Information Spread through Social Media and Engagement in Crime:

Evidence from a National Wave of Car Thefts

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Abstract

This paper studies a large negative externality of social media. I leverage the unanticipated timing of a viral social media trend that spread information on how to steal particular models of Kia and Hyundai cars (KH cars) to show that exposure to criminal skills training through online videos led to a large net increase in car thefts. Using a difference-in-differences approach, I show that KH car thefts increased by over 600 percent relative to non-KH cars in the 15 months following the information shock. Additionally, cities that are more socially connected to Milwaukee, the epicenter of the information shock, experienced 55 percent more KH thefts due to amplified exposure through social networks. Highly-connected cities also experienced significantly more motor vehicle theft offenses and arrests, with no changes in the trends of other types of crime. These findings suggest that social media accelerated the spread of criminal skills, leading to a large increase in car thefts, immediate victim damages and criminal justice expenses, and potential long-term costs from perpetrator labor market scarring.

1 Introduction

In major U.S. cities, the motor vehicle theft rate increased by 82% from 2020 to 2023, the largest reversal in a declining trend since 1991 (Lopez and Boxerman, 2024). Additionally, the majority of this increase occurred from 2022 to 2023, a period when other major crime trends remained stable or declined. I show that this latter increase is caused by a viral social media trend that spread information on how to steal vulnerable models of Kia and Hyundai (KH) cars. This highlights how social media's ability to spread information rapidly through social networks can lead to a large negative externality when that information transmits criminal skills and lowers the technical barriers to committing a serious crime.

This trend began in 2021, when a decentralized group of teenagers in Milwaukee, WI, began filming themselves stealing KH cars using a simple technique (Dorrell, 2023). During this time, KH thefts increased by over 2500% in the city. In June 2022, these videos suddenly became popular on social media platforms, effectively spreading information on how to steal KH cars from Milwaulkee to individuals nationwide.

I leverage the unanticipated timing of the video virality using a difference-in-differences (DiD) strategy to estimate the effect of the information shock on monthly KH car to non-KH car thefts in a sample of major cities from 2021 to 2023, shared by (Gordon, 2023). I find that KH car thefts increase by over 600% on average relative to non-KH car thefts, an additional 64,000 car thefts 15 months post-shock. This provides evidence that criminal skills can be learned through social media, which can then induce marginal individuals to commit crimes using these newly learned skills.

Additionally, there is significant variation in the relative size and dynamics of the treatment effect across cities. While some cities experience a sharp increase in KH car thefts of the shock that levels off within months, other cities experience gradually increasing and delayed treatment effects. One mechanism that explains this heterogeneity is that a marginal individual's probability of being exposed to the videos depends on their pre-existing social connectedness to the information source. Hence, cities with a relatively higher number of social connections to Milwaukee are likely to experience higher population exposure to the videos and, thus, a larger increase in KH thefts directly following the information shock.

I test the social network exposure mechanism using a second DiD strategy to estimate the effect of the information shock on motor vehicle thefts in cities with above- versus below-median social connectedness to Milwaukee. I measure a city's pre-shock social connectedness using the Facebook Social Connectedness Index (SCI) from (Bailey et al., 2018). The SCI serves as a proxy for the different social networks across the social media platforms transmitting the KH theft videos. Furthermore, I show that the SCI is positively correlated with search intensity for video terms on both Google and YouTube.

Using a larger sample of cities from the 2021 to 2022 National Incident Based Reporting System (NIBRS), I find that monthly motor vehicle theft offenses increase by 22% and arrests by 16% in high-SCI cities six months post-shock. This provides evidence that social networks amplify exposure to the videos, causing a net increase in total motor vehicle theft. Notably, I also find no significant effect on other major types of crime. The lack of a substitution effect indicates that, on average, the shock causes a net increase in total crime, whereas the lack of a complementary effect indicates that, on average, the induced marginal individuals are not stealing cars to commit additional types of crime.

Heterogeneity analysis reveals that the increase in motor vehicle theft arrests is driven by young adult males (18-25), with diminishing effects on older male age groups (26-30, 31-35). Notably, all three age groups have similar pre-shock motor vehicle theft arrest rates, suggesting that younger males are not more likely to be induced simply because of a higher pre-shock propensity for motor vehicle theft. Instead, the incentivizing mechanism is likely a combination of higher shock exposure due to higher social media use among younger individuals and a higher propensity for risky behavior among young males; however, I am not able to directly separate these channels. Regardless, the relatively large increase in arrests will impose further human capital costs because of increased incarceration and labor market scarring effects on perpetrators. These effects are likely to be especially pronounced for young adult males who have less labor market experience and, as a result, are likely to reoffend due to their lower opportunity costs of forgoing legal work (Bell et al., 2018).

To show that the higher network exposure mechanism is primarily increasing car thefts through the KH car theft channel, I use a triple-difference specification to show that KH thefts, on average, increase 55% higher in high-SCI cities. Additionally, I find a positive spillover effect of higher exposure to non-KH car theft. On average, for every additional six cars stolen in a high SCI city as a result of the information shock, five are KH cars and one is a non-KH car. This complementary effect may be the result of falling motor vehicle theft deterrence due to temporary police resource constraints as departments reallocate additional officers to motor vehicle theft deterrence and detection. Furthermore, I show that the high SCI treatment effect is robust to higher-order quantile specifications and to accounting for additional treatment interactions with socioeconomic factors that differ between high and low SCI cities.

My findings contribute to the literature in two ways. First, I provide evidence that individuals can learn criminal skills through social media. Previous literature studies the role of peer interactions in schools, neighborhoods, and prisons in learning criminal skills and shaping future criminal behavior (Bayer et al., 2009; Damm, 2020; Billings and Hoekstra, 2023). I build on this work by showing that social media amplifies these peer effects and subsequent engagement in crime by removing the physical limitations of in-person peer interactions, and allowing the spread of criminal skills from beyond local peer networks to marginal peers nationwide. Furthermore, the specificity of the KH theft technique and its unique geographic origin allows me to estimate how criminal skills spread across peer networks over time.

More broadly, my findings contribute to the literature on the negative externalities of social media. The existing literature focuses on estimating the effects of higher population social media use on mental health outcomes and risky and criminal behavior (Braghieri et al., 2022; Ajzenman et al., 2023; Müller and Schwarz, 2021, 2023). In contrast, I take population social media use as fixed, and instead, leverage variation in population connectedness to an information source to show how social media's ability to rapidly spread information through social networks accelerates the spread of negative externalities through the same networks.

Overall, I provide evidence that by accelerating the spread of criminal skills and creation of new criminals, social media causes a net increase in a serious type of crime. Using a victim cost of motor vehicle theft of $3700 from Heaton (2010), I estimate that the viral KH theft trend caused an additional $210 million in victim damages in the sample of 60 major cities alone. These damages disproportionately fall on cities with higher social connectedness to Milwaukee, the origin city of the viral trend. Policy-wise, my findings highlight the potentially large costs of failing to prevent the spread of certain types of information, such as criminal skills, on social media. Additionally, I show the importance of accounting for an area's social connectedness to an information source when estimating which populations will be most exposed to an information shock and experience the potential consequences.

2 Background and Data

2.1 KH Car Vulnerability and Online Theft Videos

Kia and Hyundai models manufactured between 2011 - 2021 (KH cars) are particularly vulnerable to theft because a majority lacked engine immobilizers, an electronic device that ensures a vehicle's engine will only start if the transponder in the corresponding key is nearby. KH cars are not the only motor vehicles on the road that lack engine immobilizers, however they represent a disproportionate amount of vulnerable vehicles in the U.S. manufactured since 2011 hld (2022)[1]. Furthermore, this vulnerability allowed KH cars to be started with only a screwdriver and phone charger. This is the "hack" demonstrated in the viral KH theft videos Dorrell (2023).

Before these videos became highly circulated on social media platforms in June of 2022, this information could be learned by criminals through some random endogenous discovery process. Knowledgeable criminals could then share this information through their own local networks. Figure 1 depicts monthly KH thefts for 63 major city police departments from January 2020 to August 2023. KH thefts disproportionately rise in three cities before June 2022: Los Angeles, Denver, and Milwaukee – supporting the theory that knowledge of the KH car vulnerability spread through local criminal networks in a number of cities before the viral videos.

Notably, Milwaukee experienced a massive increase in KH thefts during this time period, and is also the origin city of the viral "Kia Challenge" videos. These short videos depicted members of the self-proclaimed "Kia boys," a decentralized network of adolescents in Milwaukee, demonstrating how to steal and joyride KH cars. There are reports of these videos appearing on social media platforms as early as 2021, shortly after KH thefts peak in Milwaukee, however the videos did not become popular online until summer of 2022. The random timing of the video popularity not only acts as an exogenous information shock to a viewer on how to steal KH cars, but also signals the popularity and attention value of the videos on social media. The latter can cause the videos to be further promoted by content algorithms, which amplify content that captures user's attention, and thus increases the peer attention value of engaging in the KH theft challenge.

[1]For 2015 models, passive immobilizers were standard on only 26 percent of Hyundai and Kia vehicle series, compared with 96 percent of vehicle series for all other manufacturers combined (HLDI)

2.2 Measuring the Timing of KH Theft Video Popularity Online

To determine the approximate timing of the information shock, I use Google Trends data to measure the relative search popularity of terms related to the KH theft videos online and as a proxy for the videos' popularity on social media. Figure 2 displays the relative search volume for different terms related to the videos over time. The term "Kia boys" (1a) was the main hashtag used to search for the videos on TikTok, YouTube, and other social media applications. There is a distinct increase in search volume for this term around June 1st of 2022, implying a large increase in exposure to these videos at this time.

One concern with using Google Trends data to determine treatment timing is that an increase in search popularity for certain terms may result from increases in actual thefts and not just video popularity. It is reassuring then to the see that the break in the trend for "Kia thefts" (1b) and "Hyundai thefts" (1c), which could result from people searching in response to increases in thefts, does not occur until a month after"Kia boys" goes viral. This shows that mass interest in the videos preceded a rise in search for terms that could be related to the thefts themselves. Additionally, the search term "Honda theft" (1d) serves as a control, demonstrating that searches are focused specifically on KH thefts and not by a general increase in online interest in car thefts.

2.3 Measuring Motor Vehicle Theft and Crime

To measure the impact of the increase in exposure to and popularity of the KH theft videos on criminal behavior, I use two datasets each composed of administrative data from individual police departments.

The first dataset contains monthly motor vehicle theft (m.v. theft) counts from 60 major city police departments decomposed by KH thefts and non-KH thefts from January 2021 to

August 2023, I refer to it as the "KH thefts" sample. This data was obtained by journalists at Vice Motherboard via FOIA requests sent to the 100 largest police departments in the U.S., of which 68 responded, and 63 had sufficient data coverage beginning in 2021. I drop Los Angeles, Denver, and Milwaukee from the sample because these cities are effectively pre-treated as a result of the spread of knowledge locally on the KH vulnerability before the information shock. By decomposing monthly cars stolen into KH and non-KH, the direct effect of the theft videos on KH car theft can be estimated relative to non-KH cars before and after the information shock.

Figure 3 plots the aggregate log count of KH , non-KH, and the total cars stolen per month. Before June 2022, the log count of KH and non-KH cars move in parallel over time. After the shock, monthly KH cars stolen rapidly increases relative to non-KH cars stolen. This sharp divergence demonstrates the shock's direct relevance to only KH thefts and the quick translation into actual criminal behavior. While the information shock may indirectly negatively affect the theft rates of non-KH cars through substitution or complementary effects, the non-KH trend line suggests little effect either way. I formally test for spillover effects in 4, and find suggestive evidence of a small complementary effect on non-KH car thefts.

To further measure the effect of the information shock on total motor vehicle theft and other crime offenses and arrests, I use national level data from the FBI National Incident Based Reporting System (NIBRS). NIBRS data consists of incident level observations, which include the date of the incident, the total number of offenders involved, and the type of offenses committed. Anecdotally the KH theft trend is a phenomena occurring in areas with a sufficiently high density of motor vehicles, thus I restrict the treatment sample to police departments with populations above 50,000 that consistently report monthly data[2] . This yields a sample of 825 police departments reporting monthly from 2021 – 2022. For brevity, going forward I refer to police departments in both the KH thefts sample and NIBRS samples

[2]Table B1 shows robustness of my main results to other population cutoffs

as cities.

2.4 Variation in Exposure to the Videos and Online Social Connectedness

An important factor in the intensity of KH thefts that an area experiences is the overall exposure to the KH theft videos the local population experiences on social media. Higher exposure both increases the chance that a marginal individual sees the videos and the local peer attention value of the videos. A plausible source of exogenous variation in an area's online video exposure is its number of social connections to the videos' origin city, Milwaukee. Previous papers show that pre-existing social networks partially determine how new information diffuses and influences behavior across physical spaces e.g., (mass migration in Italy Spitzer and Zimran (2024)) and online spaces e.g., (retweets on Twitter Gorodnichenko et al. (2021)). Given that the videos were originally posted on and transmitted through social media platforms, I use a measure of online social networks.

More specifically, to measure an area's online social connectedness to Milwaukee and hence the probability that individuals in the area are exposed to the videos on social media, I use Meta's Facebook Social Connectedness Index (SCI) as described in Bailey et al. (2018). Each U.S. county-pair SCI score is constructed by dividing the number of friendship links between Facebook users in the two counties by the total number of Facebook users in the two counties. The score is then normalized to be between 1 and 1,000,000,000 relative to every other county-pair score. For example, if the SCI score of county pair A and B is twice as large the score of county pair A and C, then Facebook users from A and B are approximately twice as likely to be Facebook friends as users from A and C. To demonstrate the relevance of an area's SCI to Milwaukee as a measure of exposure to the videos, figure 4 displays the relationship between a metropolitan area's SCI and Google Trends search intensity for the term 'Kia boys'. There is a clear positive relationship. A simple OLS estimate of the log-log relationship yields an elasticity of 0.31, that is on average a 10% increase in SCI to Milwaukee is associated with a 3.1% increase in search intensity for 'Kia boys'. Going forward, the term SCI score to Milwaukee is shortened to just SCI score.

