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COVID-19 Pandemic's Impact on Online Sex Advertising and Sex Trafficking

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ABSTRACT

Disruptive social events such as the COVID-19 pandemic can have a significant impact on sex trafficking and the working conditions of victims, yet these effects have been little understood. This paper examines the effect of the COVID-19 pandemic on sex trafficking in the United States, based on analysis of over one million sexual service advertisements from the online platform Rubratings.com, using indicators of third-party management as potential proxies for trafficking. Our results show that there have been measurable changes in online commercial sexual service advertising, both with and without third-party management indicators, in the United States, with a significant decrease occurring around the time of the start of the pandemic and the issuance of stay-at-home orders followed by an increase to levels well above pre-pandemic levels corresponding in time to when COVID-related restrictions were relaxed. We argue that the initial decrease could have been induced by a loss of demand for sexual services due to pandemic-related health concerns, but that a confluence of factors, including the lack of economic and social support for those working in the commercial sex industry, may have increased the number of people vulnerable to being exploited and becoming trafficking victims. This research adds to the understanding of the way sex trafficking adapts to events in the public sphere.

KEYWORDS
sex trafficking; online advertising; COVID-19 pandemic; commercial sex

Introduction

Sex trafficking is a hidden and secretive crime that is difficult to identify, analyze, and prosecute. It is challenging for researchers and law enforcement to assess the prevalence of trafficking in a given area and time period, in part because trafficking activity can be indistinguishable on the surface from independent commercial sex work, herein referred to as sex work. Victims of sex trafficking may not be recognized as such to those they come into contact with, including buyers and law enforcement, and may not even realize themselves that they are trafficked (Clawson & Dutch, 2018). An aspect of sex trafficking that has been especially poorly understood is how it is affected by events in the public sphere such as economic, social, and public health crises. Understanding how economic and other events affect demand for and supply of sex work could be useful in predicting future commercial sex and sex trafficking activity, and ultimately in directing law enforcement efforts and public spending to fight this crime.

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This paper focuses on the COVID-19 pandemic as a major social disruption that has affected all aspects of social and economic activity and is thus likely to affect the prevalence of sex trafficking throughout the United States and the world. We examined the period immediately before, during, and immediately after the official stay-at-home throughout the United States in the spring of 2020, hypothesizing that advertising for sex work and sex trafficking would decline sharply at the start of the stay-at-home orders and that sex trafficking advertising would quickly increase again when the orders were lifted. We hypothesized that advertising would decline for both sex work and sex trafficking because of a decrease in demand due to stay-at-home orders. The reason behind the hypothesis that sex advertising would increase quickly after stay-at-home orders were lifted was that traffickers would move quickly to capture increased demand to make up for revenue lost during the stay-at-home period.

In seeking to track the prevalence of sex trafficking, we focus on online ads for sexual services as the primary way in which traffickers generate demand for the services of their victims (Boecking et al., 2019; Bouche, 2015). A key challenge of this research was differentiating ads connected to sex trafficking victims from those placed by sex workers. These two types of ads have no obvious superficial features that set them apart from each other. Our interviews with law enforcement led us to develop a method of flagging advertisements based on the idea that most victims are controlled by a trafficker who manages multiple victims. Our method of analysis identifies clusters of ads with different text but identical phone numbers as leading to a manager, and thus flagged as a likely sex trafficking advertisement. Analysis based on this stratification found significantly different patterns of ad volume over time between the two different types of ads, validating that this way of stratifying ads identified a genuine difference between the two groups.

The goals of this research were twofold. First, we sought to increase public knowledge of the effect of social disruptions on commercial sex advertising, a little-understood topic with important implications for fighting sex trafficking in the future. Second, we present a method of data analysis that can be used in future research to identify online ads connected to sex trafficking.

Background

Sex trafficking is a criminal enterprise in which traffickers exploit minors or use force, fraud, or coercion to exploit adults in the commercial sex industry. Sex trafficking is an everyday problem that is widespread throughout the United States. Victims of sex trafficking can be found throughout the commercial sex industry, ranging from in-person street prostitution, to brothels, massage parlors, clubs, escort services, and online virtual sex work (Shively et al., 2012). While the term "trafficking" suggests victims are transported to another location, sex trafficking need not include movement. A victim of sex trafficking could be trafficked within their own home or neighborhood (Shively et al., 2012).

There is a lack of accurate knowledge about this hidden and secretive crime, and the problem is compounded by the fact that lawmakers and law enforcement may believe media-promoted myths. Trafficking is often mistakenly viewed by both the public and law enforcement as an exceptional crime involving "someone . . . chained in the basement" or "sex slaves being shipped over from some foreign country and held at gunpoint" (Farrell & Pfeffer, 2014, p. 50–51). Such beliefs are often fed by sensationalized reporting from mainstream media, and this media coverage plays an important role in the public understanding of sex trafficking. Such attention does not necessarily lead to positive outcomes (Ahmed & Seshu, 2012; Caulkins et al., 2019; Lederer & Wetzel, 2014). Some law enforcement officers are ill-informed about sex trafficking and do not believe it is a problem in their state or region (Clawson, 2006; Renzetti et al., 2015; Wilson et al., 2006). To counter these misconceptions, more accurate information is needed.

While sex trafficking is an ongoing activity that maintains a continuous presence, external social disruptions and events may influence its magnitude and profitability. Better understanding of the relationship between sex trafficking and these disruptions can help law enforcement predict future changes and adapt to the changing nature of the industry. Such knowledge can also help policy makers better understand the effects – and limitations – of existing policies during times of social disruption.

Review of the Literature

A substantial body of literature exists on use of advertising data to expose patterns of sex trafficking or distinguish between ads placed by sex workers and those with a suspected link to trafficking. This review of the literature is not comprehensive, but rather representative of the existing research related to labeling sex work advertisements for anti-trafficking efforts.

While analysts have long recognized the value of using computer-assisted analysis to mine through large amounts of crime-related data (Sparrow, 1991), research on online sex ads as a source of information on sex trafficking has proliferated in the past 10 years. Latonero (2011) was among the first to recognize the potential of online sex ads as a source of data for researchers and law enforcement, noting that in all recent federal cases of sex trafficking, the internet was used to advertise the victim's services. Latonero sought to determine if keywords can be used to detect trafficking, focusing on minors as a group whose availability for sex work is often signaled in ads through covert language and code words such as "candy." He focused on the frequently cited and since debunked myth that sex trafficking activity rises with the Super Bowl by analyzing Backpage Dallas (Martin & Hill, 2019). Advertisements were subjected to keyword analysis and the number of ads potentially linked to minors was tracked over time. Latonero (2011) suggests that there may be an overall rise in sex ads around the Super Bowl, but no rise in ads with indicators that the sex worker was underage. The researcher concluded that this method may not be effective in tracking sex trafficking prevalence over time but could narrow the pool of ads for law enforcement to investigate.

