Can Platform Accountability Reduce Sex Trafficking? Evidence from the Price Effect

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Abstract

On March 21, 2018, a twin bill that made it illegal for digital platforms to knowingly assist, facilitate, or support sex trafficking was passed in the U.S. Congress. The anti-sex trafficking bills, FOSTA (Allow States and Victims to Fight Online Sex Trafficking Act) and SESTA (Stop Enabling Sex Traffickers Act), have generated a great deal of controversy. However, no one has tested whether they were effective at achieving their primary goal: reducing sex trafficking in the United States.

Our research develops a novel way of measuring the impact of the twin bills on the market for underage sex trafficking victims: exploring the impact of the law on transacted prices for commercial sex services. Using data from two escort review sites, we apply both linear and double machine learning difference-in-differences frameworks and find a 7%-17% increase in transacted prices for service providers from the *youngest age group* relative to other participants. Our findings suggest that the anti-sex trafficking bills' made it more difficult to sell minors in the online commercial sex market. Our results inform policy decisions on platform regulation, and have general implications for the governance on harmful content in digital marketplaces.

Keywords: FOSTA-SESTA, Platform regulations, Sex trafficking, Internet governance, Commercial sex markets

1. Background and Introduction

Over the past two decades, digitization has transformed many sectors of the economy, changing how businesses operate and how consumers access goods and services. While the digitization of markets has brought many benefits including increased efficiency, greater consumer choice and new business models (Brynjolfsson et al., 2003; Brynjolfsson and Smith, 2000), it has also facilitated new marketplaces for illicit activities such as sex trafficking, which is defined by US law as commercial sex "induced by force, fraud, or coercion, or in which the person induced to perform such act has not attained 18 years of age."[1]

[1] See https://www.law.cornell.edu/uscode/text/22/7102.

Sex trafficking activities, especially the trafficking of minors, are rampant on the internet. The National Center for Missing and Exploited Children (NCMEC) reported an 846% increase from 2010 to 2015 in reports of suspected child sex trafficking – an increase they argue is “directly correlated to the increased use of the Internet to sell children for sex.”[2] In 2015, the U.S. Senate’s Permanent Subcommittee on Investigations conducted an investigation of the commercial sex advertising site Backpage, and found that the website was involved in “73% of all child trafficking reports that NCMEC receives from the general public.”[3] According to the Senate report, Backpage has knowingly concealed evidence of sex trafficking activities (especially the trafficking of minors) on their site by deleting terms that are indicative of child sex trafficking (e.g., “lolita,” “teenage,” “young,” “amber alert,” “little girl,” “teen,” “fresh”) prior to publishing the advertisements for these individuals on their site.

In early 2018, the US Congress moved to regulate online commercial sex advertising platforms. To encourage proactive action against online sex trafficking, a twin bill called FOSTA (Allow States and Victims to Fight Online Sex Trafficking Act)[4] and SESTA (Stop Enabling Sex Traffickers Act)[5] was put on the House floor the week of February 26, 2018. The House of Representatives passed the bill on Feb 27, 2018.[6] On March 21, 2018, the FOSTA-SESTA package bill passed the Senate and was signed into law on April 11, 2018. The FOSTA-SESTA package bill amended the Section 230 safe harbors of the Communications Decency Act, making digital platforms liable if they "knowingly assist, facilitate, or support sex trafficking".

In response to this increased legal liability, Craigslist voluntarily closed its “Personals" ads section within its US domain on March 23, 2018.[7] Then on April 6, 2018 the site Backpage was seized by the Department of Justice (DOJ).[8] Thus, within a few weeks of each other, the two largest commercial sex advertising platforms in the US ceased operation.

The passage of FOSTA-SESTA stirred controversy in 2018, and remains controversial to this day. Specifically, it has been criticized for not being effective in reducing sex trafficking and sexual exploitation.[9] In spite of this criticism, however, there has been very little rigorous research into the impact of the law on the sex trafficking market. We seek to address this gap in the literature by using a novel measure: the price of commercial sex services across different age groups before and after the passage of the twin bills and the shutdown of Backpage and Craigslist. Our data show a

[2]See https://www.courthousenews.com/wp-content/uploads/2017/02/Backpage-Report.pdf.
[3]Id.
[4]See https://www.congress.gov/bill/115th-congress/house-bill/1865/text.
[5]See https://www.congress.gov/bill/115th-congress/senate-bill/1693/text.
[6]See https://www.washingtonpost.com/news/true-crime/wp/2018/02/27/house-passes-anti-online-sex-trafficking-bill-allows-targeting-of-websites-like-backpage-com/.
[7]See https://www.wired.com/story/craigslist-shuts-personal-ads-for-fear-of-new-internet-law/.
[8]See https://www.reuters.com/article/us-usa-backpage-justice/sex-ads-website-backpage-shut-down-by-u-s-authorities-idUSKCN1HD2QP.
[9]See https://www.eff.org/deeplinks/2018/03/how-congress-censored-internet; https://www.globalpolicyjournal.com/blog/18/11/2021/expanding-circles-failure-rise-bad-anti-trafficking-and-what-do-about-it.

causal 7-17% increase in marketplaces prices of participants in the youngest reported age groups on two commercial sex review sites relative to the prices of older participants. This result is consistent with the hypothesis that the passage of the anti-sex trafficking bills reduced the supply of underage sex trafficking victims, and represents what we believe is the first academic study demonstrating the effectiveness of the law in its primary purpose: reducing online sex trafficking.

2. Literature Review

There is scarce available literature examining online child sexual exploitation, sex trafficking, or more broadly commercial sex markets on the internet. Extant studies analyzing the economics in the prostitution market mostly focus on markets outside of the US (e.g., Hawkins et al. 2009; Rao et al. 2003). Mergenthaler and Yasseri (2022) examine the price of the market using the data from UK's largest network for solicitation and finds that nationalities, age and services provided are primary drivers for rates of commercial sex services.

Our paper is relevant to the prior work that studies digitization of the prostitution market and its impact on sexual exploitation and health outcomes. Outside the domain of Information Systems, there is a stream of literature in social sciences and criminology that attempts to address the use of technology in prostitution and sex trafficking. This research suggests that the rise of the internet and digital networks has largely exacerbated the problem of sex trafficking activities (Alvari et al., 2017), by enabling traffickers to reach a wider audience and exploit a larger number of victims (Ibanez and Suthers, 2014), increasing the offenders' chances to find buyers through advertisements and websites (Volodko et al., 2020) and facilitating the purchase of sex through various encounters like "escorting" or "massages" at illicit massage parlors (DeLateaur, 2016). Similarly, in the Information Systems literature, Chan, Mojumder and Ghose (2019) find the online escort advertising leads to a 17.58% increase in prostitution cases, and the study conducted by Chan and Ghose (2014) suggests that the online classified ad site, Craigslist, promotes risky behaviors and results in 15.9% increase in HIV cases. In contrast, Cunningham and Kendall (2010) uncover a lower potential for the spread of sexually transmitted infection among internet-facilitated sexual activities since the internet-based providers appear to engage in relatively low levels of risky sexual practices. Our research is most closely related to that of Zeng et al. (2022), who demonstrated that the shutdowns of Backpage and Craigslist Personals had no effect on the number of sex trafficking cases in the US. Our research revisits these results by using a different variable—market price—rather than the number of trafficking cases reported to law enforcement agencies. In particular, we use market price as a proxy for the changes in the supply of underage victims in the commercial sex market.

Our study focuses on a policy intervention on the supply-side of the market, and is therefore informed by prior literature on internet governance of sex trafficking, and other criminal activities in general. It has been shown in existing literature of Information Systems and economics that enforcement against suppliers of illegal products is effective in reducing various kinds of illegal behaviors, including digital piracy (Danaher and Smith, 2014; Reimers, 2016; Dey et al., 2018), drug trafficking (Chan, He, Qiao and Whinston, 2019) and hate speech (Gibson, 2019). Conversely, there are also a number of studies demonstrating limited effectiveness in decreasing unlawful conducts through disrupting the supply side of illegal markets (e.g., Décary-Hétu and Giommoni 2017; Soska and Christin 2015). In the specific context of our study, numerous comments and articles by law scholars suggest a limited anecdotal impact of FOSTA-SESTA in reducing sex trafficking, and likely unintended consequences of harming participants in the underground sex economy (e.g., Chamberlain 2019).

3. Hypothesis Development

Immediately following the passage of FOSTA-SESTA on March 21 2018, the two largest online escort advertising platforms ceased operation. Namely, Craigslist voluntarily took down its “Personals” section within all US domains on March 23, and Backpage was seized by the Department of Justice on April 6, 2018. The prior literature (Zeng et al., 2022) has examined the impact of the shutdowns of Backpage and Craigslist’s Personals section, and suggests that the shutdowns led to relocation of online ads for commercial sex services to other websites (mostly offshore) for escort advertising. Aside from the dispersion of ads, Zeng et al. (2022) also demonstrates that a number of domestic escort advertising sites moved their domains to overseas countries to evade law enforcement from US.

Before asking how FOSTA-SESTA changed the market for commercial sex, an initial question one might ask is whether FOSTA-SESTA caused online commercial sex advertising sites to change their policies with respect to posting advertisements for underage trafficking victims. To address this question, we visit each of the major online escort advertising portals listed in Zeng et al. (2022) that were used in place of Backpage and Craigslist after the passage of FOSTA-SESTA, and use the *Wayback Machine*[10] to track the changes in the front page or terms of service of these sites in the 2 months after the passage of the twin bills.

We find significant evidence that the remaining commercial sex advertising sites did change their policies regarding posting advertisements for underage trafficking victims. Specifically slixa[11] and adultsearch[12], updated their terms of use or web page, restricting on the content involving trafficking, especially materials that exploit minors. In addition, some newly launched sites, e.g., *USAsexguide.nl*, emphasized their “Underage Policy” on their front page as part of users’ community guidelines. Details of the specific changes are provided in Appendix A. We note that similar policy terms and trafficking resources were not found on Backpage or Craigslist prior to their shutdown.

[10] https://archive.org/web/
[11] https://www.slixa.com/
[12] https://adultsearch.com/

Based on the shutdown of the two largest commercial sex advertising sites, and the observed policy changes on the most popular remaining commercial sex advertising sites, we hypothesize that FOSTA-SESTA may have made it more difficult to post materials that sell underage sex trafficked victims on the internet. Namely, we propose the following hypothesis:

H1a: The policy reform results in a decrease in the supply of underage participants in the online commercial sex market.

Due to the nature of the market (solicitation activities are likely to be going on dark web), data that could be used to measure supply, i.e., the number of participants in this unlawful market, is either unavailable or comes with limitations of not being able to measure actual amount of participants in the market. In the absence of accurate count data, we rely on a supply and demand framework which has been used in the economics literature to analyze changes in wages in labor markets (Katz and Murphy, 1992). Applying this model to our setting, we develop a new measurement, i.e., market prices for services in the online commercial sex market, to reflect the relative change in supply and demand of the market and evaluate the impact of the twin bills. Since FOSTA-SESTA is an enforcement that disrupts the supply side of the market, according to the law of supply and demand, hypothesis *H1a* suggests:

H1b: The policy reform results in an increase in the prices of underage participants in the online commercial sex market.

We provide details on how the relative variations in prices reflect the change in supply and demand in section 7, and we then test the hypothesis of *H1b* to understand how the policy change impacts the supply of minors in the US commercial sex market.

4. Data

To test this hypothesis, we scraped large-scale data sets from two escort review sites: *"Erotic Monkey"*[13] and *"the Erotic Review"* (TER)[14]. *"Erotic Monkey"* and *"the Erotic Review"* are review sites that present consumers' assessments of their experiences with providers of commercial sex services, analogous to the ratings for legitimate services offered on sites like *Yelp.com*. Data from these sites allow us to document the general information (e.g., age, ethnicity and physical features) of individuals being advertised for commercial sex online, the specific sexual services they offered, and the prices for those services. *"The Erotic Review"* blocked access to its sites from the U.S. following the passage of FOSTA-SESTA on April 6th, 2018 and returned to service in the U.S. in December 2019.[15]

[13] https://www.eroticmonkey.ch/

[14] https://www.theeroticreview.com/

[15] See https://arstechnica.com/tech-policy/2018/04/erotic-review-blocks-us-internet-users-to-prepare-for-government-crackdown/.

Before FOSTA-SESTA, *"the Erotic Review"* was the dominant review site for commercial sex services in the U.S. Its suspension of services leads to a large gap in data coverage in the post period. Because of this, we base our analysis primarily on data from *"Erotic Monkey"*, a review site that was the main substitute of TER after it closed its page in the U.S. Figure B1 in Appendix B shows the Google Trends search index for the terms *"Erotic Monkey"* and *"Erotic Review"* in the U.S. from July 2017 to the end of 2018, with the y-axis indicating normalized search volume.[16] Google Trends' search popularity measures on the y-axis of Figure B1 are normalized by term and time, with the reported values scaled relative to peak search volumes. This chart shows that the search activities for *"Erotic Monkey"*, and thus the popularity of the site, increased following the suspension of TER, which illustrates the potential relocation of users between the discussions boards after the passage of FOSTA-SESTA. The details of the scraped data are provided below.

4.1. Erotic Monkey

Buyers for commercial sex services use the site to share detailed reviews of service providers.[17] *"Erotic Monkey"* presents general information on providers (including contact information, primary location, etc.), information on their appearance and services (including age, ethnicity, tattoos, whether they smoke, and the specific services provided), and the prices charged by the providers in each review they received. Prices for two types of services, i.e., escort "incall" and "outcall"[18], are listed in the reviews.[19] This allows us to track the historical prices for each service provider across our study window. For each provider, we obtained reviews posted between July 2017 and December 2018. Detailed descriptions for the characteristics of the providers that are used as control variables are included in Table B1, and their descriptive statistics are reported in Table B2.[20] In each of the reviews, the providers are listed in one of the age groups of "18-24", "25-36", "37-45" and "45+" if age information is reported by the reviewers. We infer the group of youngest participants (potentially minors) based on the age information listed in the review data and use a dummy variable *youngest age group* to indicate this group of providers. We estimate if a provider belongs to the *youngest age*

[16]The Google Trends data in Figure B1 is compiled by requesting the search statistics associated with the two terms in the same time period.

[17]Only registered accounts of the site could post a review. The detailed reviews are only accessible to premium members of the site. Premium membership could be gained by paying $29.95 per month or publishing reviews on the site (leaving a provider review grants users a free week access).

[18]An "incall" is an escort booking that involves the consumer visiting the provider while an "outcall" is a booking where the escort travels to meet the consumer.

[19]The "incall" and "ourcall" rates are documented on a basis of "15 Minutes", "30 Minutes", "60 Minutes", "90 Minutes" or "2 Hours". For comparison across providers and reviews, we take the hourly rate (prices charged for "60 Minutes") as the transacted price of the providers. If the hourly rate of a provider is not available, we normalize the prices to the hourly level (e.g., for a provider who charges $1,000 for 2 hours services, we normalize the price to an hour rate of $500).