I assign a city the SCI score of the corresponding county containing it. If a city lies in multiple counties, I assign it the SCI of the county where a majority of the city population lives. In order to estimate the effect of increased exposure resulting from a higher SCI score, I divide agencies from both the KH thefts sample and the NIBRS sample into above and below sample median SCI [3]. Table 1 displays pre-shock socioeconomic and demographic statistics and pre- and post-shock car theft statistics for high and low SCI agencies in the KH theft sample. Notably, the gap in KH car thefts between high and low SCI agencies increases by a relatively large amount from before to after the shock, relative to the change in the gap of non-KH car thefts. This lends support to the relevance of a city's SCI score in determining exposure to the shock. Table 2 similarly displays demographic, socioeconomic, and crime statistics for high and low SCI agencies in the NIBRS sample. Notably, high SCI agencies are more populous, and have slightly higher crime rates on average than low SCI cities. I later show that the treatment effects estimated from the effect of higher SCI levels on the information shock are robust to accounting for additional interactions with factors from these tables. Finally, figure 5a plots the location of the 60 agencies in the KH thefts sample and the 825 agencies in the NIBRS sample 5b, along with whether a city has a high or low SCI score. As expected, geographic distance to Milwaukee is generally negatively correlated with SCI score. Excluding Wisconsin and the states that directly border it, most states that contain multiple agencies have agencies with both high and low SCI scores.

[3] I use the NIBRS sample median for both samples for comparability

2.5 Additional Data Sources

I use data from the single-year 2021 American Community Survey (ACS) to estimate racial demographics, median household income, and the percent of the population below the poverty line in counties before the information shock. Data on the monthly county unemployment rate comes from the Bureau of Labor Statistics(BLS) Local Area Unemployment Statistics. Data on the monthly average county temperature comes from PRISM Climate Data. For each city, I assign it the values of the county where a majority of the city population lives.

3 Empirical Specification

The exogenous timing of the KH theft video information shock induces a natural experiment. Exposure to the anti-theft vulnerability hack demonstrated in the videos increases an individual's probability of successfully stealing a KH car. Concurrently, the popularity of the videos also increases the non-pecuniary reward of stealing a KH car to create similar videos for peer attention on social media. By comparison, the utility of stealing a non-KH car is directly unaffected by the information shock. This setup lends itself to a difference-in-differences (DD) framework, where the differences between KH and non-KH car thefts are compared before and after the information shock. Due to the count nature of the data and incidence of zeros, I formally estimate the following log-linear relationship using Poisson QMLE[4],

$$log\, \mathbb{E}[CarsStolen_{ict}] = \beta KH_i \times Post_t + X_{ct} + \alpha_{ic} + \gamma_t \tag{1}$$

[4]The choice of Poisson fixed-effects QMLE compared to negative binomial or arcsin is due to the Poisson QMLE robustness to mispecification as described in Wooldridge 1999

where $CarsStolen_{ict}$ is the count of cars stolen of model type i (KH or non-KH), in city c, in year specific month t. The variable $KH_i \times Post_t$ is an indicator variable equal to 1 if model type i is KH and t occurs after May 2022. Thus β is the DD coefficient of interest and formally is the average treatment effect of the information shock on KH thefts, call it the "KH theft treatment effect". The vector X_{ct} includes the average monthly temperature and average annual unemployment rate of the county containing city c. The variable α_{ic} is a fixed effect for car model type i in city c and accounts for variation in the model composition of cars between police agencies and total thefts. Finally, γ_t is a year specific month fixed effect and accounts for variation in trends over time that effect theft of all car models.

The identification assumption is that the count of KH cars and non-KH cars stolen would evolve in parallel in the absence of the information shock. To assess the validity of the parallel trends assumption, I estimate the following event-study specification using Poisson QMLE,

$$log\,\mathbb{E}[CarsStolen_{ict}] = \sum_{t=-17}^{15} \beta_t KH_i + X_{ct} + \alpha_{ic} + \gamma_t \tag{2}$$

where β_t is the treatment effect in month t, beginning in January 2021 and ending in August 2023. The remaining variables are the same as equation 1.

While the event-study helps visualize whether theft trends evolve in parallel before treatment, comparing treatment effects post information shock only shows how KH thefts evolve relative to non-KH thefts. This does not rule out bias from treatment effect spillovers to non-KH car thefts. This could result from individuals substituting on the intensive margin from stealing non-KH cars to KH cars or complementary effects from increases in car theft on the extensive margin[5]. The raw trends in figure 3 suggest that the size of this potential bias to

[5]Intensive margin meaning the number of cars stolen by an individual and extensive margin the number of individuals stealing cars

the treatment effect is minimal. I explore strategies for formally estimating the size of the bias from treatment effect spillovers later in this section.

The DD estimate from equation 1 provides an estimate of the average effect of the information shock on KH thefts relative to non-KH thefts. This informs whether the information shock was salient in inducing people to steal KH cars. However, it does not provide insight into the mechanisms causing treatment effect heterogeneity across cities. A city's SCI score in 2021 is exogenous to average population social media use and factors into the likelihood an individual will be exposed to the videos[6].

Thus comparing the KH theft treatment effect in cities with relatively High SCI scores to cities with relatively low SCI scores, estimates the effect of higher video exposure through online social networks on the KH theft treatment effect. A natural starting place for splitting the sample into high and low SCI areas is the sample median SCI[7] This leads to the following triple difference specification,

$$\begin{aligned} log\,\mathbb{E}[CarsStolen_{ict}] =& \beta_1 HighSCI_i \times KH_i \times Post_t \;+\; \beta_2 KH_i \times Post_t \;+ \\ & \beta_3 HighSCI_i \times Post_t \;+ X_{ct} \;+\; \alpha_{ic} \;+\; \gamma_t \end{aligned} \tag{3}$$

where $HighSCI_i \times KH_i \times Post_t$ is a binary indicator equal to 1 if the count of cars stolen is model type KH, in an above median SCI city, and occurred after May 2022. Therefore, β_1 is the DDD coefficient of interest and is the average effect of the information shock on KH thefts in high SCI cities relative to low SCI cities. Thus it captures the average effect of higher video exposure through online social networks on the KH theft treatment effect. The coefficient β_2 now represents the average KH theft treatment effect in low SCI cities and β_3 represents the average effect of the information shock on non-KH thefts in high SCI cities relative to low SCI cities. Assuming that β_1 is positive, then a negative β_3 suggests that on

[6] As discussed in section 2

[7] I use the sample median from the NIBRS sample for comparability across samples

average an increase in exposure to the KH theft videos cause KH thefts to act as a substitute to non-KH thefts, while a positive sign would imply a complementary relationship. Notably, under some additional assumptions, β_3 can be used to estimate the bias from treatment effect spillovers to non-KH cars on the KH theft treatment effect in equation 1. The remaining variables are the same as in previous equations [8].

A sufficient identification assumption for identifying β_1 is that in the absence of the information shock trends between KH thefts and non-KH thefts would continue to evolve in parallel in both high and low SCI cities Olden and Møen (2022). To assess the validity of this assumption, I estimate the event-study specification in equation 2 for sub-samples of high and low SCI cities.

Additionally, I estimate a continuous version of equation 3 by replacing $HighSCI_i$ with $logSCI_i$. In this continuous specification, β_1 now represents the SCI elasticity of the KH theft treatment effect i.e. a 1% increase in SCI causes a β_1% increase in KH thefts. The identification assumption necessary for identifying β_1 is stronger than the traditional parallel trends assumption as described in Callaway et al. (2024).

Conditional on the DDD estimator being positive and significant, then the variation in SCI scores creates exogenous variation in the KH theft treatment effect among cities. Now leveraging SCI score variation in the absence of information on car model type, I use the NIBRS sample to estimate the average effect of higher SCI on offenses and arrests for total motor vehicle thefts and potential substitution and complement effects on other types of crime. Estimating spillover effects on other types of crime and decomposing arrest treatment effects by demographic subgroups provides insight into the characteristics of the average individual induced to commit motor vehicle theft as a result of the information shock and their possible incentives. Formally, I estimate the following DD equation,

[8] The binary KH and SCI treatment indicators and their interaction terms are excluded because they are co-linear with the model-city fixed effects

$$log\, \mathbb{E}[Crime_{ct}] = \theta HighSCI_c \times Post_t \; + X_{ct} \; + \; \delta_c \; + \; \gamma_t \tag{4}$$

where $Crime_{ct}$ is the count of reported criminal offenses or arrests in city c in year specific month t. The variable $HighSCI_i \times Post_t$ is a binary indicator equal to 1 city c has an SCI above the sample median and t is after May 2022. Therefore θ is the average treatment effect of higher SCI on the outcome. The additional variables remain the same as before, except the model-city fixed effect is replaced with just a city fixed effect.

To test the parallel trends identification assumption, I estimate the following event study specification,

$$log\, \mathbb{E}[Y_{ct}] = \sum_{t=-17}^{6} \theta_t HighSCI_i + X_{ct} + \delta_c + \gamma_t \tag{5}$$

where θ_t is the SCI treatment effect in month t.

4 Results

4.1 Effect of Information Shock and Higher Online Exposure on KH Car Thefts

Table 3 Panel A displays the coefficients from the DD regression, equation 1, comparing the count of KH cars stolen to non-KH cars before and after the information shock in June of 2022 for all cities in the KH theft sample. The coefficients are large and significant level for all specifications. The estimate 2.022 in column 3 (preferred specification), implies that the number of KH cars stolen increases on average by a factor of 7.55 or 656% 15 months after the information shock relative to the pre-treatment mean. In terms of the pre-treatment mean, this is an increase from approximately 10 KH cars stolen in a city per month to 75 KH cars stolen per month. Figure 6a depicts the corresponding event study treatment effects for KH cars stolen before and after the information shock. The pre-period estimates are mostly indistinguishable from a null effect and show no evidence of a pre-trend, lending credence to the identifying assumption that in the absence of the information shock the count of KH and non-KH cars stolen would have evolved similarly over time. The effect on KH cars stolen increases significantly the month of the shock and continues to grow until leveling off about 8 months after the shock. Panle A table A1 further breaks down the evolution of the treatment effect into 3 month intervals.

The treatment effect dynamic is consistent with a model in which the number of individuals exposed to the videos grows over time as information diffuses through online social networks. An implication of this model is that cities with more social connections to Milwaukee, the city where the videos originated and first gained popularity, should experience higher levels of initial exposure to the videos and hence a larger increase in KH thefts. To test this hypothesis, I split cities into two sub-samples based on their SCI to Milwaukee being above or below the sample median[9].

Table 3 Panels B and C display the same KH theft treatment effect as Panel A, but for the high and low SCI sub-samples respectively. The coefficients are large and significant at 1% across the board, demonstrating that on average the information shock increases theft of KH cars regardless of a city's SCI score. However, the average treatment effect for the high SCI sub-sample, 2.085 in Panel B column 2, is significantly larger than the average treatment effect for the low SCI sub-sample, 1.652 in Panel C column 2. This suggest that cities with higher SCI experience a larger average increases in KH thefts as a result of greater exposure to the KH theft videos through their social networks. The high SCI sample

[9]I use the sample median from the NIBRS sample of police departments because it is larger and for comparability

coefficient corresponds to an increase in KH thefts by a factor of 8.04 and low SCI sample coefficient to a factor increase of 5.21 over their respective pre-treatment means. Figure 6b depicts the corresponding event study treatment effects from 2 for both the high and low SCI sub-samples. There is no evidence of a significant pre-trend in either sub-sample, lending credence to the parallel trends identification assumption.

To formally estimate the average additional effect of high SCI on KH cars stolen, I estimate a triple-difference model, equation 3 , comparing the count of KH to non-KH cars stolen in high versus low SCI cities before and after the information shock. Table 4 Panel A contains three coefficients from equation 3. The estimate in column 3 for the $KH \times Post$ coefficient, 1.651, implies that KH thefts in low SCI cities increase on average by a factor of 5.21 or 421%. Note that this estimate is nearly identical to the low SCI sample of the KH theft treatment effect in table 3 Panel B. The estimate in column 3 for the coefficient on $HighSCI \times KH \times Post$, 0.434, corresponds to an additional average increase in KH thefts by a factor of 1.54 or 54% as a result of higher SCI. This estimate is significant for all specifications, and formally provides evidence of the significant causal effect of higher SCI on the KH theft treatment effect. Furthermore, note that adding the KH theft treatment effect for low SCI cities and the high SCI treatment effect, $(1.651 + 0.434 = 2.085)$, yields the average KH theft treatment effect (704%) for high SCI cities and is identical to the KH theft treatment effect for the high SCI sample in column 3 of table 1 Panel B. This result follows from the fact that the DDD coefficient can be written as the difference of two DD coefficients from sub-samples split by the third difference as shown in Olden and Møen (2022). Regarding identification, it has already been show in figure 6b that the parallel trends between KH thefts and non-KH theft in high and low SCI cities likely holds, which is sufficient for identification of the DDD coefficient.

An additional concern in identifying the KH theft treatment effect in equation 1, is that treatment effect spillovers to non-KH car thefts (the control group), could bias the KH theft treatment effect upwards (substitution effect) or downwards (complementary effect). Assuming that this spillover effect also scales with the KH theft treatment effect as a result of higher SCI, then the coefficient for $HighSCI \times Post$ in table 4 Panel A provides an estimate of both the sign and size of this spillover. The coefficient in column 3, 0.186, corresponds to a 20% increase in non-KH thefts in high SCI cities relative to low SCI cities. This suggests that the increase in KH thefts has a complementary effect on non-KH thefts. There are multiple channels this could occur through, such as an increase on the extensive margin of individuals engaged in car theft or a reduced police deterrence effect resulting from an increase in car thefts compared to police resources. Notably, the complementary effect also implies that the KH theft treatment effect may be biased downwards, a lesser identification concern compared to an upwards bias, since this means the already sizable effect may be even larger.

Finally, table 4 Panel B displays the DDD coefficient from the continuous version of equation 3, where the log SCI is substituted for high SCI. The coefficient in column 3, 0.205, corresponds to a 0.23 SCI elasticity of KH thefts, that is to say a 10% increase in SCI causes a 2.3% increase in KH thefts. The elasticity may seem lower than expected given the size of the average KH theft treatment effect, however there are two important factors to consider. First, the distribution of SCI in the sample has a large spread e.g. the third quartile of the SCI distribution in the KH thefts sample is 287% larger than the first quartile. Second, figure A2 shows that the elasticity grows within the first 6 months of the information shock and then begins to decline. Indeed, the average SCI elasticity in the first 6 months is 0.62, as shown in table A1 Panel C , nearly three times as large as the full sample length elasticity. This makes sense in the context of an information diffusion model, where the initial level of social connectedness to the information source has a larger effect on initial exposure and hence KH thefts, but this effect diminishes over time as more connected areas reach "full exposure" before less connected areas[10]

[10]This same pattern is present with the discrete DDD coefficient as shown in figure A1a and table A1

4.2 Effect of Higher Online Exposure on Criminal Offenses

Having now established that a city's SCI is a plausibly exogenous factor that increases the effect of the information shock on KH car thefts, the variation in SCI can now be used to estimate the effect of higher exposure to the information shock on all criminal offenses and arrests. This section presents results from the DD specification, equation 4, comparing crime outcomes in high SCI cities to low SCI cities before and after the information shock in the NIBRS sample [11].