Subsequent studies have used other methods to identify ads potentially linked to trafficking. Kennedy (2012) hoped to determine the possibility of using ads to track movement of perpetrators and victims over time and better understand their patterns. Using advice from law enforcement, Kennedy created a textual analysis application to identify posts with indicators of underage sex workers, outside management (third-person language to refer to the worker or "we" language, indicating a company rather than a sex worker), or shared management (reference to multiple girls in one ad; multiple ads with similar but nonidentical language). After cleaning and analyzing data from Backpage ads from October 2011-April 2012, Kennedy demonstrated that it could be used, for example, to track the movement of an advertiser with a specific phone number and presented this application as a possible tool for law enforcement.

Other researchers have developed variations on the technique of flagging ads with multiple sex trafficking indicators for potential investigation by law enforcement. Ibanez and Suthers (2014) identified likely trafficking ads using an audit based on indicators including discrepancies in a sex worker's listed age across ads, use of third-person language, shared phone number, out-of-state area code, listing of ethnicity in ad and mentioning "in-call only" (a sign that a worker's movement is restricted to a brothel or massage parlor). The authors analyzed 1,881 ads collected from Backpage Hawaii over approximately one month and found that 26% of ads contained three or more indicators of trafficking (the study involved no independent confirmation that those ads were linked to trafficking). They also searched the phone numbers included in the ads across multiple other escort ad sites. Based on changes of location in individual phone numbers, they identified Portland as a hub for Hawaiian sex workers; the authors state that this form of analysis may be useful for identifying the origins of traffickers. Similarly, Ibanez and Gazan (2016) analyzed a data set of 600 Backpage ads, using indicators of movement, shared phone number and management, third-person language, and restricted movement ("in-call only") as proxies for trafficking. They found that 75% of ads contained one indicator, and 15% contained three or more. These studies required manual data collection to identify ads with trafficking indicators.

A number of recent research projects have used knowledge from domain experts to train an algorithm that can then be used to analyze large sets of data. Alvari et al. (2016) trained an application using a data set labeled by law enforcement who identified features such as third-person and "we" language, multi-girl ads, and ads with code words indicating a potentially underage sex worker. The authors also note that suspicious ads have higher linguistic complexity, as more complexity makes an ad difficult to analyze, allowing managers to remain anonymous. This method was found effective at identifying suspicious ads for law enforcement to investigate. Esfahani et al. (2019) trained an application on ads containing phone numbers that are known by domain experts to be associated with trafficking. After being trained to identify language patterns and uses of words in context that are frequently used in ads placed by traffickers, the program crawled thousands of 2017 sex work advertisements from various sources and labeled those with multiple text feature sets indicative of sex trafficking. The program was found effective at identifying ads known to be linked to trafficking. Similarly, Tong et al. (2017) had expert annotators identify likely sex trafficking ads using features of images as well as uses of words in context. Using a cache of 10,000 sex work ads from the United States and Canada, the authors found that this multimodal network approach was more successful than those analyzing text alone.

Reducing the amount of expert labor required to train artificial intelligence has been a goal of researchers in recent years. Kejriwal et al. (2017) created FlagIt, a system that generates leads using minimally supervised machine learning. It was trained on a corpus of ads from online sources "known to contain high levels of human trafficking (HT) activity" (p. 2). It looks for indicators of movement, ads advertising risky services, and individual ads listing multiple girls. The authors note that it performed well against other methods, but does still require a corpus and some training and labeling. Nagpal (2017) created a text-based information extractor intended to use machine learning to determine if multiple ads are from the same source, a process known as entity resolution. It extracts basic data from ads about features such as cost, location, and phone number. Rather than requiring human training and labeling, Nagpal's process uses shared phone numbers as "proxy evidence" for advertising sources that helped label training and testing data. The algorithm is trained on ads that are likely placed by the same entity, gathers information about what other features they share in common, and finds other clusters of ads likely placed by the same person or organization.

Another tool for law enforcement based on identifying clusters of similar ads is proposed by Lee et al. (2021). The authors note that very similar ads indicate potential sex trafficking, as the same person is writing ads for multiple victims. The authors created a text analysis algorithm similar to those used in bot detection and tested it on a database with identified and labeled sex trafficking ads; it performed with few false positives. The authors note that finding clusters of related ads is more cost-effective than other forms of text analysis such as those used by Alvari et al. (2016), Esfanahi et al. (2019), Kejriwal et al. (2017), and Tong et al. (2017): "Due to the adversarial nature of escort advertisements … predefined or learned features don't stay relevant over time. These labeled ads are also expensive to obtain" (Lee et al., p. 1117).

While most research on flagging likely sex trafficking advertisements is aimed at efficiently generating leads for law enforcement, Boecking et al. (2019) aimed to determine whether large public events affect escort activity. The authors scraped a data set of 37 million commercial sex ads from a website over a nearly five year period. Using phone numbers to track movement, the researchers identified advertisers who had started posting ads in a given region within a week; these new-to-town ads were flagged as likely linked to trafficking. They then analyzed the data looking for anomalous rises in likely sex trafficking and compared the results to a list of 38 public events including sports events, holidays, and conventions. Of the top 23 anomalous results, nine coincided with identified public events. The authors note that the use of the new-to-town data analysis does not allow estimation of the true levels of trafficking, but may point to changes in such activity.

While a wide variety of methods have been proposed for identifying ads placed by sex traffickers, all existing techniques have limitations. Most existing methods require extensive training by domain experts, rendering them costly to create (Lee et al., 2021). Such applications may also quickly lose their effectiveness as traffickers abandon old code words and phrasing and adopt new ones (Kejriwal et al., 2017). Additionally, many existing methods are focused on a specific type of victim, such as underage victims or those that have recently been transported to a new location, and will miss victims outside these criteria. One possible limitation of the transportation related new-to-town strategy is its potential to generate false positives. Ibanez and Gazan's (2016) analysis showed that 48% of Backpage sex ads contained movement indicators, suggesting that recent movement is very common and may not be an effective metric for identifying the proportion of ads linked to sex trafficking.

Finally, a small body of research exists on the effects of events in the public sphere on sex trafficking (Boecking et al., 2019; Latonero, 2011); however, such research is focused on short-term events such as sports events rather than longer-term social change. Boecking et al. (2019) note that spikes in trafficking may also be large-scale and occur over a longer time, such as those linked to population booms: "The presented methodology can be used to detect the onset of temporary or more persistent changes of sex advertising activity alike" (p. 14). A need exists for further research on effects of social disruption on prevalence of sex work and sex trafficking.