[20]We note there exists some inconsistency in the reported characteristics of the providers across reviews, e.g., a provider was listed as "white" in the ethnicity column for some of the reviews and "Asian" in others. We fix the data inconsistency issue for the features of the providers by replacing the values within a variable by the mode of the variable for reviews posted between January 2017 and June 2019. These variables include "Email", "website", "answer", "photo real", "photo updated", "white", "Black", "Asian", "transsexual", "implant", "smoke", "shave", "tattoo", "pornstar", "punctuality" as shown in Table B1. Extreme services is the average number of what we define as risky services offered by providers in reviews posted between Jan 2017 to June 2019. Our main results hold if we use the reported data as in the reviews.

group with two age identification methods, i.e., "simple approach" and "age estimation algorithm" (details provided below). The summary statistics of our main variables of interest for both our OLS regression and double machine learning difference-in-differences model (details provided in the following section) are presented in Table 1.

Table 1: Summary Statistics

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Data for OLS Regression in Table 3					
$ln(hour\ rate)$	4,730	5.608	0.447	2.996	8.006
youngest age group[1]	4,730	0.084	0.277	0	1
youngest age group[2]	4,730	0.090	0.287	0	1
Data for DMLDiD in Table 4					
$ln(hour\ rate)$	1,255	5.595	0.407	4.317	7.496
youngest age group[1]	1,255	0.515	0.500	0	1
youngest age group[2]	1,255	0.565	0.496	0	1

[1] *youngest age group* identified with "simple approach".
[2] *youngest age group* identified with "age estimation algorithm".

4.2. The Erotic Review

As mentioned above, *"the Erotic Review"* (TER) blocked access US users two weeks after FOSTA-SESTA passed the Senate, leaving a large gap of missing data for reviews in the post period. We scraped the review data from TER for supplementary analysis and also to ensure price information is comparable across platforms. TER provides very similar look-and-feel to *"Erotic Monkey"*. However, the information of a service provider on TER is up to date when the provider received the last review or last updated their profile. Thus, we only have the most recent price for each service provider. Additionally, TER uses its own coding system that documents the features of the providers in a way slightly different from the site of *"Erotic Monkey"*. We took down the profiles of providers who received their last review/last updated their profile between July 2017 to December 2018 and report the details of the features, summary statistics of these features as well as our main variables of interest in Table B3 and Table B4.

5. Models and Results

In our study, we use prices as a proxy to reflect the change in supply and demand for sellers from various age groups in the online market. As discussed above, on *"Erotic Monkey"*, providers are listed in one of the age groups of "18-24", "25-36", "37-45" and "45+" in the reviews they received if age information is available. The listed age is thus the providers' perceived age by their reviewers rather than their true age. Notably, it is not possible to list someone's age as under 18 on either review site, but this is exactly the age group that we aim to study. To identify providers who are below the true age of consent, we start our analysis with the assumption that underage participants are most likely to be listed in the youngest age group, i.e., "18-24". Thus, while older age groups likely contain very few trafficked minors, we assume the 18-24 age group to be comprised of both providers whose true age is between 18 and 24 as well as most of the trafficked minors who are below age 18.

In our study window from the mid of 2017 to the end of 2018, we first fix the issue of reporting inconsistency by replacing the age values within a provider by the most frequent category of age data in the reviews the individual received from January 2017 to June 2019.[21] Based on our assumption, minor participants should be included in the age bin of "18-24", and the higher the percentage of their reviews are in this youngest age group, the more likely the providers are below the legal age of consent.

To test our hypothesis and the validity of our assumption, we first apply a difference-in-differences model to compare the transacted prices of participants from various age groups before and after the time of FOSTA-SESTA's passage. Specifically, we estimate the following model:

$$ln(\textit{hour rate}_{pi}) = \alpha * \textit{Youngest Age Group}_p * \textit{Post}_{pi} + \beta * X_{pi} + FE_{month} + FE_{city} + \varepsilon_{pi} \tag{5.1}$$

where $\textit{hour rate}_{pi}$ is the hourly rate in the i-th review of of provider p[22], $\textit{Youngest Age Group}_p$ is a dummy variable that takes the value of 1 if provider p is identified in the age group of "18-24" and 0 otherwise, $\textit{Post}_{pi}$ is a dummy that equals to 1 if the posting time of the review is after the passage of FOSTA-SESTA[23], α represents the change in price of the *youngest age group* of participants after the bills' passage relative to that of other age groups, X_{pi} are a series of confounding variables that include the characteristics of provider p along with the type of services provided in review i (listed in Table B1) that could affect the transacted prices, FE_{month} and FE_{city} represent the vector of *month*- and *city*[24]-fixed effects, and ε_{pi} is the error term. We take the log of the hourly rate for two reasons: first, the distribution of hourly prices is right skewed; and second, we expect to compare the relative change in prices before and after the policy reform.

Results for (5.1) are presented in Table 2. In the regression results, we use the prices of providers identified to be in the older age groups, i.e., "25-36", "37-45" and "45+", as our control. In columns (1) - (4), we report the estimated coefficient α using providers from the youngest age bin "18-24" as the group of treatment with the percentage of reviews (from January 2017 to June 2019) distributed in the youngest age group "18-24" varying from

[21] For example, for a provider who is listed to be "25-36" in 80% of the reviews and "37-45" in the remaining 20% of the reviews received in the time period from January 2017 to June 2019, we infer individual's age to be "25-36". Such computation is based on reviews where age information is available. We impute the missing age data with the same mode value as well.

[22] The reviews are arranged in the order in which they were posted.

[23] The time stamp of reviews is on the month-level. We take the cut-off point for the pre- and post-period of the bills' passage to be March 2018, around when FOSTA-SESTA was passed by the House and Senate, and when multiple escort advertising portals started to respond to the reform.

[24] Location of transaction.

Table 2: OLS Regression Results for (5.1)

Dependent variable	$ln(\textit{hour rate}_{pi})$			
	(1)	(2)	(3)	(4)
Youngest Age Group$_p$ $*$ *Post*$_{pi}$	0.155***	0.152***	0.135***	0.134***
	(0.049)	(0.046)	(0.045)	(0.045)
Percentage of reviews in the age group “18-24”	100%	75%-100%	50%-100%	25%-100%
Observations	4,006	4,026	4,066	4,069
Clusters	1,599	1,613	1,639	1,641

Robust standard errors clustered at individual provider level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

100%, 75%-100%, 50%-100% and 25%-100% respectively. Namely, column (1) shows the results using the providers with all of their reviews distributed in the age bin of “18-24” as the treatment group; column (2) adds providers with at least 75% of the reviews in “18-24” to the treatment group, and 50%, 25% for columns (3) and (4) respectively. The results in Table 2 are close in both magnitude and precision, suggesting that there is a 13.4% - 15.5% higher increase in the hourly rates for individuals in the *youngest age group* after the passage of FOSTA-SESTA relative to prices in other age groups. The estimates are decreasing from column (1) to (4), with the decrease in composition of reviews from the youngest age bin and thus hypothetically decrease in number of participants who are minors. We infer with the basic and straightforward signal, i.e., the makeup of age information in the reviews, that underage sellers are likely to experience a larger corresponding increase in the market price after the policy reform compared to sellers from older age groups.

To better evaluate changes in prices among the group of participants who are minors, we go beyond this simple strategy and propose an algorithm (details provided in the following section) to estimate a set of true ages (dates of birth) of the providers that are “consistent" with the observed reviews in our data, and we use this algorithm to extrapolate which providers are most likely below the age of 18 in actuality.

5.1. *Algorithm for Age Estimation*

Consider provider $p \in \{1, 2, ..., n\}$ who has a total number of m_p reviews, and the time stamp for review $i \in \{1, 2, ..., m_p\}$ is $t_{p,i}$ (as mentioned earlier, $t_{p,i}$ reports posting time of reviews on monthly level). We use $\gamma_{p,i}$ to denote the reported age of p in review i, i.e., $\gamma_{p,i} \in \Upsilon$ such that $\Upsilon = \{$“18-24”, “25-36”, “37-45” and “45+”$\}$. We assume that the m_p reviews are independent.[25] $\theta_p \in \mathbb{R}$ is used to denote the true date of birth (DOB) of provider p. θ_p could be very fine-grained. For simplicity, we discretize θ_p at the year level[26], and assume that there exists a shared probability distribution (across all providers and across all reviews) of being reported in a certain age group in the

[25] This perhaps is a reasonable assumption as for the same provider we consider the reviews from different reviewers.

[26] We set θ_p to be from the set of $\{$1967, 1968,..., 2006$\}$ so that a provider in our study window is aged between 11 and 50. As the eldest age group in the reviews is “45+”, considering the oldest possible age going above 50 leads to the same mathematical outcome. We set the minimum possible age to be 11 so the youngest provider in our data is still underage up to this day.

review given a true age group the provider comes from, i.e., $\mathbb{P}(\text{reported age group} = b|\text{true age group} = a) = \Omega_{b,a}$, where we specify the true age group $a \in \Upsilon_{\text{true}}$ such that Υ_{true} = {"Below 18", "18-24", "25-36", "37-45", "45+"}. In this regard $\Omega_{b,a}$ for $b \in \Upsilon$ and $a \in \Upsilon_{\text{true}}$ form a 4×5 matrix Ω where the row indicates the reported age group b, column the true age group a, and the column sum of the matrix is 1. We can now write the likelihood function

$$\begin{aligned}\mathbb{L}(\Omega, \theta_1, \theta_2, ..., \theta_n) &= \prod_{p=1}^{n}\prod_{i=1}^{m_p} \mathbb{P}(\text{reported age group} = \gamma_{p,i}|\text{age group}\{t_{p,i} - \theta_p\}) \\ &= \prod_{p=1}^{n}\prod_{i=1}^{m_p} \Omega_{\gamma_{p,i},\text{age group}\{t_{p,j}-\theta_p\}}\end{aligned}$$

where $\mathbb{L}(\Omega, \theta_1, \theta_2, ..., \theta_n)$ represents the probability of having the reported age bins in the review data with matrix Ω and true DOB of providers to be $\theta_1, \theta_2, ..., \theta_n$, age group$\{t_{p,j} - \theta_p\}$ indicates the age group of $t_{p,j} - \theta_p$ in Υ_{true}. Our goal then is to estimate the conditional probability matrix Ω and the set of true DOBs of providers $\theta_1, \theta_2, ..., \theta_n$ that maximize $\mathbb{L}(\Omega, \theta_1, \theta_2, ..., \theta_n)$. We estimate these quantities through the following steps:

Steps for Age Estimation	
Step 1:	Start with an initial guess of true year of birth $\theta_1, \theta_2, ..., \theta_n \in \{1967, 1968, ..., 2006\}$ for provider $1, 2, ...n$. The initial guess is denoted as $\hat{\theta}_1, \hat{\theta}_2, ..., \hat{\theta}_n$.
Step 2:	(a) Treating $\hat{\theta}_1, \hat{\theta}_2, ..., \hat{\theta}_n$ as true year of birth for the providers, update the estimated probability distribution matrix $\hat{\Omega}$ correspondingly s.t. $\hat{\Omega}_{b,a} = \frac{\sum_{p=1}^{n}\sum_{i=1}^{m_p}\mathbb{1}(\gamma_{p,i}=b,\, \textit{age group}\{t_{p,i}-\hat{\theta}_p\}=a)}{\sum_{p=1}^{n}\sum_{i=1}^{m_p}\mathbb{1}(\textit{age group}\{t_{p,i}-\hat{\theta}_p\}=a)}$ (b) Treating the value in matrix $\hat{\Omega}$ as fixed, update age $\hat{\theta}_p$ for each provider p s.t. the probability of the reported data would be maximized, i.e., $\hat{\theta}_p = \max_{\theta_p} \prod_{i=1}^{m_p} \hat{\Omega}_{\gamma_{p,i},\text{age group}\{t_{p,i}-\theta_p\}}$. (Repeat ***Step 2*** until convergence)

To ensure the independence of data in our price analysis, we first execute the above steps and estimate the matrix Ω for conditional probabilities of reporting with the set of providers who are not included in our analysis on price. We perform 10 runs for estimation on Ω. For each run, we estimate Ω along with the set of birth years $\theta_1, \theta_2, ..., \theta_n$ by starting with 5,000 different sets of initial guess for $\theta_1, \theta_2, ..., \theta_n$. We then select the estimates that leads to the highest likelihood of $\mathbb{L}(\hat{\Omega}, \hat{\theta}_1, \hat{\theta}_2, ..., \hat{\theta}_n)$ among final estimates from the 5,000 initial points. The estimation results on Ω are identical when rounded to 2 decimal places across 10 runs. The estimated probabilities in $\hat{\Omega}$ are presented in Appendix B.[27] We observe a relative high positive correlation between the reported age group and true age group. Notably, our

[27]For some providers, there might exist multiple years of birth that could result in the same highest likelihood. Our final estimates on matrix $\hat{\Omega}$

estimation shows that minor participants are reported almost exclusively in the age bin of "18-24", which validates our previous assumption on age reporting. We then estimate the true ages for the providers in our price analysis with the set of reviews where either price data is missing or the posting time is outside our study window from July 2017 to December 2018.[28]

5.2. Price Analysis

The above algorithm provides us with a set of estimated ages of the service providers in our study window. Following the age estimation, we repeat the analysis in (5.1) by using the set of providers estimated to be under the age of 18 at the beginning of our study window[29], i.e., 2017, as treatment group to identify the changes in price for underage participants relative to those recognized to be above 18. The results are presented in Table 3. In Table 3, we report the results for (5.1) by using two different approaches of estimating providers' ages. Column (1) shows the results with the simple approach outlined above where providers' ages are estimated as the mode age value in their reviews posted between 2017 and mid 2019. In particular, we distinguish the providers among the age group of "18-24" and identify the younger participants (potentially minors) to be the ones with 100% of their reviews distributed in the age bin of "18-24". This group of providers are recognized as "*youngest age group*" for the specification in column (1) of Table 3. Other participants from the age group of "18-24" (listed in older age bins in at least one of their reviews) are included as part of the control group. The results when "*youngest age group*" are defined as underage participants detected based on the algorithm in section *5.1* are presented in column (4) of Table 3. We label these two age identification strategies as the "simple approach" and the "age estimation algorithm" respectively in Table 3. In the first row of the table, we observe that there is a 14% (column (1)) to 16.3% (column (4)) relative increase in the hourly rates of the *youngest age group* after the passage of FOSTA-SESTA.

The estimated coefficients for control variables X_{pi} can be found in corresponding columns in Table B5 of Appendix B. Overall, we observe that younger age is associated with higher market prices. We leave out the service providers aged between 18 and 36 from the control group as reference. Providers estimated to be from the age group of "37-45" are on average transacted with a price that is around 8-11% lower (row *"Age Group 37-45"* of columns (1) and (4) in Table B5) than that from the reference group. Average hourly rates drop more significantly as ages increase with the sellers listed above 45 transacted more than 20% lower (row *"Age Group 45+"* in columns (1) and (4)) than those in the reference group. Race affects the listing prices as well. We leave out the providers listed as non-Asian,

are independent from the choice from those years in executing Step 2(b).

[28]We split the data set for age estimation and price analysis, i.e., the observations used for analysis on price are not used to estimate ages, to ensure the independence of data for inference on prices. Specifically, for age estimation, we expand to include the reviews from 2013 to 2023 to ensure sufficient amount of data for estimation purpose.