Table 5 Panel A displays the DD coefficient from equation 4, comparing the effect of the information shock in high SCI cities relative to low SCI cities, on motor vehicle theft. The coefficient of 0.202 implies that high SCI cities on average experience a 1.22 factor or 22% increase in m.v. thefts relative 6 months after the shock. This provides further evidence that the average effect of higher SCI significantly increases the effect of the information shock on car thefts. Assuming that KH cars make up 5% of cars in most cities and ignoring any complementary effects on non-KH cars, this increase would correspond to a 220% increase in KH car thefts. This is similar to the high SCI effect on KH thefts estimated in the previous section after 6 months, 0.693, which corresponds to a 263% in KH thefts over the pre-treatment mean[12]. The corresponding event-study treatment effects shown in figure 7, lend support to the identifying assumption that the relative number of m.v. thefts would have evolved similarly in high and low SCI cities in the absence of the information shock. The dynamics of the treatment effect are similar to that of the KH theft treatment effect in the first 6 months, and appear to increase over time. This is again consistent with the pattern of an information diffusion model.

Panel B

[11] The NIBRS sample uses data from 2021-2022, thus when comparing these results to those in the previous section, one should use the treatment effect average from only the first 6 months of the KH theft sample shown in column 2 of table A1

[12] To see this, note that the KH treatment effect in low SCI cities is 0.967 after 6 months, then exp(0.967 + 0.693) - exp(0.967) $\approx$ 2.63

While the information shock only directly induces the marginal individual to commit motor vehicle theft, it may also indirectly increase or decrease the relative frequency of other crimes to the degree that a crime acts as a compliment or substitute to motor vehicle theft. Ex ante, it is not clear without knowing an individuals underlying incentive for engaging in crime whether a specific crime acts as a substitute or compliment. For example, given information on how to exploit the KH car vulnerability, an individual already engaged in crime for economic gain, who otherwise would commit burglary, may now gain marginally more utility from committing motor vehicle theft and selling the car [13]. On the other hand, an individual previously uninvolved in crime, who commits motor vehicle theft may lower the cost of committing other types of crimes through possession of a stolen vehicle [14].

Table 5 Panel B contains the DD coefficient from equation 4 for the effect of high SCI on other types of crime excluding m.v. theft. The null effect on total, violent, and drug crime, lends support to the identifying assumption that higher SCI increases motor vehicle theft as a result of increases in exposure to the videos and not as a result of different increasing crime trends between high and low SCI cities . The marginal positive effect on property crime may be a result of certain property crimes acting as a complement to m.v. theft. Figure B1 , displays the corresponding event study treatment effects for all four aggregate crime types, showing no evidence of significant pre-trends and providing support to the parallel trends assumption. To further investigate the positive effect on property crime, I further break it down into it's major types. The increase appears to be driven by a significant increase in vandalism. The effect size for dealing stolen property is also relatively large, but it is imprecisely estimated. The increase in vandalism is likely due a direct result of an increase in motor vehicle theft attempts [15].

Notably, the offense results suggests that individuals incentivized to commit m.v. theft as

[13]Given that KH cars are relatively inexpensive and their value was falling during this period, this may be unlikely

[14]In this sense motor vehicle theft is known as a "keystone" crime

[15]Vandalism insurance claims for KH cars also rapidly rose during this time period hld (2023)

a result of higher exposure to the videos through higher SCI are not being incentivized to commit any other types of crime. This is further supported by looking at effects on arrests for the same types of crime. Table 6 Panel A displays the high SCI treatment effect on m.v. theft arrests. The coefficient 0.151 translates to a 16% increase in m.v. theft arrests (0.7 monthly arrests) in high SCI versus low SCI cities[16]. The corresponding treatment effects in figure 8 are noisy, and while, however there is no evidence of a distinct pre-trend, lending credence to the identification assumption. The treatment effect immediately increases in size the month of the information shock and appears to grow over time, however it does not become statistically different from zero until 6 months after the shock. The noisiness of the event study suggests the effect on m.v. theft arrests should be interpreted with some caution. Table 6 Panel B displays null effects on arrests for all major crime types, which again supports that the treatment effect on m.v. theft is not a result of different crime trends in high and low SCI cities.

4.3 Mechanisms and Arrest Heterogeneity

The results in the previous section reveal that higher exposure to the KH theft videos through online social networks increases the motor vehicle theft rate. Furthermore, the null effects on all other types of crime, besides those directly related to the act of stealing a vacant car, suggests that the average individual induced by higher exposure to the videos is not motivated by monetary gains from selling the car, nor for use in committing other crimes. Instead, the incentivizing mechanism may be a product of the attention economy on social media platforms.

A majority of platforms associated with the KH theft videos use advertising based business models. These models use algorithms to promote content to users that will increase their

[16]The m.v. theft arrest clearance rate was 9% in 2022, scaling the treatment effect on m.v. theft offenses by this, 0.09(12.3) = 1.1 monthly arrests, yields a similar effect size

time spent on the platform and ad consumption. Beknazar-Yuzbashev et al. (2024) show that a profit-maximizing social media firm can even choose to show users harmful content as long as it's sufficiently complementary to time spent on the platform. At the same time, a large sociological literature shows that adolescents and young adults will partake in potentially harmful risky behaviours to gain attention from peers. Murphy (2019) incorporates this behaviour into a consumption model to show that it may be individually rational for an adolescent to engage in a harmful behaviour if it sufficiently signals their status to peers. Combining these two factors with high social media use among adolescents, creates an environment where social media algorithms initially promote the KH theft videos to users, increasing both exposure to the videos and the attention gaining value of participating in the challenge. This leads to a positive feedback loop, where the rising attention value of the videos causes further promotion by the algorithm and hence higher exposure and value of participating for adolescents.

While it is not possible to directly observe an individual's motive for committing motor vehicle theft, if gaining attention on social media is the primary incentivizing mechanism, then adolescents and young adults should be more likely to commit motor vehicle theft as a result of higher exposure to the videos than slightly older adults. To test this empirically, I follow equation 4, comparing arrests in high versus low SCI cities before and after the information shock for the following age groups: minors (¡ 18), 18-25, 26-30, and 31-35 years old. A concern with using arrest data to estimate offending rates by a demographic group is that groups may differ in their likelihood of being arrested (e.g. minors may be more likely to get caught). However, unless this systematically differs between high and low SCI cities, then the treatment effect on arrests for a group should be proportional to the treatment effect on offenses for a group.

Table 7 displays the high SCI treatment effect for the following age groups: minors (<18), 18-25, 26-30, and 31-35. The treatment effect on the younger age groups is relatively large and significant, 0.240 (27%) for minors and 0.283 (33%) for 18-25. While the effect is still marginally significant (¡10%) for ages 26-30, 0.122 (13%), the increase is notably smaller and the effect for ages 31-35 is null [17]. Figure B2 displays the corresponding event study treatment effects. Similar to the event study for total m.v. theft arrests, the treatment effects are again noisy, but show no evidence of a pre-trend. The treatment effect for minors in particular should be interpreted with caution, however the effect for ages 18-25 is clear. Additionally, table 7 Panel B shows null effects on all other major types of crime for all age groups, demonstrating that the age group specific effects on m.v. theft are again not a result of different crime trends for age groups in high and low SCI cities.

To further demonstrate that the high SCI treatment effect on arrests by age is robust to variation in the choice of age cutoffs, figure 9 displays the higher exposure treatment effect on mv theft arrests for each individual age from ages 10 - 35. Unsurprisingly, the treatment effect is relatively large for approximately ages 16 to 22, and declines for younger and older age groups. Taken together, this suggests that higher online exposure to the videos mainly induces young adults and adolescents to commit motor vehicle theft, and supports the theory of the social media attention mechanism as the primary incentivizing mechanism. Additional robustness of the age specific m.v. theft arrest effect to alternative quantile specifications is shown in section respectively.

[17] For context, the median arrest age for m.v. theft before the information shock is 31

5 Robustness Checks

5.1 Robustness of SCI Treatment Effect to Interactions with Additional Socioeconomic Factors

A concern with using the SCI to measure the effect of higher video exposure on m.v. theft is that areas with higher shared SCI scores are also likely to share similar socioeconomic characteristics Bailey et al. (2018), that may interact with and amplify or diminish the treatment effect. For example, as shown in table 2, cities with high SCI have slightly higher pre-treatment crime rates. As a result, the average high SCI city may have a higher rate of individuals on the margin of engaging in crime, and hence the effect of higher video exposure as measured through the SCI could overstate the treatment effect.

To formally test the robustness of the higher SCI effect to additional interactions of the information shock with other socioeconomic factors, I run the following specifications building on the DDD specification, equation 3, using the KH thefts dataset, and the SCI DD specification, equation 4, using the NIBRS dataset,

$$\begin{aligned} log\,\mathbb{E}[CarsStolen_{ict}] = \; & \beta_1 HighSCI_c \times KH_i \times Post_t \; + \; \beta_2 HighSCI_c \times Post_t \; + \\ & \beta_3 Factor_c \times KH_i \times Post_t \; + \; \beta_4 Factor_c \times Post_t \; + \\ & \beta_5 KH_i \times Post_t \; + X_{ct} \; + \; \alpha_{ic} \; + \; \gamma_t \end{aligned} \tag{6}$$

$$log\,\mathbb{E}[Crime_{ct}] = \theta_1 HighSCI_c \times Post_t \; + \theta_2 Factor_c \times Post_t \; + X_{ct} \; + \; \delta_c \; + \; \gamma_t \tag{7}$$

where $Factor_c$ is one of the following pre-treatment socioeconomic variables in city c: m.v. theft rate, total crime rate, unemployment rate, median household income, poverty rate, log population, population density, or the percent of households without a car. The additional variables are the same as in equation 3 and equation 4 respectively.

Figure 10 displays the high SCI treatment effect after adding in additional treatment interactions for each socioeconomic factor on the following outcomes: KH thefts (a), β_1 from equation 6, and m.v. theft offenses (b) and arrests (c), θ_1 from equation 7. The high SCI effect remains relatively large and significant for all three outcomes. There are two cases where the KH thefts treatment effect is now marginally significant (<10%), however the effect size remains relatively large. The imprecision is partially a result of the KH thefts dataset having a smaller sample size and the DDD specification requiring additional power. Overall, the robustness of the high SCI treatment effects to additional interaction terms reassures that the SCI treatment effect results mainly from exogenous variation in online exposure to the theft videos and not from socioeconomic factors correlated with the SCI amplifying or diminishing the treatment effect.

5.2 Non-Linearity and Robustness of SCI Treatment Effect to Additional Quantile Specifications

In my main specifications that leverage SCI exposure, I divide cities into high and low SCI using the sample median. The sample median is a natural starting point without a priori knowledge on the relationship between SCI exposure and car theft, and also preserves statistical power by splitting cities into only two groups. However, this specification does not provide insight into the likely non-linear nature of the treatment effect. As shown in table A1, the KH theft treatment effect grows over time and the initial rate of growth is higher for cities with high SCI. In fact, the aggregate effect of SCI exposure on the KH theft treatment effect grows in the first 6 months after the information shock, and then begins to decrease, but the aggregate effect remains significant 15 months post shock. Given that the NIBRS sample only uses data from 2021 and 2022, the effect of high SCI exposure on m.v. theft offenses and arrests can only be measured 6 months after the information shock. Thus, following the KH theft results, the bulk of the treatment effect on m.v. theft is likely being driven by cities at the very top of the SCI distribution versus evenly by cities in the top 50% of the distribution i.e. the sample median specification.

To further investigate the non-linearity of the SCI treatment effect on m.v. theft offenses and arrests, as well as demonstrate the robustness of the treatment effect to specifications including more quantiles, I estimate the following specification,

$$log\,\mathbb{E}[Crime_{ct}] = \theta_1 Q_1 SCI_c \times Post_t \; + ... + \theta_{n-1} Q_{n-1} SCI_c \times Post_t \; + X_{ct} \; + \; \delta_c \; + \; \gamma_t \tag{8}$$

where θ_1, ..., θ_{n-1} are the DD coefficients from comparing the outcome of interest in cities in the highest through second lowest SCI quantiles, to cities in the lowest SCI quantile. For example, if cities are split into quartiles by SCI, then θ_1,θ_2, and θ_3 represent the treatment effects of the information shock for cities in the three highest quartiles relative to cities in the lowest quartile. The remaining variables are the same as in equation 4.

Table 8 displays the SCI treatment effects from equation 8 for $n = 3, 4, 5$ on m.v. theft offenses and arrests. As predicted, the SCI treatment effect remains large and significant for the highest quantile for all three specifications. The treatment effect then generally diminishes monotonically, with almost all the lower quantile treatment effects not being statistically significant. This pattern suggests that the SCI treatment effect is disproportionately driven by cities at the top of the SCI distribution. This is consistent with a model in which cities that experience higher initial online exposure to the KH theft videos also experience an initially disproportionately higher treatment effect. If the SCI treatment effect on m.v. theft offenses and arrests follows the same pattern as the effect on KH thefts, then the gap in the treatment effect between the highest quantile and lower quantiles may begin to diminish after 6 months. This will be able to be tested after NIBRS data for 2023 is released in October.

6 Conclusion

This paper provides the first causal estimates of the economic costs that can result from the modern phenomena of viral online challenges and the mechanism responsible for their spread and engagement. I study the effects of the"Kia challenge"–videos that went viral on social media platforms in June of 2022, depicting adolescents demonstrating and showing off how to steal vulnerable models of Kia and Hyundai cars (KH cars).

Using a difference-in-differences strategy, I first show that KH car thefts increase on average by 654% relative to non-KH car thefts. This demonstrates that the videos not only induce individuals to commit motor vehicle theft, but also are able to effectively teach individuals the knowledge necessary to successfully exploit and steal vulnerable KH cars. This is the first evidence of individuals learning criminal skills through an online media. This has particularly notable implications for the risk of failing to properly regulate content on social media platforms, since these skills can both be taught to non-criminals, but also rapidly spread through online social netoworks.

I provide evidence of this later effect by leveraging exogenous variation in a city's online social connectedness to the videos origin city. I show that online social networks amplify exposure to the videos, leading more connected cities to experience 55% more KH thefts.

Additionally, I show that more connected cities experience a significant increase in total motor vehicle theft offenses and arrests post shock, with null effects on all other major types of crime.