Hypotheses

Based on the review of the literature and our interactions with law enforcement officials, we formulated a set of hypotheses about the effects of COVID-related stay-at-home orders on sex work advertising to test with the online commercial sex advertising data. These hypotheses are:

(1) The onset of social-distancing orders is associated with a decrease in advertising for commercial sex work that does not contain indicators of trafficking as well as advertising that does contain indicators of possible trafficking.
(2) Advertising with indicators of possible trafficking rose rapidly after restrictions were lifted, but advertisement for commercial sex work that does not contain indicators of trafficking did not increase as rapidly.

Hypothesis 1 was based on (1) our conjecture that buyers and providers would be reluctant to contract the virus, and (2) that potential buyers would travel less for work and recreation. It has been documented that in other sectors of the economy business declined sharply due to provider and client concerns about contracting the virus, and it has been documented that buyers patronize sex workers more frequently while traveling. While sex work is a 24-hour a day business, research shows that sex workers often encounter "a lot of day business, business men on lunch, married men while their wife is at work" (Dank et al., 2014), making it likely that the COVID-related decline in travel would affect the sex industry. Putting this more generally, the combination of decreased customer travel and reluctance of some customers to risk contracting the virus would decrease demand for services provided by both commercial sex workers and sex trafficking victims.

Hypothesis 2 was drawn from our research and interviews with law enforcement. Our sources suggested that the desire on the part of traffickers to make up for lost revenue would lead to a rapid increase in sex trafficking advertising and activity after restrictions lifted. In addition, trafficking victims do not have the agency to decide whether or not they will work and advertise. Non-trafficking commercial sex work, on the other hand, involves providers with potentially greater agency to decide whether or not to return to work. If they continued to be concerned about infection risk they may delay returning to work, leading to a delay in advertising increases relative to advertising with indicators of trafficking. We also speculated that the outsized economic impact on vulnerable populations because of the pandemic could lead to an increase in the number of people vulnerable to being trafficked, leading to an increase in potential victims and advertisements (Smith & Cockayne, 2020; US Department of State, 2016).

Materials and Methods

Building off other anti-trafficking research (Boecking et al., 2019; Latonero, 2011; Nagpal et al., 2015), we used the volume of sex work advertisements as an indicator of the prevalence of in-person sex work in a given region.[1] We made use of a data analysis strategy, described below, to separate ads we consider likely connected to sex workers to those we flagged as likely connected to trafficking victims. We then analyzed the changes in volume in both types of ads before, during, and after the COVID-related lockdown orders in 140 U.S. cities.

Data Description

Data used in this research consisted of over one million sex advertisements from the online platform Rubratings.com. The internet hosts numerous online platforms for sexual services advertisements, which serve as a basis for providers to connect with buyers of sex work. The landscape of available platforms has changed rapidly in the past two years. Prior to the United States' legislative enactment of Fight Online Sex Trafficking Act – Stop Enabling Sex Trafficking Act (FOSTA-SESTA; Allow States and Victims to Fight Online Sex Trafficking Act, 2017), Backpage.com and Craigslist.com had become the favored sites to facilitate sex work and sex trafficking (DeLateaur, 2016). After FOSTA-SESTA took effect, legislation effectively rendered Backpage.com's and Craigslist.com's personals advertisements ineffective on the internet for commercial sex advertising. Our informal expert interviews with law enforcement consistently inform us that a single replacement has not emerged to replace Backpage.com. Instead, websites spring up periodically and "hobbyists" and "mongers" (the terms used to describe frequenters of these websites) find their way to them by word of mouth (Feeney, 2013). However, in these conversations, one site that was consistently mentioned as a leading advertisement site was Rubratings.com.

This research is the first that we have been able to find that addresses sex trafficking anomaly detection in a post – FOSTA-SESTA era. We recognize that without one lead website that hosts the majority of advertisements to replace Backpage.com, we are analyzing only a portion of all existing online commercial sex advertisements, potentially affecting our assessment. However, our interviewees indicated that despite the changes brought about by the FOSTA-SESTA era, online advertisements are still helpful indicators of the market for commercial sex in a given region.

The data from Rubratings.com were scraped in the Python programming language with the use of the BeautifulSoup package. This facilitated a regular automated scrape of the website from 140 cities across 47 U.S. states. The automated scrapers for this analysis retrieved 1,019,709 total advertisements in the United States over the period from January 3, 2020 to September 29, 2020. Data collected include paid advertisements used by clients to browse photos, services, rates, and other descriptions of sex workers. Typically, the advertisement will list an e-mail address, a phone number, or both, in order for the client to make contact and set up a "date." The collected data were the pageid, date modified, description text, location, phone number, and date scraped. No images were scraped or saved.

We were unable to obtain completely continuous data (i.e., every day) over the time period selected, as the Rubratings.com website and other similar websites are evolving and becoming savvier about how to block scraping. Over the 270 days between January 3, 2020 and September 29, 2020, there were 57 days on which the scraper did not run or was actively blocked. However, it is common for a given advertisement to be listed on the site for multiple days. Approximately 56% of ads were considered "duplicates" and ran on multiple days. This duplication means that most advertisements that ran on days the scraper was not running were caught by the scraper on a different day. The data for the remaining 213 days are thus likely representative of the entire time period under study. With this in mind, we removed the duplicated advertisements to accurately characterize the actual daily advertising behavior and to prevent inadvertently overweighting advertisements. We accomplished this by comparing the dates the advertiser posted the ad with the date the scraper captured the ad. If those dates matched, we identified this as the advertisement's unique appearance, appended that advertisement to the analytic sample, and deleted any identical copies. This procedure reduced the data set significantly.

[1]While sex trafficking occurs in all segments of the commercial sex industry, this paper focuses only on in-person sex work, as the riskiest to sex workers and most likely to be affected by COVID-19.

Data Stratification

A key question was how to identify advertisements that indicate the worker whose services are being advertised is potentially being trafficked. For this purpose, we focused on indicators that the sex worker is managed by a third-party. An indication of a manager in an advertisement for commercial sexual services suggests that the provider is not an independent sex worker. While it is possible that an individual who is voluntarily participating in sex work may have a third-party manager, our informal interviews with law enforcement experts and other experts familiar with sex trafficking suggest that this situation is rare.[2] Third-party management is thus strongly indicative of the individual being trafficked, as argued in previous literature (Ibanez & Gazan, 2016).

Exploring the website and probing some advertisements quickly made it clear that many of these advertisements were scams attempting to obtain credit card information. Classified advertisements are fertile ground for scammers (Al-Rousan et al., 2020; McCormick & Eberle, 2013), and our informal interviews with anti-sex trafficking experts agreed that this is a common practice on these types of websites. One coauthor (Guikema) confirmed this by contacting all advertisers in Ann Arbor, MI, who listed only an e-mail address and found that all of them were scams attempting to steal credit card information.[3] In related research in the context of spam detection, researchers found that 78% of fake or spam advertisements did not include phone numbers, while 87% of real advertisements did include phone numbers (Tran et al., 2011). For these reasons, the analytic sample includes only the advertisements with phone numbers for further analysis.

