# Can Increased Platform Liability Reduce Sex Trafficking? Evidence from the Price Effect

(Authors' names blinded for peer review)

*Digital platforms generate substantial welfare gains but also new negative externalities. Platform liability has emerged as a debated policy tool for addressing these externalities and aligning private incentives with social welfare. We exploit a U.S. law that imposed liability on platforms facilitating trafficking of minors to study how such interventions affect market behavior. Using detailed data from two major review platforms, we find that platform liability increased transaction prices by 8–16% for participants in the youngest age group. The evidence suggests a contraction in the effective supply of underage participants—consistent with higher screening costs, platform exit, or greater legal risk.*

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*Keywords: Platform Liability, Child Trafficking, Digital Markets*

## I. Introduction

Over the past two decades, digital platforms have transformed economic activity by lowering coordination costs (Einav et al. 2016, Goldfarb and Tucker 2019), improving market matching (Horton 2017), and expanding access to income-generating opportunities (Hall and Krueger 2017). Yet these same platforms have also generated new externalities, ranging from illicit trade (Bhaskar et al. 2019, Zeng et al. 2022, Moore et al. 2009) to the spread of harmful content (Ilbiz and Kaunert 2023) and terrorist recruitment (Do et al. 2023). This has raised fundamental questions about how liability should be allocated in two-sided markets.

In March 2018, the U.S. Congress enacted the twin bills FOSTA (Fight Online Sex Trafficking Act) and SESTA (Stop Enabling Sex Traffickers Act), which extended legal liability to digital intermediaries that "knowingly assist, facilitate, or support sex trafficking." Under U.S. law, any commercial sex act involving a person under the age of eighteen is legally defined as sex trafficking, regardless of consent or coercion. This legislation therefore offers a rare natural experiment for evaluating how liability alters platform incentives, market behavior, and the equilibrium allocation of risky or illegal transactions. Using detailed data from two large online commercial sex services review sites, we study whether the introduction of platform liability reduced the effective supply of underage participants in the market. Because we observe prices, but not complete market quantities, we use transaction prices conditional on service characteristics and reported age as the most reliable equilibrium outcome. In markets with imperfect observability, price movements reflect the interaction of supply and demand, allowing us to infer changes in market participation from relative price shifts.

This paper studies a specific externality facilitated by digital platforms: the trafficking of minors in online sex markets. The internet has become a dominant channel for such activity. The National Center for Missing and Exploited Children (NCMEC) reported an 846% increase in suspected child trafficking cases between 2010 and 2015 — an increase attributed to the growing use of the Internet to sell children for sex."[1] In 2015, a U.S. Senate's investigation found that the website Backpage was involved in roughly "73% of all child trafficking reports that NCMEC receives from the general public."[2] The report found that Backpage has actively concealed evidence of such activity by deleting terms indicative of the advertisement of minors (e.g., "teen," "lolita," "fresh") prior to posting advertisements on its platform.

The regulation of online harms remains one of the most debated policy areas worldwide. A central issue is whether digital platforms should be treated as publishers — with editorial rights and corresponding liability — or as common carriers, which provide infrastructure without responsibility for user-generated content.[3] In early 2018, FOSTA-SESTA narrowed Section 230 of the Communications Decency Act, removing safe harbor protections for platforms that knowingly facilitate sex trafficking.[4]

From an economic perspective, liability regulation is a mechanism for aligning provider incentives with social welfare (Henry et al. 2022). Yet its effectiveness for digital intermediaries remains uncertain. Critics argue that such laws may simply drive illegal activity underground or offshore rather than reducing it. FOSTA-SESTA, in particular, has been criticized for allegedly failing to achieve its stated goals.[5] Nonetheless, understanding whether liability changes equilibrium behavior — by increasing screening, altering incentives, or raising the effective cost of participation — remains a first-order question for platform governance.

We provide early causal empirical evidence that platform liability can reduce a measurable harm facilitated by digital markets. Using data from two escort-review platforms, we analyze changes in transaction prices for providers in different age groups before and after the enactment of FOSTA-SESTA. Because the supply of minors is unobserved, we adapt a framework from labor economics (Katz and Murphy 1992) that infers supply shifts from relative price movements. Given that the review platforms do not allow reviewers to categorize a provider as under 18, we develop an algorithm to estimate the most probable true age of each provider, allowing us to identify those most likely to be underage. Our empirical strategy combines standard linear difference-in-differences with a double machine learning difference-in-differences estimator that accommodates high-dimensional covariates and changing group composition.

[1] See https://www.courthousenews.com/wp-content/uploads/2017/02/Backpage-Report.pdf.
[2] Id.
[3] https://cacm.acm.org/opinion/free-speech-vs-free-ride-navigating-the-supreme-courts-social-media-paradox/
[4] See https://www.law.cornell.edu/uscode/text/47/230
[5] See https://www.eff.org/deeplinks/2018/03/how-congress-censored-internet

Our main finding is that government-imposed platform regulation, FOSTA-SESTA, increased transaction prices for participants in the youngest age group by 8-16% relative to other age groups. Within a supply-and-demand framework, this price increase implies either a reduction in effective supply of underage participants, or a reallocation of demand toward older providers — both consistent with a tightening of the market segment most associated with trafficking risk. We further show that the observed changes coincide with modifications to platform policies and site design following the introduction of liability.

This evidence speaks directly to the broader debate over how to govern digital intermediaries. As regulators in the United Kingdom, the European Union, and the United States pursue liability regimes (e.g., the Online Safety Act,[6] Digital Services Act,[7] and EARN IT Act[8]), our findings provide the rare empirical evidence that liability can effectively internalize externalities, and improve welfare in digital markets.

Our research contributes to three strands of the economics literature. First, it extends the literature on the economics of platform governance by empirically testing a central prediction of liability theory: that legal accountability can alter intermediary behavior and reduce socially costly outcomes (Kraakman 1986, Lefouili and Madio 2022, Hua and Spier 2020). Second, it adds to the literature on the regulation of prostitution and semi-coerced markets, where supply is jointly determined by consenting and trafficked participants (Acemoglu and Wolitzky 2011, Lee and Persson 2022). Third, it connects to research on the digitization of commercial sex markets, which has documented how online platforms affect safety, prices, and market expansion (Chan and Ghose 2014, Chan et al. 2019, Cunningham and Kendall 2010, Cunningham et al. 2025).

The remainder of the paper proceeds as follows. Section II describes the institutional context and the natural experiment. Section III introduces the data. Section IV presents our empirical framework and main estimates. Section V provides robustness checks, Section VI develops a simple supply-demand interpretation, and Section VII concludes.

## II. Context and Platform Liability

In early 2018, Congress enacted FOSTA-SESTA, amending Section 230 of the Communications Decency Act to create platform liability for knowingly assisting or facilitating sex trafficking. The House passed the bill on February 27,2018, the Senate on March 21, 2018, and the President signed it on April 11, 2018. Online intermediaries — classified ads sites, social media, and chatrooms — hosted a wide spectrum of content, including illegal and harmful material. By the 2000s, U.S. commercial sex markets had moved primarily online, with Craigslist's "personals" and Backpage serving as dominant hubs. Investigations documented the presence of prostituted minors and related harms, while Section 230 historically immunized platforms from liability for third-party postings. (Leary 2014, McCabe 2008, DeLateaur 2016) These facts motivate our focus on a liability shock that plausibly changes

[6] `https://www.legislation.gov.uk/ukpga/2023/50`

[7] `https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/digital-services-act_en`

[8] `https://www.congress.gov/bill/117th-congress/senate-bill/3538`

platform behavior relevant to minors.

Immediately around the Senate vote and before/around the signature, major platforms exited: Craigslist voluntarily removed its personals section on March 23, 2018,[9] and the Department of Justice seized Backpage on April 6, 2018.[10] Zeng et al. (2022) find that these shutdowns primarily shifted traffic to alternative, offshore sites, having little effect on outcomes like prostitution arrests or sex trafficking incidents. These highly salient events are not the treatment per se, but they coincide with window of our policy shock. Our study focuses on the policy shock — platform liability associated with FOSTA-SESTA — and we absorb broad shifts resulting from the market's adjustment to the law via time and location controls, focusing specifically on differential price movements by age groups.

The mechanism we test is straightforward. The liability regime raises platform's expected costs of hosting content involving minors and increases the expected penalties for insufficient screening. Using *Wayback Machine*,[11] we tracked changes in the landing pages, front pages, and terms of service of all prominent escort advertising platforms analyzed in Zeng et al. (2022) as well as several new platforms that emerged as alternatives to Backpage and Craigslist after their closures. Our analysis reveals significant updates to the policies, website practices, or design of these platforms. For example, both *Slixa*[12] and *AdultSearch*[13] revised their terms of use or web pages to explicitly prohibit content involving trafficking, particularly materials exploiting minors. Additionally, some newly launched platforms, such as *USAsexguide.nl*, prominently featured their "Underage Policy" on their front pages as part of community guidelines for users. Further details of these policy changes are provided in Appendix A. Such updates and anti-trafficking resources were not observed on Backpage, Craigslist, and other platforms before the policy intervention. Although the liability regulation holds platforms accountable for all sex trafficking content (including coerced adults), we observe that the updated website practices specifically focus on addressing sexual abuse materials involving minors. Based on the observed changes, we hypothesize that government-imposed platform liability has raised barriers to posting content involving underage victims, thereby reducing the supply of minors in the online commercial sex market.

Previous research has highlighted that the available measures of reported sexual trafficking incidents are limited and serve only as imperfect proxies for actual occurrence of such cases (Zeng et al. 2022). Because solicitation often occurs in hard-to-observe online venues (including the dark web), credible supply-side data — such as counts of trafficked victims or consensual participants — are largely inaccessible or too incomplete to capture the market's true scale. Instead, our unit of observation is the individual review-level price quote. Because we do not observe demand or supply quantities, we treat prices as the equilibrium outcome that reflects changes in effective supply or demand across age bins. This approach

[9] See `https://www.wired.com/story/craigslist-shuts-personal-ads-for-fear-of-new-internet-law/`.

[10] See `https://www.reuters.com/article/us-usa-backpage-justice/sex-ads-website-backpage-shut-down-by-u-s-authorities-idUSKCN1HD2QP`.

