)	(2)	(3)	(4)
Agg Assault	0.022	-0.022	0.026	-0.021
	(0.027)	(0.020)	(0.028)	(0.020)
Agg Batt	-0.068**	-0.026	-0.063**	-0.025
	(0.028)	(0.025)	(0.029)	(0.025)
Robbery	-0.030*	-0.004	-0.018	-0.003
	(0.017)	(0.015)	(0.017)	(0.015)
Sex Assault	-0.035	0.010	-0.036	0.011
	(0.052)	(0.047)	(0.055)	(0.047)
Homicide	-0.190**	-0.152*	-0.193**	-0.152*
	(0.087)	(0.084)	(0.086)	(0.084)
Burglary	-0.055***	-0.017	-0.065***	-0.017
	(0.014)	(0.014)	(0.015)	(0.014)
Larceny	0.025***	0.001		
	(0.006)	(0.003)		
Mvt	0.014	0.004	0.011	0.004
	(0.014)	(0.012)	(0.014)	(0.012)
Arson	-0.012	-0.002	-0.023	-0.003
	(0.090)	(0.081)	(0.085)	(0.081)
Larceny Cheap			0.058***	-0.002
			(0.017)	(0.011)
Larceny Expensive			-0.010	-0.001
			(0.015)	(0.008)
Control mean	58.091	58.091	58.091	58.091
Observations	4958	4958	4958	4958
Cluster	67	67	67	67
Sector FE	Yes	Yes	Yes	Yes
Month by year FE	Yes	Yes	Yes	Yes
Sector*Year FE	No	Yes	No	Yes

Notes: Columns 1-2 shows the estimates for a regression or safety indicator on lagged safety, actual crimes, including only the index crimes. Column 1 is not consider the sector by year fixed effect, while column 2 is considering the sector by year fixed effect. Columns 3-4 uses the same outcomes variable and specification as in column 1 and 2, but now the Larceny crimes are disaggregated into Larceny Cheap (Crimes involving less than 500 dollars) and Larceny Expensive (Crimes involving more than 500 dollars). Standard errors clustered at sector level. *, **, and *** indicate 10, 5, and 1 percent

Table 2: Safety Perception disaggregating by volume of Homicide in a Period

	(1)	(2)	(3)	(4)
High Homicide	-0.711**	-0.415*	-0.646**	-0.384*
	(0.298)	(0.226)	(0.293)	(0.222)
Low Homicide	0.162	0.151	0.134	0.144
	(0.197)	(0.147)	(0.193)	(0.148)
Agg. Assault			0.021	-0.022
			(0.027)	(0.020)
Agg. Batt			-0.070**	-0.028
			(0.028)	(0.024)
Robbery			-0.031*	-0.004
			(0.017)	(0.015)
Sex assault			-0.035	0.009
			(0.052)	(0.047)
Burglary			-0.056***	-0.018
			(0.014)	(0.014)
Larceny			0.025***	0.002
			(0.006)	(0.003)
Mvt			0.013	0.004
			(0.014)	(0.012)
Arson			-0.015	-0.003
			(0.090)	(0.081)
Control mean	58.091	58.091	58.091	58.091
Observations	4958	4958	4958	4958
Cluster	67	67	67	67
Sector FE	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes
Sectorxyear FE	No	Yes	No	Yes

Notes: Columns 1-2 shows the estimates for a simple regression including only the variable for safety indicator on a sector that in that given period is on the 95th percentile (High Homicide) and on the 5th percentile (Low Crime). Column 1 is not consider the sector by year fixed effect, while column 2 is considering the sector by year fixed effect. Columns 3-4 uses the same outcomes variable and specification as in column 1 and 2, but now adding all the other index crimes as control. Standard errors clustered at sector level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table 3: Safety Perception by periods with increase and decrease of homicide rate

	(1)	(2)	(3)
l1.Safety	0.608***	0.437***	0.437***
	(0.015)	(0.015)	(0.015)
$D_{homicide}$	0.168*	0.153*	0.152*
	(0.088)	(0.089)	(0.089)
D=1 × $D_{homicide}$	-0.387***	-0.321**	-0.321**
	(0.145)	(0.149)	(0.149)
$D_{NoHomicide}$			0.001
			(0.002)
Control mean	58.077	58.013	58.013
Observations	4891	4824	4824
Cluster	67	67	67
Sector FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes
Sector*Year FE	No	Yes	Yes

Notes: Column 1 contains the estimate of the regression of safety on the difference in homicide in the present period relative to the previous period , and on the indicator on whether such difference in positive or negative, including the Sector and Month-year Fixed Effect. Column 2 includes the Sector-Year Fixed Effect, and column 3 contains the Sector-Year fixed effect and an indicator of No Homicides in a given period as a control.