The data are also stratified to separate ads likely connected to sex trafficking from those likely connected to sex work. Literature reviewed earlier in this article suggests there exists a number of methods that attempt to identify online ads placed by sex traffickers. We contend that the sex trafficking labeling associated with transportation is potentially misleading because it bounds sex trafficking to movement. As mentioned earlier, sex trafficking does not require movement, and this characterization may overlook the persistent risk to victims every day in their own neighborhoods. Instead of a stratification associated with movement, this research uses phone number clustering. Some advertisements point to the same phone number, whereas other phone numbers have single appearances in our data set. The informal interviews we conducted with law enforcement, current and former sex workers, and anti-trafficking experts suggested that multiple advertisements pointing to one phone number are indicative of a call center or third-party management. These experts confirmed that the use of third-party management is a likely indicator of sex trafficking.[4] Each trafficker typically controls advertisements for four to eight trafficked victims, which would result in clusters of ads placed by one person.

The idea of clustering advertisements by common elements to identify sex trafficking is not unique to this research. Recent research on detecting sex trafficking in online advertisements hypothesizes that clusters of similar phrasing suggests organized activity and is reason to be suspicious that the ads are placed by a third-party manager (Lee et al., 2021).[5] Our research similarly uses commonality among ads as a sign of trafficking, but builds on this idea by using a common phone number as an indicator of suspicious activity. This concept of phone number clustering is reinforced by the informal interviews we conducted with current and former sex workers, who described their phone number as their "lifeline" and a way to stay in touch with their "regulars," thereby suggesting that their singular advertisement would be connected only to their number. We incorporated this concept into our data

[2]We are not attributing any feedback to a particular interviewee in order to honor their need to remain anonymous.

[3]We chose Ann Arbor, MI because our familiarity with the area might allow us to pick up on fraudulent activity more readily if advertisers made inaccurate reference to locations or local culture; in addition, because Ann Arbor, MI has a manageable number of advertisers in the area, this allowed us to contact all advertisers in the area.

[4]Researchers investigating trafficking have found that "the average number of girls per facilitator was between 4.58 as reported by male facilitator, and 8.1 as reported by female facilitators and prostitutes," further highlighting the tendency for a single trafficker to manage multiple victims (Carpenter & Gates, 2016, p. 83).

[5]Other research (Ibanez & Gazan, 2016; Ibanez & Suthers, 2014) uses shared phone number as one of multiple indicators of trafficking; because these applications also rely on linguistic features, they must be trained by domain experts.

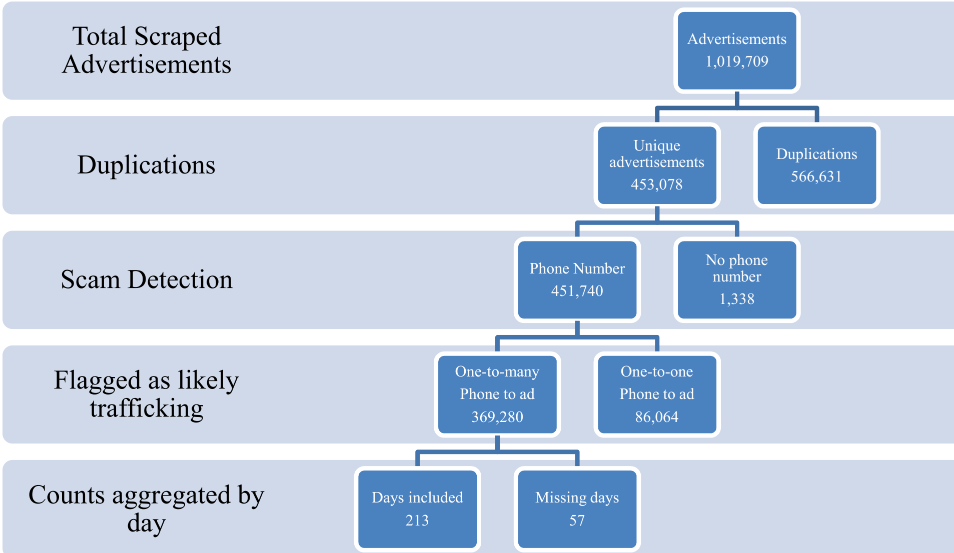

Figure 1. Data stratification for online advertising scraped from Rubratings.com from January 3, 2019 to September 29, 2020.

by parsing the advertisements that had a relationship with only one phone number that did not appear to be related to any other advertisement (one-to-one relationship between phone number and ad) from the clusters of many ads that pointed to one phone number (one-to-many relationship between phone number and ads). Figure 1 above summarizes the stratification of the data set.

Furthermore, our deduplication process focused only on unique ads (as indicated by their website designated identifier) and did not take any steps to identify ads that were highly similar but nonidentical. The reason for this is that advertisers have to pay an additional fee for running multiple ads with different text, even if the text is changed only slightly. This makes it an uneconomical strategy for one advertiser to run an advertisement with trivial changes made from a previous version. We recognize that a method that included some degree of co-reference resolution between similar advertisements would further add desirable specificity to phone number clusters. Our method, though imperfect, is easily implementable and does not require the costly act of training and labeling data.

Data Limitations

Temporal understanding is key in our analysis. Although we do not have data regarding sex worker ad volume in previous years, we draw conclusions about hypothesized decreases in online commercial sex advertising. We recognize that this may affect our analysis and that there exist many alternative hypotheses that would benefit from more data to improve accuracy.

Despite the richness of the data scraped from the online advertisements, they admittedly have many limitations as well. First, as mentioned previously, the automated scrapers did not capture advertising activity every day as intended. Instead, there were days when the scraper did not run or was actively blocked by the website. Despite regular retooling and restructuring of the scraper, some partial or entire days were not scraped; these were distributed at random throughout the entire data set. This observation is consistent with similar research (Boecking et al., 2019).

Other limitations include the imperfect way the data are stratified for detection of scams and flagging for potential sex trafficking. We recognize that some sex trafficking victims are likely using one phone number that will not appear elsewhere. We also recognize that the use of short-term phone numbers associated with a disposable phone or a “soft”/internet phone number is common in nefarious practices; this labeling will not capture those third-party managers who cycle through multiple disposable numbers (Chen et al., 2019). We do not wish to exclude these victims, but rather use this flagging as a generalized sex trafficking indicator. Lastly, we recognize that law enforcement and antitrafficking nonprofit organizations place decoy advertisements on these types of websites to disrupt the criminal activity of those seeking paid sexual services. These decoys have the ability to add noise to the data, as they could be counted as advertisements for either sex work or sex trafficking.