[11] `https://archive.org/web/`

[12] `https://www.slixa.com/`

[13] `https://adultsearch.com/`

follows Katz and Murphy (1992), who used a supply and demand framework to explain changes in the wage premium for college-educated workers relative to high school-educated workers. We limit attention to U.S. markets and include saturated fixed effects (city and month) to net out migration and macro seasonality.

We hypothesize that *the liability regulation leads to an increase in prices of underage participants compared to adult participants in the online commercial sex market.* We test this hypothesis by analyzing price changes in Section IV. In Section VII, we explore how the observed relative price variations reflect shifts in supply and demand, providing insights into the impact of the platform liability imposed by FOSTA-SESTA on the supply of minors in the commercial sex market.

## III. Data and Summary Statistics

To test the impact of the platform-liability legislation on the supply of underaged trafficking victims, we scraped large-scale data sets from two escort review sites: *"Erotic Monkey"*[14] and *"the Erotic Review"* (TER)[15]. These two review sites are central venues where consumers share their experiences with providers of commercial sex services. Existing literature has demonstrated the welfare gains for consumers associated with online reviews (Reimers and Waldfogel 2021). In markets for commercial sex, reviews offer observable signals of a seller's presence and activity.

The data from these sites enable us to document the general information (e.g., age, ethnicity, and physical features) of individual sellers of commercial sex online, the specific sexual services they offered, and the prices charged for those services. Notably, *"Erotic Monkey"* has independent review pages for each service provider, enabling us to track historical reviews along with price information at different points in time. To the best of our knowledge, *"Erotic Monkey"* is the only platform that allows for the tracking of historical market prices for individual service providers, making it uniquely well suited for testing our hypothesis on price shifts. Because *"the Erotic Review"* has substantial gaps in coverage, we base our analysis primarily on data from *"Erotic Monkey"* and use *"the Erotic Review"* to replicate our main results.[16] The details of the scraped data from the two sites are provided below.

### *A. "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

[14] `https://www.eroticmonkey.ch/`

[15] `https://www.theeroticreview.com/`

[16] Prior to the passage of FOSTA-SESTA, *"the Erotic Review"* was the leading review site for commercial sex services in the U.S. It blocked access to its sites from the U.S. in April 2018 following the legislation, and returned to service in December 2019. Its suspension of services during the interim leads to a large gap in data coverage in the post period. *"Erotic Monkey"* became the primary substitute of TER after it closed its page in the U.S.

[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).

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 B.1 in Appendix B, and their descriptive statistics are reported in Table B.2. 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*$_p$, to indicate whether provider $p$ falls into this group. We estimate if a provider belongs to the *youngest age 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 (DMLDiD) (details provided in the following section) are presented in Table 1.[20]

Table 1—Summary Statistics

| Variable | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Data for OLS Regression in Table 3** | | | | | |
| ln(*hour rate*$_{pi}$) | 4,730 | 5.608 | 0.447 | 2.996 | 8.006 |
| *Youngest Age Group*$_p$[1] | 4,730 | 0.084 | 0.277 | 0 | 1 |
| *Youngest Age Group*$_p$[2] | 4,730 | 0.090 | 0.287 | 0 | 1 |
| **Data for DMLDiD in Table 4** | | | | | |
| ln(*hour rate*$_{pi}$) | 1,255 | 5.595 | 0.407 | 4.317 | 7.496 |
| *Youngest Age Group*$_p$[1] | 1,255 | 0.515 | 0.500 | 0 | 1 |
| *Youngest Age Group*$_p$[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".

### B. "The Erotic Review" (TER)

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

[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 hour services, we normalize the price to an hour rate of $500).

[20] The sample used for the DMLDiD analysis is smaller because we exclude observations that do not satisfy the propensity score overlap assumption of the model.

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. As a result, we observe only the most recent price for each 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 collected profiles of providers whose last review or profile update occurred between July 2017 and December 2018, and we report the details of the features, summary statistics of these features as well as our main variables of interest in Table B.3 and Table B.4 of Appendix B.

## IV. Empirical Framework and Main Results

In our study, we use posted prices as a proxy to reflect shifts in supply and demand across various age groups in the online commercial sex market. As noted above, on the platform *"Erotic Monkey"*, providers are listed in one of four reviewer-assigned age groups: 18-24," 25-36," 37-45," and 45+," based on the reviewer's perception of age rather than verified information. Notably, the platform does not permit reviewers to indicate that a provider is under 18. However, several news reports indicate that the site has been involved in, or investigated by law enforcement for, cases involving underage girls.[21] Because our primary interest is in outcomes for individuals who are, in fact, below the legal age of consent, we proceed under the assumption that underage providers are most likely to be listed in the youngest available category, "18–24." Accordingly, we treat the "18–24" group as a composite category that may include both legal adults and minors.

To address inconsistencies in age reporting,[22] we first assign each provider to a single age group based on the most frequently reported category across reviews the individual received from January 2017 to June 2019.[23] Based on our identifying assumption, minor participants are mostly likely to appear in the "18-24" age group, the youngest category permitted on the review site. Accordingly, providers with a higher share of reviews placing them in the "18–24" age bin are more likely to be below the legal age of consent.

To test our hypothesis and assess the validity of our assumption, we first apply a difference-in-differences framework to compare the transaction prices across various participant age groups before and after the platform liability intervention. Specifically, we estimate the following model:

$$\ln(\textit{hour rate}_{pi}) = \alpha * \textit{Youngest Age Group}_p * \textit{Post}_{pi} + \beta * X_{pi} + FE_{month} + FE_{city} + \varepsilon_{pi}, \tag{1}$$

where $\textit{hour rate}_{pi}$ is the hourly rate in the $i$-th review of of provider $p$,[24]

[21] See https://missoulacurrent.com/human-trafficking-2/ and https://gizmodo.com/dhs-doj-now-looking-into-escort-and-massage-sites-that-1838131975.

[22] We note that the reported age data for providers on this review platform exhibit some inconsistencies across reviews. For instance, a provider listed in the age bin of "25-36" in a review posted in January 2017 could appear in the "18-24" age group in a subsequent review.

[23] For example, if a provider is listed as "25-36" in 80% of the reviews and "37-45" in the remaining 20%, we assign the individual to the "25-36" group. This assignment is based on reviews that include age information. For reviews with missing age data, we impute the age category using the provider's modal age group.

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

*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, $Post_{pi}$ is a dummy variable that takes the value of 1 if the review was posted during the post-period following the platform liability regulation,[25] $\alpha$ represents the change in price of the *youngest age group* of participants following the regulatory intervention relative to that observed in 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 B.1) that could affect the transacted prices, $FE_{month}$ and $FE_{city}$ represent the vector of *month*- and *city*[26]-fixed effects, and $\varepsilon_{pi}$ is the error term. We take the logarithm of the hourly rate for two reasons: first, the distribution of hourly prices is right skewed; and second, it allows us to interpret the results as percentage changes in prices before and after the platform liability intervention.

Table 2—OLS Regression Results for (1)

| **Dependent variable** | ln(*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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Results for (1) are presented in Table 2. In these regressions, providers identified to be in the older age groups, i.e., "25-36," "37-45," and "45+," serve as the control group. In columns (1) - (4), we report the estimated coefficient $\alpha$ using providers from the youngest age bin "18-24" as the treatment group with the share of reviews (from January 2017 to June 2019) distributed in the youngest age category "18-24" varying from 100%, 75%-100%, 50%-100% and 25%-100% respectively. Namely, column (1) shows the results using the providers whose reviews are exclusively in the "18-24" age bin as the treatment group; column (2) expands the treatment group to those with at least 75% of reviews in this bin; and columns (3) and (4) extend this threshold to 50% and 25%, 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* relative to older age groups following the platform liability intervention. The estimates decline from column (1) to (4), consistent with the decreasing share 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

[25]The time stamp of reviews is on the month level. We designate March 2018 as the cutoff between the pre- and post-periods, corresponding to the passage of the FOSTA-SESTA legislation in the U.S. House and Senate and the subsequent responses of multiple escort advertising platforms.

[26]Location of transaction.

reviews, that underage sellers are likely to experience a disproportionately larger increase in the market price after the intervention compared to their older counterparts.

To more accurately assess changes in prices among the group of participants who are minors, we go beyond this simple strategy and develop an algorithm, that we discuss in the following section, to estimate a set of true ages (years of birth) for providers that are "consistent" with the observed review data. This algorithm allows us to identify and extrapolate which providers are most likely below the age of 18 in actuality.

### A. *Expectation Maximization (EM) 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 the posting time of reviews at a 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.[27] $\theta_p \in \mathbb{R}$ is used to denote the true year of birth of provider $p$.[28] We further assume the existence of a common probability distribution—shared across providers and across reviews—that governs the likelihood of being reported in a given age group conditional on the provider's true age group, 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 $\Upsilon_{\text{true}} = \{$"Below 18", "18-24", "25-36", "37-45", "45+"$\}$. In this setup, $\Omega_{b,a}$ for $b \in \Upsilon$ and $a \in \Upsilon_{\text{true}}$ form a $4 \times 5$ matrix $\Omega$ where the rows correspond to reported age groups $b$, columns to true age groups $a$, and each column sums to one. 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 observing the reported age bins in the review data, given matrix $\Omega$ and providers' true birth years $\theta_1, \theta_2, ..., \theta_n$. And age group$\{t_{p,j} - \theta_p\}$ indicates the age group of $t_{p,j} - \theta_p$ in $\Upsilon_{\text{true}}$. Our goal then is to estimate the conditional probability matrix $\Omega$ and the set of true birth years of providers $\theta_1, \theta_2, ..., \theta_n$ that maximize $\mathbb{L}(\Omega, \theta_1, \theta_2, ..., \theta_n)$. These quantities are estimated following the steps outlined in the table below.

To ensure the independence of data in our price analysis, we first execute the steps in the table above and estimate the matrix $\Omega$ for conditional probabilities of reporting with the

[27] The assumption is plausible because reviews for the same provider come from distinct reviewers.