[29]Due to the relatively short period of time in our study window, i.e., from July 2017 to December 2018, we hold a provider's age to be constant throughout that period of time and do not consider the progression of ages from one group to the other.

Table 3: OLS Regression Results for (5.1)

Dependent variable	ln(hour rate)					
	(1)	(2)	(3)	(4)	(5)	(6)
$Youngest\ Age\ Group_p * Post_{pi}$	0.140***	0.114*	0.213**	0.163***	0.095*	0.125
	(0.047)	(0.060)	(0.104)	(0.045)	(0.055)	(0.089)
$Youngest\ Age\ Group_p * Post_{pi} * \mathbb{1}(Extreme\ Services > 3)$		0.068			0.198**	
		(0.076)			(0.091)	
$Youngest\ Age\ Group_p * Post_{pi} * white$			-0.120			0.043
			(0.110)			(0.102)
$Youngest\ Age\ Group_p * Post_{pi} * Black$			-0.056			0.025
			(0.169)			(0.156)
$Youngest\ Age\ Group_p * Post_{pi} * Asian$			0.055			0.146
			(0.139)			(0.126)
$Youngest\ Age\ Group_p$	Reported as "18-24" in all reviews	Reported as "18-24" in all reviews	Reported as "18-24" in all reviews	Underage	Underage	Underage
Age identification strategy	Simple approach	Simple approach	Simple approach	Age estimation algorithm	Age estimation algorithm	Age estimation algorithm
Observations	4,730	4,730	4,730	4,730	4,730	4,730
Clusters	1,838	1,838	1,838	1,838	1,838	1,838

Robust standard errors clustered at individual provider level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Black or white as the ethnicity reference group (e.g., mixed races, Hispanics). Prices vary drastically across different ethnic groups, with white service providers generally listed with the highest market prices and Black providers with the lowest. Specifically, on average white sellers charge a price that is more than 20% higher than that of Black participants (row *"white"*, *"Black"* in columns (1) and (4) of Table B5). Asian participants are in general priced around 5% lower than the reference group (row *"Asian"* Table B5).

On the basis of specification (5.1), we further include a series of interaction terms between $Youngest\ Age\ Group_p * Post_{pi}$ and a vector of control variables. Some individual characteristics of the providers could be used as weak indicators for sex trafficking. For example, higher number of extreme ("niche") services provided could be a sign of forced labor; most victims exploited at illicit massage parlors in U.S. that often serve as fronts for sophisticated multinational human trafficking rings are Asian.[30] We incorporate into (5.1) the interaction term between $Youngest\ Age\ Group_p * Post_{pi}$ and the dummy for higher number of extreme services, i.e., the average number of "niche" services offered by the providers is greater than 3, and report the results in columns (2) and (5) of Table 3 for age estimated with the "simple approach" and "age estimation algorithm" respectively. Columns (3) and (6) show the results after controlling for the interaction terms between $Youngest\ Age\ Group_p * Post_{pi}$ and ethnicity dummies, again with the two age identification strategies ("simple approach" in column (3) and "age estimation algorithm" in column (6)). The estimate for α becomes marginally significant in column (6). All of the sum of α and the corresponding individual coefficient of each interaction term is positive. This suggests that there exists a set of positive heterogeneous treatment effects and our estimate in columns (1) and (4) may be a weighted average of these heterogeneous treatment

[30] See https://www.chron.com/news/houston-texas/houston/article/Illicit-massage-parlors-prolific-and-lucrative-12256818.php.

effects. Specifically, we note that after the passage of FOSTA-SESTA, higher number of extreme services provided is associated with higher increase in prices, and the group of Asian participants are likely to experience highest growth in prices among all sellers in the market.

As pointed out by Abadie (2005), it is ideal to treat the control variables nonparametrically when there exists heterogeneous treatment effects to avoid underlying inconsistency caused by functional form misspecification. Besides, the linear difference-in-differences framework in (5.1) is built upon the stationary assumption, i.e., the distribution of covariates X_{pi} and treatment dummy *Youngest Age Group*$_p$ are stationary, which rules out settings with compositional changes in $(\textit{Youngest Age Group}_p, X_{pi})$ over time (Abadie, 2005; Sant'Anna and Zhao, 2020). This assumption does not account the potential shift in the distribution for the supply of sellers with various characteristics, especially after the enactment of FOSTA-SESTA, or the probable distribution shift of sellers in our data set.

To address these underlying issues, we further estimate the average treatment effect using the "double/debiased machine learning difference-in-differences (DMLDiD)" estimator proposed by Zimmert (2020). The estimator is based on the generic "double machine learning" framework developed by Chernozhukov et al. (2018). DMLDiD delivers point estimators that are rate double robust, approximately unbiased and normally distributed for our coefficient of interest (Zimmert, 2020).

Specifically, we construct our data in a 2-group 2-period (2×2) repeated cross section, i.e. $(Y_{pi}, D_p, T_{pi}, X_{pi})$, where Y_{pi} represents the outcome variable $ln(\textit{hour rate}_{pi})$ in (5.1) for the i-th review of provider p, D_p the treatment dummy for providers in the *youngest age group*, as denoted as *Youngest Age Group*$_p$ in (5.1), T_{pi} the dummy for post-treatment period and X_{pi} the set of covariates as in (5.1).[31] Again, we assume independence of the observations as in section *5.1* as we only include the reviews from different reviewers for the same provider. We start by establishing two nonparametric prediction models for the outcome variable Y_{pi} and the propensity score respectively in the first-step estimation. Specifically, we estimate the following:

$$Y_{pi} = g_{dt}(X_{pi}|D_p = d, T_{pi} = t) + \mu_{pi} \qquad \text{for } d, t \in \{0, 1\} \tag{5.2}$$

$$p(D_p = d, T_{pi} = t|X_{pi}) = e_{dt}(X_{pi}) + v_{pi} \qquad \text{for } d, t \in \{0, 1\} \tag{5.3}$$

In the above equations, p and i index reviews in our data. d and t represent the possible values of the binary variables D_p and T_{pi}, with the combination values indicating the treatment status. Namely, $(d, t) = (0, 0)$ and $(d, t) = (0, 1)$ indicate pre- and post-period of the control units (participants from the older age groups as defined above), and $(d, t) = (1, 0)$, $(d, t) = (1, 1)$ for pre- and post-period for observations in the treatment group (*youngest age group*). $g_{dt}(\cdot)$ and $e_{dt}(\cdot)$

[31] In our model setup, treatment represents the passage of FOSTA-SESTA with the post-treatment period starting from March 2018.

denote nonparametric functions through which the confounding factors X_{pi} affect the outcome variable Y_{pi} (hourly rates) and the propensity score $p(D_p = d, T_{pi} = t|X_{pi})$ conditional on the treatment status of (d, t). We are going to construct machine learning estimators for $g_{dt}(\cdot)$ and $e_{dt}(\cdot)$ for the 2 groups ($D_p = d$, $d \in \{0, 1\}$) and 2 periods ($T_{pi} = t$, $t \in \{0, 1\}$). μ_{pi} and v_{pi} are idiosyncratic disturbances with conditional mean 0, i.e., $\mathbb{E}(\mu_{pi}|X_{pi}, D_p, T_{pi}) = 0$ and $\mathbb{E}(v_{pi}|X_{pi}) = 0$.

We follow to estimate the effect of FOSTA-SESTA's passage on prices (Y_{pi}) with the score function as proposed in Zimmert (2020):

$$\psi(W_{pi}; \theta, \eta) = \frac{e_{11}(X_{pi})}{p(D_p = 1, T_{pi} = 1)}\psi^a(W_{pi}) + \frac{D_p T_{pi}}{p(D_p = 1, T_{pi} = 1)}\left\{\sum_{d=0}^{1}\sum_{t=0}^{1}(-1)^{d+t} g_{dt}(X_{pi}|d, t) - \theta\right\} \tag{5.4}$$

$$\psi^a(W_{pi}) = \sum_{d=0}^{1}\sum_{t=0}^{1}(-1)^{(d+t)}\frac{\mathbb{1}(D_p = d, T_{pi} = t)}{e_{dt}(X_{pi})}(Y_{pi} - g_{dt}(X_{pi}|d, t)) \tag{5.5}$$

$$E(\psi(W_{pi}; \theta, \eta)) = 0 \tag{5.6}$$

where the nuisance parameters are $\eta = (g_{dt}(\cdot), e_{dt}(\cdot))$ for $d, t \in \{0, 1\}$, and $W_{pi} = (Y_{pi}, D_p, T_{pi}, X_{pi})$.

In equations (5.4)-(5.6), θ denotes the main coefficient for the effect of FOSTA-SESTA on the transacted prices of the participants from the *youngest age group* relative to those of older providers that we would like to infer. θ is estimated by setting the average of the score function $\psi(W_{pi}; \theta, \eta)$ to be equal to be 0 in equation (5.6). $p(D_p = 1, T_{pi} = 1)$ represents the unconditional probability of $D_p = 1$ and $T_{pi} = 1$. The estimated results for the coefficient of interest θ are reported in Table 4. We report results based on three simple methods for estimating the nuisance functions $g_{dt}(\cdot)$ and $e_{dt}(\cdot)$. Namely, we consider the "ℓ_1-penalization" based method, labeled "Lasso", support vector machine labeled as "SVM" and a tree-based method, labeled "Random Forest". For each model, we tune parameters through a grid search and select the best model by 2-fold cross-validation. For example, for "Lasso", we choose the best penalty parameter with iterative fitting along a regularization path. Except from the 3 basic models, we also consider a hybrid method labeled "Best". The 3 basic models are assembled as follows: after obtaining estimates from the 3 ML methods listed above, the hybrid approach "Best" combines the 3 simple methods by selecting the best method for estimating each nuisance function based on the average out-of-sample prediction performance for the target variable. As a result, the reported estimate in the column of "Best" uses different ML approaches to estimate different nuisance functions.

We report estimates for θ obtained using 2-fold cross-fitting. Namely, we split the data into two folds, use one of them for the first-step estimation to build estimators for nuisance functions $g_{dt}(\cdot)$ and $e_{dt}(\cdot)$, and the other to identify the parameter of interest, θ. Then we swap the roles of the two samples to obtain another estimate and average the

Table 4: DMLDiD Results for (5.2)-(5.6)

	Machine learning estimator for η							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Lasso	SVM	Random Forest	Best	Lasso	SVM	Random Forest	Best
θ	0.146***	0.112**	0.070	0.090	0.169***	0.116**	0.094*	0.146***
	(0.051)	(0.056)	(0.071)	(0.056)	(0.054)	(0.058)	(0.051)	(0.051)
Youngest Age Group$_p$	Reported as "18-24" in all reviews	Reported as "18-24" in all reviews	Reported as "18-24" in all reviews	Reported as "18-24" in all reviews	Underage	Underage	Underage	Underage
Age identification strategy	Simple approach	Simple approach	Simple approach	Simple approach	Age estimation algorithm	Age estimation algorithm	Age estimation algorithm	Age estimation algorithm
Observations	1,255	1,255	1,255	1,255	1,255	1,255	1,255	1,255

Standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

results. The procedure of hyperparameter-tuning is conducted on the fold of data for first-step estimation. All results are based on taking 10 different sample splits. We summarize results across the sample splits using the median method. We report final estimate as the median across 10 splits and standard errors adjusted for variability across the sample splits using the median method in parentheses.

Columns (1)-(4) in Table 4 show the results when using "simple approach" for age identification and the results for providers' ages estimated with the algorithm in section *5.1* are presented in columns (5)-(8).[32] The DMLDiD model identifies a 7-17% relative increase in hourly rates charged by providers in the *youngest age group* compared with those from older age groups. The identified increase is different from 0 at any conventional level of statistical significance except for the estimates in column (3) and (4) where the coefficient is marginally significant in (4) and still suggests a 7-9% higher increase in prices.

The results of increases in prices are replicated with data from "the Erotic Review". The details of the analysis are presented in Appendix C.

6. Robustness Check

In this section we perform a parallel pre-trends test and a randomization test to validate our causal inferences, with the details provided below.

6.1. Parallel Pre-Trends Test

We first test whether treated and control units have parallel trends prior to treatment for the results in Table 3 using the following model:

$$ln(hour\ rate_{pi}) = \alpha_q * Youngest\ Age\ Group_p * month_q + \beta * X_{pi} + \delta_q month_q + FE_{city} + \varepsilon_{pi} \tag{6.1}$$

[32]For the results in Table 4, we only include the observations where the covariates do not fully determine the treatment status, i.e., $p(D_p = d, T_{pi} = t|X_{pi})$ is bounded away 0 for all four combination values of (d, t). This ensures for each value of the covariates X_{pi} in our sample, there are observations of that in each of the two groups $d = 0, 1$ and two periods $t = 0, 1$. We do so to ensure the overlap condition is fulfilled as it is crucial for guaranteeing nonparametric regular inference procedures (Khan and Tamer, 2010; Zimmert, 2020). We drop the providers offering lowest 10% number of extreme services as this group of participants usually associated with a relatively lower transacted price, which could bias our estimates toward zero.

where the variables are defined as in (5.1): $month_q$ is a vector of dummy variables for each month in our study period, where q takes the value from -8 to 10 with q indicating q months before the time of treatment if $q < 0$, and month q in the post-period if $q > 0$ (the month before the bills' passage, Feb 2018, is omitted). In (6.1), $Youngest\ Age\ Group_p * month_q$ is a dummy variable set to one if provider p is identified to be from the *youngest age group* and the review i is posted in $month_q$. δ_q represents the time trend on a monthly level for the units in the control group, and α_q indicates any differential trends between treated and control units in our study window. Under the parallel pre-trends assumption, we would expect α_q to be zero for all months in the pre-period. For the months in the post-period, α_q indicates the causal effect of FOSTA-SESTA on the outcome variable.

We estimate (6.1) with the two age identification strategies and report the results for α_q in Table B6, with column (1) showing the estimates using "simple approach" for age group identification and column (2) showing results using our age estimation algorithm. Figure 1 plots the estimated coefficients for α_q and their 95% confidence intervals. The pre-treatment coefficients are all statistically indistinguishable from 0, with the coefficients identified using age estimation algorithm being particularly close to 0 in magnitude in the pre-period (right graph in Figure 1), suggesting that the control and treatment groups had parallel trends prior to the passage of the bills. After treatment, α_q shifts into the positive region, and becomes statistically significant for a few months in the post-period.

In addition, we also conduct the parallel pre-trends test for our results of DMLDiD model in Table 4. To do that, we take all of the months from 2017 to 2018 in the pre-treatment period, use each of the months from March to October 2017[33] as fake treatment time and estimate the effect of the "fake" treatment with equations (5.2)-(5.6). Again, we conduct the placebo test using both of our age identification strategies. The estimates for our coefficient of interest are presented in Table B7. For simplicity, we show the results obtained using "Lasso" for the outcome variable and propensity score prediction in (5.2) and (5.3). Such results largely replicate when using other models for estimation in Table 4. The coefficients in Table B7 hover around 0 and remain statistically insignificant for each of the "fake" dates in the pre-period, implying the parallel trends of control and treatment groups prior to treatment.