Table 4: Instrumental Variable Estimates disaggregated by High and Low Homicide Rates periods

	(1)	(2)
L.Above 75th Percentile	-23.51***	
	(6.26)	
L.Below 25th Percentile		18.18***
		(4.00)
Wald F-Statistic	11.867	18.915
Observations	4866	4866

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Column (1) contains the estimate of periods homicides above the 75th percentile, while column (2) shows the estimates below the 25th percentile. From this, it is possible to notice that the intensity of the effects are not proportional, which corroborates with the TWFE model. All estimates are lagged.

Table 5: Instrumental Variable Estimates disaggregated Violent and Property Crimes

	(1)	(2)	(3)	(4)
L.Homicide	-3.59***	-3.39***		
	(0.71)	(0.66)		
L.Robbery	0.05	0.04		
	(0.05)	(0.04)		
L. Violent Crimes			-0.18***	-0.16***
			(0.04)	(0.04)
L.Property Crimes			0.02***	0.01***
			(0.00)	(0.00)
Wald F-Statistic	26.190	27.849	12.938	13.687
Observations	4875	4866	4875	4866

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Columns (1) and (3) contains IV estimates considering only sports events to construct the instrument, while columns (2) and (4) includes all events. From this, it is possible to notice that the intensity of the effects are not proportional, which corroborates with the TWFE model. All estimates are lagged. Notice that the intensity is similar for both cases, such that even with fewer observations it is possible to obtain the statistically significant effect for violent crimes and property crimes. However, it is possible to notice that the intensity for property crimes much lower relative to violent crimes, which corroborates with the results found under the TWFE specification.

6 Conclusion

This study reveals a substantial gap between reported crime and public perceptions of safety in Chicago. Our findings suggest that, while people tend to update their perception of safety in response to crime events, the reaction is asymmetrically stronger during periods with an increased number of homicides. This implies that even when crime indicators improve, the perception formation—possibly influenced by negative bias and loss aversion—prevents increases in the public's perception of safety. This asymmetry highlights an important challenge for policymakers: addressing not only the actual incidence of crime but also public's perception of safety, which may be influenced by media reporting and the different types of crime.

Our study contributes to the literature by offering a theoretical framework that explains how and why individuals may assign different weights to positive and negative crime shocks. In addition, it underscores the potential for a misalignment between public opinion and

actual crime trends, a misalignment that could influence the allocation of public resources and the development of crime prevention strategies.

Similar discrepancies between perception and reality can also be observed in other areas. For example, the public view of the economy can diverge from key economic indicators, affecting people's economic decisions, such as investment and spending habits. In public health, people might overestimate or underestimate the risks associated with health crises or have a misperception about risky behaviors, affecting both personal and public health. Future research could reveal the broader implications of such biases and misalignment, which could deepen our understanding of human cognition and help design policies that close the gap between reality and public perception in order to have more effective interventions.

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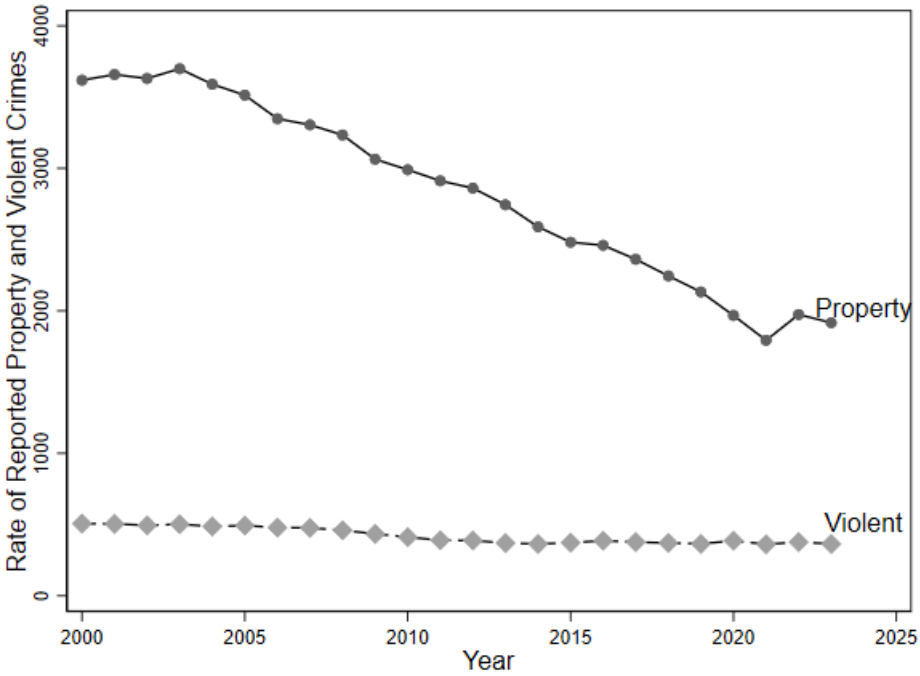
7 Appendix