[28] $\theta_p$ could be very fine-grained. For simplicity, we discretize $\theta_p$ at the year level. Without loss of generality, we restrict $\theta_p$ to be from the set {1967, 1968,..., 2006}. This guarantees that for every calendar year in our review data for age estimation (from 2013 to 2023), the implied ages $year - \theta_p$ span the endpoints of our bins—"below 18" and "45+." Because these are boundary categories, expanding the birth-year earlier than 1967 or later than 2006 yields identical results.

| 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. $\hat{\Omega}_{b,a} = \frac{\sum_{p=1}^{n} \sum_{i=1}^{m_p} \mathbb{1}(\gamma_{p,i}=b,\ age\ group\{t_{p,i}-\hat{\theta}_p\}=a)}{\sum_{p=1}^{n} \sum_{i=1}^{m_p} \mathbb{1}(age\ group\{t_{p,i}-\hat{\theta}_p\}=a)}$<br><br>(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) |

set of providers who are not included in our analysis on price. We perform 10 runs for estimation on $\Omega$. For each run, we estimate $\Omega$ along with the set of birth years $\{\theta_1, \theta_2, ..., \theta_n\}$, initializing the algorithm with 5,000 distinct sets of starting values 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 $\Omega$ are identical when rounded to 2 decimal places across 10 runs. The estimated probabilities in $\hat{\Omega}$ are presented in Table B.5 of Appendix B.[29] We observe a relative high positive correlation between the reported and true age groups. Notably, our 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.[30]

### B. *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 (1), designating providers estimated to be under the age of 18 at the start of the study period (2017) as the treatment group to assess changes in prices for underage participants relative to those estimated to be 18 or older. The results are presented in Table 3. In Table 3, we report the results for (1) by using two different approaches of estimating providers' ages. Column (1) shows the results with the simple approach outlined earlier in this section where a provider's age is assigned as the modal age reported in their reviews posted between 2017 and mid

[29]For some providers, there might exist multiple years of birth that could result in the same highest likelihood. Our final estimates on matrix $\hat{\Omega}$ are independent from the choice from those years in executing Step 2(b).

[30]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.

2019. Within this framework, 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 constitutes the "*youngest age group*" for the specification in column (1) of Table 3. Other participants in the "18–24" age group who appear in older age bins in at least one review are included as part of the control group—a distinction not made in the analysis reported in Table 2. The results when "*youngest age group*" are defined as underage participants detected based on the age estimation algorithm described in subsection IV.A are presented in column (4) of Table 3. For clarity, we label these two age identification strategies as the "simple approach" and the "age estimation algorithm" respectively in Table 3. Across both approaches, the estimates in the first row indicate a relative increase in hourly rates of approximately 14% (column (1)) to 16.3% (column (4)) for the "*youngest age group*" following the enactment of the platform liability regulation.

Table 3—OLS Regression Results for (1)

| **Dependent variable** | ln(*hour rate*) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Youngest\ Age\ Group_p * Post_{pi}$ | 0.140*** | 0.130*** | 0.213** | 0.163*** | 0.155*** | 0.125 |
| | (0.047) | (0.049) | (0.104) | (0.045) | (0.047) | (0.089) |
| $Youngest\ Age\ Group_p * Post_{pi} * \mathbb{1}(Extreme\ Services > 4)$ | | 0.140* | | | 0.126* | |
| | | (0.079) | | | (0.075) | |
| $Youngest\ Age\ Group_p * Post_{pi} * white$ | | | -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) |
| Age identification strategy | Simple approach | | | 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The estimated coefficients for control variables $X_{pi}$ can be found in the corresponding columns in Table B.6 of Appendix B. Overall, we observe that younger aged providers are 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 B.6) than that from the reference group. Average hourly rates drop more significantly as ages increase with the sellers estimated 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, Black or white as the ethnicity reference group (e.g., mixed races, Hispanics). Prices vary significantly 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 B.6). Asian participants are in general priced around 5% lower than the reference group (row *"Asian"* in Table B.6).

On the basis of specification (1), we further include a series of interaction terms between $Youngest\ Age\ Group_p * Post_{pi}$ and a vector of control variables. Recent research (Coxen et al. 2023) suggests that online advertisements contain no reliable indicators of sex trafficking, even among those commonly relied upon by law enforcement. We examine whether certain provider characteristics may nonetheless serve as weak signals. For example, offering a higher number of extreme ("niche") services may indicate forced labor; most victims exploited at illicit massage parlors in U.S.—often operating as fronts for sophisticated multinational trafficking networks—are of Asian descent.[31] We incorporate into (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 4, 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)). In column (6), the estimate for $\alpha$ becomes statistically insignificant, though its magnitude remains largely unchanged. The sum of $\alpha$ and the corresponding individual coefficient of each interaction term is positive. This suggests that there exists a set of heterogeneous positive treatment effects and our estimate in columns (1) and (4) may be a weighted average of these heterogeneous treatment effects. Specifically, we note that following the platform liability intervention, providers offering a greater number of extreme services experienced larger price increases—around 13% higher than those offering fewer such services (columns (2) and (5) of the row "$Youngest\ Age\ Group_p * Post_{pi} * \mathbb{1}(Extreme\ Services > 4)$" in Table 3). In addition, the group of Asian participants appear to have faced the 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 in the presence of heterogeneous treatment effects to avoid underlying inconsistency caused by functional form misspecification. Modeling the control variables nonparametrically allows the treatment effect to vary across individuals and with observable characteristics (Chang 2020). To address this issue, Abadie (2005), Chang (2020), Sant'Anna and Zhao (2020) develop semiparametric difference-in-differences (DiD) estimators. However, these estimators—like the linear DiD framework in (1)—rely on the stationary assumption, i.e., the distribution of covariates $X_{pi}$ and treatment dummy $Youngest\ Age\ Group_p$ are time invariant. This assumption rules out settings in which $(Youngest\ Age\ Group_p, X_{pi})$ change composition over time (Hong 2013). In our context, this restriction may be vio-

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

lated, since the composition of *Youngest Age Group*$_p$ (or the control group) can shift with the entry/exit of providers with diverse characteristics, particularly following the platform-liability intervention. That said, we must be cautious to ensure that the price increase in *Youngest Age Group*$_p$ identified with (1) is not merely driven by compositional changes in characteristics of sellers in our dataset.

To address these concerns, we additionally estimate the average treatment effect using the "double/debiased machine learning difference-in-differences (DMLDiD)" estimator proposed by Zimmert (2020), which builds on the generic "double machine learning" framework of Chernozhukov et al. (2018). The DMLDiD estimator by Zimmert (2020) is derived under less restrictive assumptions that consider time-varying treatment group compositions and covariates, and it delivers point estimators that are rate double robust and efficient for our coefficient of interest.

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 (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 (1), $T_{pi}$ the post-treatment dummy and $X_{pi}$ the set of covariates as in (1). Again, we assume independence of the observations as in age-estimation algorithm because 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:

$$Y_{pi} = g_{dt}(X_{pi}|D_p = d, T_{pi} = t) + \mu_{pi} \qquad \text{for } d, t \in \{0, 1\}, \tag{2}$$

$$p(D_p = d, T_{pi} = t|X_{pi}) = e_{dt}(X_{pi}) + v_{pi} \qquad \text{for } d, t \in \{0, 1\}. \tag{3}$$

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 $T_{pi}$, respectively, with each $(d, t)$ combination indicating the treatment status. Namely, $(d, t) = (0, 0)$ and $(d, t) = (0, 1)$ correspond to the pre- and post-period of the control units (providers from the older age groups), 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 $e_{dt}(\cdot)$ denote nonparametric functions through which the confounding factors $X_{pi}$ affect the outcome variable $Y_{pi}$ (natural log of 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 ($T_{pi} = t$, $t \in \{0, 1\}$). $\mu_{pi}$ and $v_{pi}$ are idiosyncratic disturbances with conditional mean 0, i.e., $\mathbb{E}(\mu_{pi}|X_{pi}) = 0$ and $\mathbb{E}(v_{pi}|X_{pi}) = 0$.

We follow to estimate the effect of platform liability on prices ($Y_{pi}$) with the score function as proposed in Zimmert (2020):

$$(4)\quad \psi(W_{pi};\theta,\eta) = \frac{e_{11}(X_{pi})}{p(D_p=1,T_{pi}=1)}\psi^a(W_{pi};\eta) + \psi^b(W_{pi};\eta)\left\{\sum_{d=0}^{1}\sum_{t=0}^{1}(-1)^{d+t}g_{dt}(X_{pi}|d,t) - \theta\right\}$$

$$(5)\quad \psi^a(W_{pi};\eta) = \sum_{d=0}^{1}\sum_{t=0}^{1}(-1)^{(d+t)}\frac{\mathbb{1}(D_p=d,T_{pi}=t)}{e_{dt}(X_{pi})}(Y_{pi} - g_{dt}(X_{pi}|d,t))$$

$$(6)\quad \psi^b(W_{pi};\eta) = \frac{D_pT_{pi}}{p(D_p=1,T_{pi}=1)}$$

$$(7)\quad E(\psi(W_{pi};\theta,\eta)) = 0$$

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 (4)-(7), $\theta$ denotes the main coefficient for the effect of platform liability intervention on the transacted prices of the participants from the *youngest age group* relative to those of older providers that we would like to infer. $\theta$ is estimated by setting the average of the score function $\psi(W_{pi};\theta,\eta)$ to be equal to be 0 in equation (7). $p(D_p = 1, T_{pi} = 1)$ represents the unconditional probability of $D_p = 1$ and $T_{pi} = 1$ (proportion of sample belonging to the treatment group in the post-period). The terms $\psi^a(W_{pi})$ and $\psi^b(W_{pi})$ referenced in (4) are defined in equations (5) and (6), respectively. The estimated results for the coefficient of interest $\theta$ are reported in Table 4. We report results based on three machine learning (ML) methods for estimating the nuisance functions $g_{dt}(\cdot)$ and $e_{dt}(\cdot)$. Namely, we consider the "$\ell_1$-penalization" based method, labeled "Lasso" (linear "Lasso" for the outcome nuisance and logit "Lasso" for the propensity score) , 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 ML 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 the nuisance functions.