6.2. *Randomization Test*

Next, we perform a randomization test to determine if the identified increase in transacted prices for providers from the *youngest age group* after the passage of FOSTA-SESTA is robust to randomly assigned ages to providers. To do this we randomly assign an age group to the providers in our data based on the true distribution of the estimated ages. Specifically, we re-estimate equation (5.1) for 1,000 times, each time randomizing the age groups in the same manner. This yields a distribution of 1,000 randomized "fake" treatment coefficients plus our true treatment coefficient. We

[33]The dates outside this window leaves us with insufficient amount of data in estimating the "fake" effect.

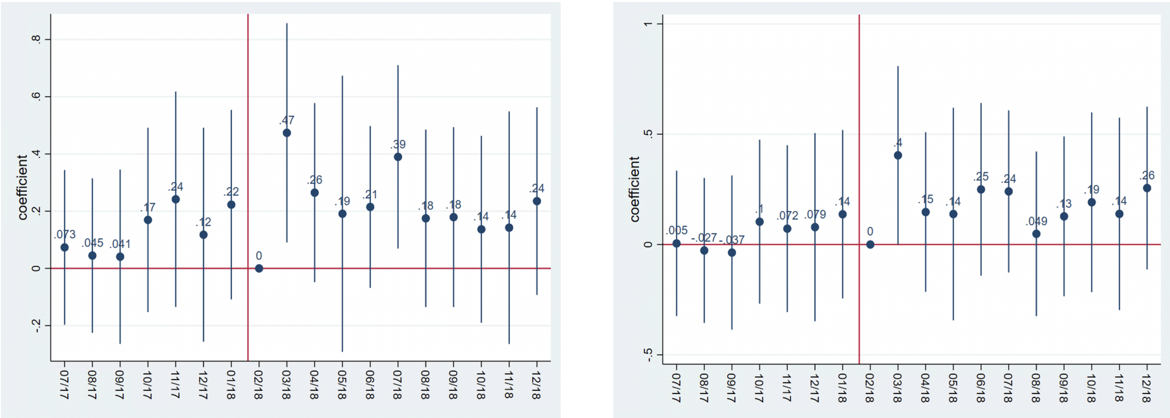

Figure 1: Regression Coefficient Box Plots from (6.1) for $ln(hour\ rate_{pi})$ with Providers' Ages Identified Using "Simple Approach" (Left) and "Age Estimation Algorithm"(Right).

conduct the randomization test using both methods of estimating providers' age and report the 5th and 95th percentile of the 1,001 estimates for the effects of the bills' passage on transacted prices in Table B8. We plot the distribution of the 1,001 estimates (1,000 coefficients from the randomization inference merged with the true coefficient) in Figure B2. The true effects under both of the age identification approaches in columns (1) and (4) in Table 3 are greater than the 95th percentile of the randomized sample. We find that the true effect of 0.14 of the bills' passage on the hourly rates of providers identified using "simple approach" is statistically significant at the 2.7% level, where the significance is the coefficient's rank order divided by 1,001, and the true effect from "age estimation algorithm" is statistically significant at 0.2%. The results suggest that the identified increase in prices is associated with the precise structure of age distribution of the service providers on the review site.

7. A Basic Supply and Demand Framework

Using data from the escort review site *"Erotic Monkey"*, we identify that the policy reforms in the FOSTA-SESTA bills result in an increase in price differentials by age, with a particularly sharp rise in the relative hourly prices charged by service providers with the youngest reported ages in the market, including those that potentially have not attained the age of 18. Namely, our analyses suggest the average prices of youngest providers in the market increased by 7-17% relative to that of older providers in the 10 months after the passage of the bills in Congress. In this section, we use a basic supply and demand framework from Katz and Murphy (1992) to infer the changes in supply of youngest service providers (especially the underage participants) following the federal legislation reform in US in 2018.

The basic framework we use to explain the changes in supply and demand of providers with various characteristics in the commercial sex market starts with a factor demand function:

$$z_t = \phi_t f(L_t) \tag{7.1}$$

In (7.1), we consider K types of providers in the market, i.e., $K = 1$ for providers in the *youngest age group* and $K = 2$ for those from older age bins. We define the providers from these two categories as the two types of "labor inputs" in this market. z_t represents Kx1 vector of demand for escort services from the K types of providers at time t, for $t \in (0, 1)$ where $t = 0, 1$ indicate pre- and post-period respectively, L_t is a Kx1 vector of "labor inputs" in the market at time t, where ϕ_t indexes the state of the economy, risks associated with doing transactions in this underground market, and f is the function (similar to the concept of a "production function" in labor markets) that specifies the relationship between "labor inputs" and "services demand" in the underground sex trade.

Following the law of diminishing returns, we assume f to be concave (Friedman, 1973). The concavity of f implies that:

$$[f_l(L_t) - f_l(L_{t-1})]'(L_t - L_{t-1}) \leq 0 \tag{7.2}$$

where f_l is the Kx1 vector of derivatives of f with respect to the K inputs. Under the assumption that marginal services provided is set equal to factor prices (Katz and Murphy, 1992), we have

$$\left[\frac{W_t}{\phi_t} - \frac{W_{t-1}}{\phi_{t-1}}\right]'(L_t - L_{t-1}) \leq 0 \tag{7.3}$$

where W_t represents Kx1 vector of market prices for providers from different age groups (controlling for other covariates that could affect prices). Thus a higher relative increase in price, i.e., $\frac{W_t - W_{t-1}}{W_{t-1}}$, is likely to be driven by a relative decrease in supply, i.e., $L_t < L_{t-1}$, or a relative increase in demand, i.e., $\phi_t > \phi_{t-1}$.

Notably, our identified increase in prices after the policy reform comes from providers in the *youngest age group*, which, likely includes a mix of underage participants and participants who are actually 18-24 years old. There are two possible scenarios that could explain this result:

1) If the identified increase in prices is driven by the price differentials of underage providers, we infer that the higher relative increase in prices suggest a larger decrease in supply of underage sellers, conditional on the assumption that the administration change occurred due to the passage of FOSTA-SESTA is unlikely to increase demand for sexual services from providers that have not attained the age of 18.

2) If the identified increase in prices is driven by the price differentials of the youngest adult providers in the market

who are 18-24 years old, the higher relative increase in prices could suggest a larger increase in demand for 18-24 year olds if this age group represents the closest substitute for consumers when it is more difficult to buy services from underage participants. Specifically, we draw the inference based on the assumption that among the providers who are above the legal age of consent, the policy does not intervene the supply-side differently based on providers' age.[34] In this regard, when it is more difficult to sell a 16-year-old in the online commercial sex market, consumers are likely to substitute towards services provided by 19-year-old, which would raise the demand for the youngest adult participants, and thus their corresponding prices.

8. Discussion and Conclusion

Our study compares the price differentials of service providers by age before and after the passage of the anti-trafficking bill FOSTA-SESTA in March 2018. To do this we use data from two escort review sites, *"Erotic Monkey"* and *"the Erotic Review."* Our results show a 7%-17% higher increase in price for the providers from the *youngest age group* relative to other age groups. We then apply the supply and demand framework of Katz and Murphy (1992) to argue that the most likely explanation for the observed increase in price for the youngest commercial providers after FOSTA-SESTA is that it was caused by a decrease in the supply of underage participants in the online marketplace for commercial sex after FOSTA-SESTA. In short, our research shows a a potential benefit of FOSTA-SESTA: That the law may have made it more difficult to sell minors for sex on the internet.

As with any empirical analysis, our study has limitations. First, our results of an increase in prices for service providers from the *youngest age group* are relative to the price changes for providers in older age groups. Our analysis is limited in identifying FOSTA-SESTA's impact on providers above the legal age of consent. Although the existing literature suggests the ease to move to alternative platforms (Zeng et al., 2022) and the launch of new sites (e.g., Red Umbrella Hosting) that host advertisements for consensual (adult) participants in the commercial sex market after FOSTA-SESTA's passage, it still requires further validation for our use of older providers as control in our analysis. Second, our analyses are based on data from two escort review sites. Although our study investigates a sensitive outcome variable that could be used to reflect the change in supply and demand of the market, it remains unclear if the data used in our analysis is a representative sample of the transactions in this underground economy where a great portion of buying and selling is likely to be conducted on dark web. In terms of that, our results are limited in addressing the effect of the law on remaining sellers in the market, i.e., whether the acts made it riskier to take a part in the commercial sex trade for the group of providers who are inelastic in leaving the industry.

[34] The supporting evidence for our assumption includes the examples in Appendix A that escort advertising portals changed terms of use targeting to remove materials involved minors after FOSTA-SESTA.

In spite of these limitations, we believe that our study makes several important contributions to the academic literature. First, to the best of our knowledge, our paper is the first empirical study that provides evidence in supporting the beneficial impact of the federal legislation FOSTA-SESTA passed in 2018, addressing its effectiveness in reducing materials exploiting minors on the internet. Also, our paper is the first study we are aware of that uses individualistic review data to analyzes supply-side anti-trafficking policy intervention — an important policy question which thus far has not been well informed by academically rigorous analysis. Second, our paper builds on the supply and demand framework by Katz and Murphy (1992) and incorporates the substitution effect in inferring the supply change of underage providers in the commercial sex market, providing an extension on the existing theoretical structure on price and market supply/demand change that could be used in similar market analysis for future studies. Third, our study develops an approach in fixing the inconsistency in reported data and predicting the true age of the participants that could be applied to other similar contexts or policy interventions in future research.

The question of the impact of FOSTA-SESTA becomes more relevant today as there's an expanding amount of discussions around and legislative efforts on eradicating child sexual abuse materials on the internet, and improving online safety in the public policy domain in both U.S. and foreign jurisdictions. For example, the EARN IT Act[35], a bill that's aimed to combat the spread of online child sexual abuse material (CSAM), was reintroduced to US Congress in 2022, and the Online Safety Bill[36], a proposed legislation that targets to protect users from harmful content, was introduced in Parliament of UK in 2021. The goal of these legislative efforts is to reduce sexual abuse of children online, the same legislative goal as FOSTA-SESTA which holds online platforms accountable for knowingly hosting advertisements for minors being sold for sex. By addressing the potential benefit of FOSTA-SESTA, our results have general implications on internet governance of illegal activities. Namely, our results highlight the importance of platform regulations and speak to the values of combating illegal activities on the internet by emphasizing platform accountability.

[35]Eliminating Abusive and Rampant Neglect of Interactive Technologies Act. See https://www.congress.gov/bill/117th-congress/senate-bill/3538.

[36]See https://bills.parliament.uk/bills/3137.

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Appendix

Appendix A: Examples of Websites Updating Their Front Page Or Terms of Use Post FOSTA-SESTA

A1: Adultsearch.com

The site Adultsearch (*adultsearch.com*) introduced a *"Report Trafficking"* tab at the bottom of its webpage after FOSTA-SESTA. Figure A1 and Figure A2 below show *archive.org* captures of the bottom section of Adultsearch's homepage in February and June in 2018, with the newly added *"Report Trafficking"* tab highlighted with a red rectangle in Figure A2.[37] This new tab links to an Anti-Trafficking Advocacy information page on Adultsearch (as shown in Figure A3), with the contact information for organizations like NCMEC, *Children of the Night* listed on the page. Two months after the bills' passage, Adultsearch also added a "Terms and Conditions" page that users must agree to before entering the site. The newly set up "Terms and Conditions" page (shown in Figure A4) highlights the site's efforts at curtailing child abuse materials and informs users about the rules against sex trafficking (relevant terms are highlighted in red rectangle).

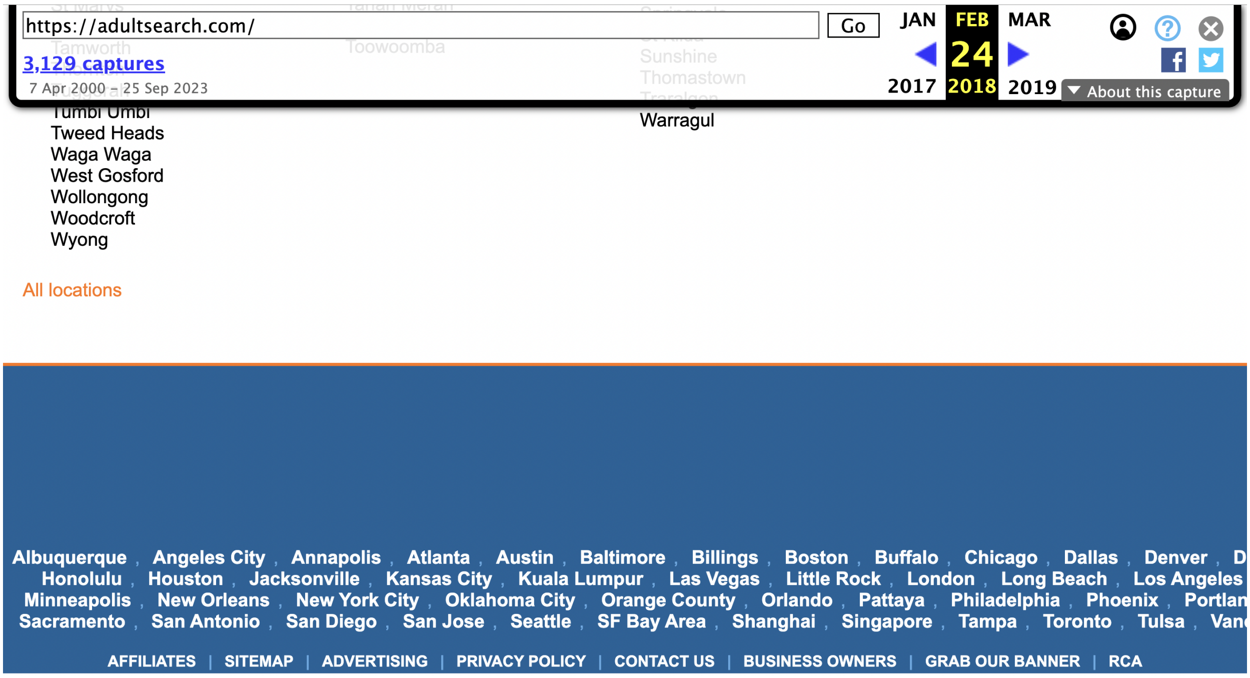
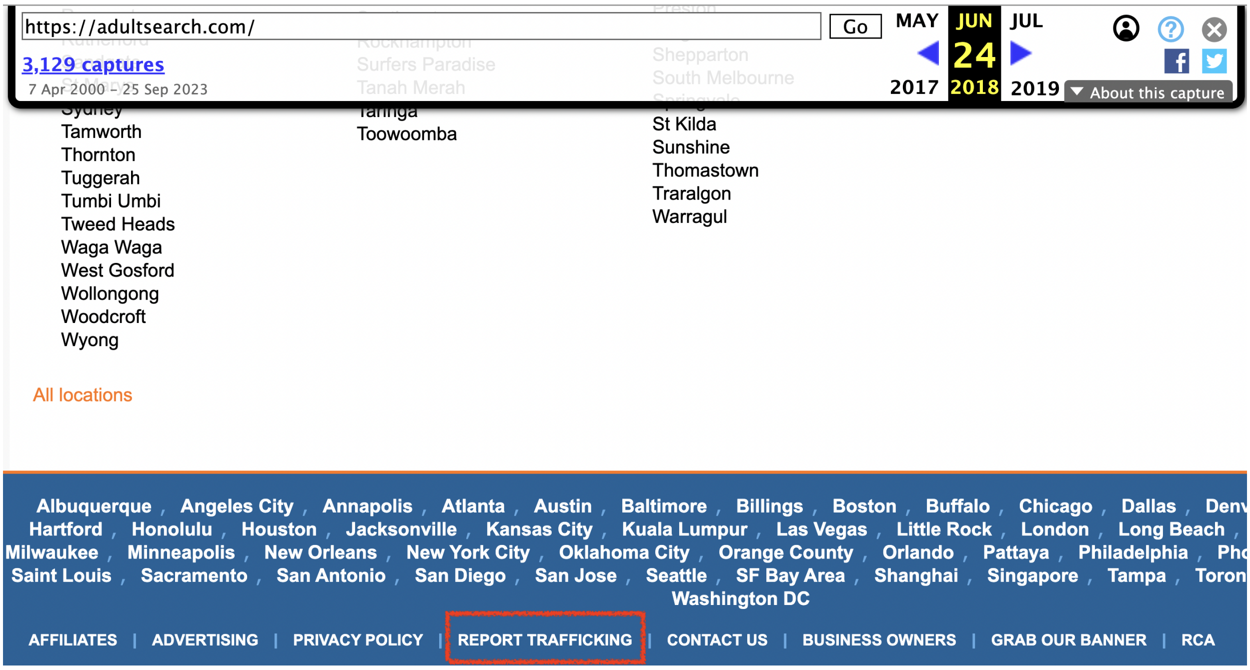