The increase in arrests is driven by minors and adults ages 18-25, suggesting that gaining peer attention online is the dominant mechanism incentivizing new engagement in car thefts. Overall these results demonstrate how attention maximizing social media algorithms can amplify exposure to and teach criminal skills while increasing the value of engaging in crime at the same time, leading to severe property damages in the short run and long run losses to human capital through increased involvement with crime and the criminal justice system.

7 Tables and Figures

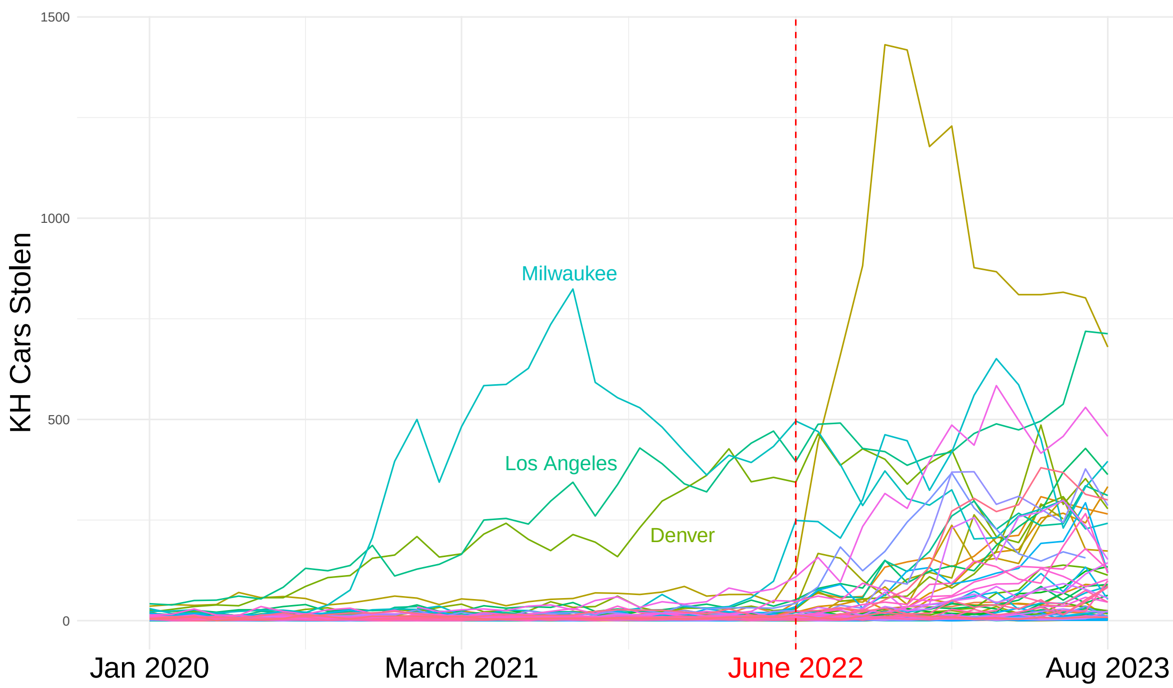
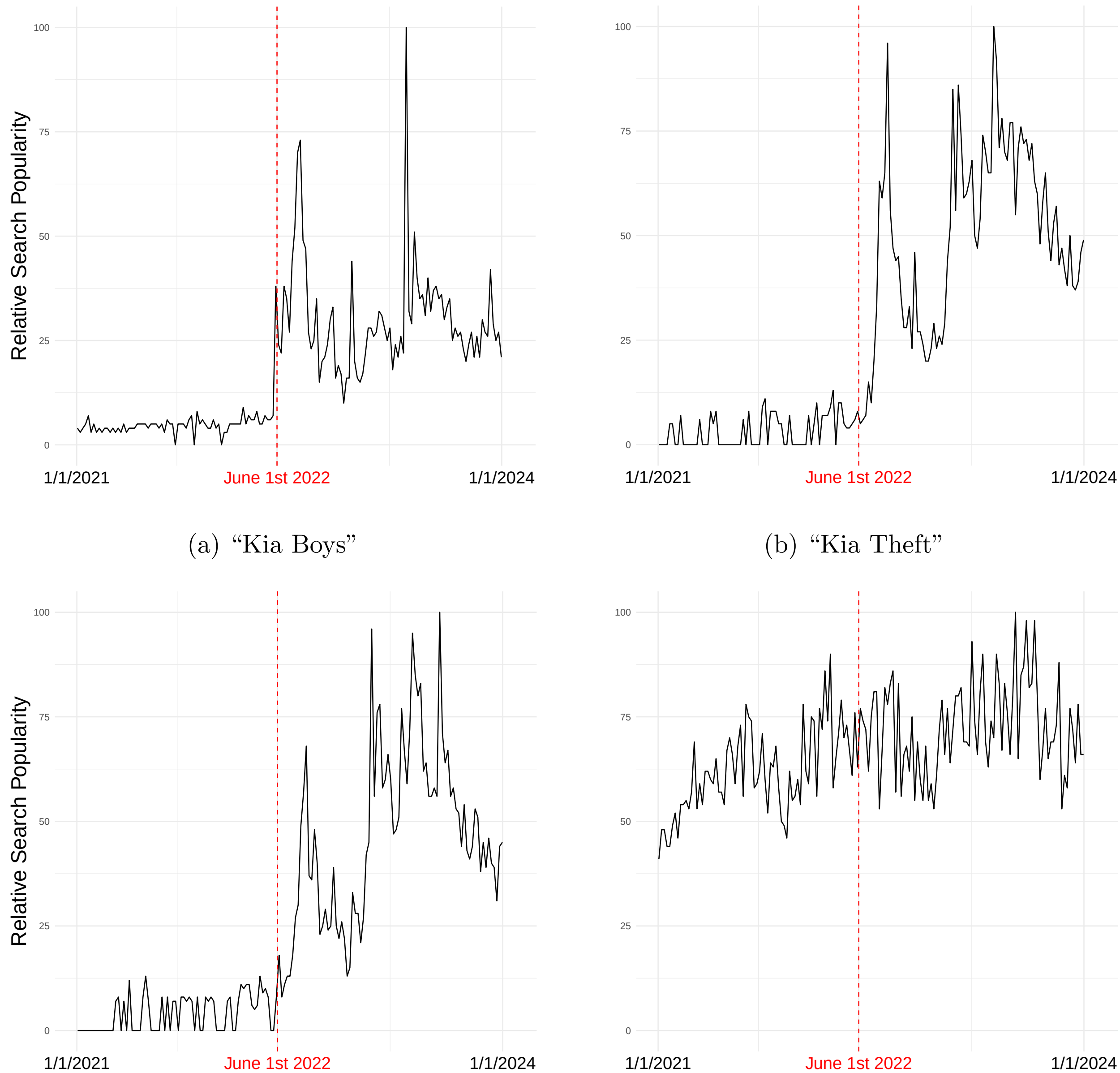


Figure 1: KH Thefts Increase in Three Cities before June 2022

Notes: This plot displays monthly KH thefts in 63 major city police departments from January 2020 to August 2023. Data Source: FOIA requests to major police departments submitted by journalists at Vice Motherboard



(a) “Kia Boys”

(b) “Kia Theft”

(c) “Hyundai Theft”

(d) “Honda Theft”

Figure 2: Google Search Popularity of KH Theft Video Terms Increase in June 2022

Notes: This figure displays time series data for the search popularity of terms related to the KH theft phenomena. The term Honda Theft serves as a control. The y-axis is a normalized index of the relative search popularity of the term, where 100 indicates the highest proportion of search volume achieved for the term from Jan. 1st 2021 to Dec. 31st 2023. Data Source: Google Trends

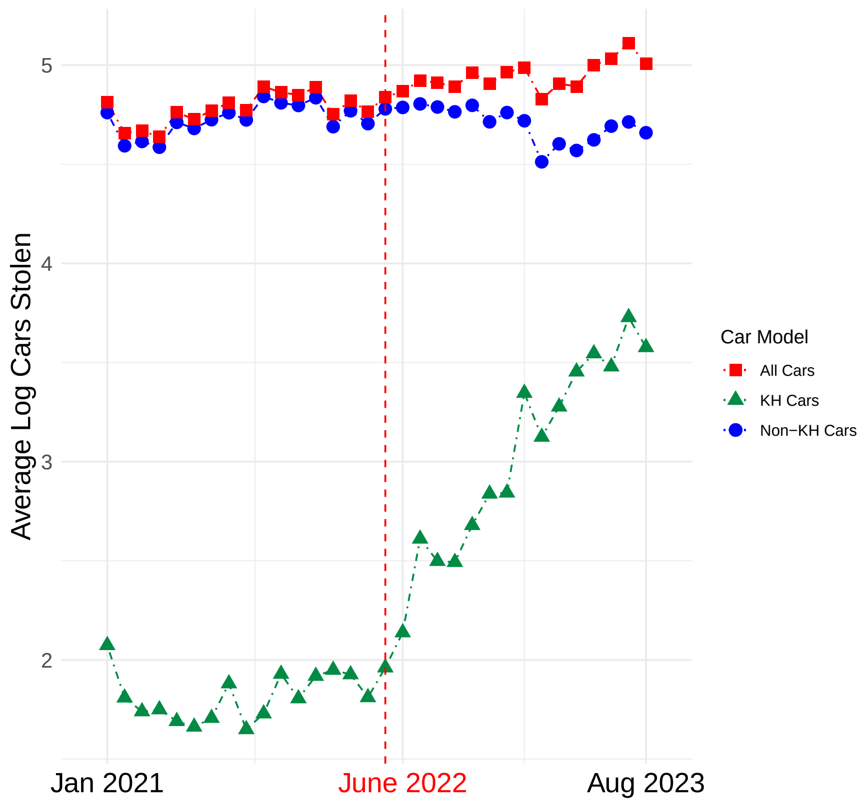


Figure 3: Viral KH Theft Videos Act as an Information Shock that Increases KH Thefts

Notes: This figure displays the average monthly log cars stolen for KH, Non-KH, and all cars from 60 major city police departments. Three city police departments are excluded, Milwaukee, Denver, and Los Angeles, because knowledge of the KH car anti-theft vulnerability spread locally before the KH theft videos went viral. Data Source: FOIA requests to major police departments submitted by journalists at Vice Motherboard

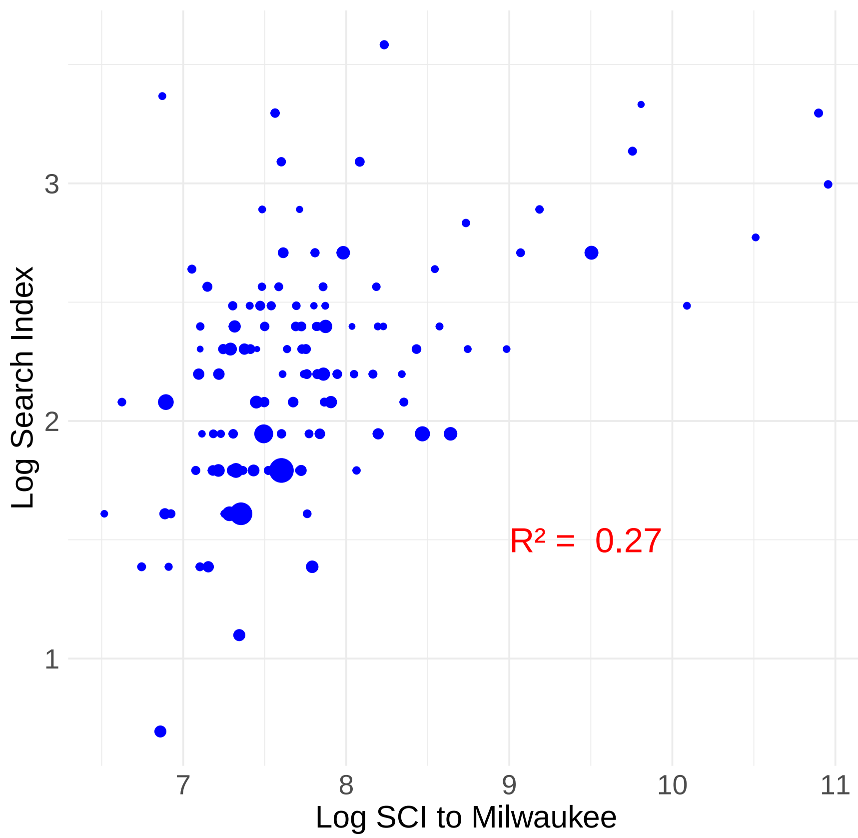
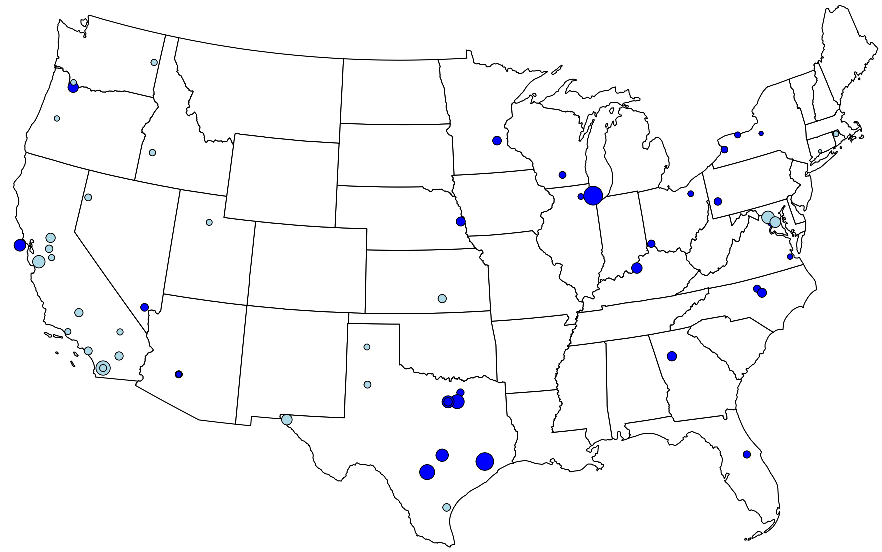
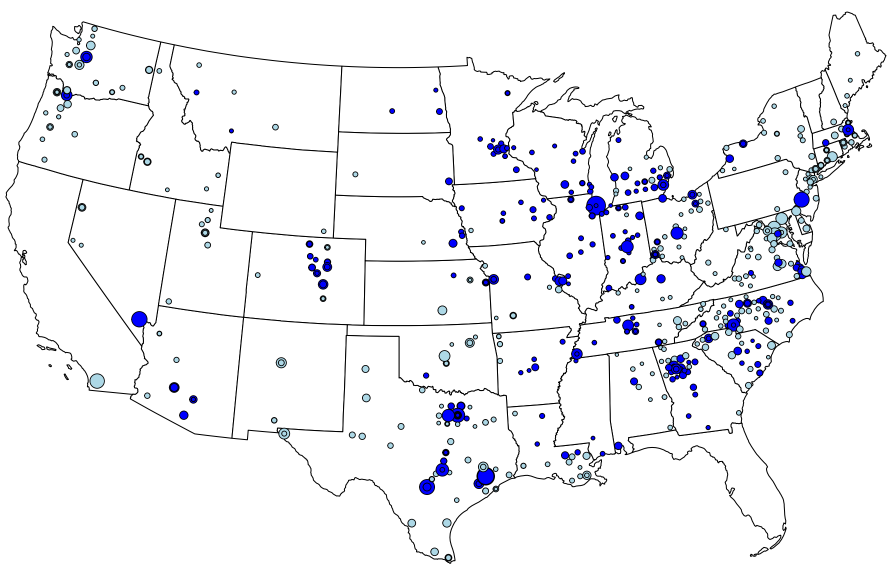