We estimate $\theta$ using 2-fold cross-fitting. Namely, we randomly split the data into two equal folds. On one fold, we estimate the nuisance functions $g_{dt}(\cdot)$ and $e_{dt}(\cdot)$, and apply the resulting estimators to the complementary sample to construct the score function (4); we then swap the roles of the two folds. The final estimator of $\theta$ is obtained by setting the average score function equal to zero, as in (7). Hyperparameter-tuning is conducted within the fold of data used for first-step estimation. This procedure ensures that the nuisance functions and treatment effect are estimated on separate subsamples to avoid overfitting bias. To make the results more robust with respect to the partitioning, we repeat the

Table 4—DMLDiD Results for (4)-(7)

| | Machine learning estimator for $\eta$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Lasso | SVM | Random Forest | Best | Lasso | SVM | Random Forest | Best |
| $\theta$ | 0.138*** | 0.126** | 0.079 | 0.141** | 0.144*** | 0.132** | 0.086 | 0.107* |
| | (0.053) | (0.063) | (0.062) | (0.067) | (0.055) | (0.062) | (0.069) | (0.064) |
| Age identification strategy | Simple approach | | | | Age estimation algorithm | | | |
| Observations | 1,255 | 1,255 | 1,255 | 1,255 | 1,255 | 1,255 | 1,255 | 1,255 |

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

cross-fitting procedure with 10 independent random splits of the data and aggregate the results using the median method of Chernozhukov et al. (2018). Specifically, we report the final estimate as the median across the 10 splits, with standard errors adjusted for cross-split variability shown 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 subsection IV.A are presented in columns (5)-(8).[32] The DMLDiD model identifies a 8-14% relative increase in hourly rates charged by providers in the *youngest age group* compared with those from older age groups. The estimated increase is statistically different from zero at conventional levels, except for the specifications in columns (3) and (7) using the “Random Forest” method for nuisance functions prediction, though even these estimates imply roughly an 8% price increase.

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

## V. 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.

### A. 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:

$$\ln(hour\ rate_{pi}) = \alpha_q * Youngest\ Age\ Group_p * month_q + \beta * X_{pi} + \delta_q month_q + FE_{city} + \varepsilon_{pi} \tag{8}$$

[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 in the DMLDiD model (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 (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 preceding the intervention, Feb 2018, is omitted). In (8), $Youngest\ Age\ Group_p * month_q$ 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 $month_q$. $\delta_q$ represents the time trend on a monthly level for the units in the control group, and $\alpha_q$ indicates any differential trends between treated and control units in our study window. Under the parallel pre-trends assumption, we would expect $\alpha_q$ to be zero for all months in the pre-period. For the months in the post-period, $\alpha_q$ indicates the causal effect of the platform liability legislation on the outcome variable.

We estimate (8) using both age identification strategies and report the results for $\alpha_q$ in Table B.7, with column (1) showing the estimates based on "simple approach" for age identification and column (2) showing results using our age estimation algorithm. Figure 1 plots the estimated coefficients for $\alpha_q$ along with their 90% confidence intervals, with the left panel corresponding to the "simple approach" and the right panel to the algorithm-based approach. Across both specifications, the pre-treatment coefficients are all statistically indistinguishable from 0, with the algorithm-based estimates (right graph in Figure 1) being particularly close to 0 in magnitude. This pattern supports the validity of the parallel trends assumption between the treatment and control groups prior to the liability intervention. Following the intervention, $\alpha_q$ shifts into the positive region, and becomes statistically significant for a few months in the post-period.

In addition, we also conduct a parallel pre-trends test for our results from the 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 (4)-(7). Again, we conduct the placebo test using both of our age identification strategies. The estimates for our coefficient of interest are presented in Table B.8. For simplicity, we show the results obtained using "Lasso" for the outcome variable and propensity score prediction in (2) and (3). The coefficients in Table B.8 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 the liability intervention.

### *B. Randomization Test*

Next, we perform a randomization test to determine if the post-intervention increase in transaction prices for providers in the *youngest age group* is robust to randomly reassigning ages across 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 (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 conduct the randomization test using both approaches to age

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

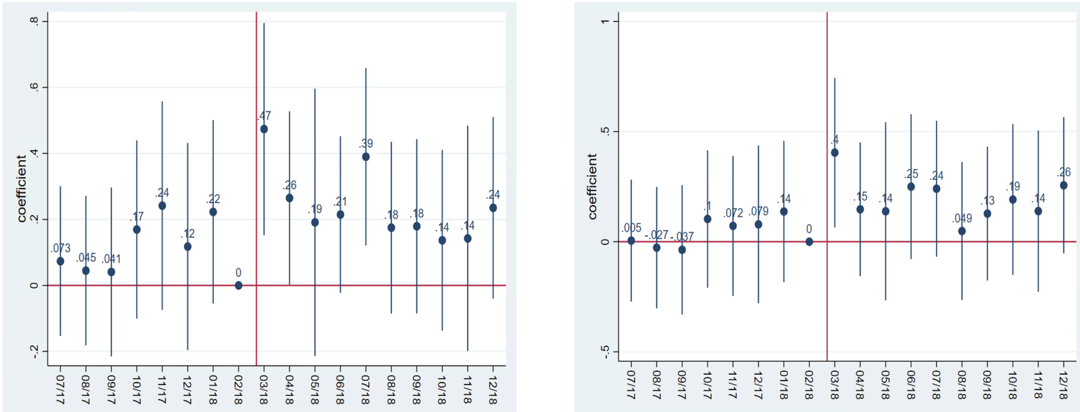


FIGURE 1. REGRESSION COEFFICIENT BOX PLOTS FROM (8) FOR ln(*HOUR RATE*$_{pi}$) WITH PROVIDERS' AGES IDENTIFIED USING "SIMPLE APPROACH" (LEFT) AND "AGE ESTIMATION ALGORITHM"(RIGHT).

estimation, and report the 5th and 95th percentile of the resulting 1,001 estimates for the effects of the platform-liability intervention on transacted prices in Table B.9. We plot the distribution of the 1,001 estimates (1,000 coefficients from the randomization inference merged with the true coefficient) in Figure B.1. In both age-identification approaches—columns (1) and (4) of Table 3—the true effects exceed the 95th percentile of the randomized sample. We find that the true effect of 0.14 increase on hourly rates of providers under our "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 observed increase in prices is associated with the precise structure of age distribution of the service providers as identified from the review data.

## VI. A Graphical Analysis with a Basic Supply and Demand Framework

We next interpret relative price shifts across age groups, as documented in previous sections, through the lens of a basic supply and demand framework. Drawing on the work of Katz and Murphy (1992), which use such a framework to analyze changes in the U.S. wage structure from 1963 to 1987, we employ it here to explain the observed relative hourly price differentials across age groups identified in our analysis as the outcome of interacting supply and demand factors.

Specifically, we consider providers from different age groups as distinct labor inputs and interpret the relative price changes between these groups as being generated by shifts in relative supplies and shifts in factor demand schedules. Following Katz and Murphy (1992), we consider the aggregate production function for commercial sex services as incorporating 2 groups of labor inputs, sexual services provided by participants in the *youngest age group* and those from older age bins. We assume that the associated factor demands can be written as:

$$\mathbf{L}_m = D(\mathbf{V}_m, \mathbf{U}_m) \tag{9}$$

where $\mathbf{L}_m$ represents the $2 \times 1$ vector of labor inputs of services from providers in the *youngest age group* and the older age group in the market during month $m$, $\mathbf{V}_m$ is the $2 \times 1$ vector of market prices for services provided by individuals in these two age groups during month $m$, and $\mathbf{U}_m$ denotes a vector of demand shift variables in month $m$. The demand shifters $\mathbf{U}_m$ capture external factors that shift the demand for labor, such as population change or government policies.

Assuming the aggregate production function is concave—which should be a reasonable assumption for the commercial sex market, as the average hourly rate for commercial sex services tends to decrease with longer service durations—the $2 \times 2$ matrix of cross-price effects on factor demands, $D_v$, is negative semidefinite. By taking the differentials of (9), we obtain:

$$d\mathbf{L}_m = D_v d\mathbf{V}_m + D_u d\mathbf{U}_m \tag{10}$$

and the negative semidefiniteness of $D_v$ implies that

$$d\mathbf{V}'_m(d\mathbf{L}_m - D_u d\mathbf{U}_m) = d\mathbf{V}'_m D_v d\mathbf{V}_m \leq 0. \tag{11}$$

The discrete version of (11) is

$$(\mathbf{V}_m - \mathbf{V}_l)'[(\mathbf{L}_m - \mathbf{L}_l) - (D(\mathbf{V}_l, \mathbf{U}_m) - D(\mathbf{V}_l, \mathbf{U}_l))] \leq 0 \tag{12}$$

where the left-hand side represents the inner product of the change in market prices from month $m$ to month $l$ ($m < l$), $\mathbf{V}_m - \mathbf{V}_l$, with the changes in net supplies, $(\mathbf{L}_m - \mathbf{L}_l) - (D(\mathbf{V}_l, \mathbf{U}_m) - D(\mathbf{V}_l, \mathbf{U}_l))$. These net supplies are defined as the actual change in supply, $\mathbf{L}_m - \mathbf{L}_l$, minus the change in demand for labor inputs across different age groups that would have occurred under fixed pricing schemes, $D(\mathbf{V}_l, \mathbf{U}_m) - D(\mathbf{V}_l, \mathbf{U}_l)$. (12) suggests that that upward movements in the price of a particular group are consistent with either a reduction in labor supply or an outward shift in factor demand. In other words, the price increase $(\mathbf{V}_m - \mathbf{V}_l)$ aligns with net excess demand for labor inputs captured by $(\mathbf{L}_m - \mathbf{L}_l) - [D(\mathbf{V}_l, \mathbf{U}_m) - D(\mathbf{V}_l, \mathbf{U}_l)]$. If the change in price is not driven by shifts in supply or demand, it may be attributed to the change in costs, especially if demand or supply is highly inelastic to price changes.

Because the *youngest age group* in which we observe a price increase may include both underage participants and young adults, we propose two potential explanations for the results.