Figure A1: Footnote on the Front Page of Adultsearch on February 24th, 2018

[37] The two dates of the archived pages for Figure A1 and Figure A2 are the closest possible dates around the time of the policy intervention that are available on *wayback machine*. Similar situation of the limited availability of the archive data applies to other sites listed in the appendix.



https://adultsearch.com/ Go MAY JUN JUL
3,129 captures 24
7 Apr 2000 – 25 Sep 2023 2017 2018 2019 About this capture

Tamworth
Thornton
Tuggerah
Tumbi Umbi
Tweed Heads
Waga Waga
West Gosford
Wollongong
Woodcroft
Wyong

Surfers Paradise
Tanah Merah
Toowoomba

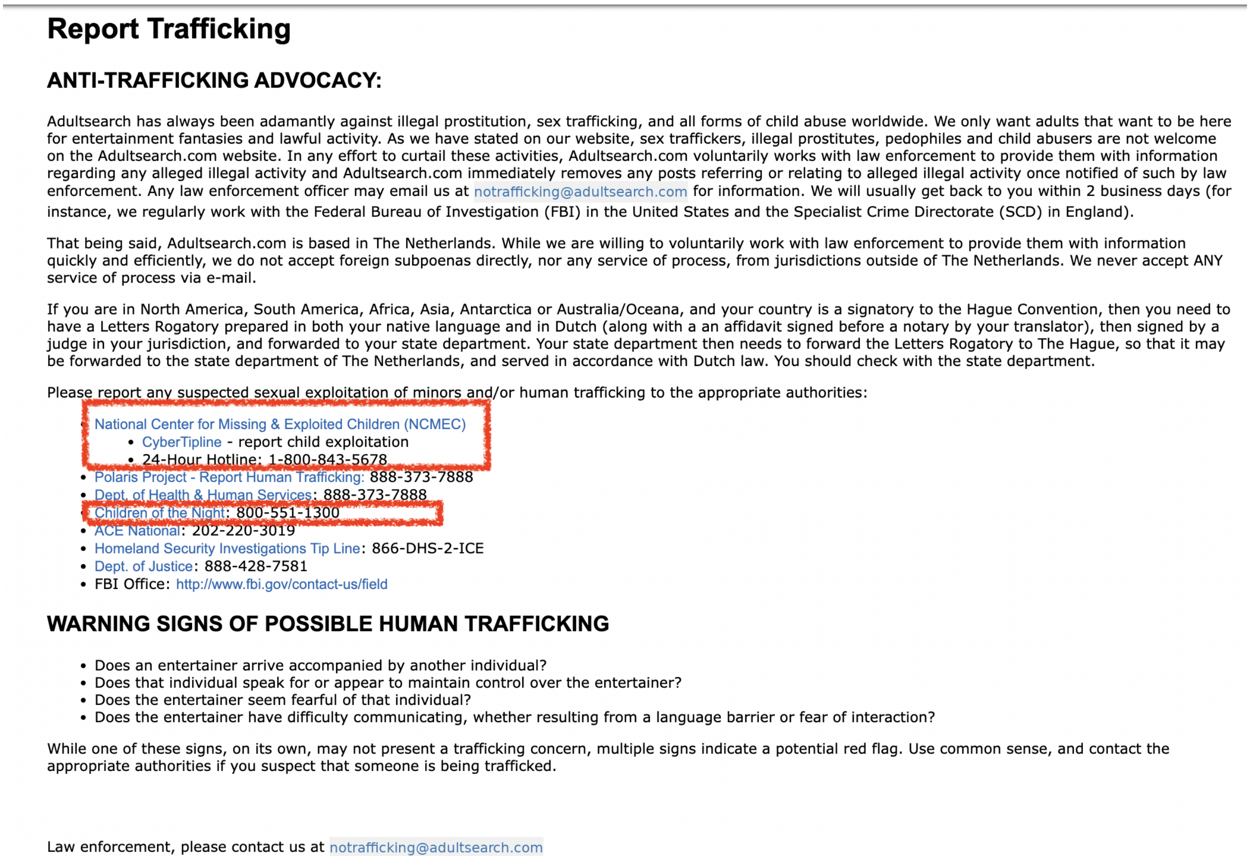
Shepparton
South Melbourne
St Kilda
Sunshine
Thomastown
Traralgon
Warragul

All locations

Albuquerque , Angeles City , Annapolis , Atlanta , Austin , Baltimore , Billings , Boston , Buffalo , Chicago , Dallas , Denv
Hartford , Honolulu , Houston , Jacksonville , Kansas City , Kuala Lumpur , Las Vegas , Little Rock , London , Long Beach ,
Milwaukee , Minneapolis , New Orleans , New York City , Oklahoma City , Orange County , Orlando , Pattaya , Philadelphia , Pho
Saint Louis , Sacramento , San Antonio , San Diego , San Jose , Seattle , SF Bay Area , Shanghai , Singapore , Tampa , Toron
Washington DC

AFFILIATES | ADVERTISING | PRIVACY POLICY | REPORT TRAFFICKING | CONTACT US | BUSINESS OWNERS | GRAB OUR BANNER | RCA

Figure A2: Footnote on the Front Page of Adultsearch on June 24th, 2018



Report Trafficking

ANTI-TRAFFICKING ADVOCACY:

Adultsearch has always been adamantly against illegal prostitution, sex trafficking, and all forms of child abuse worldwide. We only want adults that want to be here for entertainment fantasies and lawful activity. As we have stated on our website, sex traffickers, illegal prostitutes, pedophiles and child abusers are not welcome on the Adultsearch.com website. In any effort to curtail these activities, Adultsearch.com voluntarily works with law enforcement to provide them with information regarding any alleged illegal activity and Adultsearch.com immediately removes any posts referring or relating to alleged illegal activity once notified of such by law enforcement. Any law enforcement officer may email us at notrafficking@adultsearch.com for information. We will usually get back to you within 2 business days (for instance, we regularly work with the Federal Bureau of Investigation (FBI) in the United States and the Specialist Crime Directorate (SCD) in England).

That being said, Adultsearch.com is based in The Netherlands. While we are willing to voluntarily work with law enforcement to provide them with information quickly and efficiently, we do not accept foreign subpoenas directly, nor any service of process, from jurisdictions outside of The Netherlands. We never accept ANY service of process via e-mail.

If you are in North America, South America, Africa, Asia, Antarctica or Australia/Oceana, and your country is a signatory to the Hague Convention, then you need to have a Letters Rogatory prepared in both your native language and in Dutch (along with a an affidavit signed before a notary by your translator), then signed by a judge in your jurisdiction, and forwarded to your state department. Your state department then needs to forward the Letters Rogatory to The Hague, so that it may be forwarded to the state department of The Netherlands, and served in accordance with Dutch law. You should check with the state department.

Please report any suspected sexual exploitation of minors and/or human trafficking to the appropriate authorities:

- National Center for Missing & Exploited Children (NCMEC)
  - CyberTipline - report child exploitation
  - 24-Hour Hotline: 1-800-843-5678
- Polaris Project - Report Human Trafficking: 888-373-7888
- Dept. of Health & Human Services: 888-373-7888
- Children of the Night: 800-551-1300
- ACE National: 202-220-3019
- Homeland Security Investigations Tip Line: 866-DHS-2-ICE
- Dept. of Justice: 888-428-7581
- FBI Office: http://www.fbi.gov/contact-us/field

WARNING SIGNS OF POSSIBLE HUMAN TRAFFICKING

- Does an entertainer arrive accompanied by another individual?
- Does that individual speak for or appear to maintain control over the entertainer?
- Does the entertainer seem fearful of that individual?
- Does the entertainer have difficulty communicating, whether resulting from a language barrier or fear of interaction?

While one of these signs, on its own, may not present a trafficking concern, multiple signs indicate a potential red flag. Use common sense, and contact the appropriate authorities if you suspect that someone is being trafficked.

Law enforcement, please contact us at notrafficking@adultsearch.com

Figure A3: Landing Page for the Newly Added Tab of "*Report Trafficking*" on Adultsearch

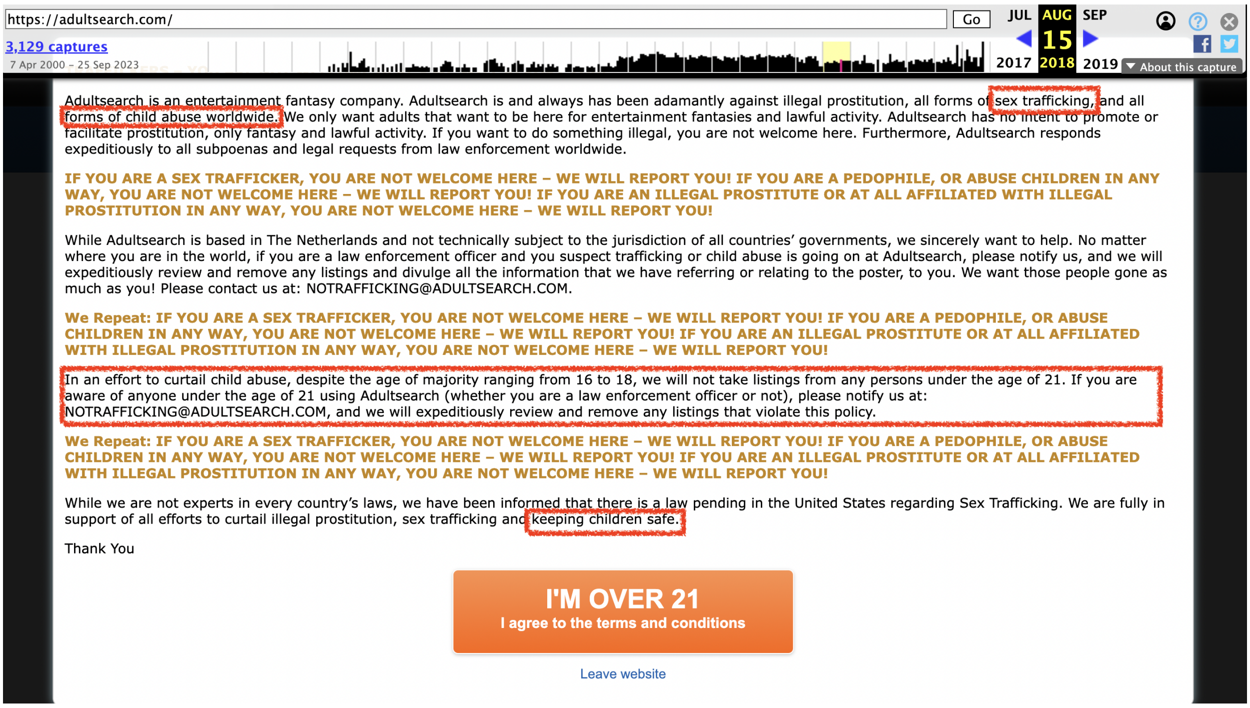


Figure A4: The Newly Launched "Terms and Conditions" Page on Adultsearch

A2: Slixa.com

Similarly, Slixa (*slixa.com*) added a statement titled *"STOP HUMAN TRAFFICKING"* at the bottom of its frontpage after the passage of FOSTA-SESTA (as shown in Figure A5 and Figure A6). The statement includes a link of *trafficking.help*, which connects to a page of anti-trafficking resources (shown in Figure A7).

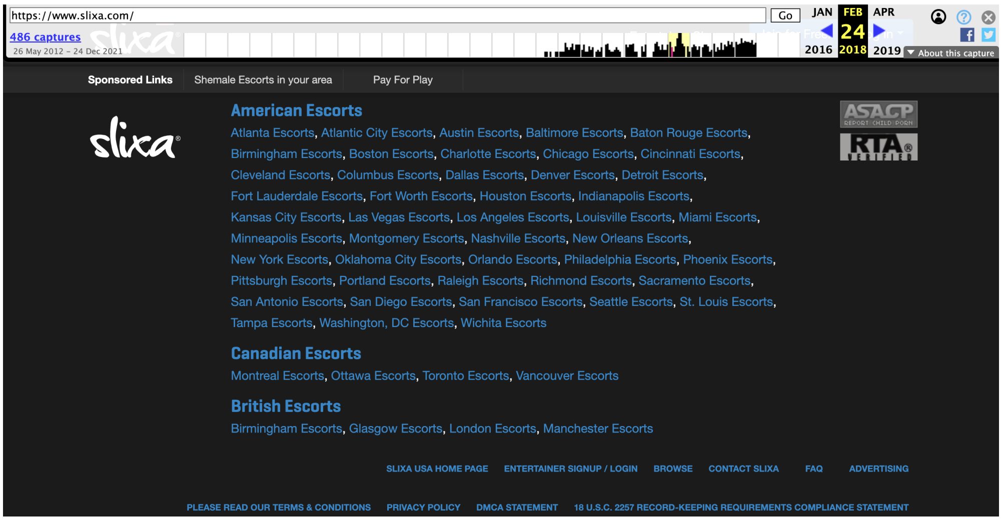


Figure A5: Footnote on the Front Page of Slixa on February 24th, 2018

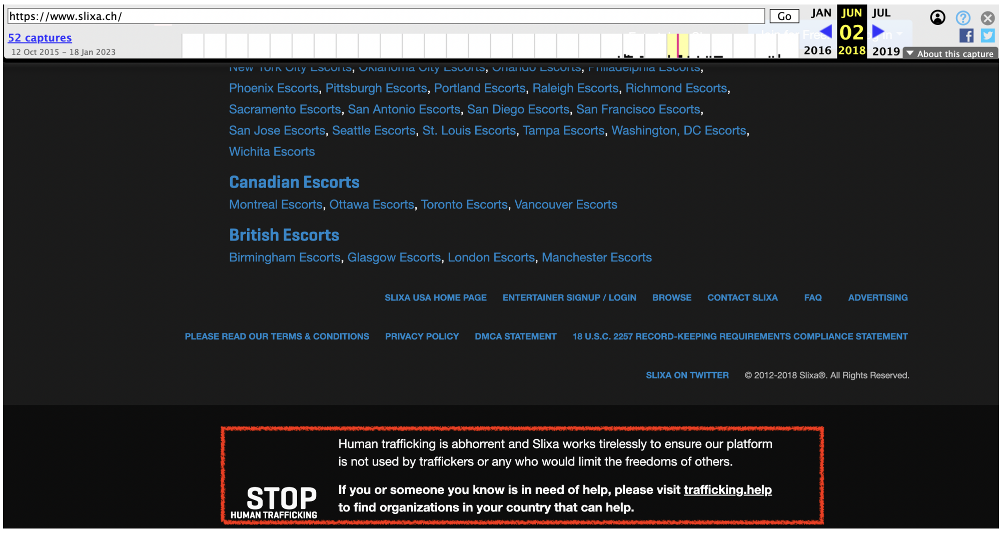


Figure A6: Footnote on the Front Page of Slixa on June 2nd, 2018

National Center for Missing & Exploited Children (NCMEC)

Over the last 31 years, our national toll-free hotline, 1-800-THE-LOST® (1-800-843-5678), has handled more than 4 million calls. With help from corporate partners, we have circulated billions of photos of missing children, and our employees have assisted law enforcement in the recovery of more than 208,000 missing children.