Our method is just one of many potential strategies for identifying ads flagged for trafficking and is unable to identify ads that show signs of trafficking other than shared phone numbers. As discussed above, trafficking detection has also been done through analyzing the advertisement description itself through various types of machine-learning classification, by analyzing movement patterns (Ibanez & Suthers, 2014; Nagpal et al., 2015; Szekely et al., 2015), and by identifying microclusters of similar phrasing (Lee et al., 2021).

Lastly, our data are limited by the lack of comparable data from previous years, which could help us distinguish pandemic-related effects from seasonal trends. As discussed later in the Discussion section, we recognize that our analysis would benefit from many more years of data in order to correctly address any yearly seasonality that may account for nuanced changes in advertising count. We also acknowledge that the shutdown of websites such as Cityxguide.com, a site that gained popularity after the passage of the FOSTA-SESTA anti-sex trafficking legislation, could affect our analysis. Furthermore, some early media reporting suggest that many sex workers chose to move online to websites such as Onlyfans.com in the wake of stay-at-home orders (Boseley, 2020), which may also affect our analysis. Despite these acknowledged limitations, we believe this analysis can still be meaningful and contribute to a larger discussion of the pandemic's impact.

Methods

Following data stratification, we were left with 369,280 advertisements that met our criteria for indicators of potential sex trafficking; see Table 1. We then aggregated these remaining advertisements by day and by each individual city. We normalized the number of daily sex work advertisements by assessing an average number of advertisements between the start of our data set and the beginning of the pandemic, and then dividing by that average over the hypothesized anomalous period. We also applied a 3-day moving average to smooth out the noise and emphasize the trends. We took the raw mean number of advertisements pre – COVID-19. Those entries were then divided by the pre – COVID-19 average to produce respective normalized values.

While data were collected from throughout the United States, we highlight eight major U.S. cities from a variety of geographic areas in order to demonstrate the varied impacts across the wide spectrum of stay-at-home order implementation dates. We chose to highlight the following regions based on the variety of stay-at-home implementation dates: Atlanta (April 3, 2019), Dallas/Fort Worth (April 2, 2019), Seattle (March 23, 2019), New York (March 22, 2019), Houston (April 2, 2019), Miami/Fort Lauderdale (April 3, 2020), and Detroit (April 3, 2019), as well as the entire United States (varied stay-at-home implementation dates; Kaiser Family Foundation, 2020). The process described above was repeated for all eight regions to obtain normalized values for each.

We systematically tested our hypothesis that there existed a decreasing trend of commercial sex advertisements after stay-at-home orders were instituted by systematically comparing baseline and testing intervals around each individual state's stay-at-home orders (Kaiser Family Foundation, 2020). We

Table 1. Daily Descriptive Statistics for Scraped Advertisements (Rubratings.Com) January 3, 2020 Through September 29, 2020. Compiled: Entire Data Set; Flagged: Records That Exhibited the Sex Trafficking Indicator; Sex Work: Records That Did Not Exhibit the Sex Trafficking Indicator, Proxy for Independent Commercial Sex Workers.

Data	U.S. Ad Count (total)	Minimum (by day)	Maximum (by day)	Mean (by day)	Std. Dev. (by day)
Compiled	1,019,709	210	8821	3711	1704
Flagged	369,280	183	3194	1718	773
Sex work	86,064	93	883	406	274

compared the days immediately prior to the inflection point in 15-, 30-, 45-, and 60-day increments to the 15-, 45-, and 60-day increments immediately following the lockdown orders. We tested these pairings within the cities mentioned in the main test with a two-sided Welch's t test of the two independent samples. This statistical method tested the null hypothesis that the two samples have the same expected values. If the p value is smaller than 0.1, we reject the null hypothesis of equal expected values.

This testing helps us draw conclusions about the testing ranges' statistical significance. We are presenting a family of multiple hypothesis tests at the city level. We therefore make a Bonferroni correction at the city level and use a lower p value that accounts for the probability of getting one significant result from the family at the 10% level (Miller, 2012). We use the Bonferroni method because it is one of the most conservative and common ways to account for the number of comparisons. We acknowledge that because the testing intervals are overlapping, each of the pairwise-comparisons is not independent of the others. While the Bonferroni correction does not require independence, a lack of independence between the hypothesis test further increases the degree of conservatism in the Bonferroni correction.

After using these methods to analyze records we flagged as potential sex trafficking advertisements, we repeated the same methods for the records that were not classified by our approach as indicative of sex trafficking. We refer to these records later as a proxy for sex workers. We conducted this same analysis for all eight cities as well as the United States as a whole.

Results

Our results support our hypotheses that the onset of stay-at-home orders was likely associated with advertising for sex work and advertising flagged as potential sex trafficking declines and their respective rapid increase after those orders were lifted. Figure 2 presents a time-series graph of total commercial sex advertising volume and flagged advertising volume for all regions studied. It shows the number of daily online advertisements for both the raw data (Figure 2a) and the subset flagged as likely sex trafficking (Figure 2b), normalized by the pre-COVID advertising volume at the city level. Included in the graph are Atlanta, Chicago, Dallas/Fort Worth, Seattle, New York, Houston, Miami/Fort Lauderdale, and Detroit, as well as the United States as a whole.

Additionally, we list computed features of the trajectory and behavior of the ads for each city that we flagged as likely linked to sex trafficking (Table 2). The table is sorted by the earliest stay-at-home order, with the date at which each city's decrease in likely sex trafficking advertisements began,

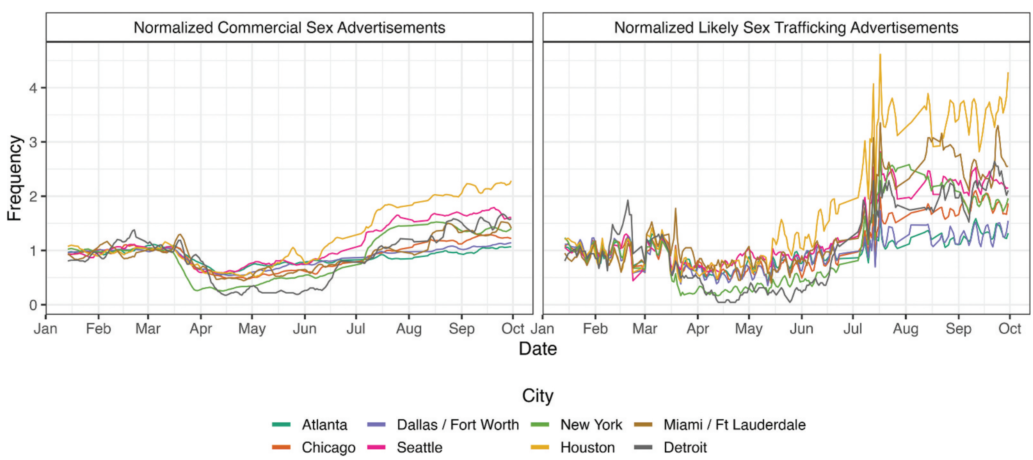

Figure 2. Advertisements for both compiled data and data flagged with likely sex trafficking indicator. Left (2a): Normalized time-series of daily ad counts of all compiled commercial sex advertisements. Right (2b): Normalized time-series of daily ad counts flagged with a sex trafficking indicator.

followed by the average number of advertisements that appeared for that city from January 1, 2020 until each city's decline began. We also calculated the velocity (approximate slope) at which each city's advertisements declined. The lowest number of advertisements at the bottom of each time series, along with their corresponding dates, follow in the table; all of these figures assist in the calculation of the depth percentage of the decline.