1) If the observed price increase is driven mainly by underage participants in the *youngest age group*, we assume that the demand for sexual services involving underage individuals did not rise following the intervention of the liability intervention. With demand remaining constant or declining, the higher prices for underage providers would then reflect either a

reduction in supply or an increase in costs.

Consider the case where the observed price increase reflects higher operational costs for underage providers rather than reduced supply. In this case, the transactions involving underage providers may not decline if demand for their services is highly inelastic to changes in price. Existing literature on the price elasticity of demand in prostitution markets is relatively scarce, but the available studies consistently point to elastic demand. Kara (2009), Aronowitz. and Koning (2014) suggest that demand for sexual service is elastic, with price fluctuations exerting a strong impact on demand. Similarly, Martin and Lotspeich (2014) surmises a relatively elastic demand for sexual services. In an analysis of the sex industry in Thailand, Brodeur et al. (2018) estimate a price elasticity of demand of -1.7, indicating that a 10% increase in prices would reduce the number of participants in the sex trade by approximately 17%. Taken together, this implies that an observed increase in price would likely lead to fewer transactions within the group of interest (underage group).

Different tiers within prostitution markets may demonstrate varying levels of demand elasticity, influenced by the ease with which consumers can substitute toward similar services. Studies on the economics of illicit markets indicates that when the supply of a particular illicit good or service is restricted, consumers often shift to available substitutes (Becker et al. 2006, Reimers 2016). In the case of commercial sex services involving underage individuals, a close substitute could be services provided by participants within the youngest adult age group, as discussed further below.

2) If the observed price increase is primarily associated with shifts in the pricing of adult providers at the younger end of the age spectrum, we argue that this increase is more likely driven by a shift in demand rather than supply. This reasoning stems from the fact that recent changes in website practices predominantly target content involving minors. Consequently, we assume that the liability intervention does not disproportionately impact the supply or costs of the youngest adult participants compared to other adult participants. The higher prices among this cohort may reflect a relative increase in demand: as the operational costs and risks associated with underage participation rose—and the corresponding transaction volume within this group declined, as discussed above—some buyers may substitute toward services provided by the youngest adult providers, generating the observed price increase.

## VII. Conclusion

This paper provides causal evidence that extending legal liability to digital intermediaries can alter equilibrium outcomes in markets for illicit or risky transactions. Using data from two large review platforms for commercial sex services, we find that the introduction of FOSTA-SESTA raised transaction prices for the youngest group of providers by 8%–16% relative to older groups. Because we directly observe prices but not complete market quantities, these results imply a contraction in the effective supply of underage participants — consistent with higher screening costs, platform exit, or greater risk following the imposition of liability.

While our setting involves conduct that constitutes sex trafficking under U.S. law, the mechanisms uncovered here speak to a broader class of issues with digital market design. Liability operates as an indirect regulatory instrument: rather than banning a market outright, it induces intermediaries to internalize the externalities created by user behavior. Our evidence suggests that such liability can meaningfully shift equilibrium behavior even when transactions can migrate across platforms, demonstrating the potential for governance through intermediaries to complement or substitute for direct enforcement.

Several caveats remain. The elasticity of demand for underage services — and the degree of substitutability between those and the youngest adult providers — remains uncertain, limiting our ability to translate price changes into precise effects on quantity. Moreover, the same mechanisms that raise the cost of exploiting minors may displace activity to foreign or less-regulated venues, an issue that warrants further empirical investigation.

More broadly, our findings contribute to ongoing debates over the appropriate scope of digital platform liability laws such as the U.K. Online Safety Act, the E.U. Digital Services Act, and the U.S. EARN IT Act. We find that legal accountability can reduce measurable harms facilitated by online intermediaries, offering rare evidence that platform liability — long theorized as a means to align private incentives with social welfare — can be effective in practice.

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# APPENDICES

## APPENDIX A Examples of Websites Changing Their Practices or Design Following the Platform Liability Policy Intervention

### A1: Adultsearch.com

The site Adultsearch (`adultsearch.com`) introduced a *"Report Trafficking"* tab at the bottom of its webpage after FOSTA-SESTA, as shown in Figure A.1 and Figure A.2 below showing *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 A.2.[34] This new tab links to an Anti-Trafficking Advocacy information page on Adultsearch (as shown in Figure A.3), with the contact information for organizations like NCMEC, *Children of the Night* listed on the page. Within two months after the intervention, Adultsearch also added a "Terms and Conditions" page that users must agree to before entering the site. The newly established "Terms and Conditions" page (shown in Figure A.4) highlights the site's efforts to curtail child sex abuse materials, and to informs users about the site's rules against sex trafficking (relevant terms are highlighted in the red rectangle).

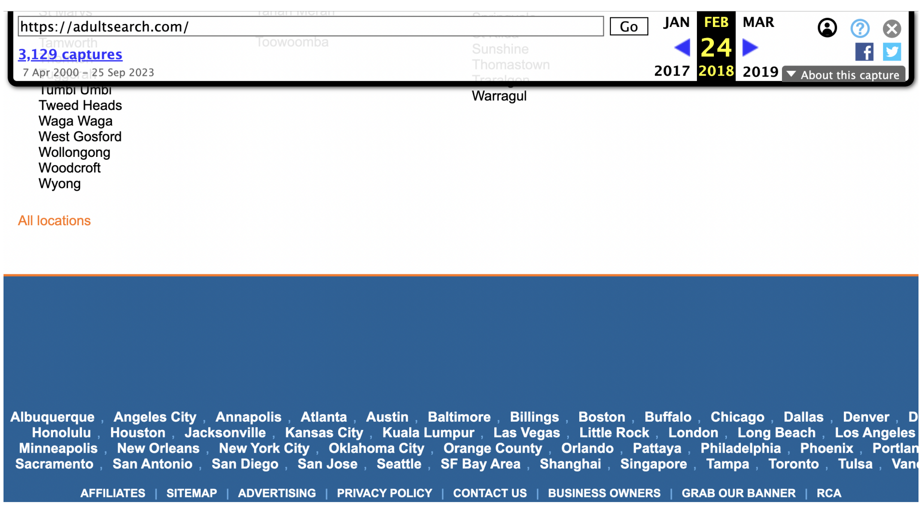



Figure A.1. Footnote on the Front Page of Adultsearch on February 24th, 2018

[34] The two dates of the archived pages for Figure A.1 and Figure A.2 are the closest possible dates around the time of the policy intervention that are available on *archive.org*. Similar limited availability of archive.org data applies to the other sites listed in Appendix A.

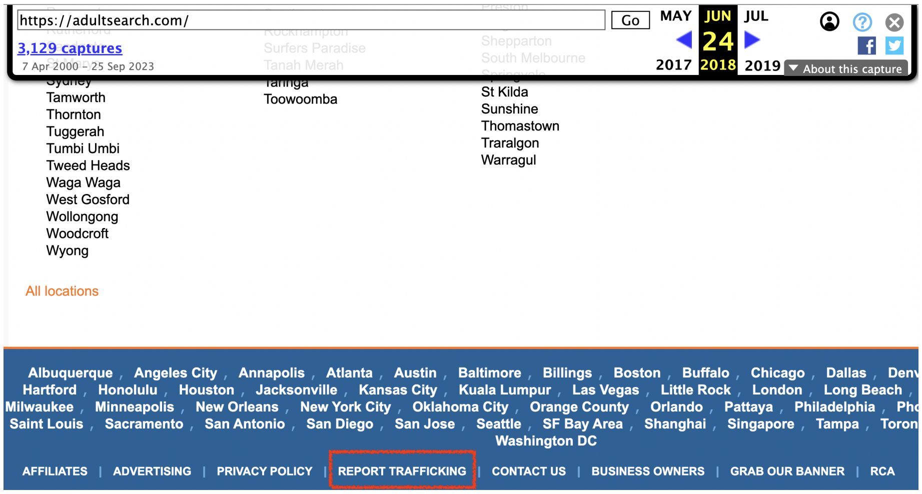
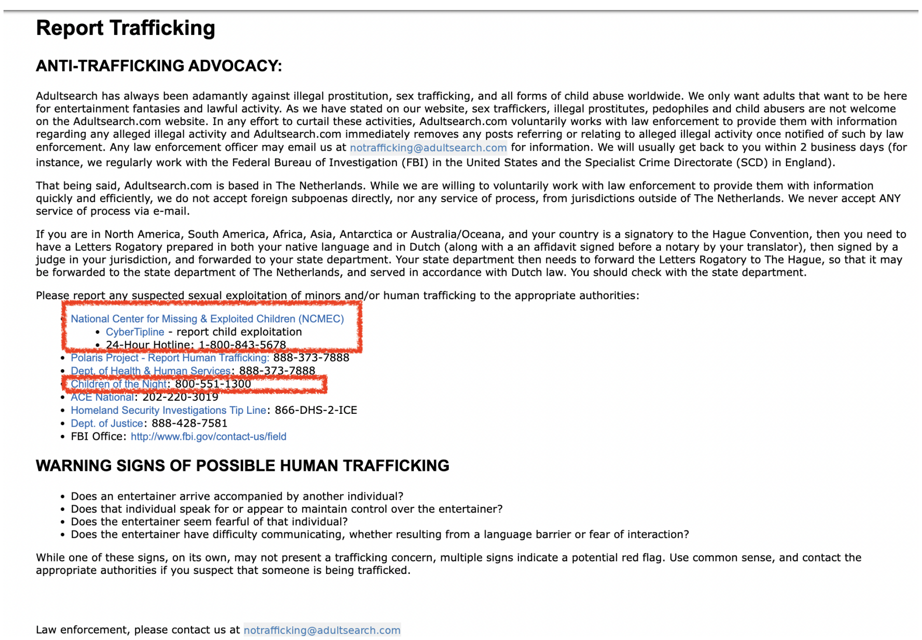



Figure A.2. Footnote on the Front Page of Adultsearch on June 24th, 2018



## 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 A.3. Landing Page for the Newly Added "*Report Trafficking*" Tab on Adultsearch