Website: http://www.missingkids.org/home
Phone: 1-800-843-5678 24 hours

CyberTipline

The CyberTipline® receives leads and tips regarding suspected crimes of sexual exploitation committed against children. More than 4.3 million reports of suspected child sexual exploitation have been made to the CyberTipline between 1998 and April 2015. If you have information regarding possible child sexual exploitation, report it to the CyberTipline.

Website: http://www.missingkids.org/cybertipline
Email: at_nationalcoordinator@mrp.gov.al
Phone: 1-800-843-5678 24 hours

National Human Trafficking Resource Center

The National Human Trafficking Resource Center (NHTRC) is a national anti-trafficking hotline and resource center serving victims and survivors of human trafficking and the anti-trafficking community in the United States. The toll-free hotline is available to answer calls from anywhere in the country, 24 hours a day, 7 days a week, every day of the year in more than 200 languages.

Website: https://traffickingresourcecenter.org/
Phone: 1-888-373-7888

Children of the Night

The Children of the Night home is open to child prostitutes throughout the United States, and the Children of the Night hotline is ready and able to rescue these children 24 hours a day. We provide free taxi/airline transportation nationwide for America's child prostitutes who wish to escape prostitution and live in our home.

Website: https://www.childrenofthenight.org/
Phone: 1.800.551.1300

Recognizing the Signs of Human Trafficking

The National Human Trafficking Hotline maintains a list of potential red flags and indicators of human trafficking to help you recognize some of the signs of human trafficking.

Common Work and Living Conditions

- Is not free to leave or come and go as he/she wishes
- Is in the commercial sex industry and has a pimp / manager
- Is unpaid, paid very little, or paid only through tips
- Owes a large debt and is unable to pay it off
- Was recruited through false promises concerning the nature and conditions of his/her work
- High security measures exist in the work and/or living locations (e.g. opaque windows, boarded up windows, bars on windows, barbed wire, security cameras, etc.)

Lack of Control

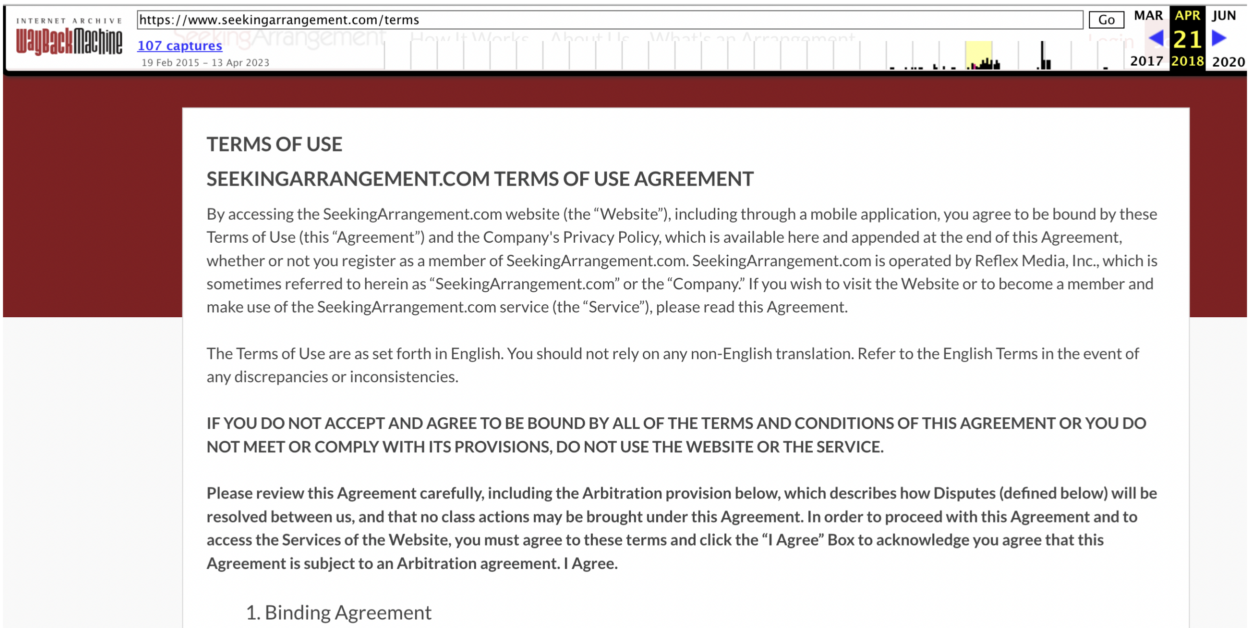
- Has few or no personal possessions
- Is not in control of his/her own money, no financial records, or bank account
- Is not in control of his/her own identification documents (ID or passport)
- Is not allowed or able to speak for themselves (a third party may insist on being present and/or translating)

This is only a partial list, please visit humantraffickinghotline.org for more information. If you believe you are a victim of human trafficking or someone who is, please contact one of the organizations listed on this page.

Figure A7: The Page for *trafficking.help* in the Newly Added Section of "*STOP HUMAN TRAFFICKING*" on Slixa

A3: Seekingarrangement.com

The prostitution website[38] Seekingarrangement (*seekingarrangement.com*), updated their terms of use on May 8th 2018. Figure A8 and Figure A9 show the users' terms of seekingarrangement in April and May 2018 respectively. In its updated terms of use, Seekingarrangement highlights provisions that prohibit the use of the website for human trafficking, along with penalties for users who post or send materials exploiting individuals under the age of 18 (shown in Figure A10).



TERMS OF USE

SEEKINGARRANGEMENT.COM TERMS OF USE AGREEMENT

By accessing the SeekingArrangement.com website (the "Website"), including through a mobile application, you agree to be bound by these Terms of Use (this "Agreement") and the Company's Privacy Policy, which is available here and appended at the end of this Agreement, whether or not you register as a member of SeekingArrangement.com. SeekingArrangement.com is operated by Reflex Media, Inc., which is sometimes referred to herein as "SeekingArrangement.com" or the "Company." If you wish to visit the Website or to become a member and make use of the SeekingArrangement.com service (the "Service"), please read this Agreement.

The Terms of Use are as set forth in English. You should not rely on any non-English translation. Refer to the English Terms in the event of any discrepancies or inconsistencies.

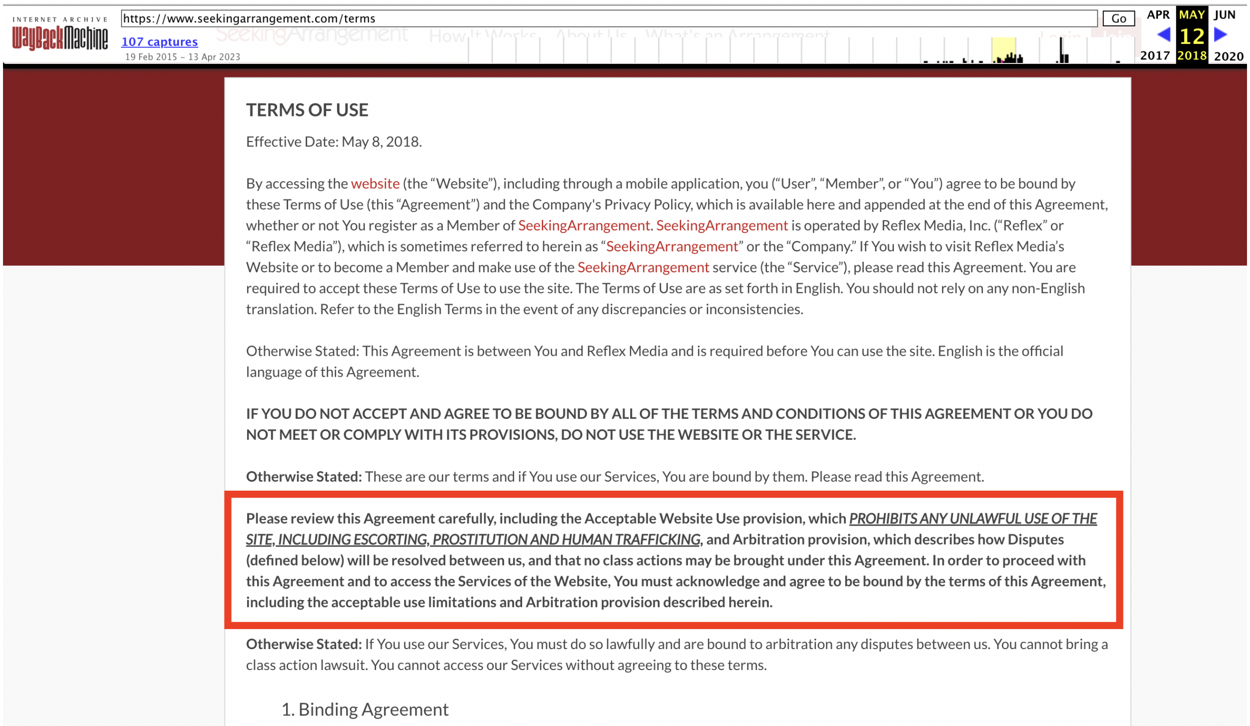
IF YOU DO NOT ACCEPT AND AGREE TO BE BOUND BY ALL OF THE TERMS AND CONDITIONS OF THIS AGREEMENT OR YOU DO NOT MEET OR COMPLY WITH ITS PROVISIONS, DO NOT USE THE WEBSITE OR THE SERVICE.

Please review this Agreement carefully, including the Arbitration provision below, which describes how Disputes (defined below) will be resolved between us, and that no class actions may be brought under this Agreement. In order to proceed with this Agreement and to access the Services of the Website, you must agree to these terms and click the "I Agree" Box to acknowledge you agree that this Agreement is subject to an Arbitration agreement. I Agree.

1. Binding Agreement

Figure A8: Terms of Use on Seekingarrangement on April 21st, 2018

[38] See https://endsexualexploitation.org/seekingarrangement/.



https://www.seekingarrangement.com/terms Go APR MAY JUN

107 captures 12

19 Feb 2015 - 13 Apr 2023 2017 2018 2020

TERMS OF USE

Effective Date: May 8, 2018.

By accessing the website (the "Website"), including through a mobile application, you ("User", "Member", or "You") agree to be bound by these Terms of Use (this "Agreement") and the Company's Privacy Policy, which is available here and appended at the end of this Agreement, whether or not You register as a Member of SeekingArrangement. SeekingArrangement is operated by Reflex Media, Inc. ("Reflex" or "Reflex Media"), which is sometimes referred to herein as "SeekingArrangement" or the "Company." If You wish to visit Reflex Media's Website or to become a Member and make use of the SeekingArrangement service (the "Service"), please read this Agreement. You are required to accept these Terms of Use to use the site. The Terms of Use are as set forth in English. You should not rely on any non-English translation. Refer to the English Terms in the event of any discrepancies or inconsistencies.

Otherwise Stated: This Agreement is between You and Reflex Media and is required before You can use the site. English is the official language of this Agreement.

IF YOU DO NOT ACCEPT AND AGREE TO BE BOUND BY ALL OF THE TERMS AND CONDITIONS OF THIS AGREEMENT OR YOU DO NOT MEET OR COMPLY WITH ITS PROVISIONS, DO NOT USE THE WEBSITE OR THE SERVICE.

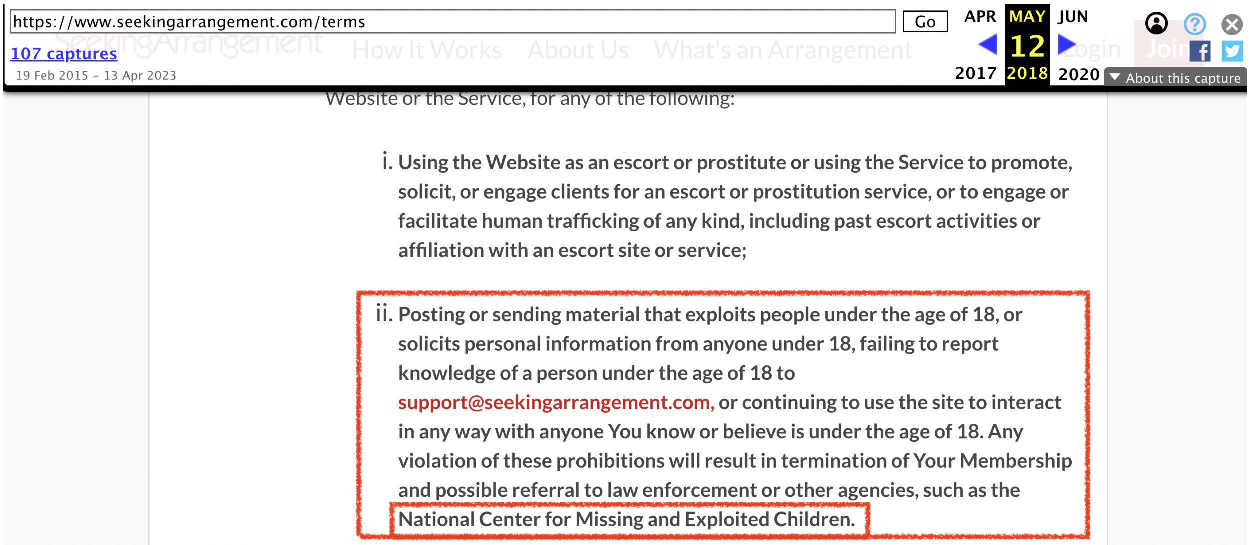
Otherwise Stated: These are our terms and if You use our Services, You are bound by them. Please read this Agreement.

Please review this Agreement carefully, including the Acceptable Website Use provision, which *PROHIBITS ANY UNLAWFUL USE OF THE SITE, INCLUDING ESCORTING, PROSTITUTION AND HUMAN TRAFFICKING*, and Arbitration provision, which describes how Disputes (defined below) will be resolved between us, and that no class actions may be brought under this Agreement. In order to proceed with this Agreement and to access the Services of the Website, You must acknowledge and agree to be bound by the terms of this Agreement, including the acceptable use limitations and Arbitration provision described herein.