We observed these statistics to be consistent with the visualized time-series graph in Figure 2. The dips in likely sex trafficking advertisements all began prior to the state-mandated stay-at-home order. This may have occurred in anticipation of government-required social distancing. Third-party managers of sex trafficked victims may have known that in-person sex work demand would decline, and were perhaps conserving the fees associated with posting advertisements online; alternately, they may have perceived an overall decline in business and reluctance on the part of customers to take part in activities with infection risk starting around mid-March. This is consistent with findings for the U.S. advertising industry as a whole and for pandemic-affected industries such as tourism, in which revenue dropped rapidly in early or mid-March, rather than coinciding exactly with the start of the stay-at-home orders (Lim, 2020; Schaal, 2020; Wakabayashi et al., 2020).[6] We would expect the response to the danger of the virus to be evidenced in a dramatic and rapid decline of in-person commercial sex, and that is indeed what we find in the data. Table 2 below supports this characterization, as New York reflects the fastest velocity toward its lowest ad count.

Decrease in Sex Work Advertising During Stay-At-Home Order

A statistically significant decrease is evident in both total compiled advertisements and likely sex trafficking advertisements immediately after stay-at-home orders were issued in most but not all cities. The trend of decreased advertising during lockdown was consistent for the United States as a whole and specific cities. Table 3 shows an example of the results for the advertisements we flagged for sex trafficking for New York, which began their stay-at-home order on March 22, 2020. Taking New York as an example, we found a pre-COVID mean number of advertisements of 419.52 (see Table 2). The first four entries for the 3-day moving average for New York were 396, 374.4, 350.2, and 331.4. Those entries were then divided by the pre – COVID-19 average to produce their respective normalized values of 0.944, 0.892, 0.835, and 0.790.

Table 2. Statistics by City Describing Behavior of Advertisements Flagged with a Sex Trafficking Indicator. Period Covering January 2020 to May 2020, Sorted in Order of Stay-At-Home Orders.[7]

City	Stay At Home Date	Dip Began	Pre-Covid Average	Dip Velocity	Lowest Ad Count	Lowest Ad Date	Increase Began	Depth (%)
Chicago	3/21/20	3/18/20	332.5	−6.24	164	4/14/20	4/30/20	49.3%
New York	3/22/20	3/12/20	419.5	−19.53	107	3/28/20	4/14/20	25.5%
Seattle	3/23/20	3/12/20	111.0	−2.37	66	3/31/20	4/20/20	59.5%
Detroit	3/24/20	3/20/20	22.7	−0.72	4	4/15/20	6/11/20	17.6%
Dallas/Fort Worth	4/2/20	3/17/20	606.7	−11.32	335	4/10/20	4/24/20	55.2%
Houston	4/2/20	3/11/20	93.3	−1.71	54	4/3/20	5/5/20	57.9%
Atlanta	4/3/20	3/16/20	333.2	−6.17	179	4/10/20	4/10/20	53.7%
Miami/Ft Lauderdale	4/3/20	3/20/20	64.0	−1.67	29	4/10/20	4/27/20	45.3%

[6]For instance, Facebook saw a reduction in revenue over "the last three weeks of March" (Lim, 2020), and "airlines were all but absent from U.S. TV as of March 11" (Schaal, 2020), suggesting an overall pattern of business and advertising contracting in early to mid-March.

[7]*Note.* dip_velocity $= \frac{(lowestadcount - preCovidavg)}{(lowestaddate - dipbegan)}$; lowest_ad_count = lowest raw number of advertisements; lowest_ad_date = date at which lowest_ad_count captured; increase_began = approximate date at which ad count began to rise again; depth(%) $= \frac{(lowestadcount)}{(preCovidavg)} * 100$

Table 3. New York City Intervals Before and After Stay-At-Home Order (March 22, 2020).

City	Pre-Covid	Base Interval (Days)	Stay at Home	Testing Interval (Days)	t statistic	p-value
New York	3/6/20–3/21/20	15	3/22/20–4/6/20	15	−4.77	5.2×10^{-4}
New York	3/6/20–3/21/20	15	3/22/20–5/6/20	45	−4.68	6.4×10^{-4}
New York	3/6/20–3/21/20	15	3/22/20–5/21/20	60	−4.37	1.0×10^{-3}
New York	2/20/20–3/21/20	30	3/22/20–4/6/20	15	−8.21	6.9×10^{-8}
New York	2/20/20–3/21/20	30	3/22/20–5/6/20	45	−8.12	1.0×10^{-7}
New York	2/20/20–3/21/20	30	3/22/20–5/21/20	60	−7.70	2.1×10^{-7}
New York	2/5/20–3/21/20	45	3/22/20–4/6/20	15	−23.85	1.7×10^{-46}
New York	2/5/20–3/21/20	45	3/22/20–5/6/20	45	−25.19	3.9×10^{-65}
New York	2/5/20–3/21/20	45	3/22/20–5/21/20	60	−23.21	2.2×10^{-61}
New York	1/21/20–3/21/20	60	3/22/20–4/6/20	15	−23.85	1.7×10^{-46}
New York	1/21/20–3/21/20	60	3/22/20–5/6/20	45	−25.19	3.9×10^{-65}
New York	1/21/20–3/21/20	60	3/22/20–5/21/20	60	−23.22	2.2×10^{-61}

In the New York example, a p value greater than .0087 would indicate that there exists no significant difference in the expected values of the baseline and testing ranges. In Table 3, we see that New York's data show that all range comparisons reveal statistical anomalies. Furthermore, the negative t statistic indicates that the advertising rate decreased. We can confidently conclude that New York experienced a downward trend in advertising for the those that were flagged as likely trafficking and also associated with the first stay-at-home orders. One can also observe that the decrease began prior to the state-mandated stay-at-home order. We could surmise that advertisements started to drop in preparation for, or perhaps in anticipation of, the orders. Alternately, perhaps the drop indicated an overall lack of business as a result of potential clients' fear of COVID-19 transmission, rather than the stay-at-home orders specifically. As observed above, this finding is consistent with a rapid decline in advertising spending across multiple industries that began in early to mid-March, rather than coinciding exactly with the start of lockdown.