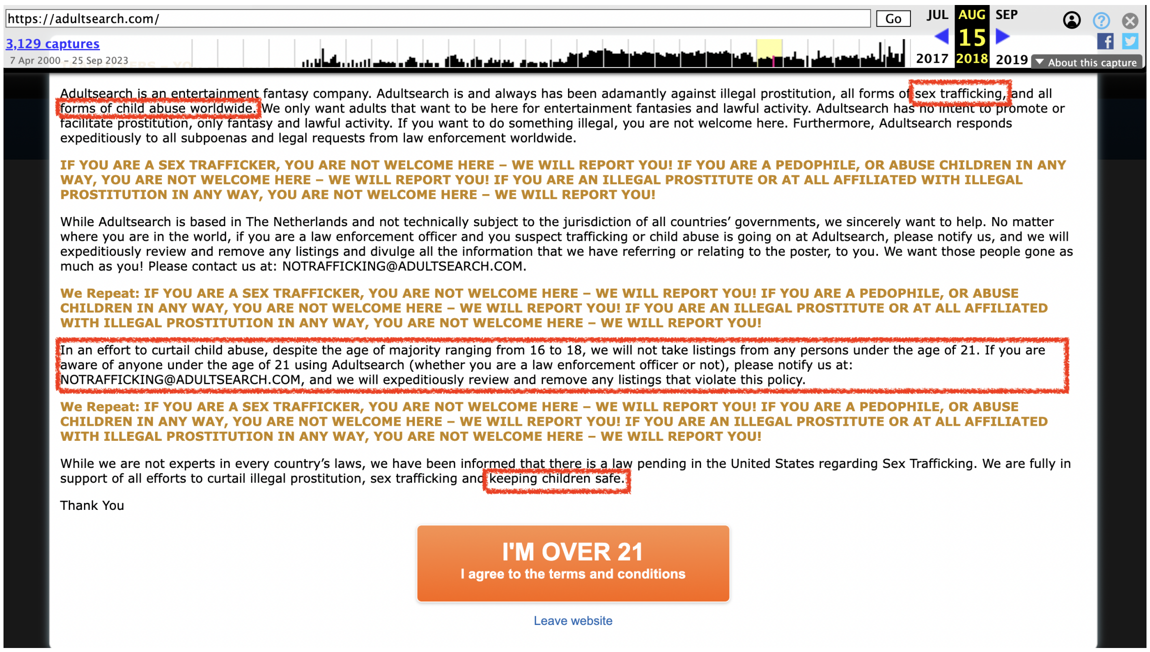



Figure A.4. The Newly Launched "Terms and Conditions" Page on Adultsearch

## A2: Slixa.com

Similarly, Slixa (*slixa.com*) added a statement titled *"STOP HUMAN TRAFFICKING"* at the bottom of its frontpage after the passage of the liability regulation (as shown in Figure A.5 and Figure A.6). The statement includes a link to *trafficking.help*, which connects to a page of anti-trafficking resources (shown in Figure A.7).

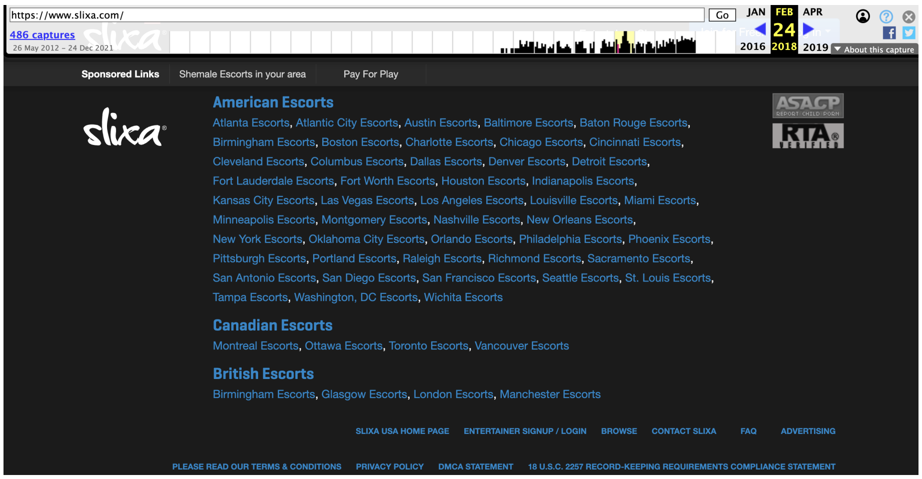



Figure A.5. Footnote on the Front Page of Slixa on February 24th, 2018

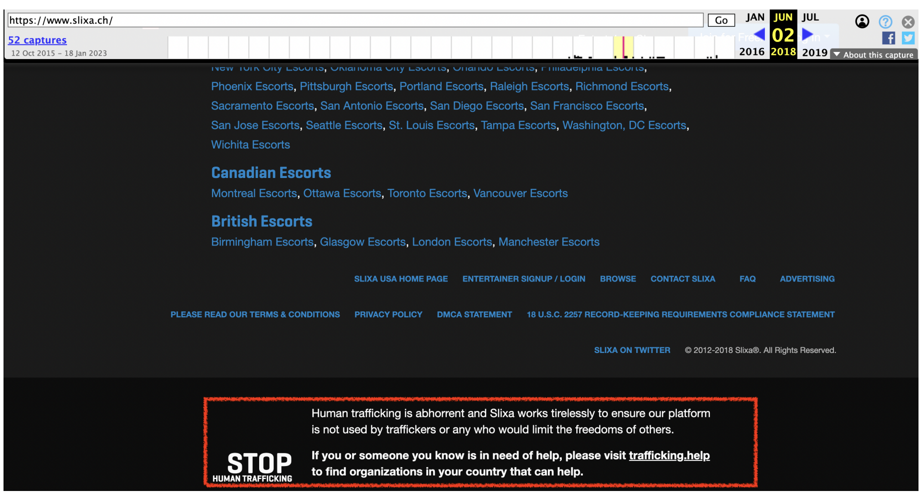
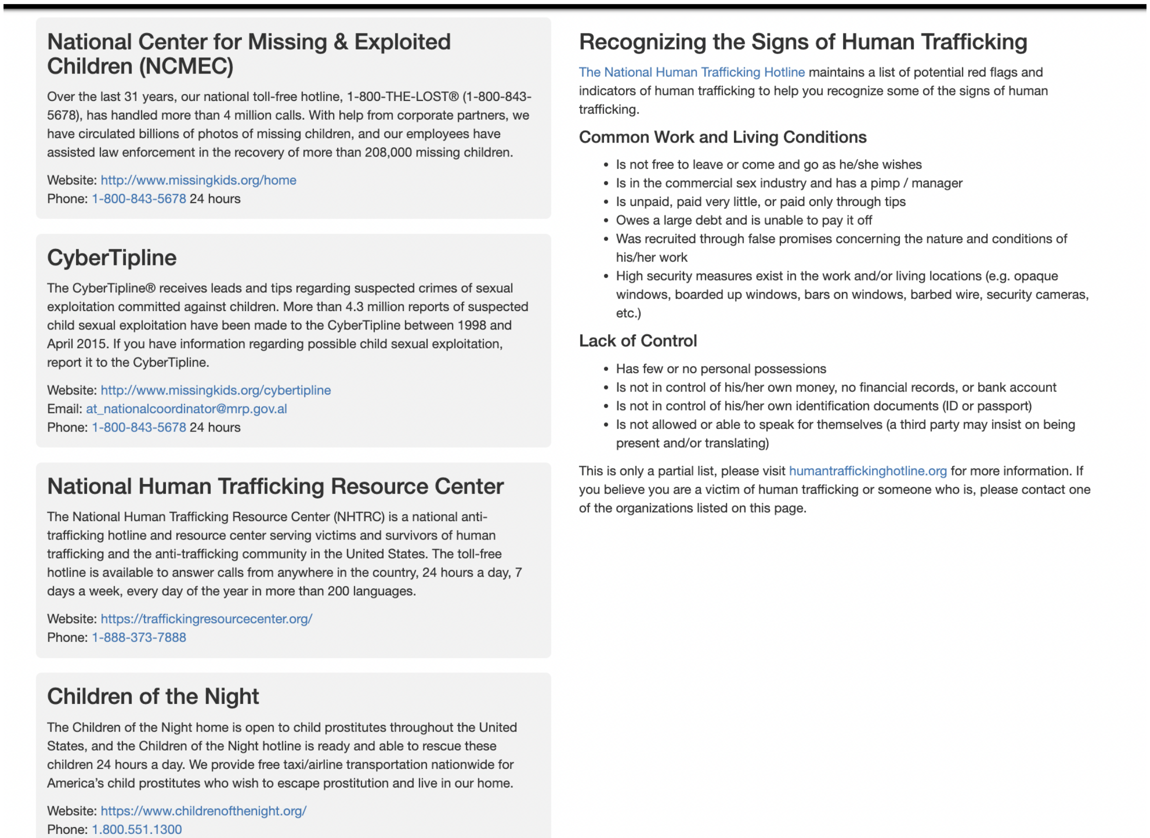



Figure A.6. Footnote on the Front Page of Slixa on June 2nd, 2018



## 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

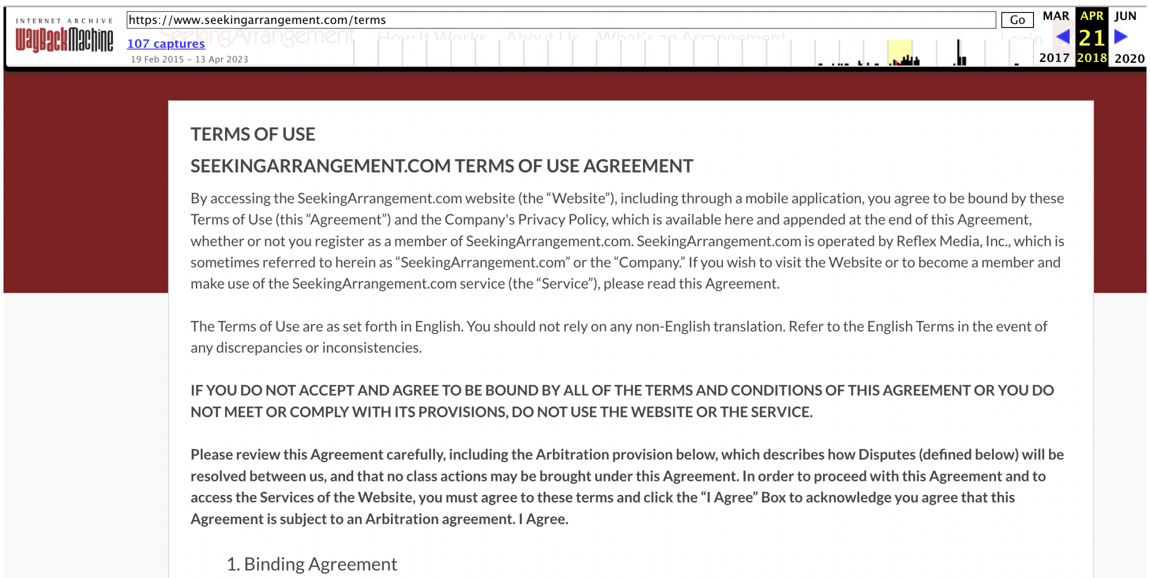
- Has few or no personal possessions
- Is not in control of his/her own money, no financial records, or bank account
- Is not in control of his/her own identification documents (ID or passport)
- Is not allowed or able to speak for themselves (a third party may insist on being present and/or translating)

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 A.7. THE PAGE FOR *TRAFFICKING.HELP* IN THE NEWLY ADDED SECTION OF "*STOP HUMAN TRAFFICKING*" ON SLIXA

## A3: Seekingarrangement.com

The prostitution website[35] Seekingarrangement (*seekingarrangement.com*), updated their terms of use on May 8th 2018. Figure A.8 and Figure A.9 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 A.10).