Otherwise Stated: If You use our Services, You must do so lawfully and are bound to arbitration any disputes between us. You cannot bring a class action lawsuit. You cannot access our Services without agreeing to these terms.

1. Binding Agreement

Figure A9: Updates on the Terms of Use on Seekingarrangement on May 8th, 2018



https://www.seekingarrangement.com/terms Go APR MAY JUN

107 captures 12

19 Feb 2015 - 13 Apr 2023 2017 2018 2020 About this capture

Website or the Service, for any of the following:

i. Using the Website as an escort or prostitute or using the Service to promote, solicit, or engage clients for an escort or prostitution service, or to engage or facilitate human trafficking of any kind, including past escort activities or affiliation with an escort site or service;

ii. Posting or sending material that exploits people under the age of 18, or solicits personal information from anyone under 18, failing to report knowledge of a person under the age of 18 to support@seekingarrangement.com, or continuing to use the site to interact in any way with anyone You know or believe is under the age of 18. Any violation of these prohibitions will result in termination of Your Membership and possible referral to law enforcement or other agencies, such as the National Center for Missing and Exploited Children.

Figure A10: Added Penalty Terms for Materials Exploiting Minors on Seekingarrangement

A4: USAsexguide.nl

USAsexguide.nl is a new escort review site launched after the passage of FOSTA-SESTA, as a replacement for "the Erotic Review" which blocked access to its site for US users after the passage of FOSTA-SESTA. *USAsexguide.nl* includes a tab labeled "Underage Policy" in its navigation menu on the front page, as shown in Figure A11. The specific terms in the "Underage Policy" are shown in Figure A12, which emphasizes the website's rules against posting materials for the sexual exploitation of minors.

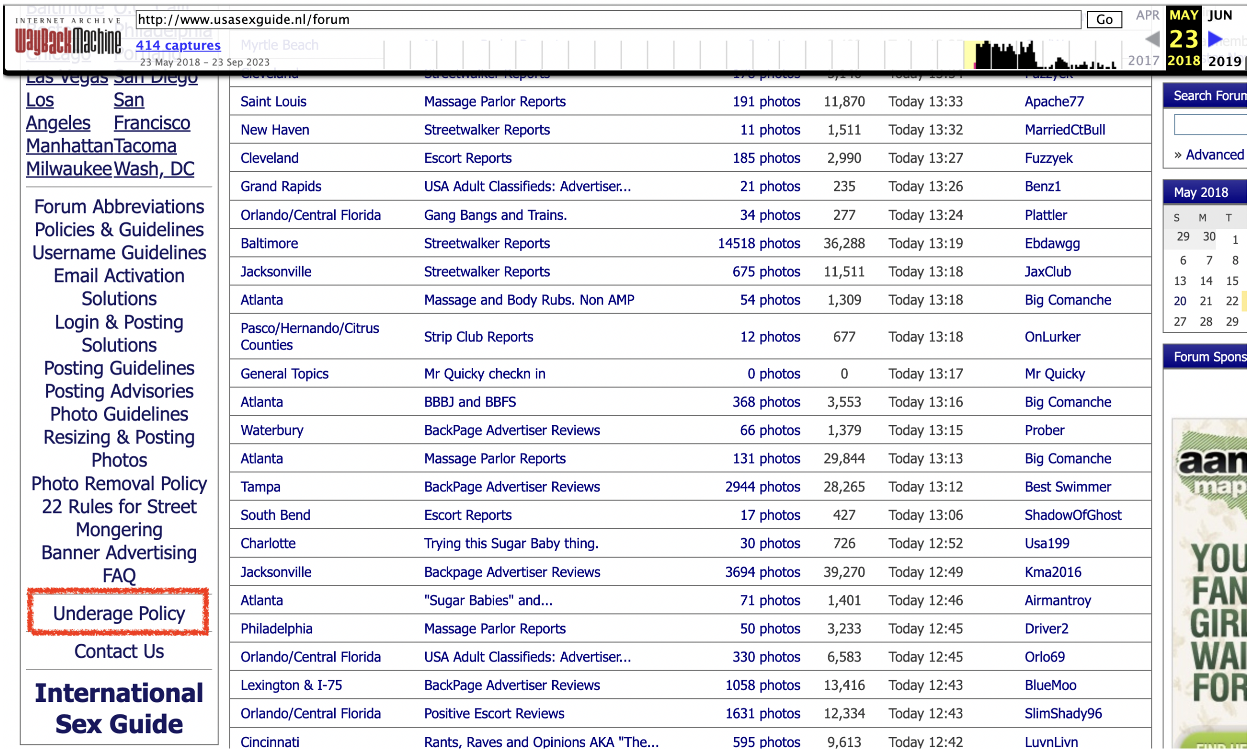


Figure A11: "Underage Policy" on the Front Page of *USAsexguide.nl*

Underage Policy

Why does this site prohibit discussions of sex with persons under the age of 18?

First, it amazes me that I even need to state what I consider to be obvious facts, but ocassional discussions in the forum have illustrated to me that some people just don't get it. Therefore, I'm going to make these arguments for the sake of those among us who have difficulty realizing their responsibilities to the human race.

1. As MEN, it is our responsibility to protect women and children.
2. Underage persons, as the most vulnerable members of the human race, are especially deserving of our protection.
3. Regardless of the specific age when a female has passed biological puberty, young females are not EMOTIONALLY capable of handling the EMOTIONAL turmoil of prostitution. If you have any teenage daughters yourself, or if you have any friends with teenage daughters, this observation is self-evident.
4. As educated, intelligent, civilized men, we are expected by our peers to operate on a higher moral plain in these matters than other cultures may tolerate. Therefore, we do not participate in the exploitation of underage persons, regardless of the behavior of others.

I hope that those of you who may have been confused on this subject now have an understanding of your responsibility to protect underage persons, not exploit them under the justification that others have already done so first. However, because I know that some of you will postulate the usual justifications for this immoral and reprehensible behavior, let me respond to these common arguments:

1. "*Hey man, lighten up. In these girl's cultures they start having sex as soon as they pass puberty, and many girls here get married very young.*"
   - First, it doesn't matter if the indigenous culture is willing to exploit these girls, as an educated, intelligent, civilized man, you are expected to refrain from this type of exploitation.
   - Second, there is a big difference between getting married and engaging in prostitution. When a young woman gets married, she receives the emotional support of her immediate family and friends, and theoretically a supportive husband. Conversely, when a young woman gets involved in prostitution, she is typically thrust into a situation where she receives no emotional support, and in fact is usually confronted with mental and physical stress.
2. "*These girls need the money to buy food and to eat. It's wrong to deny them the only method by which they can earn enough money to survive. I think I'm doing a good thing by fucking them for money.*"
   - Don't kid yourself, the prostitution business isn't big enough to make an appreciable dent in the suffering of underage persons in these countries. The unfortunate reality is that in many of these countries, many underage persons are suffering from lack of basic necessities, including food. The fact that a small fraction of one percent earns money for food through prostitution isn't exactly a universal solution.
   - If you genuinely want to help these underage persons, then give them a few bucks for food. Now, I know that this advice would make a Tri-F (find them, fuck them, forget them) explode in anger, but you can afford it, and in fact you'll never know it's gone.
3. "*You call them "girls" but many of them are battle-hardened veterans by the time they're 16. It doesn't matter if I pay them for sex, they're used to it.*"
   - Let me see if I understand this argument: It's okay to victimize somebody who's been victimized before? So I guess it's okay to rob somebody who's already been robbed, and I guess it's also okay to rape a woman who was raped before? Come on guys, just because someone is already a victim doesn't give you license to continue the abuse.

The Forum has a Zero Tolerance policy regarding prohibiting reports containing any references to any persons under the age of 18. Please read the Forum's Posting Guidelines for further information. Persons violating this policy will have their membership terminated immediately.
Please remember, this is a website for MEN who were always men looking for sex with WOMEN who were always women.

As always, your comments are welcomed.

Figure A12: Terms in "Underage Policy" of *USAsexguide.nl*

Appendix B: Tables and Figures

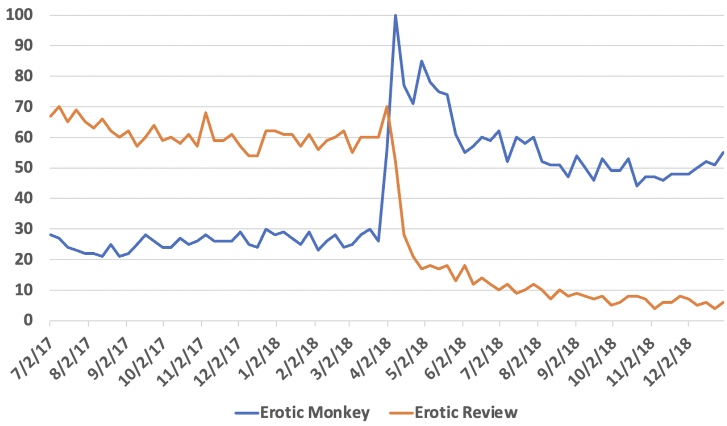


Figure B1: Google Trends Search Index for *"Erotic Monkey"* and *"Erotic Review"*

Table B1: Descriptions of Control Variables for Data from *"Erotic Monkey"*

Feature	**Description**
	Erotic Monkey
Incall	Dummy variable for escort "incall" service, 1 for "incall" rate and 0 for "outcall"
Extreme services	Average number of extreme services offered by providers
Email	Dummy variable indicating whether the provider's email address is listed, 1 for yes and 0 for no
Website	Dummy variable indicating whether the provider's personal website is listed, 1 for yes and 0 for no
Answer	Dummy variable indicating whether the provider answers the phone call, 1 for yes and 0 for no
Photo real	Dummy variable indicating whether the provider's photo is real, 1 for yes and 0 for no
Photo updated	Dummy variable indicating whether the provider's photo is updated, 1 for yes and 0 for no
White	Dummy variable for white ethnicity
Black	Dummy variable for Black ethnicity
Asian	Dummy variable for Asian ethnicity
Transsexual	Dummy variable indicating whether the provider is transsexual or not, 1 for yes and 0 for no
Implant	Dummy variable indicating whether the provider has breast implants, 1 for yes and 0 for no
Smoke	Dummy variable indicating whether the provider smokes, 1 for yes and 0 for no
Shave	Dummy variable indicating whether the provider is shaved, 1 for yes and 0 for no
Tattoo	Dummy variable indicating whether the provider has tattoos, 1 for yes and 0 for no
Pornstar	Dummy variable indicating whether the provider is a porn star, 1 for yes and 0 for no
Punctuality	Dummy variable indicating whether the provider is punctual, 1 for yes and 0 for no

Table B2: Summary Statistics of Control Variables for Data from *"Erotic Monkey"*

Variable	N	Mean	Std. Dev.	Min	Max
Data for OLS Regression in Table 3					
Incall	4,730	0.867	0.340	0	1
Extreme services	4,730	4.308	1.846	1	18
Email	4,730	0.504	0.500	0	1
Website	4,730	0.329	0.470	0	1
Answer	4,730	1.000	0.021	0	1
Photo real	4,730	0.986	0.116	0	1
Photo updated	4,730	0.961	0.194	0	1
White	4,730	0.507	0.500	0	1
Black	4,730	0.057	0.231	0	1
Asian	4,730	0.212	0.409	0	1
Transsexual	4,730	0.038	0.190	0	1
Implant	4,730	0.149	0.356	0	1
Smoke	4,730	0.027	0.163	0	1
Shave	4,730	0.991	0.093	0	1
Tattoo	4,730	0.094	0.290	0	1
Pornstar	4,730	0.044	0.206	0	1
Punctuality	4,730	0.898	0.303	0	1
Data for DMLDiD in Table 4					
Incall	1,255	1	0	1	1
Extreme Services	1,255	3.775	0.690	2.533	6.333
Email	1,255	0.278	0.448	0	1
Website	1,255	0.084	0.278	0	1
Answer	1,255	1	0	1	1
Photo real	1,255	1	0	1	1
Photo updated	1,255	1	0	1	1
White	1,255	0.648	0.478	0	1
Black	1,255	0.049	0.215	0	1
Asian	1,255	0.183	0.387	0	1
Transsexual	1,255	0	0	0	0
Implant	1,255	0	0	0	0
Smoke	1,255	0	0	0	0
Shave	1,255	1	0	1	1
Tattoo	1,255	0	0	0	0
Pornstar	1,255	0	0	0	0
Punctuality	1,255	1	0	1	1

Table B3: Descriptions of Variables for Data from *"the Erotic Review"*

Feature	**Description**
	The Erotic Review
	Main Variables
18-20	Dummy variable for age group of 18-20
21-25	Dummy variable for age group of 21-25
31-35	Dummy variable for age group of 31-35
36-40	Dummy variable for age group of 36-40
41-45	Dummy variable for age group of 41-45
46-50	Dummy variable for age group of 46-50
Over 50	Dummy variable for age group of over 50
	Control Variables
Extreme services	Number of extreme services offered by providers
Email	Dummy variable indicating whether the provider's email address is listed, 1 for yes and 0 for no
Website	Dummy variable indicating whether the provider's personal website is listed, 1 for yes and 0 for no
Additional phone	Dummy variable indicating whether the provider lists more than one phone number in the contact information, 1 for yes and 0 for no
Photo real	Dummy variable indicating whether the provider's photo is real, 1 for yes and 0 for no
White	Dummy variable for white ethnicity
Black	Dummy variable for Black ethnicity
Asian	Dummy variable for Asian ethnicity
Transsexual	Dummy variable indicating whether the provider is transsexual or not, 1 for yes and 0 for no
Implant	Dummy variable indicating whether the provider has breast implants, 1 for yes and 0 for no
Smoke	Dummy variable indicating whether the provider smokes, 1 for yes and 0 for no
Shave	Dummy variable indicating whether the provider is shaved, 1 for yes and 0 for no
Tattoo	Dummy variable indicating whether the provider has tattoos, 1 for yes and 0 for no
Pornstar	Dummy variable indicating whether the provider is a porn star, 1 for yes and 0 for no
Punctuality	Dummy variable indicating whether the provider is punctual, 1 for yes and 0 for no
English	Dummy variable indicating whether the provider can speak English, 1 for yes and 0 for no
Other city	Dummy variable indicating whether the provider offers services in another city, 1 for yes and 0 for no
Piercing	Dummy variable indicating whether the provider has piercings, 1 for yes and 0 for no
Promise	Dummy variable indicating whether the service is delivered as promised, 1 for yes and 0 for no

Note: Items on the list of extreme services on TER are different from those on *"Erotic Monkey"*.