Figure 4: Search Intensity for KH Theft Video Terms is Positively Correlated with Social Connectedness to Milwaukee

Notes: This figure displays the relationship between a metropolitan area's relative search intensity for KH theft video terms and it's Social Connectedness Index score to Milwaukee. The original KH theft videos were created and first became popular in Milwaukee. The Milwaukee metro area is excluded, but would have a log search intensity score of 4.60. The circle size scales directly with the metro population size. Data Sources: Google Trends, Meta-Facebook Social Connectedness Index



(a) Agencies in KH Thefts Sample

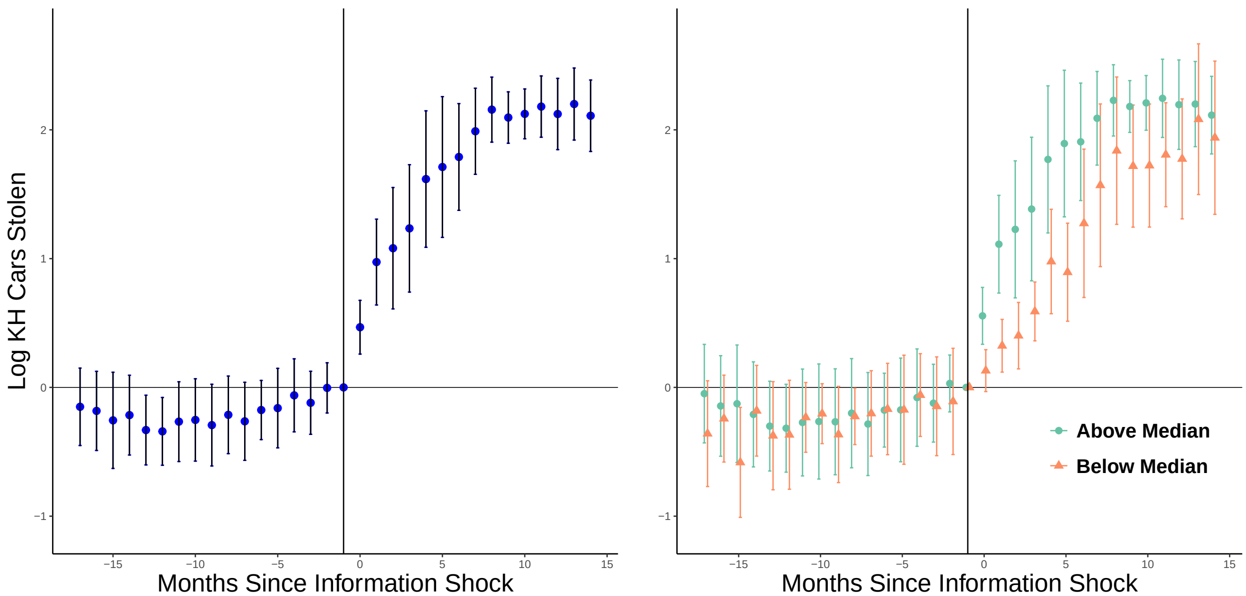


(b) Agencies in NIBRS Sample

Social Connectedness to Milwaukee ● Below Median ● Above Median

Figure 5: Geographic Distribution of Police Agencies by Social Connectedness to Milwaukee

Notes: This figure displays the geographic distribution of police agencies in each sample. The circle size scales directly with the agency population size and the SCI sample median is calculated using the NIBRS sample. Data Sources: NIBRS, Meta: Facebook Social Connected Index, and FOIA requests to major police departments



(a) Full Sample

(b) SCI Median Sample Split

Figure 6: Effect of Viral Video Information Shock on KH Thefts

Notes: This figure displays the event study treatment effects from equation 2 for monthly KH car thefts relative to non-KH car thefts before and after the information shock using the full sample of agencies (a), and subsamples of cities above and below the median SCI (b). The point estimates measure the effect in relation to the month before the information shock (May 2022). Data Sources: Meta: Facebook Social Connected Index, and FOIA requests to major police departments

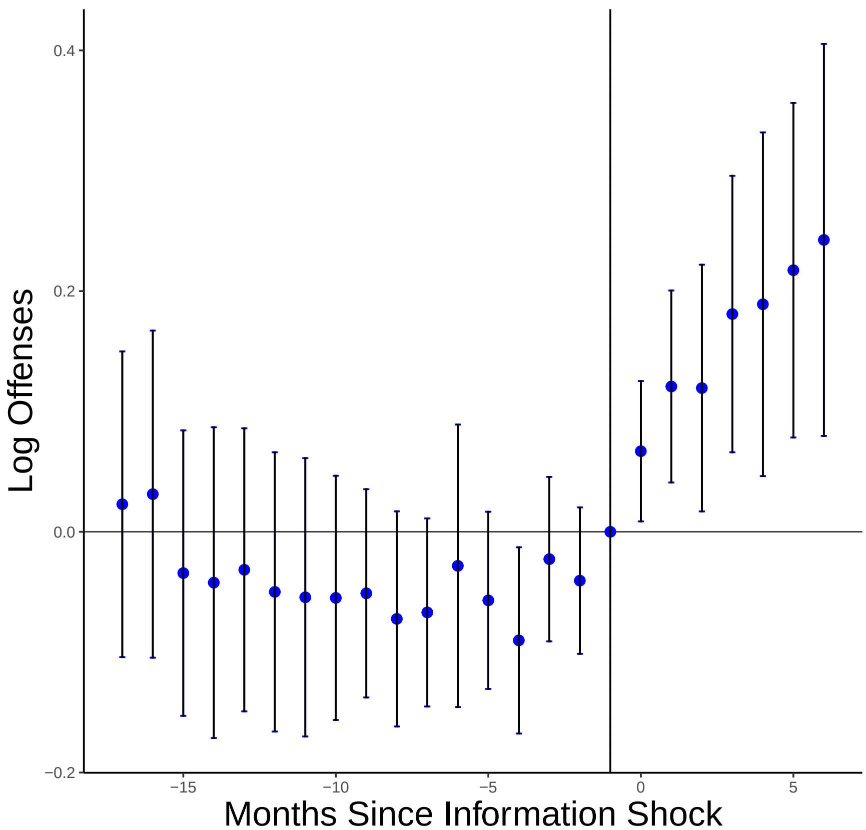


Figure 7: Effect of Higher Online Video Exposure on Motor Vehicle Theft Offenses

Notes: This figure displays the event study treatment effects from equation 5 for the count of motor vehicle theft offenses in police agencies with above median (treatment) relative to below median (control) SCI to Milwaukee. The point estimates measure the effect in relation to the month before the information shock (May 2022). Data Sources: NIBRS, Meta.

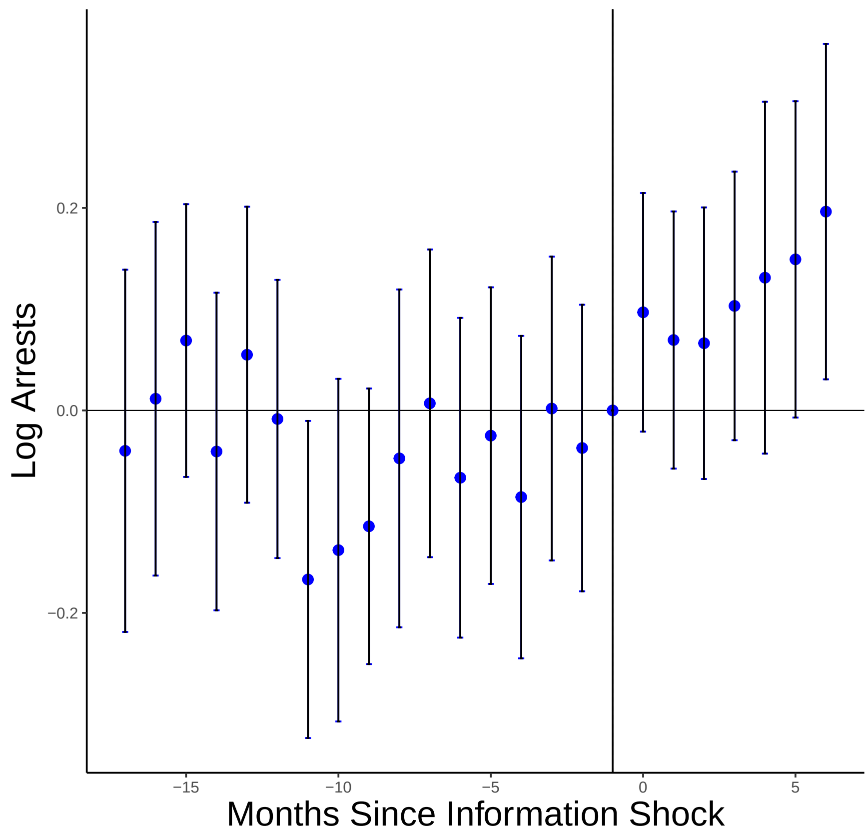


Figure 8: Effect of Higher Online Video Exposure on Motor Vehicle Theft Arrests

Notes: This figure displays the event study treatment effects from equation 5 for motor vehicle theft arrests in police agencies with above median (treatment) relative to below median (control) SCI to Milwaukee. The point estimates measure the effect in relation to the month before the information shock (May 2022). Data Sources: NIBRS, Meta: Facebook Social Connectedness Index

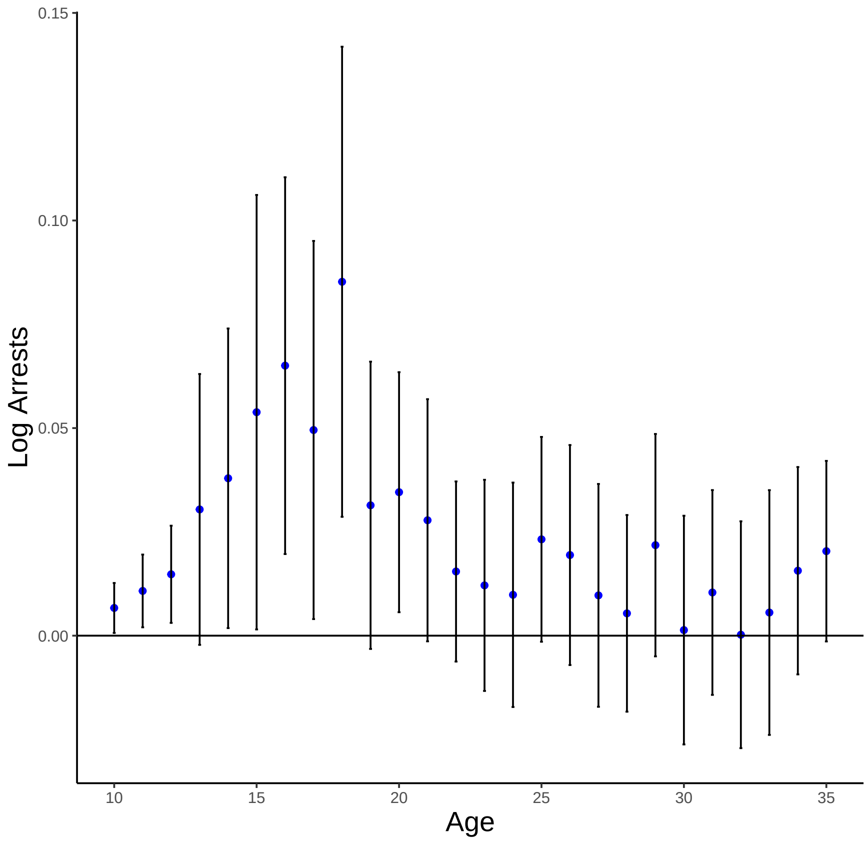
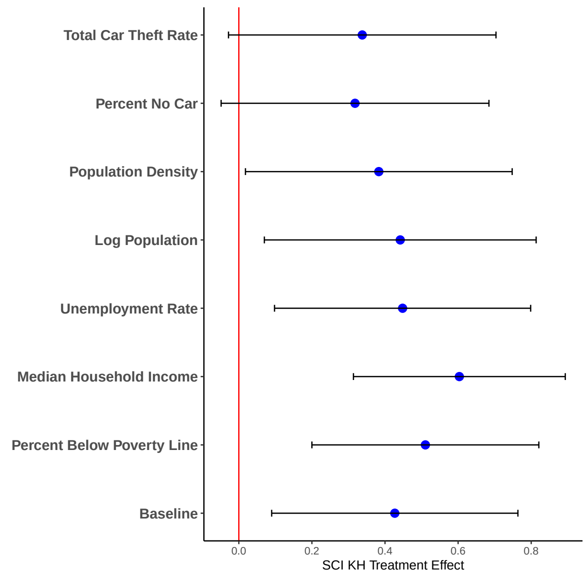
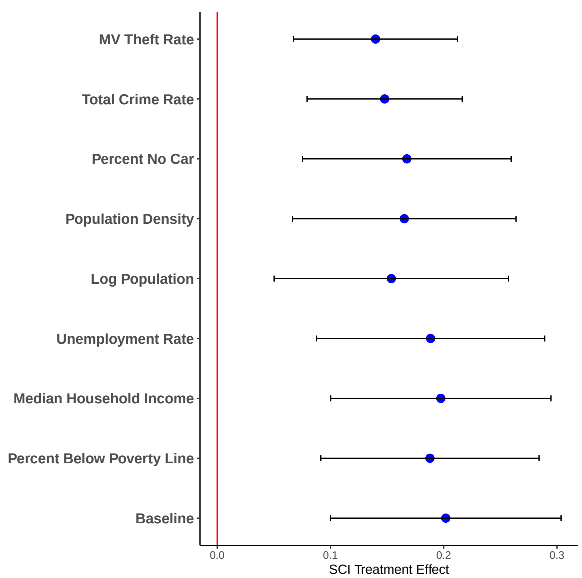