Table A.1: Safety Perception disaggregated by Index and Non-Index crimes

	(1)	(2)	(3)	(4)
Index	0.014**	-0.002	0.021***	-0.001
	(0.007)	(0.003)	(0.006)	(0.003)
Nonindex			-0.020***	-0.005
			(0.005)	(0.004)
Control mean	58.091	58.091	58.091	58.091
Observations	4958	4958	4958	4958
Cluster	67	67	67	67
Sector FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Non-Index Crime control	No	No	Yes	Yes
Sector*Year FE	No	Yes	No	No

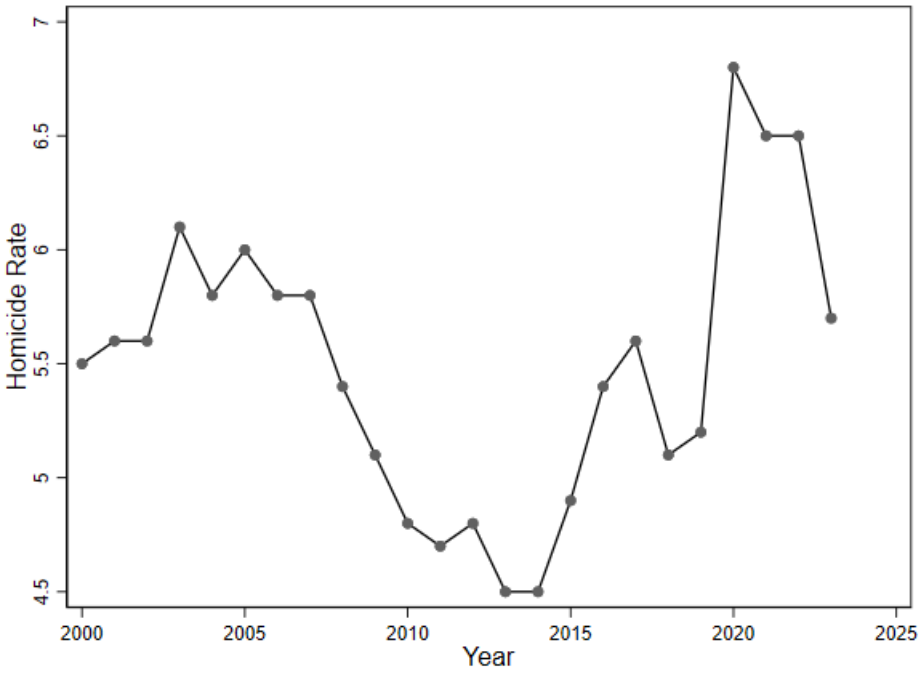
Notes: Columns 1-2 shows the estimates for the regression of safety indicator on Index Crimes and Non-Index crimes. Column 1 is not consider the sector by year fixed effect, while column 2 is considering the sector by year fixed effect. Columns 3-4 uses the same outcomes variable and specification as in column 1 and 2, but now adding nonindex crimes as control. Standard errors clustered at sector level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Figure A.1: Plot of Volume of Violent Crimes by Type of Crime



Notes: This shows the evolution of the volume of violent crimes by type, as classified by the FBI database. In that sense, it is possible to notice that property crimes have a decreasing trend, while violent crimes, despite still having decreasing trends, tends to be more linear.