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.

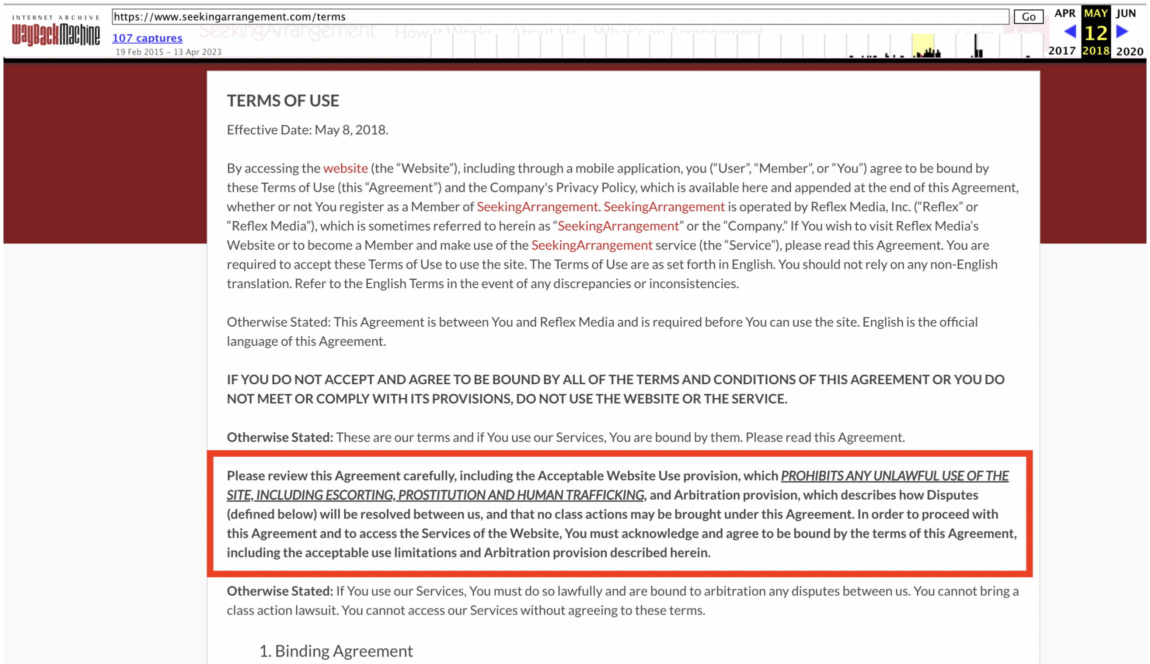
**IF YOU DO NOT ACCEPT AND AGREE TO BE BOUND BY ALL OF THE TERMS AND CONDITIONS OF THIS AGREEMENT OR YOU DO NOT MEET OR COMPLY WITH ITS PROVISIONS, DO NOT USE THE WEBSITE OR THE SERVICE.**

**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 A.8. Terms of Use on Seekingarrangement on April 21st, 2018

[35] See `https://endsexualexploitation.org/seekingarrangement/`.



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.**

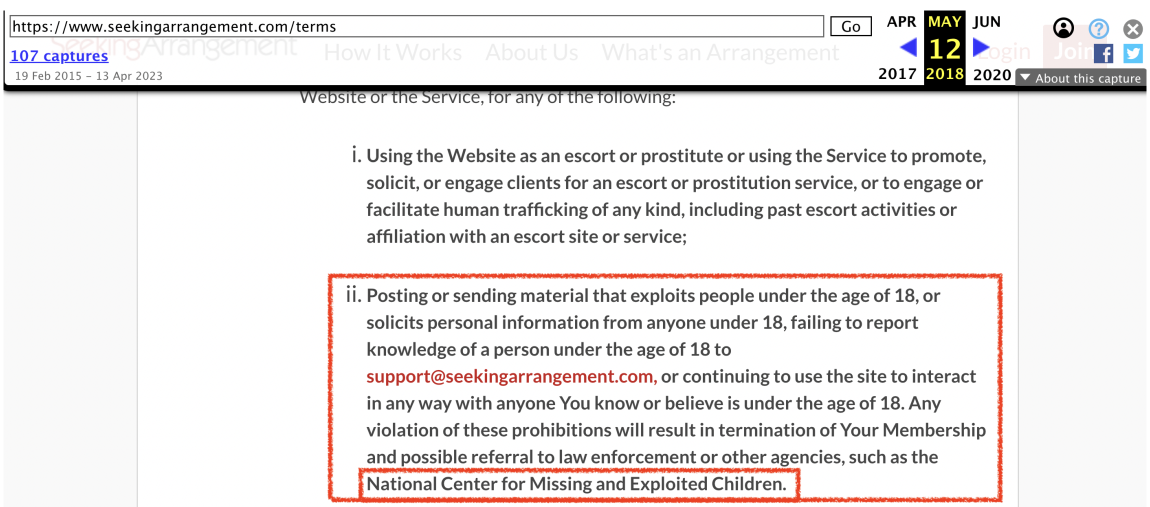
**Otherwise Stated:** These are our terms and if You use our Services, You are bound by them. Please read this Agreement.

**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 A.9. UPDATES ON THE TERMS OF USE ON SEEKINGARRANGEMENT ON MAY 8TH, 2018



Website or the Service, for any of the following:

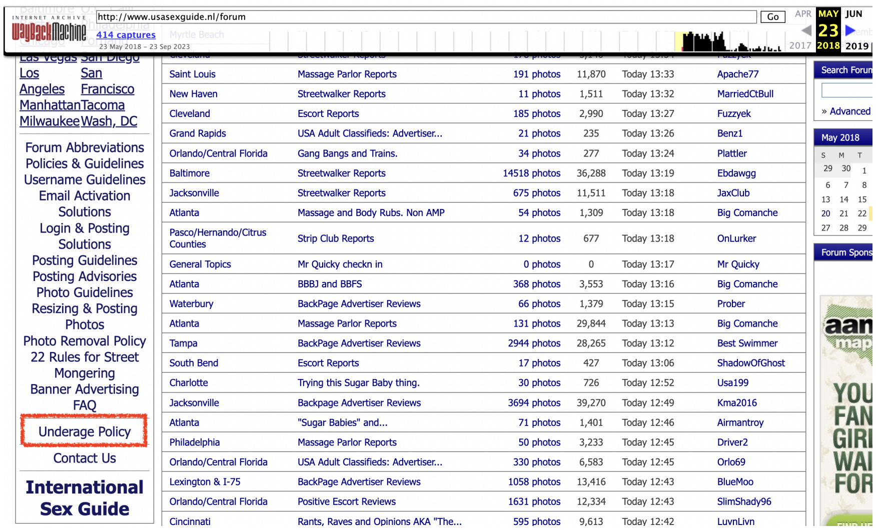
i. Using the Website as an escort or prostitute or using the Service to promote, solicit, or engage clients for an escort or prostitution service, or to engage or facilitate human trafficking of any kind, including past escort activities or affiliation with an escort site or service;

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 A.10. 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 the liability regulation, 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 A.11. The specific terms of the "Underage Policy" are shown in Figure A.12, which emphasizes the website's rules against posting materials for the sexual exploitation of minors.



http://www.usasexguide.nl/forum

414 captures

23 May 2018 – 23 Sep 2023

APR MAY JUN

23

2017 2018 2019

Los Angeles San Francisco
Manhattan Tacoma
Milwaukee Wash, DC

Forum Abbreviations
Policies & Guidelines
Username Guidelines
Email Activation Solutions
Login & Posting Solutions
Posting Guidelines
Posting Advisories
Photo Guidelines
Resizing & Posting Photos
Photo Removal Policy
22 Rules for Street Mongering
Banner Advertising
FAQ
Underage Policy
Contact Us