Figure 9: Effect of Higher Online Video Exposure on M.V. Theft Arrest by Age

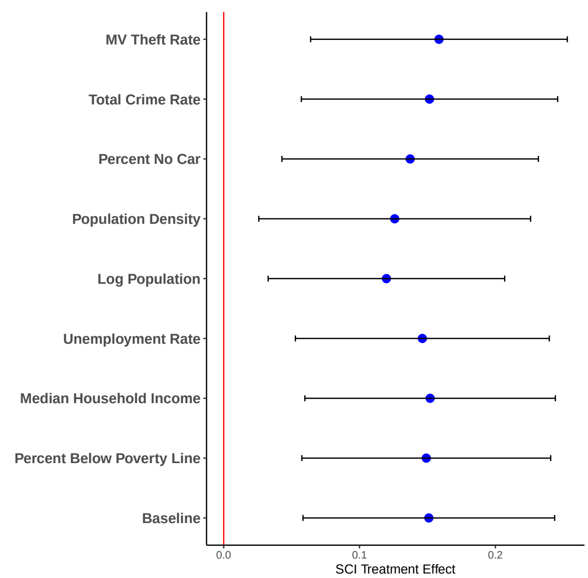
Notes: This figure displays the High SCI treatment effect from equation 4 for motor vehicle theft arrests for each age from 14-35. Data Sources: NIBRS, Meta: Facebook Social Connectedness Index



(a) KH Theft Treatment Effect



(b) M.V. Theft Offenses



(c) M.V. Theft Arrests

Figure 10: Robustness of Higher Online Video Exposure Treatment Effect to Additional Treatment Interactions

Notes: This figure displays the high SCI treatment effect from equation 6 (a) and equation 7 (b), (c), for each additional factor listed on the y-axis. Data Sources: NIBRS, Meta: Facebook Social Connectedness Index

Table 1: Summary Statistics KH Thefts Sample: High vs. Low SCI Agencies

	High SCI	Low SCI	Difference
Demographics			
Population	584.49	407.27	177.22
(1000s)	(601.97)	(322.15)	(184.33)
Percent White	54.12	51.59	2.53
	(14.36)	(18.54)	(6.01)
Percent Black	16.41	7.52	8.89*
	(10.64)	(11.46)	(4.06)
Percent Hispanic	21.20	33.15	−11.95
	(15.06)	(19.00)	(6.22)
Unemployment Rate	4.16	4.71	−0.56
	(0.80)	(1.27)	(0.38)
Median Household Income	74.86	78.25	−3.39
($1000s)	(14.23)	(20.47)	(6.34)
Percent Below Poverty Line	13.01	12.89	0.12
	(2.63)	(3.95)	(1.20)
Monthly Car Theft Rates			
(per 10000 people)			
Total			
Pre-Shock	3.78	4.60	−0.81
	(2.57)	(3.09)	(1.03)
Post-Shock	5.24	4.90	0.33
	(3.88)	(3.02)	(1.30)
KH			
Pre-Shock	0.22	0.17	0.05
	(0.15)	(0.13)	(0.05)
Post-Shock	1.76	0.75	1.01
	(2.06)	(0.84)	(0.61)
Non-KH			
Pre-Shock	3.57	4.43	−0.86
	(2.45)	(3.00)	(1.00)
Post-Shock	3.51	4.15	−0.64
	(2.22)	(2.49)	(0.86)
Number of Cities	34	26	

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

This table displays demographic, socioeconomic, and car theft statistics for police agencies and the counties they're located in from before the information shock in June 2022. The population and car theft data corresponds directly to the police agency, all other statistics correspond to the county of the police agency. High SCI agencies are located in counties with above sample median SCI to Milwaukee. Data Sources: Meta: Facebook Social Connectedness Index, ACS 2021, FOIA requests to major police departments.

Table 2: Summary Statistics NIBRS Sample: High vs. Low SCI Agencies

	High SCI	Low SCI	Difference
Demographics			
Population	172.15	122.51	49.64**
(1000s)	(277.76)	(144.88)	(15.42)
Percent White	63.39	69.01	−5.62***
	(15.57)	(16.12)	(1.10)
Percent Black	16.24	7.81	8.43***
	(13.29)	(8.60)	(0.78)
Percent Hispanic	12.82	18.52	−5.71***
	(10.91)	(17.76)	(1.03)
Median Household Income	73.45	72.69	0.76
($1000s)	(17.32)	(18.84)	(1.26)
Percent in Poverty	12.68	12.87	−0.19
	(4.96)	(5.01)	(0.35)
Unemployment Rate	4.29	4.54	−0.25**
	(1.10)	(1.36)	(0.09)
Pre-Treatment Crime Rates			
(per 10000 people)			
Total	41.12	36.26	4.86**
	(22.21)	(21.15)	(1.51)
Property	14.84	12.90	1.94**
	(8.93)	(9.02)	(0.62)
Violent	10.54	9.02	1.52**
	(7.75)	(5.93)	(0.48)
Drug	3.17	2.97	0.19
	(2.43)	(2.43)	(0.17)
Motor Vehicle Theft	2.28	1.81	0.46***
	(2.21)	(1.76)	(0.14)
Number of Agencies	412	413	-

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

This table displays demographic, socioeconomic, and car theft statistics for police agencies and the counties they're located in from before the information shock in June 2022. The population and car theft data corresponds directly to the police agency, all other statistics correspond to the county of the police agency. High SCI agencies are located in counties with above sample median SCI to Milwaukee. Data Sources: Meta: Facebook Social Connectedness Index, ACS 2021, NIBRS.

Table 3: Effect of Information Shock on KH Car Thefts Relative to Non-KH Car Thefts

	(1)	(2)	(3)	(4)	N
Panel A: DD All Cities					
KH × Post	2.023***	2.020***	2.022***	2.020***	3879
	(0.084)	(0.084)	(0.085)	(0.119)	
% Change	656%	654%	656%	654%	
Change Pre-Treatment Mean (Monthly Thefts)	74.6	74.4	74.6	74.4	
Panel B: DD Above Median SCI Cities					
KH × Post	2.086***	2.086**	2.085***	2.086***	2215
	(0.093)	(0.094)	(0.107)	(0.139)	
% Change	705%	705%	704%	705%	
Change Pre-Treatment Mean (Monthly Thefts)	103.1	103.1	103.0	103.1	
Panel C: DD Below Median SCI Cities					
KH × Post	1.700***	1.651***	1.652***	1.651***	1664
	(0.163)	(0.135)	(0.181)	(0.119)	
% Change	447%	421%	422%	421%	
Change Pre-Treatment Mean (Monthly Thefts)	32.4	30.8	30.9	30.8	
Controls	No	Yes	Yes	Yes	
Population Offset	No	No	Yes	No	
Clustered State	No	No	No	Yes	

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

This table contains the DD coefficient from equation 1 for the effect of the information shock on KH cars stolen relative to the count of non-KH cars stolen. The above and below median sub-samples, contain cities that are above or below median SCI to Milwaukee, the median is calculated from the NIBRS sample. Standard errors are clustered at the county level except when noted otherwise. Data Sources: Meta: Facebook Social Connectedness Index, ACS 2021, FOIA requests to major police departments.

Table 4: Effect of Higher Online Exposure to Videos on KH Car Thefts

	(1)	(2)	(3)	(4)
Panel A: DDD Median SCI Split				
KH × Post	1.700***	1.650***	1.651***	1.650***
	(0.161)	(0.140)	(0.139)	(0.130)
% Change KH Thefts (Low SCI Cities)	447.4%	420.7%	421.2%	420.7%
HighSCI × KH × Post	0.393**	0.437**	0.434**	0.437***
	(0.188)	(0.170)	(0.170)	(0.141)
% Additional Change KH Thefts (High vs. Low SCI Cities)	48.1%	54.8%	54.3%	54.8%
HighSCI × Post	0.125	0.166**	0.186**	0.166**
	(0.091)	(0.079)	(0.081)	(0.076)
% Change Non-KH Thefts (High vs Low SCI Cities)	13.3%	18.1%	20.4%	18.1%
Panel B: DDD Continuous SCI				
logSCI × KH × Post	0.204***	0.207***	0.205***	0.207***
	(0.066)	(0.067)	(0.067)	(0.058)
SCI Elasticity of KH Thefts	0.226	0.230	0.228	0.230
N	3879	3879	3879	3879
Controls	No	Yes	Yes	Yes
Population Offset	No	No	Yes	No
Clustered State	No	No	No	Yes

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Panel A contains coefficients from DDD equation 3 for the effect of the information shock on KH cars stolen relative to the count of non-KH cars stolen in agencies with above median SCI to Milwaukee compared to cities with below median SCI. Panel B displays the DDD coefficient from the continuous version of 3, this makes the coefficient the SCI elasticity of the KH theft treatment effect. Standard errors are clustered at the county level except when noted otherwise. Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments.

Table 5: Effect of Higher Online Exposure to Videos on Offenses

Crime	ATT	% Change	N
Panel A : M.V. Theft			
M.V. Theft	0.202***	22.4%	19567
	(0.052)		
Panel B: Excluding M.V. Theft			
Major Crime Types			
Total	0.017	1.7%	19567
	(0.019)		
Violent	−0.025	−2.5%	19567
	(0.017)		
Property	0.041*	4.2%	19567
	(0.024)		
Drug	0.005	0.5%	19521
	(0.024)		
Property Crimes			
Burglary	0.033	3.4%	19567
	(0.026)		
Theft	0.033	3.4%	19567
	(0.027)		
Vandalism	0.060**	6.2%	19567
	(0.028)		
Dealing Stolen Property	0.066	6.8%	18763
	(0.053)		

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
This table contains the DD coefficient from equation 4 comparing monthly offenses in police agencies above median (treatment) and below median (control) SCI to Milwaukee before and after the information shock in June of 2022. Data sources: Meta: Facebook Social Connectedness Index, NIBRS

Table 6: Effect of Higher Online Exposure to Videos on Arrests

Arrests	ATT	% Change	N
Panel A : M.V. Theft			
M.V. Theft	0.151***	16.3%	19304
	(0.047)		
Panel B:Excluding M.V. Theft			
Major Crime Types			
Total	−0.009	−0.9%	19376
	(0.021)		
Violent	−0.019	−1.9%	19376
	(0.020)		
Property	−0.011	−1.1%	19376
	(0.026)		
Drug	0.013	1.3%	19335
	(0.034)		
Property Crimes			
Burglary	0.035	3.6%	19350
	(0.035)		
Theft	−0.035	−3.4%	19327
	(0.033)		
Vandalism	−0.005	−0.5%	19352
	(0.023)		
Dealing Stolen Property	0.028	2.8%	17946
	(0.053)		

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
This table contains the DD coefficient from equation 4 comparing monthly arrests in police agencies above median (treatment) relative to below median (control) SCI to Milwaukee before and after the information shock in May of 2022. Meta: Facebook Social Connectedness Index, NIBRS

Table 7: Effect of Higher Online Exposure to Videos on Arrests by Age Group

Age	Under 18	18-25	26-30	31-35
Panel A : M.V. theft				
M.V. Theft	0.240**	0.283***	0.122*	0.055
	(0.116)	(0.097)	(0.068)	(0.052)
Panel B: Excluding M.V. Theft				
Major Crime Types				
All	0.003	−0.017	−0.019	0.001
	(0.040)	(0.024)	(0.023)	(0.022)
Violent	−0.026	−0.023	−0.036	−0.012
	(0.041)	(0.022)	(0.023)	(0.022)
Property	0.049	−0.007	−0.011	0.006
	(0.059)	(0.039)	(0.029)	(0.027)
Drug	0.011	0.015	0.013	0.021
	(0.058)	(0.035)	(0.039)	(0.037)

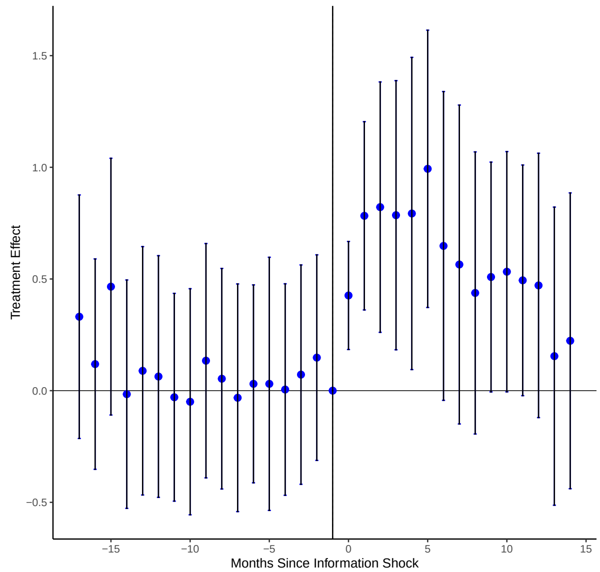
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
This table contains the DD coefficient from equation 4 comparing arrests in police agencies above median (treatment) relative to below median (control) SCI to Milwaukee before and after the information shock in June of 2022 for the stated age groups. Data sources: Meta: Facebook Social Connectedness Index, NIBRS

Table 8: Robustness of Effect of Higher Online Exposure to Videos on Motor Vehicle Theft for Higher Quantile Specifications