Figure A.2: Plot of Rate of Homicide



Notes: Rescaled Plot of Homicide Rate. Note that under this scale, we can observe that there is some variation on rate of homicide over time. This would be consistent with the idea that people would react to extreme crimes such as homicides, as this follows a similar pattern to individual's perception over time.

Table A.2: Safety Perception Estimates including Non-Index Crimes as control

	(1)	(2)	(3)	(4)
Agg. Assault	0.032	-0.020	0.029	-0.021
	(0.027)	(0.020)	(0.027)	(0.020)
Agg. Batt	-0.045*	-0.022	-0.046*	-0.024
	(0.026)	(0.024)	(0.026)	(0.023)
Robbery	-0.012	-0.003	-0.023	-0.004
	(0.016)	(0.015)	(0.016)	(0.015)
Sex Assault	-0.026	0.012	-0.019	0.011
	(0.057)	(0.047)	(0.052)	(0.048)
Homicide	-0.189**	-0.149*		
	(0.083)	(0.084)		
Burglary	-0.062***	-0.017	-0.049***	-0.017
	(0.016)	(0.014)	(0.013)	(0.014)
Larceny Cheap	0.063***	-0.001		
	(0.017)	(0.011)		
Larceny Expensive	-0.001	-0.000		
	(0.014)	(0.008)		
mvt	0.009	0.005	0.012	0.004
	(0.014)	(0.012)	(0.014)	(0.012)
Arson	-0.022	-0.001	-0.012	-0.001
	(0.084)	(0.080)	(0.090)	(0.081)
Nonindex	-0.013**	-0.004	-0.019***	-0.004
	(0.006)	(0.004)	(0.004)	(0.004)
High Percentile Homicide			-0.609**	-0.378*
			(0.291)	(0.222)
Low Percentile Homicide			0.097	0.136
			(0.189)	(0.148)
Larceny			0.031***	0.002
			(0.005)	(0.003)
Control mean	58.091	58.091	58.091	58.091
Observations	4958	4958	4958	4958
Cluster	67	67	67	67
Sector FE	Yes	Yes	Yes	Yes
year-month FE	Yes	Yes	Yes	Yes
Non-Index Crime control	Yes	Yes	Yes	Yes
Sector*Year FE	No	Yes	No	Yes

Notes: Columns 1-2 shows the estimates for the regression of safety indicator on Crimes disaggregated for types of larceny and also including the non-index crimes fixed effect. Column 1 is not consider the sector by year fixed effect, while column 2 is considering the sector by year fixed effect. Columns 3-4 uses the same outcomes variable and specification as in column 1 and 2, but now adding disaggregating the monthly homicide volume by type while the larceny crimes are now aggregated. Standard errors clustered at sector level. *, **, and *** indicate 10, 5, and 1 percent significance, respectively.

Table A.3: Instrumental Variable Estimates disaggregated by Violent and Property Crimes

	(1)	(2)
L.Violent Crimes	-0.15***	-0.14***
	(0.01)	(0.00)
L.Property Crimes	0.01***	0.00***
	(0.00)	(0.00)
Observations	862	4877

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Here we use a vector of instruments, i.e. we use multiple instruments according to the event and distance from the sector. Column (1) is considering only the sectors that do not experience large events, i.e., that do not have a large venue, which restrict our sample to 862 observations. In column (2) we consider the whole sample, but we are still controlling for distance. Notice that the intensity is similar for both cases, such that even with fewer observations it is possible to obtain the statistically significant effect for violent crimes and property crimes. However, it is possible to notice that the intensity for property crimes much lower relative to violent crimes, which corroborates with the results found under the TWFE specification.

Table A.4: Instrumental Variable Estimates disaggregated by Safe and Unsafe Periods

	(1)	(2)	(3)	(4)
L.Above Median	-32.17***	-11.15***		
	(9.48)	(2.65)		
L.Below Median	-18.27	1.35		
	(10.23)	(2.82)		
L.Above 95th Percentile			-36.64***	-29.22***
			(4.36)	(2.58)
L. Below 5th Percentile			9.82***	14.71***
			(1.99)	(1.27)
Observations	4877	4877	4877	4877

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Here we use a vector of instruments, i.e. we use multiple instruments according to the event and distance from the sector. Column (1) and (3) contains the IV estimates considering all crimes. Column (2) and (4) shows the IV estimates for violent crimes. From this, it is possible to notice that the intensity of the effects are not proportional, which corroborates with the TWFE model. All estimates are lagged.