Table B4: Summary Statistics for Data from *"the Erotic Review"*

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
$ln(hour\ rate)$	4,441	5.593	0.481	3.689	7.650
18-20	4,441	0.042	0.201	0	1
21-25	4,441	0.450	0.498	0	1
31-35	4,441	0.112	0.315	0	1
36-40	4,441	0.050	0.219	0	1
41-45	4,441	0.026	0.158	0	1
46-50	4,441	0.011	0.103	0	1
Over 50	4,441	0.008	0.090	0	1
Extreme services	4,441	6.517	2.830	0	17
Email	4,441	0.491	0.500	0	1
Website	4,441	1.000	0.015	0	1
Additional phone	4,441	0.092	0.289	0	1
Photo real	4,441	0.845	0.362	0	1
White	4,441	0.360	0.480	0	1
Black	4,441	0.067	0.251	0	1
Asian	4,441	0.225	0.418	0	1
Transsexual	4,441	0.031	0.174	0	1
Implant	4,441	0.182	0.386	0	1
Smoke	4,441	0.014	0.117	0	1
Shave	4,441	0.876	0.329	0	1
Tattoo	4,441	0.468	0.499	0	1
Pornstar	4,441	0.021	0.142	0	1
Punctuality	4,441	0.852	0.355	0	1
English	4,441	0.966	0.182	0	1
Other city	4,441	0.001	0.034	0	1
Piercing	4,441	0.487	0.500	0	1
Promise	4,441	0.895	0.307	0	1

Estimated Matrix $\hat{\Omega}$

		True age group				
		"Below 18"	"18-24"	"25-36"	"37-45"	"45+"
Reported age group	"18-24"	0.999	0.762	0.018	0.013	0.028
	"25-36"	0.001	0.199	0.976	0.042	0.016
	"37-45"	0	0.026	0.005	0.937	0.028
	"45+"	0	0.013	0.002	0.008	0.927

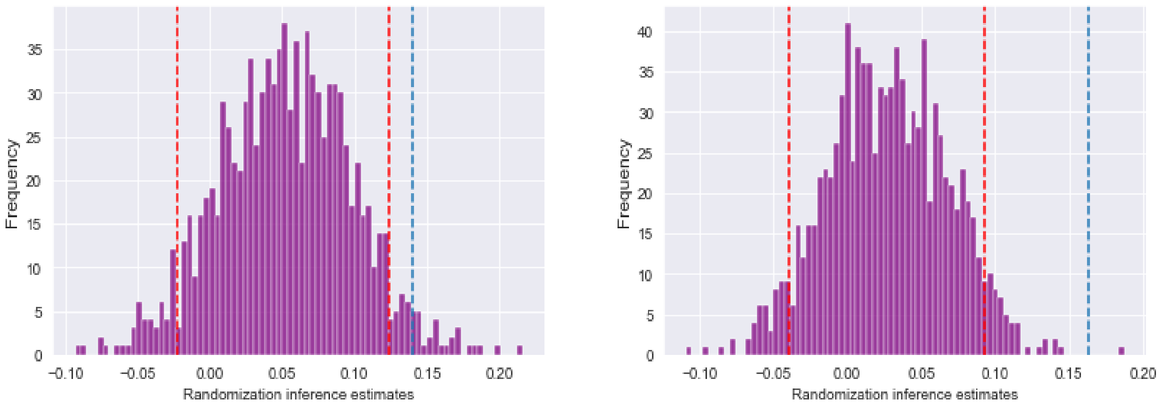


Figure B2: Distribution of Estimates for α in (5.1) with 1,000 Randomized Age Assignments for Inference with Providers' Ages Identified Using "Simple Approach" (Left) and "Age Estimation Algorithm" (Right). Blue Dashed Line is the True Effect; Red Dashed Lines are 5th and 95th Percentiles.

Table B5: OLS Regression Results for (5.1)

Dependent variable	ln(hour rate)					
	(1)	(2)	(3)	(4)	(5)	(6)
Youngest Age Group$_p$ $*$ *Post*$_{pi}$	0.140***	0.114*	0.213**	0.163***	0.095*	0.125
	(0.047)	(0.060)	(0.104)	(0.045)	(0.055)	(0.089)
Youngest Age Group$_p$ $*$ *Post*$_{pi}$ $* \mathbb{1}($*Extreme Services* $> 3)$		0.068			0.198**	
		(0.076)			(0.091)	
Youngest Age Group$_p$ $*$ *Post*$_{pi}$ $* white$			-0.120			0.043
			(0.110)			(0.102)
Youngest Age Group$_p$ $*$ *Post*$_{pi}$ $* Black$			-0.056			0.025
			(0.169)			(0.156)
Youngest Age Group$_p$ $*$ *Post*$_{pi}$ $* Asian$			0.055			0.146
			(0.139)			(0.126)
Youngest Age Group$_p$	-0.016	-0.016	-0.016	-0.007	-0.008	-0.008
	(0.031)	(0.031)	(0.031)	(0.034)	(0.034)	(0.034)
Age Group 37-45	-0.082**	-0.082**	-0.082**	-0.113***	-0.113***	-0.113***
	(0.038)	(0.038)	(0.038)	(0.042)	(0.042)	(0.042)
Age Group 45+	-0.318***	-0.318***	-0.319***	-0.209***	-0.208***	-0.209***
	(0.056)	(0.056)	(0.056)	(0.047)	(0.047)	(0.047)
white	0.070**	0.069**	0.073**	0.064**	0.062**	0.063**
	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.031)
Black	-0.138***	-0.138***	-0.138***	-0.142***	-0.142***	-0.142***
	(0.045)	(0.045)	(0.047)	(0.045)	(0.045)	(0.047)
Asian	-0.054	-0.054	-0.053	-0.049	-0.050	-0.051
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.039)
Extreme Services	0.044***	0.044***	0.044***	0.043***	0.042***	0.043***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Incall	-0.109***	-0.109***	-0.109***	-0.109***	-0.109***	-0.109***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Email	0.223***	0.223***	0.223***	0.226***	0.226***	0.227***
	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)
Website	0.080***	0.080***	0.080***	0.075**	0.075**	0.075**
	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)
Answer	0.273***	0.274***	0.272***	0.252***	0.253***	0.251***
	(0.061)	(0.062)	(0.062)	(0.061)	(0.061)	(0.062)
Photo real	0.059	0.060	0.058	0.017	0.018	0.016
	(0.098)	(0.098)	(0.098)	(0.103)	(0.103)	(0.103)
Photo updated	-0.079	-0.079	-0.079	-0.033	-0.034	-0.033
	(0.076)	(0.076)	(0.076)	(0.087)	(0.087)	(0.087)
Transsexual	-0.067	-0.067	-0.066	-0.062	-0.062	-0.062
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
Implant	0.231***	0.231***	0.231***	0.229***	0.230***	0.229***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Smoke	-0.080	-0.080	-0.081	-0.082	-0.082	-0.082
	(0.056)	(0.056)	(0.056)	(0.059)	(0.059)	(0.059)
Shave	-0.006	-0.006	-0.006	0.011	0.012	0.011
	(0.091)	(0.091)	(0.091)	(0.104)	(0.104)	(0.104)
Tattoo	-0.069	-0.069	-0.069	-0.066	-0.066	-0.066
	(0.046)	(0.046)	(0.046)	(0.047)	(0.047)	(0.047)
Porn star	0.136	0.136	0.136	0.132	0.131	0.132
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Punctuality	0.071*	0.071*	0.072*	0.054	0.054	0.054
	(0.040)	(0.040)	(0.040)	(0.041)	(0.041)	(0.041)
Youngest Age Group$_p$	Reported as "18-24" in all reviews	Reported as "18-24" in all reviews	Reported as "18-24" in all reviews	Underage	Underage	Underage
Age identification strategy	Simple approach	Simple approach	Simple approach	Age estimation algorithm	Age estimation algorithm	Age estimation algorithm
Observations	4,730	4,730	4,730	4,730	4,730	4,730
Clusters	1,838	1,838	1,838	1,838	1,838	1,838

Robust standard errors clustered at individual provider level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B6: OLS Regression Results for (6.1)

Dependent variable	ln(hour rate)	
	(1)	(2)
Youngest Age Group$_p$ $*$ *month*$_{-8}$	0.073	0.005
	(0.138)	(0.168)
Youngest Age Group$_p$ $*$ *month*$_{-7}$	0.045	-0.027
	(0.138)	(0.168)
Youngest Age Group$_p$ $*$ *month*$_{-6}$	0.041	-0.037
	(0.155)	(0.178)
Youngest Age Group$_p$ $*$ *month*$_{-5}$	0.169	0.103
	(0.164)	(0.190)
Youngest Age Group$_p$ $*$ *month*$_{-4}$	0.242	0.072
	(0.192)	(0.193)
Youngest Age Group$_p$ $*$ *month*$_{-3}$	0.118	0.079
	(0.191)	(0.218)
Youngest Age Group$_p$ $*$ *month*$_{-2}$	0.223	0.137
	(0.169)	(0.195)
Youngest Age Group$_p$ $*$ *month*$_{1}$	0.474**	0.404*
	(0.195)	(0.206)
Youngest Age Group$_p$ $*$ *month*$_{2}$	0.265*	0.147
	(0.160)	(0.184)
Youngest Age Group$_p$ $*$ *month*$_{3}$	0.191	0.138
	(0.246)	(0.246)
Youngest Age Group$_p$ $*$ *month*$_{4}$	0.215	0.250
	(0.144)	(0.200)
Youngest Age Group$_p$ $*$ *month*$_{5}$	0.390**	0.241
	(0.163)	(0.187)
Youngest Age Group$_p$ $*$ *month*$_{6}$	0.175	0.049
	(0.158)	(0.190)
Youngest Age Group$_p$ $*$ *month*$_{7}$	0.179	0.128
	(0.160)	(0.185)
Youngest Age Group$_p$ $*$ *month*$_{8}$	0.137	0.192
	(0.167)	(0.208)
Youngest Age Group$_p$ $*$ *month*$_{9}$	0.142	0.139
	(0.207)	(0.222)
Youngest Age Group$_p$ $*$ *month*$_{10}$	0.235	0.256
	(0.167)	(0.188)
Youngest Age Group$_p$	Reported as “18-24” in all reviews	Underage
Age identification strategy	Simple approach	Age estimation algorithm
Observations	4,730	4,730
Clusters	1,838	1,838

Robust standard errors clustered at individual provider level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B7: DMLDiD Results for (5.2)-(5.6) with Fake Treatment Time

	"Fake" treatment effect θ	
Fake treatment time	(1)	(2)
March 2017	-0.019	-0.083
	(0.051)	(0.055)
April 2017	-0.035	-0.059
	(0.039)	(0.043)
May 2017	-0.044	-0.056
	(0.039)	(0.037)
June 2017	-0.030	-0.055
	(0.036)	(0.034)
July 2017	-0.046	-0.025
	(0.039)	(0.035)
August 2017	0.037	0.015
	(0.040)	(0.038)
September 2017	0.045	0.020
	(0.037)	(0.039)
October 2017	0.063	0.015
	(0.057)	(0.049)
Youngest Age Group$_p$	Reported as "18-24" in all reviews	Underage
Age identification strategy	Simple approach	Age estimation algorithm

Standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B8: OLS Regression Results for (5.1) with Randomization Inference with 1,000 Draws

Dependent Variable	$ln(hour\ rate_{pi})$	
	(1)	(2)
True effect	0.140	0.163
5-th percentile	-0.023	-0.040
95-th percentile	0.124	0.093
p-value	0.027	0.002
Youngest Age Group$_p$	Reported as "18-24" in all reviews	Underage
Age identification strategy	Simple approach	Age estimation algorithm

Appendix C: Results on the Data from "the Erotic Review"

We seek evidence of the relative increase in prices for service providers from the *youngest age group* after the passage of FOSTA-SESTA using data from *"the Erotic Review"* (TER). As mentioned in the data section, TER is different from *"Erotic Monkey"* in that it only provides the most recent information for each service provider. Namely, TER lists the provider's information, including general characteristics, types of sexual services the individual offers along with the prices for those services, on the providers' profile pages. The information listed is updated when the provider received the last review or last changed their profile. Thus, unlike the historical price data we obtained from *"Erotic Monkey"*, we only get to access the most recent price for each service provider for data scraped from TER. Each provider is listed in one of the following age groups on their profile: "18-20", "21-25", "26-30", "31-35", "36-40", "41-45", "46-50" and "over 50." Since each of the providers only gets their age reported at one time stamp, we don't need to "estimate" the providers' true age as we did for data from *"Erotic Monkey"*.

We study the impact of FOSTA-SESTA on prices charged by participants listed in the *youngest age group*, i.e., "18-20", by using sellers from other age bins as a control. Again, we focus on the same period of time from July 2017 to December 2018 as in the main results section. The providers included in our sample are the ones whose last activity time on the website is in the study window. As mentioned earlier, TER blocked access to its site from the United States in April 2018, which leaves us very limited amount of data in the post period.[39] We identify the underlying price change for service providers listed in the *youngest age group* on the site of *"the Erotic Review"* with the following model (similar to (5.1)):

$$ln(\mathit{hour\ rate}_p^{TER}) = \alpha^{TER} * \mathit{Age\ Group\ 18\text{-}20} * \mathit{Post}_p + \beta^{TER} * X_p^{TER} + FE_{month}^{TER} + FE_{city}^{TER} + \varepsilon_p \tag{8.1}$$

where the variables are defined as in (5.1) with the superscript *TER* notating the data from *"the Erotic Review"*. $ln(\mathit{hour\ rate}_p^{TER})$ is the most recent hourly price of provider p, *Age Group 18-20* is the dummy that takes the value of 1 if provider p is listed in the 18-20 age group and 0 otherwise, and Post_p is a dummy variable that equals to 1 if the last update time of the provider's profile is after the passage of FOSTA-SESTA. X_p^{TER} are a series of confounding variables listed on the site of TER that could affect price.[40] FE_{month}^{TER} and FE_{city}^{TER} represent a vector of *month*- and *city*-fixed effects, and ε_p is the error term. α^{TER} is our coefficient of interest and represents the change in price of the *youngest age group* participants after the bills' passage relative to that of other (older) age groups.

[39] Data from the *"the Erotic Review"* only covers March and April 2018 in the post period with no data point from the period of May to December 2018.

[40] TER has slightly different coding systems from *"Erotic Monkey"*. The information on the control variables are included in Table B3 and Table B4.

Results for (8.1) are presented in column (1) of Table C1. This table shows that using the TER data, we observe a 13.4% higher increase in price after the passage of FOSTA-SESTA for participants listed in the *youngest age group*, i.e., 18-20.

To check the robustness of this result, we conduct a placebo test where we use other age groups as the treated group and repeat the analysis in (8.1) with those groups. The results of this robustness exercise are presented in column (2) to (8) of Table C1. As can be seen from the table, all the estimates are statistically indistinguishable from 0 when using providers from older age bins as the treated group. In summary, we don't identify a statistically meaningful difference in price for service providers listed in older age groups.

The primary limitation of the results using data from TER lies in the existence of the large gap of missing in the data in the post period from this site. However, the estimates largely replicate the results for the corresponding coefficient of interest using data from *"Erotic Monkey"*, and the TER effects are close in both magnitude and precision to the *"Erotic Monkey"* results reported in the main body of the paper.

Table C1: OLS Regression Results for (8.1)

Dependent variable	ln(hour rate)							
Age group as treatment	**18-20**	**21-25**	**26-30**	**31-35**	**36-40**	**41-45**	**46-50**	**over 50**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group*After	0.134**	-0.021	-0.028	0.047	-0.011	0.056	-0.141	0.079
	(0.054)	(0.024)	(0.026)	(0.039)	(0.059)	(0.097)	(0.159)	(0.193)
Observations	4,441	4,441	4,441	4,441	4,441	4,441	4,441	4,441

Standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$