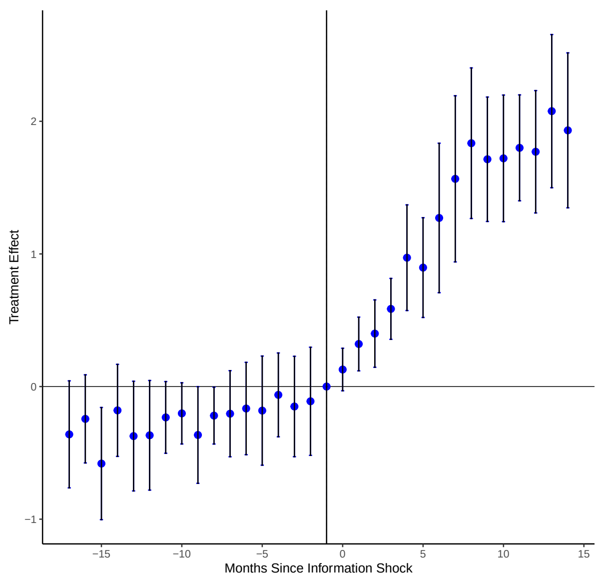
Quantile Coefficient	Offenses	% Change	Arrests	% Change
Panel A: Tertiles				
1st Tertile	0.204***	22.6%	0.161***	17.5%
	(0.063)		(0.052)	
2nd Tertile	0.058	6.0%	−0.032	-3.1%
	(0.051)		(0.043)	
Panel B: Quartiles				
1st Quartile	0.248***	28.1%	0.155***	16.8%
	(0.080)		(0.057)	
2nd Quartile	0.116***	12.3%	0.073	7.6%
	(0.040)		(0.049)	
3rd Quartile	−0.036	-3.5%	−0.058	-5.6%
	(0.040)		(0.040)	
Panel C: Quintiles				
1st Quintile	0.284***	33%	0.151**	16.3%
	(0.093)		(0.065)	
2nd Quintile	0.064	6.6%	0.077	8.0%
	(0.053)		(0.052)	
3rd Quintile	0.068	7.0%	−0.071	-6.9%
	(0.155)		(0.050)	
4th Quintile	−0.002	-0.2%	−0.062	-6.0%
	(0.244)		(0.061)	
N	19567		19304	

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
This table contains the DD coefficient from equation 8 comparing arrests in police agencies in the n - 1 highest SCI to Milwaukee quantiles relative to the lowest quantile before and after the information shock in June of 2022.
Data sources: Meta: Facebook Social Connectedness Index, NIBRS

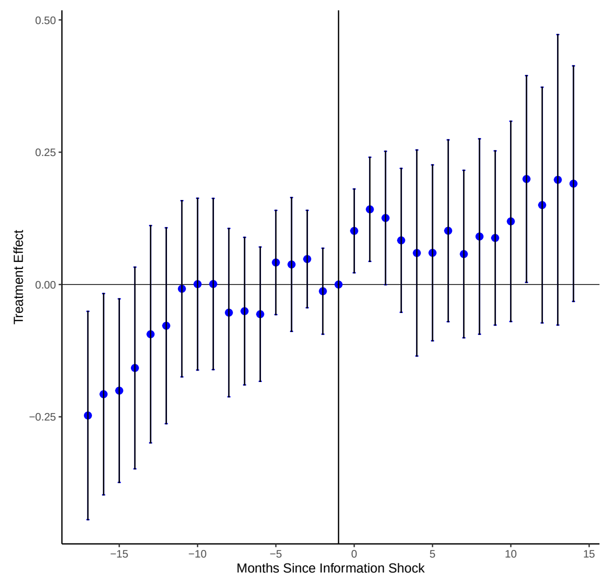
A Additional KH Theft Results



(a) Additional Effect of Higher Exposure to Information Shock on KH Thefts



(b) Effect of Information Shock on KH Thefts in Low Exposure Agencies



(c) Effect of Higher Exposure to Information Shock on Non-KH Thefts

Figure A1: Treatment Effects of DDD Specification

Notes: This figure displays the treatment effects corresponding to the DD, (b,c) and DDD (a) coefficients of the event study version of equation 3. Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments

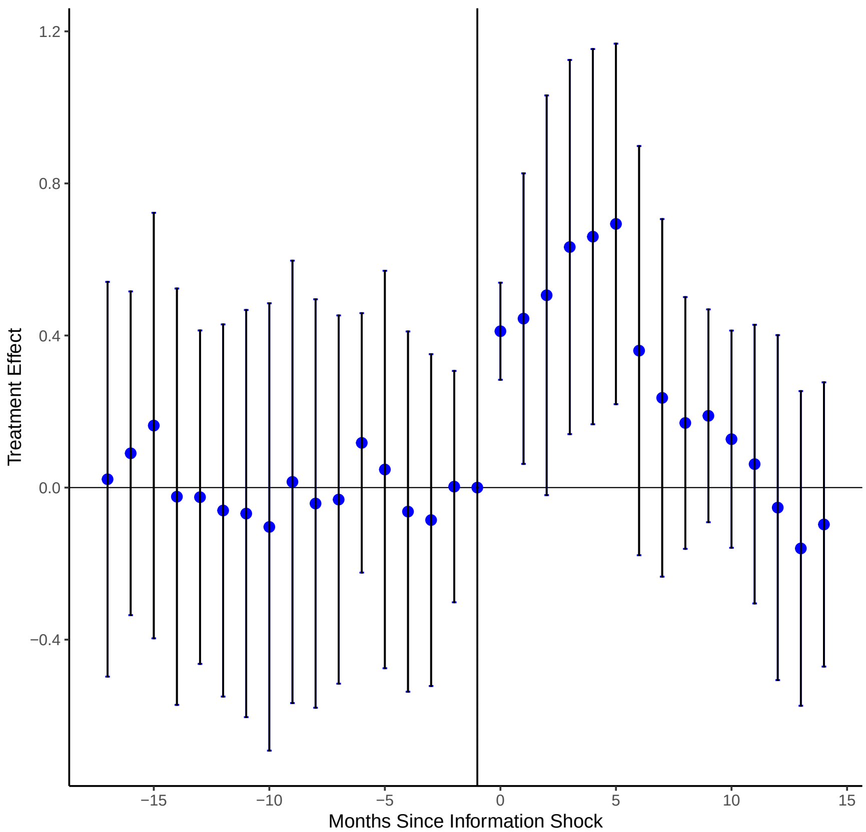
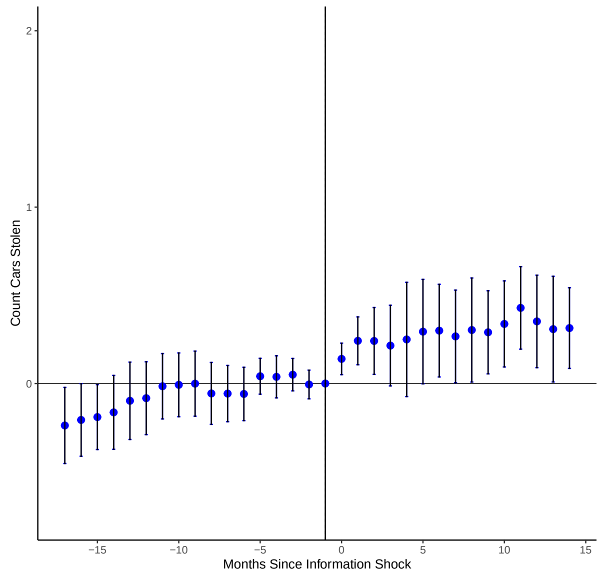
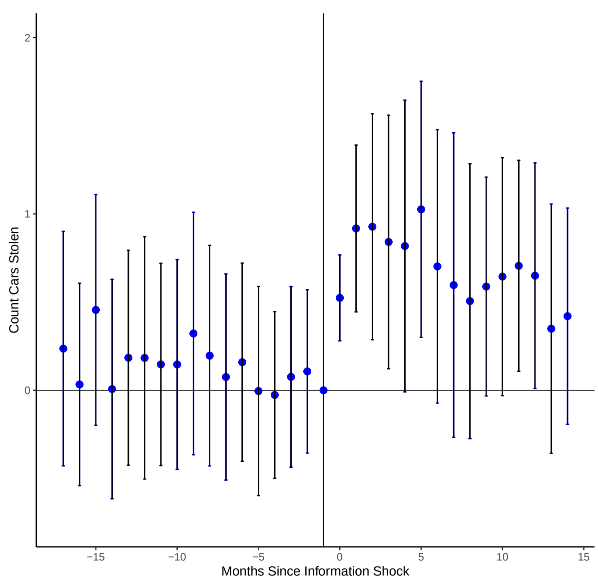


Figure A2: Dynamics of SCI Elasticy of KH Theft Treatment Effect

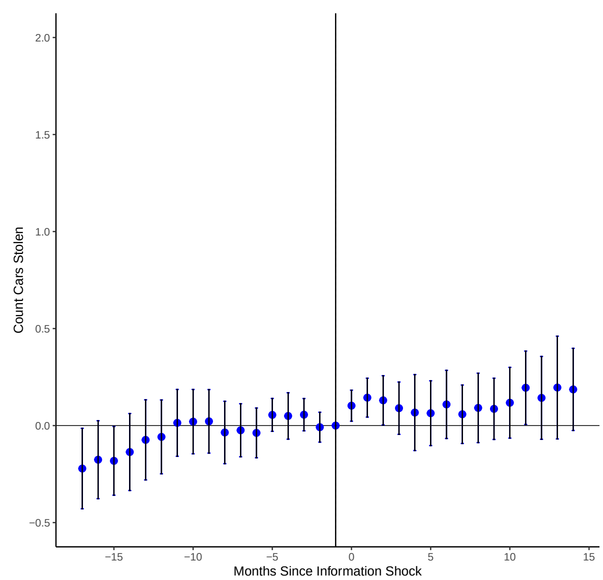
Notes: This figure displays the treatment effects of the DDD coefficient of the continuous event-study version of equation 3. Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments.



(a) All Cars



(b) KH Cars



(c) Non-KH Cars

Figure A3: Effect of Higher Online Video Exposure on Car Thefts by Brand

Notes: This figure displays the event study treatment effects from equation 5 on cars stolen in cities above (treatment) versus below (control) median sci to Milwaukee. The point estimates measure the effect in relation to the month before the information shock (May 2022). Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments)

Table A1: Dynamics of the Effect of Information Shock and Higher Exposure on KH Thefts

	3 months	6 months	9 months	12 months	15 months
Panel A: DD KH Thefts					
$KH \times Post$	1.163***	1.539***	1.802***	1.950***	2.013***
	(0.167)	(0.191)	(0.143)	(0.103)	(0.088)
% Change	220.0%	366.0%	506.2%	602.9%	648.6%
Panel B: DDD Median Split SCI					
$HighSCI \times KH \times Post$	0.660***	0.693***	0.550**	0.509***	0.430**
	(0.230)	(0.235)	(0.220)	(0.190)	(0.172)
% Change	93.5%	100.0%	73.3%	66.4%	53.7%
Panel C: DDD Continuous SCI					
$LogSCI \times KH \times Post$	0.468***	0.483***	0.352***	0.270***	0.201**
	(0.067)	(0.073)	(0.069)	(0.064)	(0.066)
SCI Elasticity of KH Thefts	0.597	0.621	0.422	0.310	0.223
N	2520	2880	3234	3588	3815

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Panel A displays the DD coefficient from equation 1 comparing KH thefts to non-KH thefts before and after the information shock in June 2022 over time. Panel B displays the DDD coefficient from equation 3 and Panel C the continuous version of the DDD coefficient from equation 3 comparing KH thefts to non-KH thefts in higher SCI agencies to lower SCI agencies before and after the information shock in June of 2022. Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments.

Table A2: Effect of Higher Exposure to the Information Shock on KH Car Thefts

Sub-Sample	$KH \times Post$	% Change	N
Panel A: Tertiles			
1st Tertile	2.065***	689%	1584
	(0.119)		
2nd Tertile	2.059***	684%	1143
	(0.124)		
3rd Tertile	1.557***	374%	1152
	(0.180)		
Panel B: Quartiles			
1st Quartile	2.093***	711%	1274
	(0.119)		
2nd Quartile	2.068***	691%	941
	(0.145)		
3rd Quartile	1.701***	448%	832
	(0.178)		
4th Quartile	1.538***	366%	832
	(0.207)		
Panel C: Quintiles			
1st Quintile	2.154***	762%	954
	(0.123)		
2nd Quintile	1.984***	627%	821
	(0.171)		
3rd Quintile	1.979***	624%	760
	(0.155)		
4th Quintile	1.089***	197%	640
	(0.244)		
5th Quintile	1.603***	397%	704
	(0.211)		

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
This table contains the DD coefficient from equation 1 comparing KH thefts relative to non-KH thefts before and after the information shock in June 2022 for each quantile sub-sample.
Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments

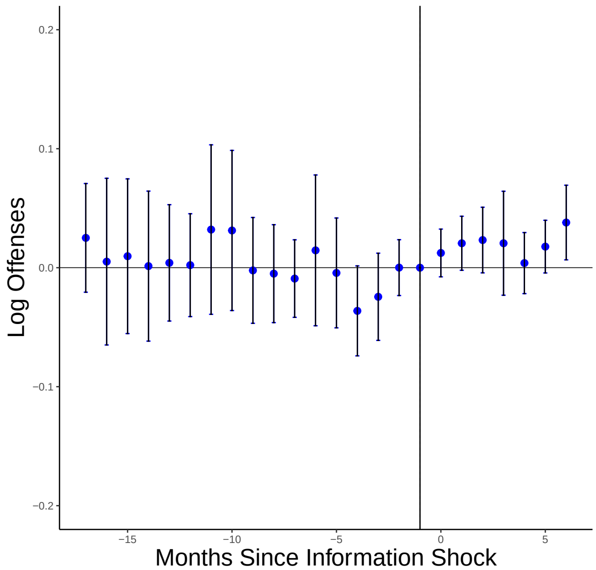
Table A3: Effect of Higher Online Exposure to Videos on Car Thefts by Brand

Stolen Car Type	1	2	3	4	N
Total	0.290**	0.342***	0.437***	0.342***	1931
	(0.118)	(0.104)	(0.146)	(0.112)	
KH	0.520**	0.501***	0.382	0.501***	1948
	(0.217)	(0.174)	(0.297)	(0.136)	
Non-KH	0.113	0.153*	0.282**	0.153*	1931
	(0.094)	(0.086)	(0.110)	(0.085)	
Controls	No	Yes	Yes	Yes	
Weights	No	No	Yes	No	
Clustered State	No	No	No	Yes	

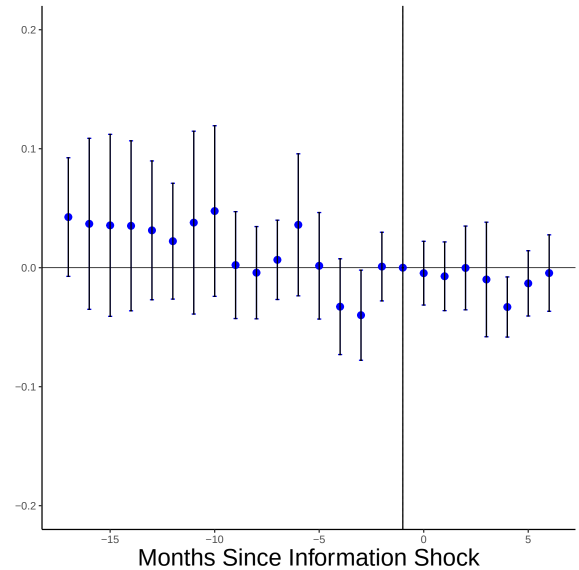
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

This table displays the DD coefficient from 4 for monthly cars stolen in high SCI agencies relative to low SCI agencies before and after the information shock in June 2022. Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments).