International Sex Guide

| | | | | | |
|---|---|---|---|---|---|
| Saint Louis | Massage Parlor Reports | 191 photos | 11,870 | Today 13:33 | Apache77 |
| New Haven | Streetwalker Reports | 11 photos | 1,511 | Today 13:32 | MarriedCtBull |
| Cleveland | Escort Reports | 185 photos | 2,990 | Today 13:27 | Fuzzyek |
| Grand Rapids | USA Adult Classifieds: Advertiser... | 21 photos | 235 | Today 13:26 | Benz1 |
| Orlando/Central Florida | Gang Bangs and Trains. | 34 photos | 277 | Today 13:24 | Plattler |
| Baltimore | Streetwalker Reports | 14518 photos | 36,288 | Today 13:19 | Ebdawgg |
| Jacksonville | Streetwalker Reports | 675 photos | 11,511 | Today 13:18 | JaxClub |
| Atlanta | Massage and Body Rubs. Non AMP | 54 photos | 1,309 | Today 13:18 | Big Comanche |
| Pasco/Hernando/Citrus Counties | Strip Club Reports | 12 photos | 677 | Today 13:18 | OnLurker |
| General Topics | Mr Quicky checkn in | 0 photos | 0 | Today 13:17 | Mr Quicky |
| Atlanta | BBBJ and BBFS | 368 photos | 3,553 | Today 13:16 | Big Comanche |
| Waterbury | BackPage Advertiser Reviews | 66 photos | 1,379 | Today 13:15 | Prober |
| Atlanta | Massage Parlor Reports | 131 photos | 29,844 | Today 13:13 | Big Comanche |
| Tampa | BackPage Advertiser Reviews | 2944 photos | 28,265 | Today 13:12 | Best Swimmer |
| South Bend | Escort Reports | 17 photos | 427 | Today 13:06 | ShadowOfGhost |
| Charlotte | Trying this Sugar Baby thing. | 30 photos | 726 | Today 12:52 | Usa199 |
| Jacksonville | Backpage Advertiser Reviews | 3694 photos | 39,270 | Today 12:49 | Kma2016 |
| Atlanta | "Sugar Babies" and... | 71 photos | 1,401 | Today 12:46 | Airmantroy |
| Philadelphia | Massage Parlor Reports | 50 photos | 3,233 | Today 12:45 | Driver2 |
| Orlando/Central Florida | USA Adult Classifieds: Advertiser... | 330 photos | 6,583 | Today 12:45 | Orlo69 |
| Lexington & I-75 | BackPage Advertiser Reviews | 1058 photos | 13,416 | Today 12:43 | BlueMoo |
| Orlando/Central Florida | Positive Escort Reviews | 1631 photos | 12,334 | Today 12:43 | SlimShady96 |
| Cincinnati | Rants, Raves and Opinions AKA "The... | 595 photos | 9,613 | Today 12:42 | LuvnLivn |

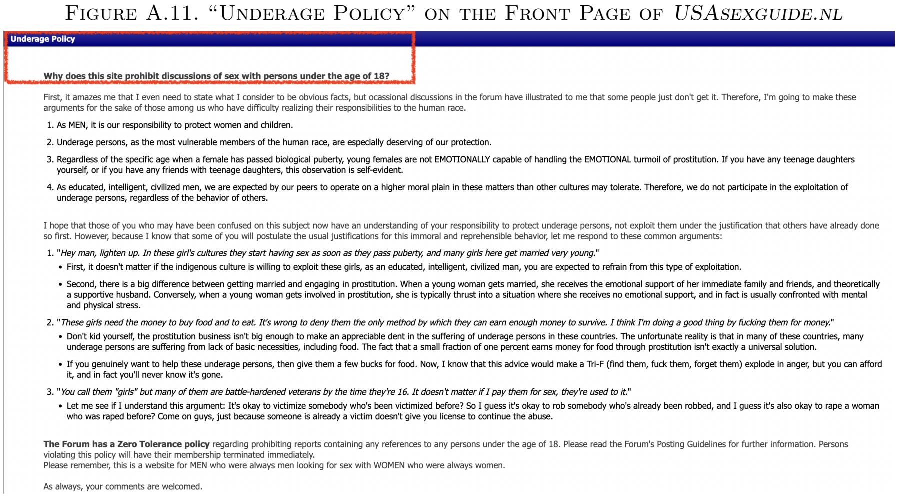
Search Forum

» Advanced

May 2018

Forum Sponsors

FIGURE A.11. "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 A.12. TERMS IN "UNDERAGE POLICY" OF *USASEXGUIDE.NL*

## APPENDIX B Tables and Figures

Table B.1—Descriptions of Control Variables for Data from *"Erotic Monkey"*

| Feature | Description |
|---|---|
| | *Erotic Monkey* |
| Incall | Dummy variable for escort "incall" service, 1 for "incall" services and 0 for "outcall" |
| 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 |
| 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 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 B.2—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 | 0.093 | 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 B.3—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 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 B.4—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 |

Table B.5—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 |

Table B.6—OLS Regression Results for (1)

| **Dependent variable** | ln(*hour rate*) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Youngest\ Age\ Group_p * Post_{pi}$ | 0.140*** | 0.130*** | 0.213** | 0.163*** | 0.155*** | 0.125 |
| | (0.047) | (0.049) | (0.104) | (0.045) | (0.047) | (0.089) |
| $Youngest\ Age\ Group_p * Post_{pi} * \mathbb{1}(Extreme\ Services > 4)$ | | 0.140* | | | 0.126* | |
| | | (0.079) | | | (0.075) | |
| $Youngest\ Age\ Group_p * Post_{pi} * white$ | | | -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 | -0.007 | -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*** | -0.209*** | -0.209*** |
| | (0.056) | (0.056) | (0.056) | (0.047) | (0.047) | (0.047) |
| *white* | 0.070** | 0.070** | 0.073** | 0.064** | 0.064** | 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 | -0.049 | -0.051 |
| | (0.038) | (0.038) | (0.038) | (0.038) | (0.038) | (0.039) |
| *Extreme Services* | 0.044*** | 0.044*** | 0.044*** | 0.043*** | 0.043*** | 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*** | 0.273*** | 0.272*** | 0.252*** | 0.251*** | 0.251*** |
| | (0.061) | (0.061) | (0.062) | (0.061) | (0.061) | (0.062) |
| *Photo real* | 0.059 | 0.060 | 0.058 | 0.017 | 0.017 | 0.016 |
| | (0.098) | (0.098) | (0.098) | (0.103) | (0.103) | (0.103) |
| *Photo updated* | -0.079 | -0.079 | -0.079 | -0.033 | -0.033 | -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*** | 0.229*** | 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 | 0.011 | 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 | 0.132 | 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) |
| Age identification strategy | Simple approach | | | 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 B.7—OLS Regression Results for (8)

| 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) |
| 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 B.8—DMLDiD Results for (4)-(7) with Fake Treatment Time

| | “Fake” treatment effect $\theta$ | |
|---|---|---|
| Fake treatment time | (1) | (2) |
| March 2017 | -0.008 | -0.006 |
| | (0.051) | (0.055) |
| April 2017 | -0.036 | -0.030 |
| | (0.042) | (0.042) |
| May 2017 | -0.056 | -0.048 |
| | (0.037) | (0.037) |
| June 2017 | -0.034 | -0.024 |
| | (0.040) | (0.037) |
| July 2017 | -0.043 | -0.042 |
| | (0.044) | (0.043) |
| August 2017 | 0.023 | 0.021 |
| | (0.042) | (0.046) |
| September 2017 | 0.053 | 0.044 |
| | (0.039) | (0.041) |
| October 2017 | 0.085 | 0.095 |
| | (0.064) | (0.063) |
| Age identification strategy | Simple approach | Age estimation algorithm |

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

Table B.9—OLS Regression Results for (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 |
| Age identification strategy | Simple approach | Age estimation algorithm |

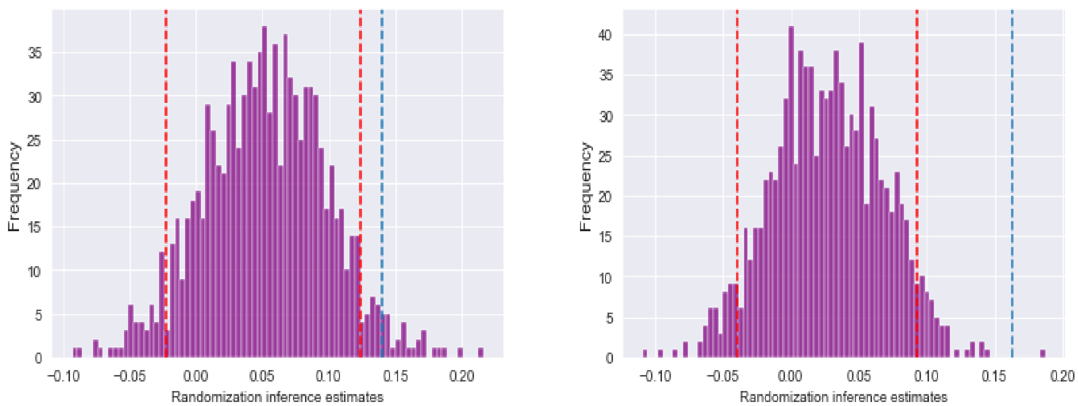



Figure B.1. Distribution of Estimates for $\alpha$ in (1) with 1,000 Randomized Age Assignments for Inference with Providers' Ages Identified Using "Simple Approach" (Left) and "Age Estimation Algorithm" (Right). Blue Dashed Line is the True Effect; Red Dashed Lines are 5th and 95th Percentiles.

## 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 platform-liability regulation 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 have access to 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 has 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 imposing platform liability 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 earler, TER blocked access to its site from the United States in April 2018, which leaves us with a very limited amount of data in the post period.[36] 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 (1)):

$$\ln(\textit{hour rate}_p^{TER}) = \alpha^{TER} * \textit{Age Group 18-20} * \textit{Post}_p + \beta^{TER} * X_p^{TER} + FE_{month}^{TER} + FE_{city}^{TER} + \varepsilon_p \tag{C.1}$$

where the variables are defined as in (1) with the superscript $TER$ notating the data from *"the Erotic Review"*. $\ln(\textit{hour rate}_p^{TER})$ 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 $\textit{Post}_p$ is a dummy variable that equals to 1 if the last update time of the provider's profile is in the post period. $X_p^{TER}$ are a series of confounding variables listed on the site of TER that could affect price.[37] $FE_{month}^{TER}$ and $FE_{city}^{TER}$ represent a vector of *month*- and *city*-fixed effects, and $\varepsilon_p$ is the error term. $\alpha^{TER}$ is our coefficient of interest and represents the change in price of the *youngest age group* participants after the passage of the liability regulation relative to that of other (older) age groups.

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

[36] 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.

[37] TER has slightly different coding systems from *"Erotic Monkey"*. The information on the control variables are included in Table B.3 and Table B.4.

groups.

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 (C.1) with those groups. The results of this robustness exercise are presented in column (2) to (8) of Table C.1. 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 C.1—OLS Regression Results for (C.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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$