Table 4 below shows the results of statistical comparisons of pre-pandemic advertising to two post-pandemic time periods: immediately after stay-at-home orders were issued, and in the longer term after stay-at-home orders were lifted. In addition to the statistically significant decrease associated with the first stay-at-home orders discussed above, we also see a statistically significant increase in advertisements with trafficking indicators in all cities when comparing the pre-COVID period with the period immediately following lifted restrictions. From Figure 2b we see that this advertising increased from between 1.25 and 3.5 times pre-COVID levels, depending on the city.

Table 4 summarizes the statistical testing that characterizes the decrease in advertising during lockdown, as well as the increase in advertising immediately following the lifting of restrictions for both the advertisements that we flagged as likely linked to sex trafficking and those likely linked to sex workers. Each cell represents 12 systematic pairings; the presence of an arrow represents statistical

Table 4. Summary of Testing. Each Cell Represents 12 Systematic Pairings and the Presence of an Arrow Represents Statistical Significance in 6 or More of Those Testing Intervals, and the Direction of the Arrow Indicates an Increasing or Decreasing Trend.

City	All Ads (Stay at home)	All Ads (Lifted)	Flagged Ads (Stay at home)	Flagged Ads (Lifted)	Independent Sex Workers (Stay at Home)	Independent Sex Workers (Lifted)
Atlanta	↓ (6)	−(4)	↓ (10)	↑ (8)	↓ (12)	↑ (12)
Chicago	↓ (9)	−(2)	↓ (11)	↑ (12)	↓ (12)	−(3)
Dallas/Fort Worth	−(3)	−(1)	↓ (9)	↑ (11)	↓ (12)	↑ (9)
Seattle	−(3)	↑ (7)	↓ (7)	↑ (12)	↓ (11)	−(4)
New York	↓ (12)	↑ (6)	↓ (12)	↑ (12)	↓ (12)	↑ (8)
Houston	−(2)	↑ (8)	−(3)	↑ (12)	↓ (9)	↑ (6)
Miami/Ft Lauderdale	↓ (12)	−(2)	↓ (6)	↑ (12)	↓ (9)	↑ (8)
Detroit	↓ (8)	−(2)	↓ (9)	↑ (12)	↓ (8)	−(4)
USA	↓ (6)	−(2)	↓ (12)	↑ (12)	↓ (11)	↑ (12)

Table 5. Houston, Texas Intervals Before and After Stay-At-Home Order (April 4, 2020).

City	Pre-Covid	Base Interval (Days)	Stay at Home	Testing Interval (Days)	t statistic	p-value
Houston	3/17/20–4/1/20	15	4/2/20–4/17/20	15	0.17	0.867
Houston	3/17/20–4/1/20	15	4/2/20–5/17/20	45	1.69	0.105
Houston	3/17/20–4/1/20	15	4/2/20–6/1/20	60	2.96	6.6×10^{-3}
Houston	3/2/20–4/1/20	30	4/2/20–4/17/20	15	−1.56	0.126
Houston	3/2/20–4/1/20	30	4/2/20–5/17/20	45	−0.32	0.75
Houston	3/2/20–4/1/20	30	4/2/20–6/1/20	60	0.94	0.35
Houston	2/16/20–4/1/20	45	4/2/20–4/17/20	15	−0.44	0.667
Houston	2/16/20–4/1/20	45	4/2/20–5/17/20	45	2.12	0.036
Houston	2/16/20–4/1/20	45	4/2/20–6/1/20	60	4.12	6.7×10^{-5}
Houston	2/1/20–4/1/20	60	4/2/20–4/17/20	15	−0.44	0.667
Houston	2/1/20–4/1/20	60	4/2/20–5/17/20	45	2.12	0.036
Houston	2/1/20–4/1/20	60	4/2/20–6/1/20	60	4.12	6.7×10^{-5}

significance in six or more of those testing intervals, the number in parentheses indicates the number of pairings that were statistically significant, and the direction of the arrow indicates an increasing or decreasing trend.

We found statistically anomalous decreases in sex trafficking advertisement in Atlanta, Chicago, Dallas/Fort Worth, Seattle, Miami, Detroit, New York, and the aggregated data across the United States. As Table 4 exhibits, however, most of the tested ranges for Houston evidenced *p* values greater than our critical value. This finding implies that Houston did not experience a statistically significant dip in likely sex trafficking advertisement after their stay-at-home order. The result is consistent with media reporting about generalized compliance with stay-at-home orders and the accelerated or constant growth rates of new coronavirus cases in those regions (Advisory Board, 2020). We found that all cities experienced a statistically significant decrease in advertising after the stay-at-home restrictions compared to their pre – COVID-19 average; see Table 5.

Increase in Sex Work Advertising After Stay-At-Home Orders

After stay-at-home restrictions began to ease, commercial sex advertising quickly rose again. Flagged advertisements increased consistently in all regions studied. However, we found differing results for likely sex workers across the different cities. Table 4 and Figure 2 show that in the period following the lifting of restrictions, the change in volume for advertisements likely associated with sex workers are mixed, with some rising rapidly in July (New York, Detroit) while others rise gradually (Dallas) or decline soon after the lifting of restrictions (Miami). By contrast, likely sex trafficking advertising is seen to rise rapidly in July across all of our tested cities. This disparity may be due to a reluctance on the part of sex workers to enter the market, whereas sex trafficking victims may be forced into client interactions sooner than their sex worker peers. Alternately, it could indicate a difference in marketing strategy between sex workers who run a single ad and those who run multiple ads for their services. However, the choice to run a single ad for one worker would be less economical, as each different ad is assigned a different ID and costs more money to run compared to rerunning the same ad.

The substantial and statistically significant increase in flagged advertising could be explained by an increase in the number of sex trafficking victims post-COVID. Alternately, traffickers experiencing significant declines in income due to the pandemic could be attempting to make up for this through increased advertising. As will be discussed below, we believe the former reason may account for some of the rise in advertising, as the increased economic precarity associated with the pandemic may make more people vulnerable to being trafficked.

Discussion

Reasons for Trends in Sex Advertising

The present research is consistent with our hypotheses and suggests that the pandemic has had a measurable impact on online sex work ads. In addition, the observed discrepancy between data for ads we identified as leading to sex workers versus those we flagged as possible sex trafficking victims show a clear difference, indicating that the chosen method of identifying ads linked to trafficking victims may be effective.

As discussed above, we would expect the COVID-19 pandemic to be associated with a temporary decrease in advertising for both sex work and sex trafficking. Under normal conditions, an overall decrease could indicate the favorable outcome of fewer sex trafficking victims. The pandemic's confluence with a variety of socioeconomic, environmental, and policy factors, however, creates a potential wave of sex trafficking victims.