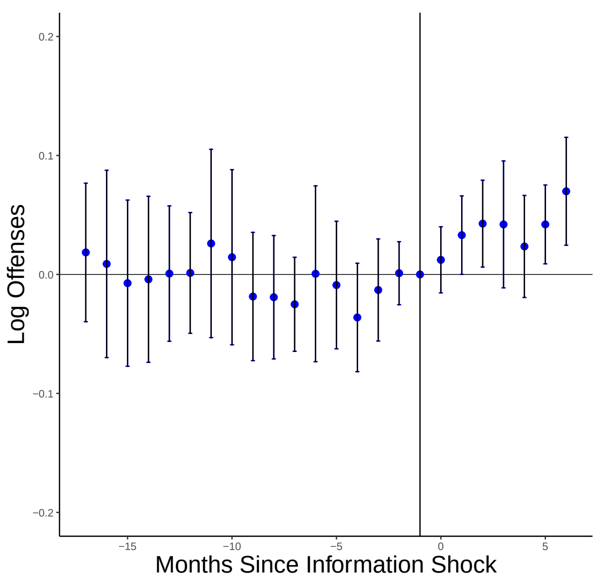
B Additional NIBRS Results



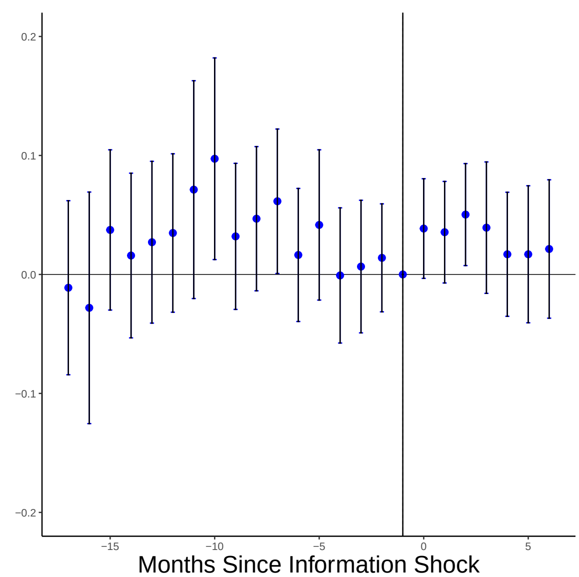
(a) Total Crime



(b) Violent Crime



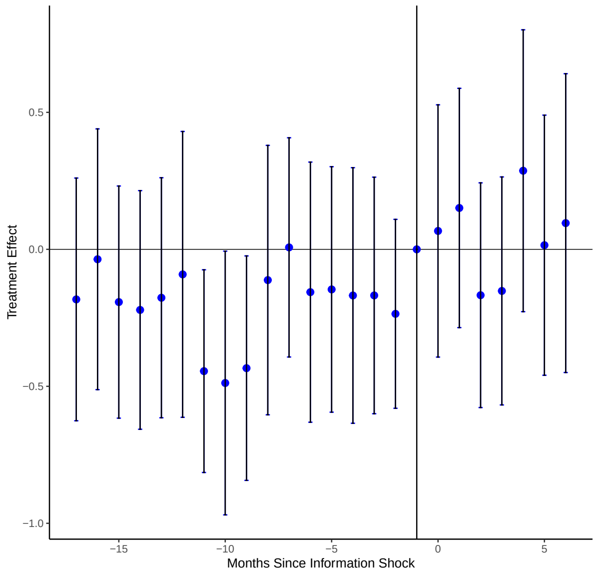
(c) Property Crime



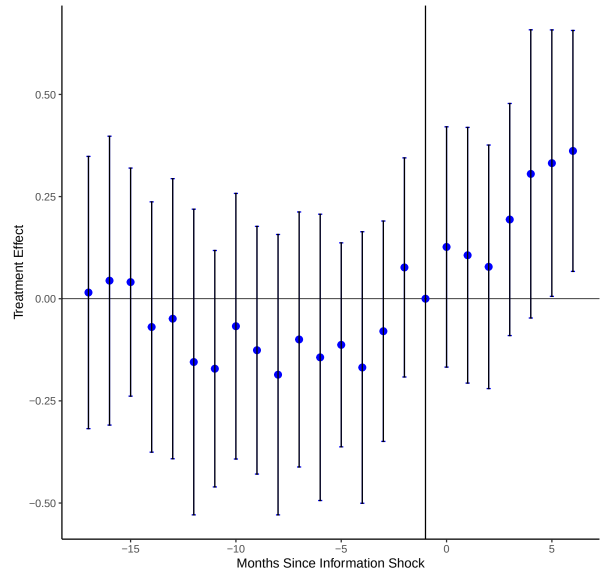
(d) Drug Crime

Figure B1: Effect of Higher Online Video Exposure on Aggregate Crime Offenses

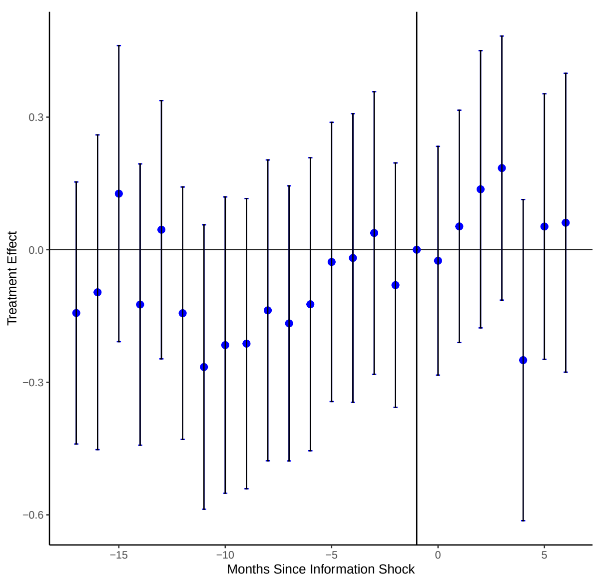
Notes: This figure displays the event study treatment effects from equation 5 for the count of monthly aggregate crime types in police agencies with above median (treatment) relative to below median (control) SCI to Milwaukee. Motor vehicle theft is excluded from total and property crime. The point estimates measure the effect in relation to the month before the information shock (May 2022). Data Sources: Meta: Facebook Social Connectedness Index, NIBRS



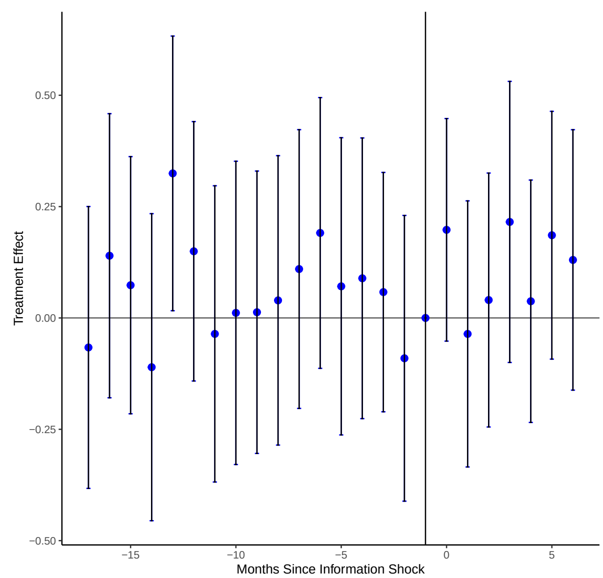
(a) Under 18



(b) 18 - 25



(c) 26 -30



(d) 31 - 35

Figure B2: Effect of Higher Online Video Exposure on M.V. Theft Arrests by Age Group

Notes: This figure displays the event study treatment effects from equation 5 for monthly aggregate crime categories for each age group. Data Sources: Meta: Facebook Social Connectedness Index, NIBRS

Table B1: Robustness of Higher Exposure Effect on M.V. Theft to City Population Size

City Population	Offenses	% Change	N	Arrests	% Change	N
Baseline (> 50k)	0.202***	22.4%	19567	0.151***	16.3%	19304
	(0.052)			(0.047)		
> 0	0.195***	21.5%	181780	0.103***	10.8%	133998
	(0.044)			(0.035)		
> 10K	0.193***	21.3%	88769	0.114***	12.1%	80849
	(0.045)			(0.037)		
> 100K	0.229***	25.7%	7407	0.169***	18.4%	7312
	(0.059)			(0.060)		
> 250K	0.328***	38.8%	2157	0.271***	31.1%	2135
	(0.069)			(0.083)		
> 500K	0.268***	30.7%	841	0.329***	39.0%	822
	(0.077)			(0.097)		

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
This contains the DiD coefficient from equation (1) for the effect on the log count of KH cars stolen using the log count of non-KH cars stolen as the control group. Above and below median are sub-samples of cities that are above or below social connectedness to Milwaukee median calculated from the NIBRS data. Standard errors are clustered at the county level except when noted otherwise. Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments.

Table B2: Effect of Higher Online Video Exposure on Arrests by Sex

Sex	Male	Female
Panel A : M.V. Theft		
M.V. Theft	0.147***	0.165***
	(0.047)	(0.063)
Panel B: Crime Excluding MV Theft		
Major Crime Types		
All	−0.010	−0.008
	(0.022)	(0.020)
Violent	−0.023	−0.010
	(0.020)	(0.022)
Property	−0.010	−0.014
	(0.027)	(0.031)
Drug	0.015	0.006
	(0.034)	(0.035)

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$
This table contains the DiD coefficient from equation (*) comparing the count of arrests in police agencies above median (treatment) and below median (control) SCI to Milwaukee before and after the information shock in May of 2022. Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments.

Table B3: Effect of SCI Exposure on M.V. Theft Arrests by Age Group and Sex and Race

	Male				Female			
	<18	18-25	26-30	31-35	<18	18-25	26-30	31-35
Panel A: Total	0.217*	0.303***	0.144*	0.011	0.361**	0.201	0.049	0.187*
	(0.119)	(0.102)	(0.080)	(0.059)	(0.174)	(0.133)	0.096	0.091
N	15625	17794	16984	16894	10016	13096	11991	12446
Panel B: White	0.094	0.143*	0.144*	0.004	0.016	−0.046	−0.039	0.158
	(0.118)	(0.094)	(0.084)	(0.067)	(0.201)	(0.120)	(0.117)	(0.115)
N	12500	15950	15199	15527	6961	10917	10308	11441
Panel C: Black	0.341**	0.356**	0.066	−0.050	0.671***	0.456*	0.341	0.050
	(0.170)	(0.160)	(0.142)	(0.139)	(0.232)	(0.257)	(0.225)	(0.265)
N	11714	12938	10756	15527	6072	6652	4935	4208

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
This table contains the DD coefficient from equation 4 comparing arrests in police agencies above median (treatment) and below median (control) SCI to Milwaukee before and after the information shock in May of 2022. Data Sources: Meta: Facebook Social Connectedness Index, FOIA requests to major police departments.

Table B4: Higher Online Video Exposure Does Not Effect the Overall Probability of Arrest for Demographic Groups

Age Bin	ATT	sd	Pre-Treat Mean
Panel A: Age			
10 - 13	0.001	(0.001)	0.015
14 - 17	0.001	(0.002)	0.068
18 - 21	−0.001	(0.002)	0.108
22 - 25	−0.001	(0.001)	0.119
26 - 29	−0.001	(0.001)	0.134
30 - 33	0.001	(0.001)	0.133
34 - 37	0.001	(0.001)	0.112
Panel B: Sex			
Male	−0.0004	(0.002)	0.736
Panel C: Race			
White	−0.001	(0.002)	0.583
Black	0.001	(0.002)	0.385
Asian	0.001	(0.001)	0.014
Native American	0.000	(0.001)	0.014
Num. obs.	2,658,158	–	–

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
This table contains the DD coefficient for equation 4, comparing arrests in agencies with high SCI to agencies with low SCI before and after the information shock in June 2022. The unit of observation is now an individual arrest and the outcome is the probability an arrested individual belongs to one of the above demographic groups.

Table B5: Effect of Higher Video Exposure on Motor Vehicle Theft Arrests

Quantile Coefficient	Under 18	% Change	18-25	% Change	26-30	% Change	31-35	% Change
Panel A: Tertiles								
1st Tertile	0.199	22.1%	0.299^{**}	34.9%	0.113	12.0%	0.098	10.3%
	(0.141)		(0.118)		(0.078)		(0.061)	
2nd Tertile	0.001	0.1%	−0.071	-6.9%	−0.125	11.8%	0.034	3.5%
	(0.121)		(0.089)		(0.080)		(0.059)	
Panel B: Quartiles								
1st Quartile	0.081	8.4%	0.295^{**}	34.3%	0.147^{*}	15.8%	0.069	7.1%
	(0.137)		(0.131)		(0.082)		(0.084)	
2nd Quartile	0.071	7.4%	0.104	11.0%	0.104	11.0%	0.073	7.6%
	(0.121)		(0.090)		(0.102)		(0.070)	
3rd Quartile	−0.248	-22.0%	−0.125	-11.8%	0.005	5.0%	0.025	2.5%
	(0.121)		(0.102)		(0.082)		(0.073)	
Panel C: Quintiles								
1st Quintile	0.094	9.9%	0.251^{*}	28.5%	0.168^{*}	18.3%	0.072	7.5%
	(0.151)		(0.140)		(0.090)		(0.091)	
2nd Quintile	0.201	22.3%	0.043	4.4%	0.087	9.1%	0.049	5.0%
	(0.137)		(0.093)		(0.114)		(0.077)	
3rd Quintile	−0.076	-7.3%	−0.158	-14.6%	−0.081	-7.8%	−0.010	-1.0%
	(0.165)		(0.102)		(0.097)		(0.071)	
4th Quintile	−0.147	-13.7%	-0.221^{**}	-19.8%	0.081	8.4%	−0.003	-0.3%
	(0.143)		(0.104)		(0.096)		(0.081)	
N	16464		18066		17596		17484	

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
This contains the DiD coefficient from equation (1) for the effect on the log count of KH cars stolen using the log count of non-KH cars stolen as the control group. Above and below median are sub-samples of cities that are above or below social connectedness to Milwaukee median calculated from the NIBRS data. Standard errors are clustered at the county level except when noted otherwise. Data Sources: 61 police departments representing major cities and MSA counties (VICE: Motherboard).

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