The effects of COVID-19 have been most profoundly felt in marginalized communities experiencing heightened vulnerability due to factors such as race, income, gender, and housing instability (Smith & Cockayne, 2020). Although sex trafficking affects every demographic, a common factor is the victim's vulnerability to exploitation (Department of State, 2016). The pandemic creates conditions that further restrict the access these already marginalized communities have to social services and amplifies their existing risk of sex trafficking (Todres & Diaz, 2020). Examples of this include the following:

- The economic aid provided by the U.S. government through the Coronavirus Aid, Relief, and Economic Security (CARES) Act is subject to anti-sex work measures built into the eligibility provisions, as aid is not available to businesses of a "prurient sexual nature" (Code of Federal Regulations, 2017).
- Those who have lost jobs due to COVID-19 and work in the gig economy may not have access to unemployment insurance as they are not a part of the formal economy. Qualifying for such benefits will therefore likely be challenging for these individuals and, consequently, make these individuals more susceptible to being trafficked.
- Preventive measures to quell the spread of the coronavirus have led to the displacement of sex trafficking victims who worked in brothels, thereby causing them to become homeless during this crisis (Berger, 2020).
- As federal stimulus unemployment benefits and eviction bans expire across the United States, evictions are on the increase, making vulnerable individuals homeless (Cowin et al., 2020; Eviction Lab, 2021; Gowen, 2021).

This confluence of conditions has the potential to keep existing victims in dangerous sex trafficking situations or place others at risk of entering sex trafficking.

Limitations

This study has several limitations. Identifying trafficking situations from online advertisements presents significant challenges. Trafficking is a secretive crime and those placing ads try to conceal the nature of their activity from both potential clients and law enforcement. We attempted to get around this limitation with a data handling technique based on suggestions from experts. Our results showed different patterns of ad volume between the flagged and nonflagged advertisements, indicating that a difference does exist between the ads that do and do not include shared phone numbers. However, multiple explanations are possible. The flagged ads may represent voluntary sex workers who have chosen to work with a manager, or sex workers who run a variety of ads in hopes of attracting clients with different interests. This difference in strategy could account for differences in patterns of ad volume. However, the information we received from our sources indicates that third-party management is a strong indicator of trafficking, leading us to consider our proposed explanation a plausible one for the observed difference. In addition, the choice to work with a manager is often not truly voluntary, but involves an element of coercion, even if the sex worker in question would not describe themselves as trafficked (Merodio et al., 2020). While it is possible that a sex worker would choose to run multiple different ads for their services in an attempt to appeal to multiple client bases, as discussed in the Data Stratification section, we consider it unlikely, since running multiple ads is more expensive than running the same ad multiple times.

Because our data cannot show causality, multiple possible explanations exist for the observed decline and then rise in both flagged and total sex worker ads. We speculate that ad volume began to decline before the stay-at-home orders went into effect because those placing them were anticipating the order or perceived potential customers as unwilling to risk COVID-19 transmission beginning around mid-March 2020. However, having access to additional years of data on sex worker advertising volume would provide additional insight into how much the observed changes in volume differ from normal yearly patterns. Past research examining years' worth of search data has shown a seasonal pattern in U.S. searches on terms related to prostitution, pornography, and other sex-related topics and found a 6-month pattern, with peaks in interest in prostitution and pornography in early winter and early summer and lows in early spring and early fall (Markey & Markey, 2012; see also Wood et al., 2017). It is thus possible that some of the decline in ad volume in March and rise in July can be explained by seasonal patterns in demand for sex workers. Markey and Markey (2012) found that "a 6-month cycle accounted for … 24% of the variance in prostitution searches." Our research showed a much more dramatic variance, with flagged likely sex trafficking ad volume increasing as much as threefold in a period of a few months. This, along with the temporal match between the end of lockdown and the sharp spike in ad volume, suggests the association of the pandemic as causative factor. However, further research on the volume of sex worker advertising on Rubratings and other platforms is needed to clarify whether this is the case.

We identified a rise in likely sex trafficking advertisements immediately around the end of the stay-at-home orders, and a more gradual rise in ads not flagged as indicating possible trafficking. While we speculate that this is because trafficked victims were forced to return to work with little regard for safety, other explanations are possible. Sex workers placing ads at the end of lockdown may have been more financially precarious and felt a greater need to return to work soon, rather than being forced by a third party. Alternately, they or their managers may have had more financial resources to pay for ads without certain results, while those who returned to placing ads later may have adopted a more cautious approach and placed ads only after they felt certain that clients would return. Other methods of research, such as interviews with victims of trafficking, would be necessary to confirm or disprove our suggested explanation that traffickers frequently forced victims to return to sex work immediately after the end of lockdown.

We identify a rise in sex worker advertising in July 2020 to above pre-pandemic levels. However, our data are unable to reveal whether this is because more people entered sex work, more people were forced into sex trafficking situations during this time period, or because advertisers (sex workers and managers) ran ads more frequently for the same number of workers to drive revenue following a long period of low profits. Further research is necessary to determine whether pandemic conditions caused a rise in number of people forced into trafficking situations.

Conclusions and Suggested Policy Measures

Our data analysis suggests that the hypothesized rapid increase in flagged potential sex trafficking advertising may already be happening. Our flagged sex trafficking advertising has increased substantially above pre-pandemic levels, and these increases are statistically significant. If governments do not address the potential effects of the pandemic on marginalized populations, we may see a sustained rise in sex trafficking prevalence.

In addition to policies that continue to stigmatize sex workers during COVID-19, it is important to consider the ways in which public health measures to contain the virus through contact tracing may further exclude sex workers and sex trafficking victims from protection. In most of the United States, because sex work is criminalized, there may be gaps and underreporting in surveillance and tracing, as compliance may jeopardize sex workers' ability to maintain their privacy and client confidentiality. Policing may further threaten the health and financial well-being of sex workers, who may face lost wages or clientele not willing to participate in public health surveillance efforts that may require documentation and reporting. In this way, the criminalization of sex work may have an inadvertent influence on increased post-pandemic sex work and sex trafficking levels.

One way to contain the spread of the virus is to implement policy measures that will not criminalize sex workers, while continuing to advocate for criminalization of all other parts of the sex trafficking enterprise to protect victims. Decriminalization of sex work would not only eliminate the burden of police interactions, but also allow sex workers and sex trafficking victims to qualify for economic relief currently reserved for members of the formal economy. A full decriminalization strategy may face insurmountable legislative constraints, but even temporarily reinforced social services and local policing strategies that limit interactions with sex workers would help keep them from becoming further marginalized and vulnerable to victimization.

While the COVID-19 pandemic has been unique in its wide-ranging effects on societies over the world, other disease epidemics and economic disruptions that occur in the future may similarly have important effects on those vulnerable to trafficking. Understanding the effects of COVID-19 on sex trafficking will help law enforcement, policy makers, and analysts more accurately predict how future social disruptions will affect it.

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